AN INVESTIGATION INTO THE CONTROL OF AN UPPER-LIMB MYOELECTRIC PROSTHESIS

by

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Abstract

This thesis presents research that extends current knowledge in the area of upper-limb prosthesis design and control. A study of myoelectric signals (MES)'s using both NHS and other equipment has resulted in identification of the signal source and transmission/detection issues. A globally comprehensive and up to date survey of myoelectric research has revealed new and long-term research paths.

This thesis challenges the old model in interpreting the MES signals by providing and collecting evidence to suggest a new approach to future investigation. The historical description of a stochastic, non-deterministic MES has been shown by this research to be incomplete. An expanded, more detailed physiological description of the MES has been presented as **an improved MES model** in Chapter 7 and demonstrates that it is possible to separate the deterministic and the stochastic elements of the MES. An **original** extensive list of variables underlines the deterministic nature of the MES.

This research has used an **original** controlled **mapping** technique for surface MES's that have revealed unique spectral features for muscle actions. The feature selection and analysis and pattern recognition of the MES has been of fundamental importance to the advancement of prosthesis functionality. Spectral analysis of the MES along with exponential averaging has produced signal identification of potential high reliability and high repeatability

A phenomenon, "the **Tissue Filter Function**" (TFF), has been considered, in past research, as an undesirable consequence of the passage through tissue, of the muscle-generated signal. This TFF shows itself as a frequency shift between at least two signals that are observed at a single electrode site and has shown itself, in this work, to be a previously unused identification feature.

An **original** simplified geometry model of the hand has been devised which greatly improves prosthesis dexterity while minimising the requirement for the many degrees of freedom of the human hand.

An **original** approach proposed is the use of 3 to 4 distinct very narrow band-pass channels in the frequency-domain, signal transient-region as detected by multiple site electrodes (4 or more sites proposed). This data is then in a form suitable to be presented to a Neural Network (NN) pattern recognition tool. This research has shown that the probability is high that the cross coupling between a set of (4) surface electrodes will detect these frequency-shifted signals throughout the 3-dimensional medium of an amputee upper forearm.

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Author's Declaration

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award.

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Chapter 1

Introduction

Definition- Myoelectric: from Myo (Latin) as in muscle: The electrical potential, as detected on the skin surface, generated by underlying muscle activity

1.1 Why Develop a Myoelectric Upper-Limb Prosthesis?

The sudden loss of an upper-limb is certainly a traumatic event. It is only with the loss of the ability to manipulate tools do we realise how the upper limbs allow us to link so readily with our environment. For a many the loss is not only in their livelihood, but also in their relationship to their world. To reconnect with the environment, using an artificial (prosthetic) limb that captures some of the former ability to manipulate, is a reasonable expectation for an amputee.

Need for Research

Numerous designs of an artificial upper limb have been developed by the academic community. None in the past 20 years, except the 'Southampton Hand', were designed to be used directly as a prosthesis, but were targeted at a role as a 'robotic manipulator'. Many have manipulative merit and embody potentially useful developments for the prosthetic community. The robotic designs still suffer an inability to transform directly into a device that could be worn by an actual amputee. Even if the robotic designs were adapted to be worn as a prosthetic, there is the very fundamental issue of establishing a control strategy guided by the amputee that could operate a multifunctional prosthesis. The limited repertoire of control signals has essentially determined the pace of development in upper-limb prosthetics.

The myoelectric signal (MES) taken from the skin surface has been the preferred source of the control signals, but the information content of the MES has not been fully extracted. A

significant improvement in user-generated control actions is clearly needed. Such improvements will also enhance control in the field of robotic and teleprosthetic mechanisms.

Sadly, as will be seen by the overview (in section 1.3.5), only the most primitive of functions are currently available with commercial prostheses.

1.2 Aim and Objectives of this Research Project

The majority of upper limb amputations are below elbow. The residual limb below the elbow retains considerable muscle mass that is capable of user generated, surface-detectable, Myoelectric Signals (MES) that are representative of the intended muscle action. The aim of this research study has been to investigate, in depth, the nature of these MES and extract more "intelligence" from the signals than is currently used in commercial prostheses. The objectives of the research are:

- 1)-to investigate the information content of a MES.
- 2)-to study the nature of the Tissue Filter Function (TFF)
- 3)-to map and identify optimum upper limb (forearm) myoelectric sites
- 4)-to analyse the mapped data for frequency content and other unique identifiers
- 5)-to recommend the practical application of MES analysis for control purposes
- 6)-to provide a greater range of user-generated control signals.

The long-term objective of the programme is the development of a more functional prosthetic hand with increased control action reliability.

This remainder of this chapter will describe the historical development of upper limb prosthetic technology and the current "state" of the art. The issues affecting the development of an upper-limb prosthesis will be introduced and placed in an engineering, and socio-individual, and business-economic context. It is the intention for this context to illuminate the real and imagined barriers to progress.

1.3 Literature Review: Development of Upper Limb Prostheses

1.3.1 Early History of Prosthetics

Up until the 1970's, for an upper-limb amputee, the only serious option for a prosthetic hand/arm was that of a cable-operated device. In the past 25 years, development of the myoelectric arm/hand has been drawn inexorably along by developments in materials, robotics and semiconductor technology. The commercially available prosthesis has been limited to a matter of preference between cable-operated and myoelectric.

As far back as 200 B.C. the historical record [1] tells us of an iron hand fitted to a Roman General. Undoubtedly one-offs of this type were custom built as hooks, claws, etc. throughout the following centuries. In 1509 an Iron Hand with gears for fingers and thumb was produced for the German knight Goetz Von Berlichingen. The surgeon Ambroise Pare (1510-1590) designed and built many prostheses. These devices used ratchets, levers, springs and gears.

1.3.2 History of Prosthetics-1900 to 1950:

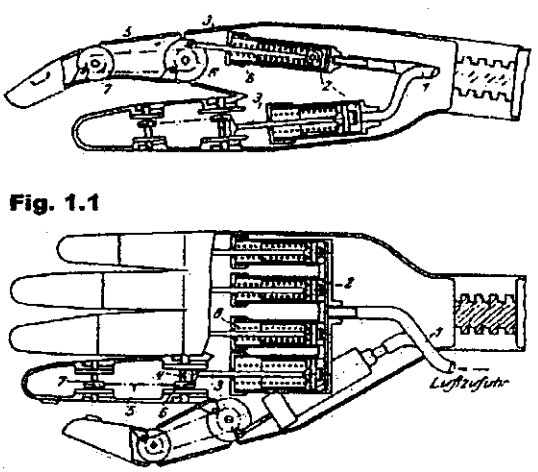

Fig. 1.1

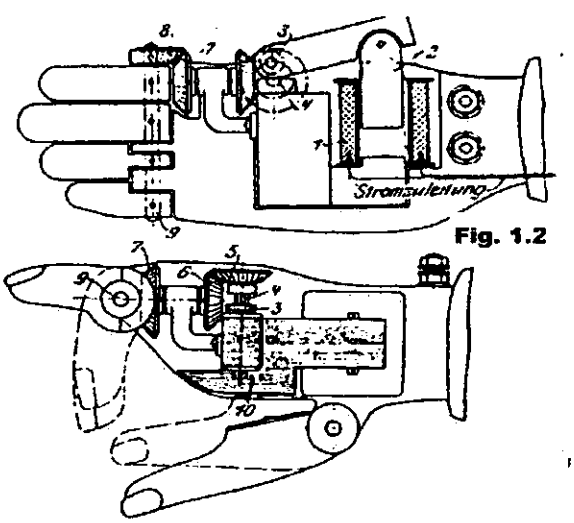

Fig. 1.2

Abb. 178 und 179 PreBluft Hand
Figure 1.1 Early compressed gas powered hand. Perhaps the first powered prosthesis Component.

Abb.180 und 181 Elektromagnetische Hand
Figure 1.2 Early electric hand component. Perhaps the first electric hand mechanism.

From Ersatzglieder und Arbeitshilfen (Limb substitutes and Work Aids 1919).

The body-powered prosthetic limb emerged in 1912 following the development of the 'split-hook' by D.W. Dorrance [2] in San Jose, California and its control by a body/shoulder-powered harness. It was in 1915 in Germany (*see Figure 1.1*) that the first powered prosthetic hand (though pneumatic in operation) was to appear [3] Probably the first prosthetic hand powered by electricity (electromagnet) was in Germany in 1919. (*see Figure*1.2). Some of the earlier work used compressed gas (CO2) power as the energy supply. These [9] were the Heidelburg Arm, Germany, (1948-72), IBM, (impractical), U.S., (1945) Hendon Arm, England (1963-69). It appears that the first myoelectric prosthetic hand was developed by a German engineer/physicist, R. Reiter [4,5] in the early 1940's with his work published in 1948. This vacuum tube amplified hand [6] was operated by electromagnet (Solenoid). From 1946-1949, IBM (Alderson) in America worked on a six degree of freedom electric arm. Apart from weight, it suffered from a lack of control signal sources [9]. In 1948, work began on a pneumatic (CO2) arm-prosthesis. (O. Hafner) at Heidelberg Univ., Germany and continued in 1955 by E. Marquardt. In the same year a pneumatic, arm-prosthesis was fitted at the University [7,8,9]. The idea of myoelectric control of a prosthetic hand surfaced throughout the 1940's and 1950's. In the U.S. (North Western University, Chicago) it was WW2 and the US military brought about the "Committee on Prosthetics Research and Development" (CPRD), which, under the National Research Council, drove much of the work in the U.S. over the following years.

1.3.3 Technical Development -1950 to 1960

The Germans, with their long historical record in prosthetics, produced the next significant development when E. Wilms and Kegel (following on from work during WW2) [10] in 1951 produced the 'Vaduz Hand' (*see Fig.1.3*) at Vaduz in Liechtenstein. The Vaduz hand [3] had remarkable similarities to the Otto Bock hands of today. The Vaduz hand used an

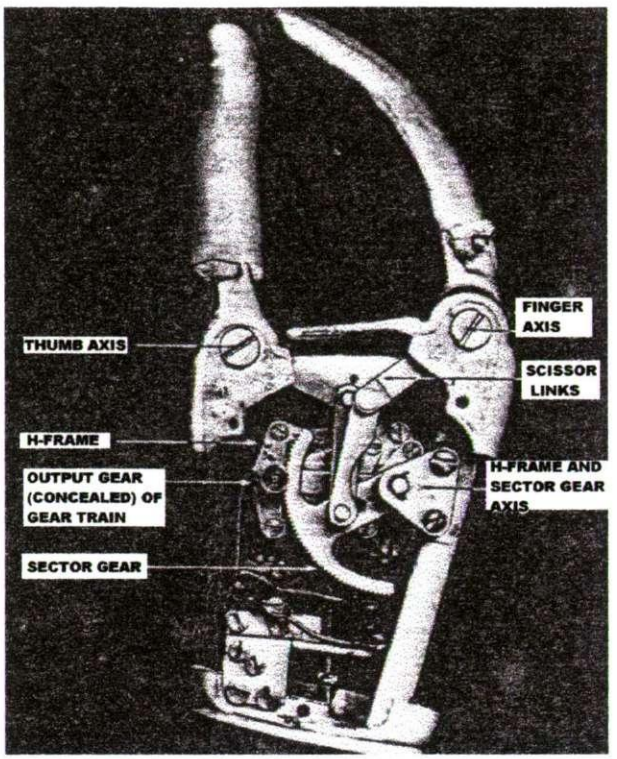

Figure 1.3 Vaduz (French) Hand. From Bulletin of Prosthetic Research, 1966.

automatic gearing mechanism, which gave fast-closing/low-gripping-force and slow-closing/high-gripping-force with the user arm-muscle expansion driving a switch servomechanism [**8**]. The Vaduz hand, sometimes known as the French hand, was available throughout the mid 1960's [**3,11**]

In 1955 Battye, Nightingale, and Whillis at Guy's Hospital, London produced one of the first myoelectrically (threshold) controlled prosthesis with one-degree of freedom [**3**]

In London, England, in 1957, A. Bottomley, K. Wilson, A. Nightingale [**4,12,6**] were developing myoelectric controls. Development of the germanium transistor and its use, by a Russian Engineer Kobrinski, at the Central Research Institute in Moscow, in the period 1957-1960 [**13**], resulted in *the first portable myoelectric hand prosthesis for clinical use.* By 1960, the Russian Hand was being marketed in Canada and the U.K. [**14**].

1.3.4 Technical Development- 1960 to 1970

Bottomley and Cowell, in England (1964) [**15**], introduced proportional control of velocity and force in a split-hook device. In 1965 A. Bottomley, K. Wilson, A. Nightingale produced "The English Hand" using proportional control.

In Yugoslavia, (1961), R. Tomovic was working on an adaptive hand and in 1968 produced "The Belgrade Hand" [**16,17**]. The hand used slip detectors (a rotating ball)

located in the fingertips to indicate movement of an object (see Chapter 1). Though not clinically applied it was to be influential in the following years.

R.N. Scott, one of the most experienced in the field of myoelectric control and active since 1960 at the University of New Brunswick in Canada, produced *the first North American myoelectric control mechanism.* Scott has investigated sensory feedback to the amputee for control purposes and work there is continuing on new and promising approaches to control methods using pattern recognition **[4,18]**.

By 1965, a multi-function adaptive hand had evolved through researchers in Sweden. It was known later as the Sven Hand, from which further Swedish work has evolved. The SVEN hand was a 4-degree of freedom hand used in research and was offered in limited commercial form in Sweden in the early 1970's as the ES hand (Ee&Holmgren and Systemteknik).

The Systemteknik Hand **[9,15]** grew out of the SVEN group and was the only small (less than 1yr. old child) size model for many years. Production was later transferred to the H.Steeper Co. U.K.

Otto Bock, the prosthetics manufacturer, was founded in 1919 in Berlin, Germany. and worked with pneumatic hands in the early 1960's. From 1963 to 1965, Otto Bock (Orthopaedic Industries) collaborated with Viennatone **[3]**, (Austrian hearing-aid company with electronics expertise **[3,16]**) and an Austrian gentleman Zeeman (inspired by his studies of the Russian hand in Moscow). Together they produced the "Viennatone Hand." This was the first "Western" commercial hand. By 1965, the Otto Bock Orthopaedic Company had produced a commercially available, one-degree-of-freedom, electromechanical, hand/arm, prosthesis (using the thumb moving in opposition to the index and middle fingers **[3,8]**). This is still the same operational action as found on all new prostheses by Otto Bock and other manufacturers.

The "Viennatone hand" underwent another incarnation through the efforts of the U.S. Veterans Administration Prosthetics Centre (VAPC) and was subsequently marketed in the U.S. by Fidelity for some years.

At the (INAIL) Centre, near Budrio, Italy, Professor Schmidl developed a driven-lead screw-and-nut operated hand prosthesis that provided a locking grasp.

D. Childress at Northwestern University in Chicago in 1968 used the Viennatone hand with his own myoelectric controller design to produce one of the first-ever self-contained, and self-suspended, below-elbow prostheses [3].

In England in 1966, J. Collins at Hugh Steeper Ltd. of London designed a simple adaptive prosthetic hand [19].

The Waseda hand, started in 1964 under Prof. Ishiro Kato in Japan, followed on from work by Barrachino of France on a multi-fingered adaptive hand [8,9]. Their work resulted in the WIME hand in 1978. The hand used pressure sensors attached to the fingers that fed back the reaction force to amputees by electrocutaneous stimulation. This hand was made commercially available by the Imasen Company, Nagoya, Japan (Note: commercial information on this hand has been unavailable and suggests low acceptance within the prosthetics community).

The human hand has more than 27 degrees of freedom (**103, p354, 402**). Multi-fingered "hands" with multiple degrees of freedom of movement became a focus of many research groups since the 1960's. The distinction between robotic manipulators and prosthetic hands became blurred as researchers tried to anthropomorphise these robotic devices.

1.3.5 Declining Rate of Improvement and Stasis: Post 1970 to date

By 1967 it had became possible to buy a powered prosthesis [4,20] but it was not until 1980 that myoelectric prostheses became a clinical alternative. Steeper and Systemteknik collaborated for a few years before Steeper began production of its own product in the 1980's [21]. Variety Village in Ontario, Canada, following work with Systemteknik,

introduced a new lightweight, children's hand [21]. *Figure* 1.4 shows the experimental Stanford University/ JPL (Jet Propulsion Lab) hand (1985, Salisbury) **[20]**, a 3-fingered (each of 3 degrees of freedom) hand operated by motor and cables. *Figure* 1.5 shows the Utah University/MIT (Mass. Institute of Technology) experimental, 5-fingered hand, (1986, Jacobsen, Iversen, Knuti, Johnson) **[22,23,24,25]**. *Figure* 1.6 shows the Belgrade Univ. /USC Hand (University of Southern California) (Tomovic, Bekey, 1990) **[16,26,27,28,29,30].** This was a five fingered device, with the fingers each

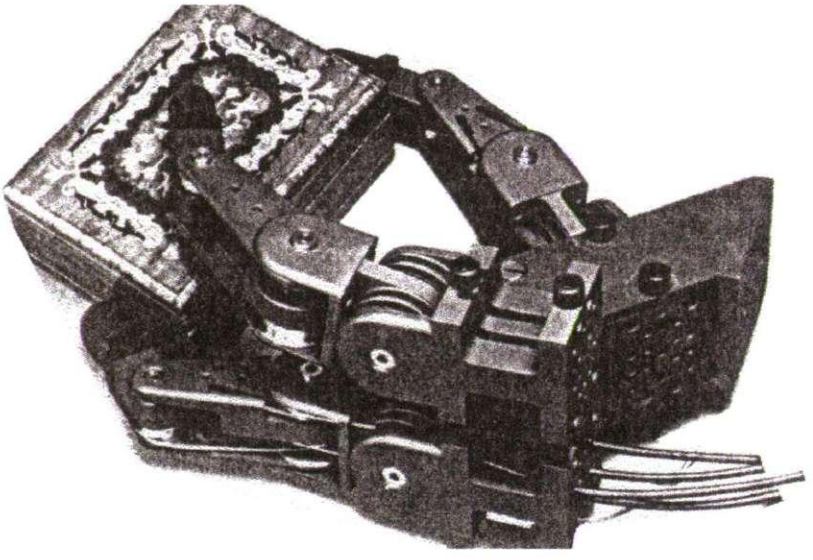

Figure 1.4 Stanford University/ Jet Propulsion Lab hand (1985).
From "Robot hands and the Mechanics of manipulation".

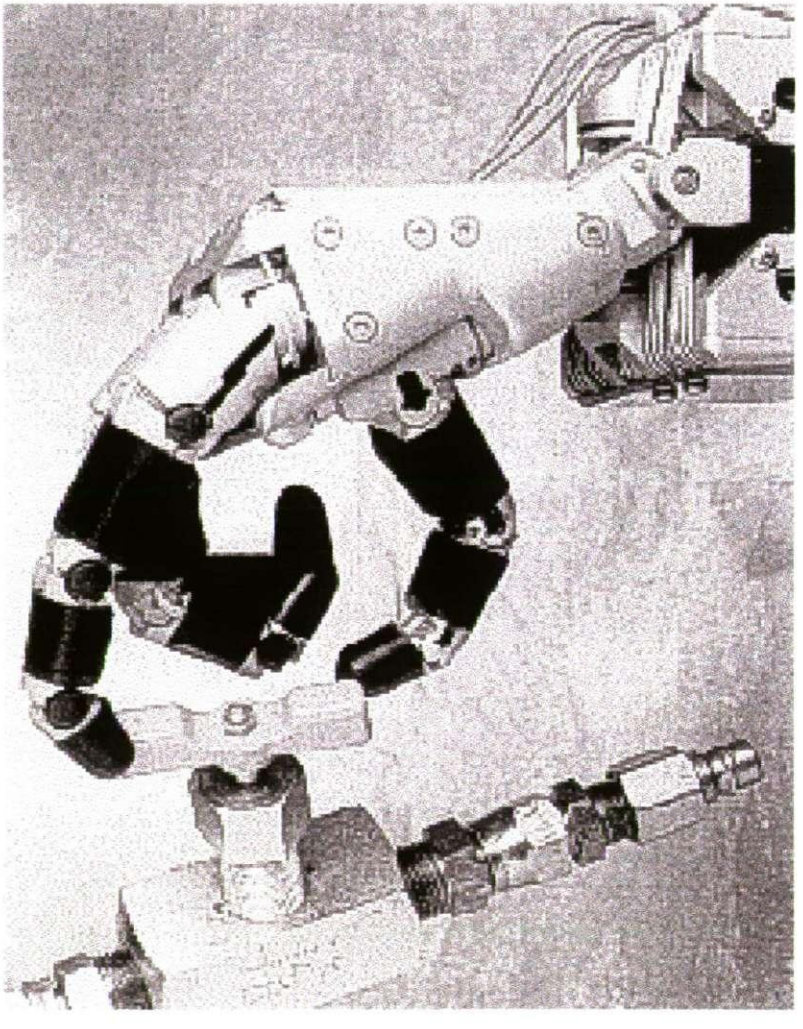

Figure 1.5 Utah University/ MIT Hand. From 'Design of the Utah University/MIT Dextrous Hand' Proceedings of the IEEE Int. Conf. Rob. and Autom.

exhibiting a single 'curving' degree-of-freedom and the thumb with 2 degrees-of-freedom. Of these three hands, none is suitable for a prosthetic hand and have really been designed as end-effectors for robot/anthropomorphic arms. Considerable control cable, actuator mechanisms, electronics and computer software control are required to operate these end-effectors.

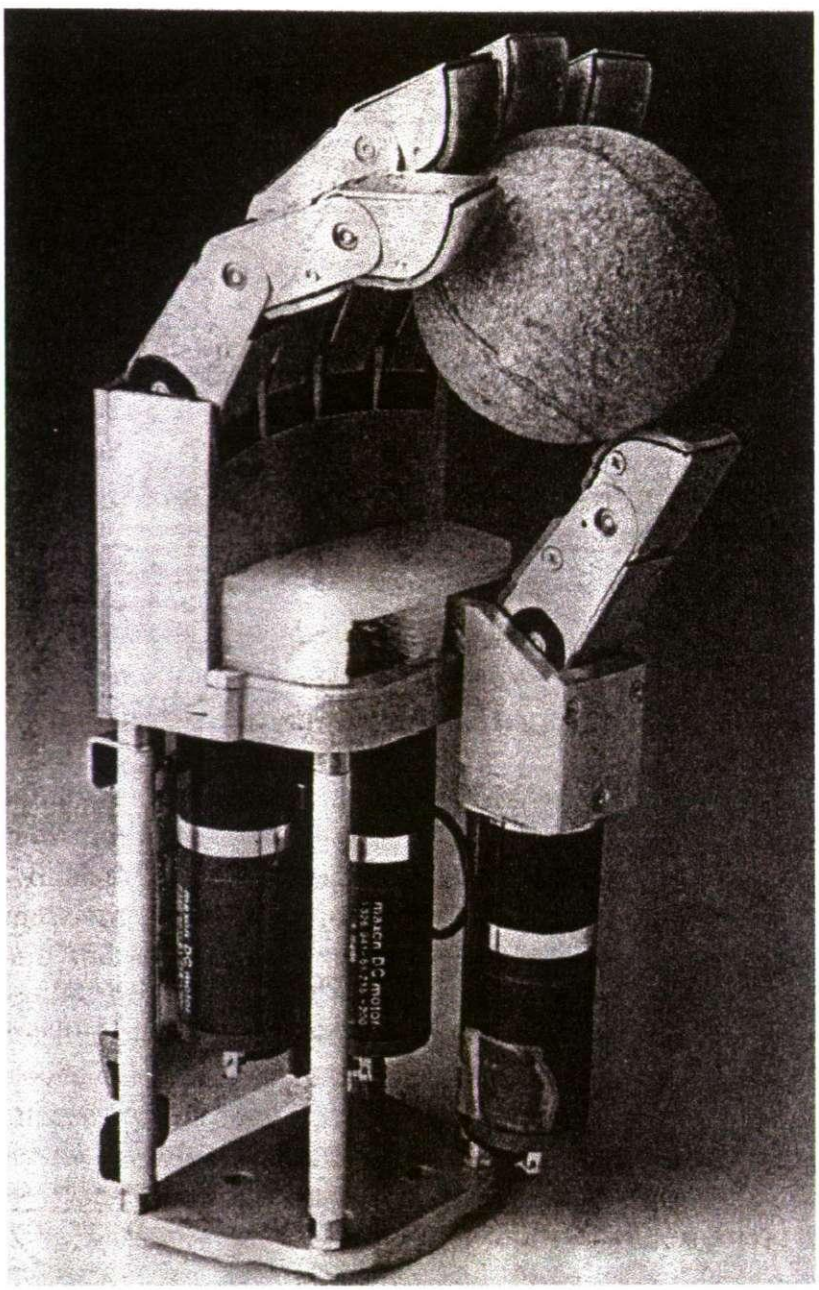

Figure 1.6 Belgrade University / USC Tomovic/ Bekey hand (1990).
From "Dextrous Robot Hands",by Venkataram and Iberall, Springer-Verlag, (1990).

1.3.6 Control-Signal Sources and Limitations

Following an amputation the amputee stump will have a residual mass of muscle that can be activated and made to cause a measurable movement of the skin surface. Just as the MES is a "downstream response" of the user intended activity, so is the movement of the muscle and skin surface.

This physical movement of the forearm stump surface produced by muscle movements can be measured and correlated to intended muscle actions using various movement detection sensors. Strain gauges, piezo materials, force-sensitive resistors, or Hall-effect movement detectors have been considered. These differing methods can be used singly, or in combination, to positively identify such signals.

1.) Piezoelectric

- The piezoelectric generator is a method that shows promise. In experimental work, at the University of Plymouth, small piezo sensors have been shown to be quite effective in producing a strong signal, in response to a muscle action that moves the skin surface. A movement sensor that has a small point/surface contact area of less than 10 mm^2 is however more sensitive to the accuracy of placement position than is the MES detector. This is due to the focus area of physical movement being smaller than the more diffuse MES signal that propagates across a wider surface before fading. This may limit its practical implementation. Other limiting factors for the piezo are:
- Vibration disturbances can induce jelly-like movement of the flesh/muscle and an unintended output response from the piezo sensors. This is a major problem.
- The difficulty is considerable in mounting these sensors, keeping in mind the need for a fixed reference point/mounting position from which **relative** movements can be established.

As a consequence of investigations at the University of Plymouth into piezo sensors, an approach using a piezo material that can "mould" itself around a stump (like a flexible thick membrane/skin) was conceptualised to address the problems encountered. The surface deflection signals would be divided into a grid pattern that could be fed back as a large array of signals that can subsequently be processed for pattern recognition.

2.) Force Sensitive Resistors (FSR)

As in the piezo material, the FSR is a candidate for detecting the surface movement, if it is presented as a moulded surface around the muscle stump. One of the problems with FSR is their non-linear response and hysteresis tendency. To utilise the FSR signal with such limitations should be weighed against the experience of users and research. This suggests a preference for wide-band, discrete, control actions.

3.) Muscle Sounds

Muscles have been shown to produce sounds **[31,32,33,34]** at the resonant frequency of the individual muscle. These sounds are in the 5 Hz to 250 Hz range and can be detected by an ordinary acoustic microphone. The peak energy/dominant frequency is found to be about 25 Hz., with power decreasing as frequency increases (known as "pink noise", or "1/f noise," or "flicker noise") in which the noise has equal power per decade of frequency). Fast-twitch muscle fibres respond in about 40 ms. (or a 1/25th of a second), due to the regeneration rate of the ATP (AdenosineTriphosphate) controlling the contraction of muscle. The 25 Hz vibration is likely to be along the long axis of the muscle. In all likelihood the muscle sound could be used as a discriminating source for prosthetic control. The problem, with muscle sounds, is they do not exist in isolation but are generated and exist within a sound-filled environment. The dominant 25 Hz peak sensitivity would be too often recreated by, and inseparable from, our environment. Differential amplification using two microphones as inputs (signals picked up simultaneously will be cancelled/ignored) could reduce extraneous sound influence. Directional sensitivity and a clever algorithm

need to be developed before muscle sounds can be reliably utilised as a prosthetic control source [35]

4.) Implantable Signal Sensors

Implanting of detection sensors for muscle, nerve, and sound-derived signal sources has a strong attraction for control of prostheses. In principle, the nearer one gets with a sensor to the source of the signal, the less signal information is lost. This is particularly true with myoelectric signals (MES) and Nerve signals. The nerve is of course the source of stimulation for a particular muscle or group of muscles. There are both biological and technical reasons [36,37] for the lack of progress along this front. These are:

- The problem of invasive surgery:

  Patients may not be amenable to surgery. Surface mounted detection methods, of course, require no surgical procedures.

- The problem of implant-reaction:

  The material used must be non-reactive with tissue and minimal in volume

- The problem of powering the implant:

  1.) Non-inductive implants require power and signal lines that pass through the skin. These entry points can be a constant source of irritation /infection

  2.) Inductive implants draw their power supply and transfer data by telemetry. The transmission requires inductive coils and associated circuitry on both sides of the skin. Efficient coupling to capture the energy is essential. In addition to the implant interference-immunity requirement, interference with other electronic equipment (under the new EEC noise emissions regulations) could prove to be a problem.

There are delicate micro-surgical requirements at the site of the muscle connections. The problem of a reliable, non-destructive, continuous attachment of the sensor to the actual site for signal extraction is compounded by the difficulty to restrain the movement of the

sensor mass and attachments.

1.4 Designing for the Amputee: The Engineering Issues

For the amputee the issues to be considered in developing an **acceptable** myoelectric prosthesis are broadly:

- Weight,
- Socket fit and comfort
- Breathe ability of socket to skin interface
- Load distribution of prosthesis to amputee stump
- User-Signal-Interpretation (natural VS substituted)
- Dexterity
- Cost,
- Cosmesis (appearance) [**4,38**].

Hardware specifications to be addressed are:

- Energy Supply
- Actuator/motor Control
- Mechanical Construction and Maintenance [**38**]

1.4.1 Kinematics

Kinematics is the description of the relationship between positions, velocities, and accelerations of the links of an artificial manipulator. With kinematics, it is possible to calculate the position of one end of the system of links, relative to the other end. These links are generally developed from a starting reference position described as the base (the unmoving fixed reference point).

With a robot arm, the repeatability of an action can be made quite reliable in response to a fixed software command. With the robot-base not moving, the links can be repeatedly directed to an object to be grasped, and the grasp action achieved. If the reference base

position is moved however, the program must be adjusted to account for that change or the grasp cannot be achieved as before. With the human arm being in a constantly changing reference position, the use of kinematics to achieve a target, using only a programmed response describing the exact positions of the link positions, is clearly going to produce poor results.

There is ***no evidence*** that the natural human movement activity is organised around a system of kinematics but **there *is evidence*** **[39,40,41]** to suggest limb movement is driven by a "**ballistic response**" method. With a "**ballistic response**", an arm is "fired" with the hand in the general direction of the target and the trajectory adjusted at intervals, en route. The first interval-adjustment occurs within close range of the target. In control theory, this would be a closed-loop control system with sensory (visual or haptic) feedback to calculate the error correction. The principle is demonstrated below (see *Figure* 1.7 below) as each arrow represents an adjusted trajectory stage.

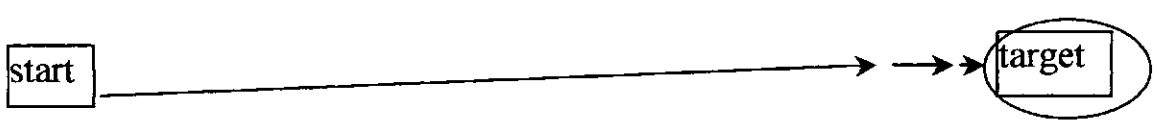

Figure 1.7 A ballistic response with trajectory-adjustment stages

With this in mind the designed control system need only be concerned with being able to return to known co-ordinate positions, e.g. relaxed /rest position for the hand, as starting positions.

The actual grasping action can be achieved using either of two differing approaches:

1) The MES can direct the digits in a ballistic type action: with the feedback pathways provided by human visual cues or hand/digit based electronic tactile sensors.

2) The MES can be used to trigger a staged grasp action: in which a complete hand pattern is formed rather than an individual digit movement. The hand pattern would be limited by force sensing

1.4.2 Reaching Action

The natural action of the human hand, in a reaching and grasping action, requires that, (using visual feedback), a reference point on the thumb or fingers be maintained with respect to the intended target contact-point [**42**].

This reference point is then guided in a fixed position relative to and along an axis set between the target and the wrist (or forearm) and on toward the target point on the object. The important point here is the relationship between the position of the reference point and the remaining digits with respect to the axis or midline of the path. The reference point consistently remains much closer to the axis (midline) than do the remaining digits. As the target object is approached, the remaining digits close upon the target and the reference point is much less active in the closing action [**43**].

The example shown in *Figure* 1.8, in which the thumb is seen to move towards the target and the index finger closes, should illustrate this natural tendency.

The natural movement relationship between user thumb and finger is such that the angular speeds of closure between finger and thumb are not equal. The thumb is used as a point of reference upon which the fingers close [**42**].

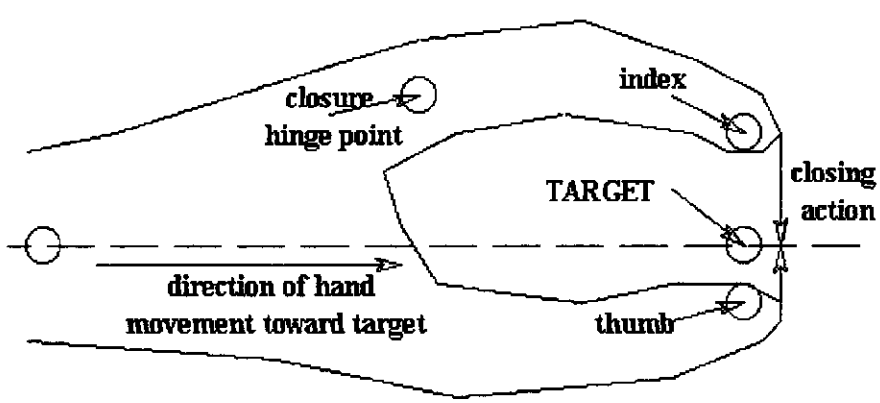

FIG. 1.8 Natural hand action of thumb moving/closing towards index finger

1.4.3 Current State Of Upper-Limb Prosthetics Technology

Commercially available prosthetic devices have a very primitive grasping action limited to movement in a single plane (one degree-of-freedom). This movement is nothing more than a pincer-like action in which the thumb and coupled ring and middle finger share a common pivot point and touch together in a three-jaw chuck configuration (*see Figure 1.8).*

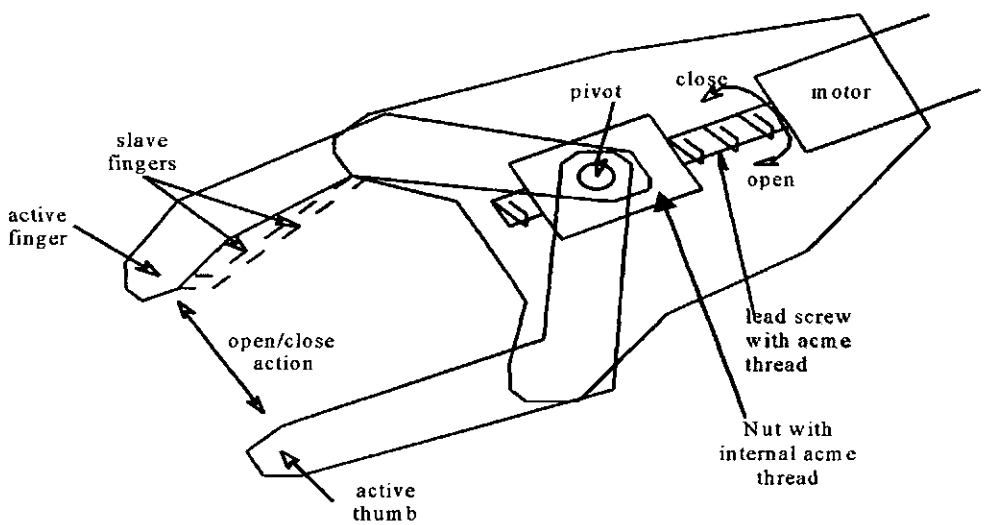

FIG 1.9 Standard pincer grasp action and simplified lead screw drive of a commercial prosthetic hand.

Figure 1.9 shows the operational action, within commercial prostheses, that has been the standard for the past 25 years [**44,45,46,47**] (see also appendix page 241-242). Not only is the grasp action very limited, but there is the problem of:

1). Exerting the correct grasp pressure that can hold a fragile object without crushing

or **2).** Preventing slippage due to gravity or low surface coefficient of friction of a held object

or **3).** Allowing for ability to release grip pressure in controlled increments

These are all aspects of the same problem of **grasp force control.**

The human hand is under intelligent supervision with very many and complex feedback paths to accomplish these grasp control requirements.

The need for reliable control signals to operate an artificial manipulator that can be configured to different grasp functions (with slippage response), could describe the needs of both the prosthetics and the robotics community.

A robotic arm operates in response to command signals generated within a highly controlled environment and "envelope" range. The software is written to take into account a very limited change in the environment of the working robot. The control algorithms must assume certain constants in order for the control action to be effective. If the reference base of the robot is not fixed or "knowable" (in some relative or calculable manner), then the robot control algorithm cannot determine its position in space. The results could be quite damaging to both the robot and the environment.

In a similar way, if the prosthetic hand is to be operated from a software control algorithm, then it must have a reliable reference point. (i.e. a fixed "base" from which it can operate and produce a desired grasp response). The prosthesis user however is constantly moving around and changing orientation of the entire prosthesis. The "base" is consequently not working in an environment known or knowable to the software. The prosthetic hand can know the relative position between its functional parts and thus calculate its own "kinematics" relative to one of those parts chosen as a reference "base". Although the amputee (the prosthesis "user") knows his/her spatial orientation and the position of objects in the working environment, the prosthesis has no access to this knowledge, unless the "user" can communicate that human knowledge to the prosthesis. This "positional/environmental orientation" is, however, the most fundamental missing feedback element for a safe and reliable control action. "Position" is but one of the missing feedback elements that we take for granted in the intelligent control actions of the human hand.

Therefore, if an amputee is to operate prosthesis, he/she must offer some assistance in the "positional" control action of the prosthesis. This assistance is usually accomplished by the

user moving (orienting) the entire body in such a way as to bring the prosthetic gripper into a position in which an open or close action can begin. It is the loss of the fine control feedback, along with the extremely limited actuator-action, which results in the exaggerated, compensatory actions taken by the user.

So we see that for improved control of a prosthesis we need to have in place a feedback mechanism that in a limited way can "complete the feedback loop" through the user.

1.4.4 Actuator/Drive Methods

The technology options for the substitution of muscle power have to date been shared out amongst the following four types of drive methods

1) **Hydraulic**: In particular, these have found a home in industrial robotic operations. The inevitable leakage of hydraulic oil associated with hydraulic systems and their need for line pressurisation and the extra weight associated with the hydraulic supply, have prevented them from becoming a prosthetic option.
2) **Pneumatic** systems have definite weight advantages over both hydraulic and electric motor drives [48]. For example, the electric hands, by Steeper and Otto Bock, weigh approximately 230 grams and the pneumatic hand potentially at 100 grams. The complete pneumatic prosthesis (with disposable CO2 gas cylinder) could weigh in at half the weight of a complete electric prosthesis. Hand opening and closure times are potentially less than half of electric systems [48]. However, a myoelectric interface would be necessary and might reduce the weight advantage. More development needs to be carried out in this area.
3) **Motor/gearbox:** The major prosthetic suppliers use this method (Otto Bock, Steeper), in various configurations. The motor is located in the hand and produces a single degree of freedom, open/close pincer-like (3-jaw chuck) action between thumb and index and middle fingers (see Appendices).

4) Motor/Cable: Robotic Researchers have used this method (e.g. Stanford and Utah/MIT) but actuator and cable weight need consideration.

1.4.5 An Artificial Muscle

Research needs to be done with synthetic polymers of solid structure that could be coerced by a low voltage to cause a small but cumulative percentage change in their length. In principle, synthetic polymers could approximate the function of natural muscles, and be controlled as if they were natural muscles. To date no such synthetic muscle has been developed. When this does occur, the issues of motor and gearbox weight, volume, backlash, and inertia will be past history and a lighter, cheaper and more responsive actuator system, that mimics the natural muscle, could be utilised. More recently, Soares, 1997, at the Univ. of Edinburgh has constructed an artificial muscle using a "shape memory alloy". Power consumption (heating) is very high with heating/cooling time constants overly long and consequently not yet suited to battery operation. Successful development to a practical prosthetic actuating mechanism will require more work [**49**].

1.5 Basic Control Methods: Past and Present

Myoelectric control requires one or more highly sensitive electrodes placed, on the skin of the amputee stump, over the muscles (flexor and extensor for below-elbow amputees). Here small electric potentials of the order of 1 to 100 microvolts corresponding to stump muscle-activity are picked up on the skin surface and amplified for the purpose of controlling the prosthetic hand action [**50,51**].

The following different control approaches have been taken.

1.5.1 The "2-site/2-state"

This is the most widespread control method. The stump muscle action is detected and any MES voltage over a set threshold is picked up by the electrode. This triggers the hand

opening action. As long as the threshold is exceeded, the hand continues to remain open. Using the same threshold method at a different site, a signal from a different stump muscle is used to close the hand. However, the amputee needs to learn to produce these isolated muscle movements from at least two sites on the stump. The forearm flexor and extensor muscles are chosen for the control muscles and some training to use these muscles in isolation is generally required.

1.5.2 The "one-site, 3-state"

This control method uses a single muscle site. A large muscle contraction opens the hand, and a smaller contraction closes it. With no muscle contraction, the hand action stops in place. A variation on **1-SITE, 3-STATE** is the use of **"RATE-OF-CHANGE OF SIGNAL"** as the signal characteristic, as compared to the basic amplitude/threshold activation.

1.5.3 The "1-site, 2 state"

This control method uses muscle action at a given threshold to open the hand, followed by automatic hand closure when the signal is less than the threshold level.

1.5.4 Proportional Control

This control method gives a hand opening and closing response that varies with muscle action intensity. The speed, torque, or position can be varied proportionally (though, as yet, only one variable can be selected).

1.5.5 Hierarchical Control

This control method uses level and proportional control and semi-autonomous states of hand-grasp (that may employ force and slippage sensing). The Southampton Hand is an example of a hierarchical control system. The Southampton Hand with its Southampton Adaptive Manipulation Scheme (SAMS) control uses a micro controller and sensors to free the amputee from the task of "holding" an object yet still allows the user to override when necessary (**52,53**) [for further details see:**54,55,56,57,58,59,60,61,62,63**].

Therefore, each electrode site can produce an on/off function with a single further intensity variation as optional. Hierarchical systems [6] have further options within states but the demand on the user is the necessity for the muscles to exert a precise control of signal levels. This requires another level of skill and practice by the amputee and may not be suitable for a broad range of prosthesis users.

1.5.6 The Southampton Hand

In England at Southampton University, the original Southampton Hand was built in 1969 [64]. The University has had an ongoing development of the hand since then with contributions by J.Baits, E.Gatto, R.W. Todd, J.Nightingale, R.D. Codd, D. Moore, P.Chappell, M. Barkhordar and P. Kyberd. Collaboration between Southampton and Oxford Orthopaedic Eng. Centre resulted, in 1992, with P. Kyberd producing a multiple degree of freedom prosthetic hand. The control method (see *Figure* 1.10) used was their SAMS (Southampton Adaptive Manipulation Scheme) [65,57]. This 3rd generation hand was built upon the earlier control work and was tested on a single degree of freedom hand (a Viennatone) and on their own 4 degree of freedom hand (*see Figure.1.11*) which has since then undergone refinements into a two degree-of-freedom hand.

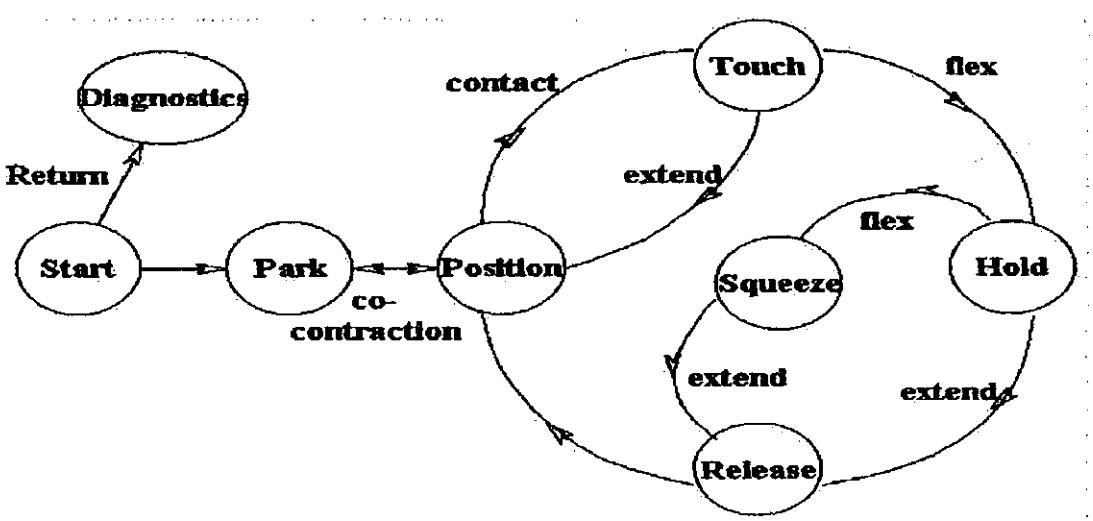

Figure 1.10 State diagram of the SAMS control scheme for the "MARCUS Hand". From IEEE Trans on Rehab. Eng., March, 1996.

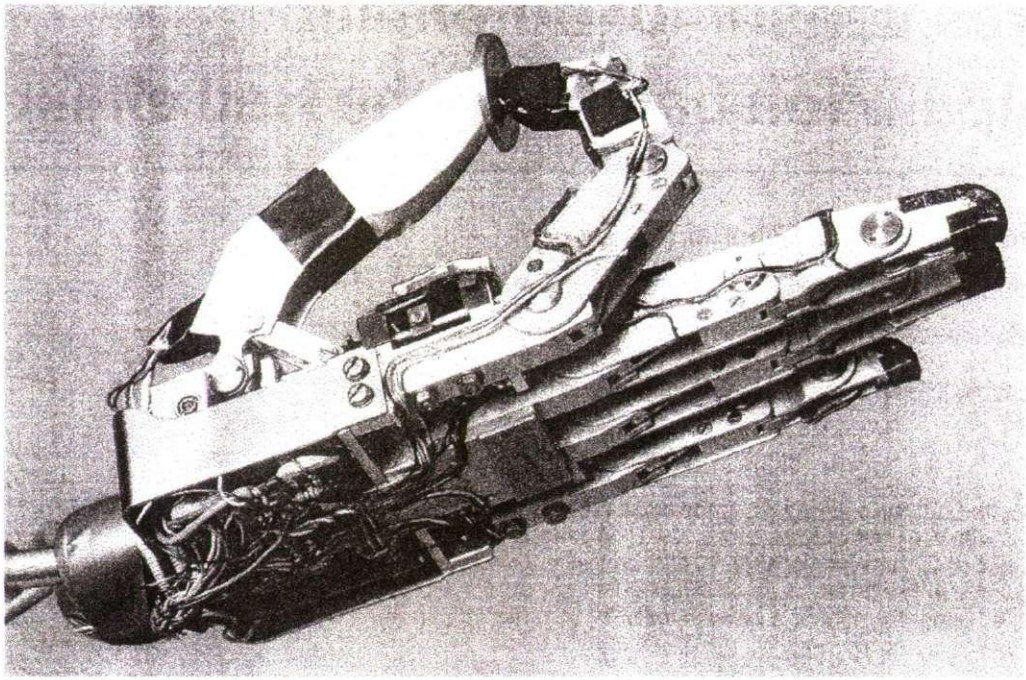

Figure 1.11 The Southampton Hand. A multi-degree-of-freedom prosthesis using SAMS control.
From Meas. Science Technology, 4, 1993.

1.6 Current Research Directions/ Pattern Recognition

1.6.1 Early Work

The use of pattern recognition as a means to identify the amputee-generated MES has had some considerable attention over the past 20 years. Using myoelectric control takes advantage of the natural myoelectric patterns produced when making a particular hand function. Myoplastic surgical techniques can preserve the original patterns by reducing atrophy and retraction of muscles.

Information concerning intended limb function by the user is buried in the EMS signal. It is the computational time, algorithmic-process, hardware-sensitivity, and user-repeatability that need to be controlled for in a practical (commercial) system. Some of the earliest work up to 1978 was examined by R Wirta **[66]** and focused on either using various parts of the body or using various muscles (e.g. shoulder region) to generate the EMG signals. Some success was shown at the time with the use of eight or more muscles to control an above elbow prosthesis. The user concentration and skill was a critical factor in the level of

success. The bulky electronics of the day did not offer any realistic advancement in practical prosthetic implementation. Research in Sweden with the Swedish multifunctional (six functions) hand prosthesis used multiple electrodes (six) over as many individual muscle sites on a below elbow-amputee as a basis for a "Phantom Limb" control process. The individual electrode pair signals were each amplified, rectified and smoothed. A method was adopted to separate the pattern classes with mathematically defined boundaries having the character of 2-dimensional surfaces. After analysis with a digital computer a weighting factor was adopted and applied to the rectified MES signal from each site and all sites then summed to produce an output for that channel **[67,68,69]**.

In Japan, investigation into the spectral relationship to hand shape was undertaken. The results when averaged over 10 subjects showed a series of spectral peaks (four) related to particular hand shapes. This work has not been shown to be repeatable by the author, nor is there found any mention in the literature of repeatable confirmation by other researchers. The lack of technical details made available in the spectral detection process may account for this **[70]**.

The problem of identifying motion commands, by the application of statistical techniques to analyse the original MES signal for extraction of control signals, has been explored by Graupe (et al). Graupe used Auto-Regressive (AR) modelling to represent the EMG stationary time-series, followed by AR analysis **[71,72,73]** of the myoelectric signal. This gave adequate function discrimination using 8-bit signal processing and could have been improved using (ARMA) Auto-Regressive-Moving-Average techniques, but for the unacceptable increased cost in computing time, in response to user commands. The use of just a few (1 to 3) electrodes distinguishes this method, as compared to those of other and earlier works which used multiple (up to six) electrode sites. Each site was an EMG function connected with a limb or hand movement. Graupe investigated signals from a single site for their time characteristics. The assumption was, that at a given surface

location, the set of parameters of the mathematical relations of the voltage /time procession of the MES, would be more or less the same for a given pattern of muscle activation. Spacing of the electrodes was made purposely very wide to use the cross talk between muscles activated over time (measured in short bursts of between 200ms. to 300 ms.). A sequential least squares algorithm (SLS) was used as the identification method [**74**].

Doerschuk [**75**] (1983), considered that, assuming all muscles have different frequency characteristics, and if the high frequency components in the MES were attenuated more rapidly than were the low frequency, it should be possible to discriminate between signals at the electrodes as a result of different muscle actions, due to the different distances of those muscles from the electrode. The discrimination information was thus contained in the cross correlation between different pairs of electrodes. Using 4 electrode pairs Doerschuk then went on to extend, refine, and improve on the work of Graupe (later shown by Triolo & Moskowitz [**76**] to be a subset of Doershuk's work). Doerschuk found discriminating on/off information in both the spatial and time correlation structure of the EMS (using a 4th order autoregressive (AR) model sampled at 2 kHz). Further developments came in processing of multi-channel, time-series MES's by Triolo and Moskowitz [**77**] which showed that operating range, peak performance and percent correct classification of MES **increases** with the number of channels used. Prewhitening methods also were used to improve the S/N ratio of the force estimate.

Other work by Lee and Saridis [**78,79**] used the probability density function of pattern/motion classes in the decision space of signal variance and zero crossings; classification occurs in a multi-class, sequential, decision-procedure.

The research mentioned to this point has interpreted the MES (a biosignal) as a stationary signal purely for analytical convenience. As biosignals are inherently nonstationary (i.e. time varying), a method that approaches the biosignal as a non-stationary model is more realistic. Schack and Grieszbach [**80,81,82**] have taken the nonstationary approach and

developed an ARMA model for the dynamic spectral-analysis of non-stationary, biosignals. Comparative merits for the ARMA approach versus other methods for spectral analysis point out the following different weaknesses:

- Short-term Fast Fourier Transform (FFT): (actually a quasi-stationary overlapping segment method applied to a non-stationary signal). Results are comparable to ARMA. Limited by inherent uncertainties
- Filter methods: band-pass (with rectification and smoothing) give comparable results to ARMA. Such methods can be limited in spectral parameters and points due to weaknesses in analogue (stability, slope, physical-size) and digital (serial processor-time) methods.
- Dynamic AR by Kalman-Filter algorithm: comparable results to ARMA algorithm and is time-consuming and restricted to AR (not ARMA) methods.

Other approaches that may have merit are:

- Instantaneous spectrum using Hilbert transforms:
- Dynamic spectrum using wavelet transforms

Although not directly related to myoelectric signal processing in the arm, a method conceived by Simpson [**83**,**84**], known as "Extended Physiological Proprioception" (EPP), can be considered as a pattern recognition method. The source of the signal (MES or switch position) was located in other body regions. Simpson was concerned with above elbow amputees and thalidomide children who had mobility of the shoulder joint but little or no arm MES to work with. The position of the shoulder joint was translated to the position of the prosthesis in space in a serial manner. A relationship has been demonstrated to exist between shoulder joint-angles and elbow/wrist joint-angles [**85**]. Such a relationship can be used as a basis for (above-elbow amputee) prosthesis control.

1.6.2 MES Features

Research into myopathic and neuropathic/neurogenic processes has produced a number of characteristic "Features" regards the MES that specialist clinicians in the EMG field have used to diagnose disorders e.g. ALS, Multiple Sclerosis, Muscular Dystrophy. The features mostly related to the MES in the Time domain and that cover the basic signal time-features are:

- maximum peak to peak amplitude
- maximum positive peak amplitude
- maximum positive slope
- maximum negative slope
- total number of signal turning points
- total positive signal area
- total negative signal area
- total number of samples
- RMS
- total number of zero crossings

These mentioned features could be further analysed for:

Clustering, factor analysis, nearest neighbour network **[86]**, shape irregularity **[87]**

Now all of these features have been generally applied to, and restricted to, the decomposed signal detected by needle (inserted into the muscle) electrodes. Needle electrodes have a much greater resolution of individual motor units and are the means by which Action Potentials (AP's) and Motor Unit Action Potentials (MUAP's) are examined after application of decomposition techniques [**88,89,90,91**]. The decomposition techniques are required due to the regional mixing of MUAP's. Surface electrodes suffer extremely poor capability to resolve specific MUAP's and are not used as such. The commercial

availability of medical MES diagnostics has brought these methods into pattern-recognition research, along with the use of time domain features, as a basis for pattern recognition by artificial intelligence methods. Neural-networks, Fuzzy Logic, and Hidden Markov models are a few of the different signal processing methods that can be applied in this area. The Neural Network is the most popular of these candidates.

1.6.3 Neural Networks (NN) and the MES

Neural Networks have been known since the 1940's but went into a decline in the late 1960's following work by Minsky that claimed severe limitations with the then existing architectures. The back-propagation algorithm by Rumelhart and McClelland in 1986 breathed fresh life into Neural Networks.

In 1988 Graupe, [**92**] having investigated control of prosthetics by pattern recognition methods such as ARMA, saw the use of NN as a tool much more suitable to medical signal processing. Medical signal-analysis problems are all too frequently, ill defined, non-linear, and defy analysis (by all but the most extremely computationally-exhaustive processes). Graupe suggested the use of a MES model to present to a Hopfield NN for decomposition of the MES into MUAP's and the NN control of a prosthesis. No implementation or test of data was reported.

In Japan, Hiraiwa [**93**] (1989) et al proposed the use of a NN using back propagation to control a prosthetic hand/arm. The input signals were stated as surface-detected from the flexor digitorum superficialis (see Chapter 2 page 61) and spectrum analysed via Fast Fourier Transform (FFT). The 10 inputs were taken from a 10-band division of the 63 Hz to 500 Hz spectrum detected. A 7- element hidden layer was used. The output was through a 5-element layer. The 5 elements represented 5 finger/thumb actions: **1**) flex all fingers **2**) flex only index finger, **3**) flex only middle finger, **4**) flex only thumb, **5**) relax all fingers. Their success rate after training claimed 20 recognitions out of 30.

Examination of their diagrams suggests the researchers were not accurate in their anatomical description, as the flexor digitorum superficialis was not actually located where they show the electrode locations. What in fact they were detecting from the position shown (wrist joint) is a region of high tendon concentration with a general proximity to several muscle sources including the thumb. This consideration then easily explains their results as follows.

1). Flex all fingers: Success was 1 in 6. The distant flexor digitorum superficialis would give only chance discrimination

2). Flex only index finger: Success was 5 in 6 as this action is stronger with the flexor digitorum superficialis

4). Flex only thumb: Success was 5 in 6 as the site of the thumb flexors is very close.

NB: In the case of a hand being amputated, the thumb flexors would ***not actually exist*** (to produce these signals).

5). Relax all fingers: Success was 3 in 6. Not a good score, as the activity in the area should have been minimal and easily recognised as a **no signal** level by an ANN. This indicates poor generalisation by the NN.

In Japan, Ito et al **[94]** (1991) proposed a back-propagation Neural Network to control a 3 degree-of-freedom (DOF) prosthetic hand/arm. The NN input signals were from four surface mounted dry electrodes mounted around the upper forearm. Each of the 4 signal lines were passed through a 10th order digital Finite Impulse Response (FIR) filter, then smoothed and rectified before presentation to the inputs of the NN. The 4 FIR filters were set with centre frequencies at 70 Hz, 160 Hz, 360 Hz, (and another at an "x" Hz **omitted** in the literature) respectively and each with a 40 Hz bandwidth per filter. The 4 FIR filters (each with a specific band-pass range) each accepted the input MES from only one electrode. The outputs from the NN controlled 6 prosthetic limb actions:

1). WRIST flexion, 2). WRIST Extension,

3). HAND Pronation, 4). HAND Supination,

5). HAND: open 6). HAND close.

Training was done using 10 stored data sets of 200 ms. intervals. The Networks learned very rapidly (under 30 iterations) and produced greater than 90% recognition success. An on-line network retraining/updating algorithm was also developed to account for the observed changes in time of the training/ use data. This was done using two parallel transputers. The 6 actions over 3 degrees of freedom could have been accomplished using a hierarchical control structure without the NN, but the clear advantage of the NN was its ability to use natural movements of the human arm. Computational requirements were high however. There are no reports of further work to be found.

At the University of New Brunswick (UNB) in Canada, Kelly, Parker, and Scott [**95,96**] (1990), proposed the use of NN to control a prosthetic arm/hand. They chose to use the MES feature set developed by Graupe and to detect these features using a Hopfield Neural Network. The network proved to be 2 to 3 times as fast as the SLS algorithm applied by Graupe. The Time-domain feature set was extracted using one pair of surface electrodes at a single site and then used to train a Multilayer Perceptron (MLP) Neural Network. The feature set was taken from a set of 4 arm functions and, once trained, the Network was successful (no specific % rate was given) in recognising those 4 functions. The notable point was that no training of subjects was given prior to data acquisition. This is a notable advance compared to past pattern recognition methods in which extensive, exhaustive training for the subjects was necessary. Kelly et al concluded that a better set of feature sets to delineate the regions of a 2-dimensional feature space could yield an even greater number of control actions. Due to the large computational effort required, this single channel control approach did not evolve beyond the laboratory. The UNB work was carried on by Hudgins, Parker, and Scott [**97**] (1991) with the development of an extended time-domain feature set using the following MES features:

- mean absolute value (MAV) in 5 consecutive 40 ms. segments,
- difference in MAV (the slope) between adjacent time segments,
- number of zero-crossings, in 5 consecutive 40 ms. segments
- the number of slope sign changes, (turns) in 5 consecutive 40 ms. segments
- the waveform length (complexity), in 5 consecutive 40 ms. segments
- the mean value of each of the mentioned features over all segments

Noticeable about Hudgins work is the recognition that the MES contains a deterministic component during the initial stages of contraction **i.e. the transient**. Previous work by others have assumed no useful information was to be found in the transient and work had focused on the steady state signal (post transient state) components. A surface-mounted, one-electrode pair arranged on the upper arm (with widely separated electrodes) was used with intention to capture the signals from all muscles in the upper arm. The 4 actions monitored were: elbow flexion, elbow extension, outward humeral rotation, and inward humeral rotation. Network recognition success results for 5 subjects tested were: 40% success (for 4 subjects) to 85% success (for one subject).

The delay between user action at the muscle site and control action response was under 250 ms. This time response is within the acceptable benchmark (300-ms. Range) for a user-acceptable, practical, prosthesis.

Hudgins again (1993) **[98]** carried on with the deterministic component of the MES found in the (transient) initial onset stage (within the first 300 ms. of the MES). Using essentially the same feature sets as in 1991, Hudgins spread these features over a 30 pattern input layer through an 8 node hidden and 4 output back-propagation NN. Successful network recognition this time was 91.2% for normal-limbed subjects and 85.5% for amputee subjects. As the tests were taken without any subject training-session, it may be that it is possible for the amputees to improve on these rates. Displacement of the electrodes from

initial site positioning resulted in a slight (close to 2%) decrease in classification performance. No attempt was made to determine the optimal electrode sites and considering the large number of possible electrode positions and the retraining of the network for each position this is not surprising. However, a method needs to be developed for this "optimum" eventuality. Hudgins concludes, "It is the "cross talk" detected at the electrodes that is producing the myoclassification". Yet, this "cross talk" is what the commercial prosthetic manufacturers have always considered as "noise"! At the UNB O'Neill **[99]** (1994) investigated the spectral features of the MES for normal vs. amputee muscles and found a shift in frequency between remnant (amputee) and intact (non-amputee) muscles. No conclusive predictor could be established however. Further work appears to be needed on the subject. It was suggested that the investigation of the deterministic component of the MES could also encompass the spectral content. Kermani, Badie, Hashemi, and Wheeler **[100]** described new features being assessed for their MUAP identification abilities.

Control of arm movements by Neural Networks, using orthoses or Functional Electrical Stimulation (FES), has seen a number of papers across the Biomedical and Robotics field. An extensive overview compiled by MacKenzie and Iberall **[101]** (1994), describe many approaches **[102,103,104,105,106,107]** taken to investigate the optimal NN control system. Of course, the capture of ***reliable*** input signals to these processors is ***assumed*** as available, which is still not yet the case. A foundation of considerable effort has been expended in investigating both the formation/operation **[108]** of the human motor-control system, and the potential of Neural Networks. Opportunities can readily be seen for their application to the control of prosthetic limbs and teleprostheses **(109)**

An extension of the research undertaken in this thesis has been carried forward at the University of Plymouth with the development of a computer simulated hand operated by a NN responding to recorded myoelectric signals **(110)**.(see also this thesis page 297)

1.7 Impediments to Progress: Political and Technical

Consider the question:" **Why do the commercial manufacturers not develop these additional control abilities into a more functional prosthesis**." The answer is complex and many faceted.

There are only a handful of upper-limb prosthetics manufacturers in the world. There are only two dominant players in Europe; H. Steeper U.K. (now Rehabilitation Services Limited, RSL Steeper) and Otto Bock (Germany*). The U.K. has a National Health Service (NHS) that offers the same level of quality in prosthetics that a private hospital could offer.* Consequently, there is no incentive for any amputees/patients to look for improvements in the private sector. They can get the best available product at no charge from the NHS. The NHS places a cost ceiling on commercial prosthetics and Otto Bock and Steeper fit into an agreed system.

If current users of the standard prosthesis were offered the option of a vastly more functional prosthesis, (that they could command in a manner similar to a natural limb), they would all line up at the door casting aside their old prosthesis on their way in. This does not make good commercial sense for an existing and profitable supply line. The setting up of prosthetic centres, the training of professional prostheticians, the parts distribution network, tooling costs and the commercial manufacturing facilities for the prosthetic components, *form a considerable inertia to overcome.* There is therefore a "status quo" in commercial manufacturing.

In order for existing commercial manufacturers to shift towards more technologically advanced prostheses, any new technology would be required to slot into the existing manufacturing and distribution network. The risk factor for the new technology would need to be reduced to the level of the "simple and tried and true".

An analogy to consider here would be the model "T" Ford. The car was simple, basic and travelled from "A to B". If demand had been limited and there were only two manufacturers of such cars, both producing only a slight variation of the basic model "T", would the "T" still be the current benchmark model?

It is no coincidence that virtually all advances in the frontiers of prosthetic control and design have been *outside* the commercial sector and in the academic research environment. To initiate new technology requires a realistic and not idealist assessment of how the private enterprise system is motivated. Consider the following:

- Idealistic: If you make a clever gadget everyone will want to buy it and it will sell itself!
- Realistic: Market potential is limited by the available funding from either NHS type public bodies (U.K.), or Insurance based private bodies (U.S.A.). The regions of highest demand for prostheses are in the least developed war-torn regions where affected persons are the least able to afford the technology.
- Idealistic: Market the technology as low risk/high return potential
- Realistic: The "Catch 22" of getting started. In order to manufacture and market an advanced prosthesis you need to have a designed and tested product. In order to design and test an advanced prosthesis you need to be a manufacturing cell with an available test market. Manufacturer and designer both need to be interwoven. Consider the tunnel-vision banker-mentality: "When can you see a positive cash flow?" Bankers (like politicians) are not generally long-term thinkers.
- Idealistic: The shareholders will be willing to take a cutback in profits/dividends in order to secure a more dominant position in the marketplace

- Realistic: The shareholder will not be accessed, consulted or presented with any proposal that affects their rate of return because that rate of return affects the directors short-term prospects.
- Idealistic: The extensive technology and expertise available within the company could be directed and focused on a. high-tech research program.
- Realistic: The existing company staffs have developed, only within their manufacturing skills environment in the company, and been optimised for their efficiency as manufacturers. There is a minimal research culture. Prosthesis equipment makers are manufacturing oriented and not research based. Budget restrictions could hinder any progress. Universities, (in contrast), have a wide range of frontline researchers and research facilities that can be shared and efficiently utilised. Inter institutional, inter academic communication and shared knowledge via lectures and conferences is part of the academic culture. In contrast, when the company is funding the academic research, it attempts to stifle both the outflow of research findings and the academic feedback system from fear of losing the competitive edge. This desire to wrap up their monetary investment in a shroud of secrecy can sometimes cripple the research progress and cause unnecessary duplication of work.
- Idealistic: The company has so much expertise and years of experience in the prosthetics field that they must be aware of any past or current technology relevant to their field.
- Realistic: Most company staffs are too busy in the day to day manufacturing of their existing range of products. They rely on serendipity and token-gesture, company representatives (more interested in selling their own products than in academic parlance) at conferences to inform themselves of any changes in wind direction. The

notion of sharing and exploring new ideas with another company (the competition) is alien to the company culture

If there are any residual hopes for the potential for novel thinking in the commercial sector then consider the statement (**98**) "Hudgins concludes that it is the "cross talk", detected at the electrodes, that is producing the myoclassification and yet this "cross talk" is what the commercial prosthetic manufacturers have always considered as "noise"!!

1.8 A Case for Myoelectric Prostheses:

Investigations [**111,112**] into usage of conventional cable-operated hand/hooks versus myoelectric prostheses indicate a need for both forms of prostheses, as they both serve different needs as summarised in the following points.

- The cable-operated device is more suitable for heavy jobs requiring lifting or for using in work environments unsuitable for a myoelectric device.
- The myoelectric prosthesis is well suited to those amputees primarily having jobs that involve office work, supervision, or public contact work: i.e. primarily light activities in a clean environment.

1.8.1 An Electrical Prosthesis: Advantages:

1) A superior pinch-force of 15 to 25 pounds (65 to 110 Newtons) versus 7 to 8 pounds (30 to 35 Newtons) for cable-operated.

2). Lack of need for a harness

3) Greater cosmetic appeal

4). Wider operating work space/ envelope

5). Hand movement is independent of the body position

6). High level (above-elbow) amputees require less effort (versus cable)

7) Sensory feedback from motor vibration (e.g. stalling sound) in prosthesis is used by amputees and is a possible area for further research.

8) Greater scope exists for the development of increased complexity of thumb/finger/wrist opening action. Cable harness can only issue an open/close command.

Disadvantages

1) Higher cost versus cable operated.

2) More maintenance and specialised maintenance centres.

3) Durability is less than cable-operated harness.

4) Hand shape can restrict some tasks (though this applies equally to cable-operated).

5) Battery recharging required. The myoelectric device will suffer an energy supply problem in very cold weather due to the phenomenon of battery power being proportional to temperature.

6) Weight is greater and speed/action generally slower than cable operated.

7) Weight leverage (weight distribution high at distal/hand end) at socket stump interface cause stresses/discomfort on the stump.

Some common reasons being given for the myoelectric prosthesis not to be used by amputees are [111]:

- too heavy,
- too slow,
- not durable enough.

The issue of cable versus electric prosthesis needs to be viewed as to what is suitable within lifestyle and activity constraints.

Other Considerations

Humid/hot conditions: or strenuous work can cause high levels of sweating within the myoelectric (and to a lesser extent in the cable-operated) prosthesis, with subsequent effects on the electrode response and prosthetic fit and comfort. Manufacturers have yet to effectively address this problem with appropriate ventilation and/or design of the prosthetic fit and materials.

Durability: This can be improved with better materials for cosmesis and moving parts. However, durability has to be fairly assessed with regards to any technological device concerning purpose and function.

With regards to **Sensory Feedback**, those who placed light load demands on a myoelectric prosthesis rated it as giving good feedback [**113**] and those requiring heavy demands rated feedback as poor.

Reductions in **Weight** and relocation of weight in prostheses can still be viable areas for research and development. Speed of operation, (hand opening/closing), have recently been addressed with improved commercial versions, but much room for improvement is still possible.

1.9 Summary of Chapter 1

A rapid journey through time brought us to the development of the 'Vaduz Hand' in 1951 and one of the earliest myoelectric controls were developed in England in 1955. From then on things began to slow down in terms of technological innovation By 1960 the Russians had developed their own myoelectric version of the Vaduz Hand and began marketing it in North America. In 1963, the Germans (Otto Bock) made a version of the Russian Hand and called it the Viennatone Hand. By 1965, they had an improved version and the product has not changed significantly since then. In 1965, the Swedes developed the SVEN Hand, which simplified into the Systemteknik hand, went to H. Steeper in the U.K. and was the

basis of the Steeper hand from then on. The Americans copied the Viennatone Hand and did little else.

As you can see, there was a great deal of prostheses inbreeding in the early 1960's and manufacturers began to carve out their patches with their inbred versions.

After this it was the academic community that undertook research; with the slant mostly toward robot end effectors {Tomovic (1968), Waseda the WIME Hand (1964-1978), Salisbury, the Stanford/JPL Hand (1985), Jacobsen the Utah/MIT Hand 1986, Bekey and Tomovic, the USC Hand (1990)}. The human arm movement action has been shown to be non-Kinematic in principle. No practical prostheses came as offshoots. Meanwhile the academic community was exploring myoelectric control. R.N.Scott and the University of New Brunswick has been pushing the bow wave since 1960 and much insight has been inspired both within and outside their University walls. D. Childress at Northwestern University in Chicago (USA) has been solidly pushing myoelectric control since 1968. Over time, this academic persistence has been tempered by the electronics of the day. Knowledge of muscle physiology has advanced and a mathematical approach has developed (see Chapter 2). Various control signal sources (Myoelectric, FSR, Piezo, Sounds, Implants) have been examined and their pros and cons outlined. Their many shortcomings have left the control engineer with a need for signal reliability with a wider control range. The hardware that constitutes the physical structure of the prosthesis has been examined from the user perspective and found to be lacking. The types of actuators (Hydraulic, Pneumatic Motor/gearbox or cable) have been examined and the author holds out hope for an artificial muscle as the next generation advance in actuators. Control systems that have used the myoelectric signals have been largely dependant on the gross muscle signal developed at one site and variations have used the signal to control either open, close velocity or force (grasp pressure). The University of Southampton has been pursuing the improvements of control using time domain MES with some success and have

a 'hierarchical' control system that gives a prosthesis with increased functionality at the cost of user control-complexity.

A number of academic research activities have inspired the development of control signals, extracted from the MES, using the concept of pattern recognition. Auto regression, SLS, and Neural Networks have been explored by others. Doerschuk (1983) suggested that muscles have different frequency characteristics, and if the high frequency components in the MES were attenuated more rapidly than were the low frequency, it should be possible to discriminate between signals at the electrodes as a result of different muscle actions. It is Doershuk that spotted the potential that is developed in this research. Pattern recognition has met with some success but computation time and accuracy has been the underlying weakness. Good ideas have foundered due to technological shortfalls and never then carried forward (probably due to funding, other commitments or retirement).

The amputee just **will not** use a prosthesis that takes a long time to respond, is heavy (weighed down with hardware) to wear, and is just as likely to poke them in the eye due to an error in pattern recognition (as humorously depicted by Peter Sellers in the film 'Dr. Strangelove'). The control potential in pattern recognition is there, but not (yet) developed to maturity.

Finally, a case is made for the concept of the improved myoelectric prosthesis. Some insight into the workings of the prosthesis manufacturing industry explains the slow rate of progress and emphasises the current need for the academic community to move the goalposts out of complacency and raise the level of play.

The first objective stated for this research program was:

1)-to investigate the information content of a MES.

This chapter has outlined the past historical discovery of the MES, and the story of slowly revealed information content, as limited by the technology and anatomy/physiology of the

time. Academic research has pushed the boundaries and exposed a deterministic potential in the MES. The application of intelligent systems will unravel more details in the information content. We now have the background to avoid dead ends and the repetition of completed past research activities. With this chapter, we now know the branches of the discovery process of information content; but the author has yet to improve on that knowledge.

1.10 Layout of Thesis

Chapter 2 will introduce the task of detecting/acquiring an effective and reliable command signal for directing an improved prosthesis by probing the anatomical and physiological origins of the myoelectric signal. By understanding the MES through it composition it will be possible to detect a true signal from an artefact and to consider what intelligence can reasonably be extracted. For those reasons outlined, the final choice of electrode sites will be explained and apparent.

As in physics, biosignal research and detection has "been built upon the shoulders of giants of past pioneers" in human physiology research. The literature is vast and extensive. In order to know how to use technology to extract a biological signal; it is necessary to know how past research through trial and error has developed. There is no excuse for repeating techniques that have been thoroughly explored and extensively described. There is however, an opportunity to draw upon the conclusions, suggestions and inferences that such explorations have produced. The optimal electrode material may not necessarily be a practical material and chapter 2 will explain and justify any compromises taken in the use of electrodes used in this research.

A mathematical modelling of the signal and its detection will be introduced. Past models will be examined and their strengths and weaknesses will become apparent. What is possible to model and describe will be attempted and some past assumptions that can be

shown to be incomplete will be explained. This incompleteness allows for the extraction of more information that has in past been assumed possible by many in the field.

Software methods for signal methods will be discussed and the time constraints inherent in a practical user acceptable prosthesis controller will be compared to the constraints of a the frequency spectrum and signal processing equipment/software.

Chapter 3 will describe the experimental equipment used to examine the surface Myoelectric Signal (MES). Time and frequency methods will be scrutinised for their reliability, accuracy and utility. The various pieces of equipment chosen for detecting the MES will be compared for pros and cons and a standard will be adopted.

Chapter 4 will examine the different muscle actions and the frequency characteristics detected as a surface MES for those actions. The question of gender differences for these muscle actions will be explored. The complexity of signal loss will be examined within the context of the distance between muscle site and detector site.

Chapter 5 will introduce the need for MES site mapping. Each of the 4 adult volunteers (2 male, 2 female) will have their lower arms entirely mapped for the surface-detected MES, for all of the 20 core muscle actions. Preliminary results for prospective common electrode placement sites will be shown. This will stimulate interest for mapping to be completed.

Chapter 6 will examine the results of the mapping exercises with respect to Gender differences. The 4 MES signal characteristics that are detectable within the mapping exercise will be shown how they can be brought together to produce a wider set of control actions. The use of the "Second moment of area "will be introduced as a unique combining method for applying to database mapping. The question of a deterministic VS stochastic description for the MES will be revisited. The similarities and differences for various muscle actions will be compared across the volunteers.

Chapter 7 will look more deeply at the question of the deterministic VS stochastic question as a conflicting description of the MES. The results of the mapping exercise will

expand more completely the understanding of the surface-detected MES as a combination of both stochastic and deterministic elements. This apparent dichotomy will be resolved into a more complete picture of the MES. The research results will show an expanded control signals range and be placed against a background of Neural Networks as suitable for applying to prosthesis control. A foundation for further research will be discussed.

1.10.1 Research Methodology

The opportunity to utilise the Tissue Filter Function (TFF) requires knowledge of the manner in which the MES from selected muscles propagate through the tissue medium and appear at the skin surface. It is known that the MES will demonstrate a different signature on the skin surface as distance varies from the MES generator source. Just how the contributions from various muscles found at any point on the skin surface offer a useful control signal will be investigated. Any differences between males (within gender) and the control signals produced under controlled conditions will be recorded and analysed. The same investigation will be undertaken to see if 'between gender' differences require special considerations for control signal purposes. A low frequency signal spectrum analyser will be coupled to moveable electrodes for the purpose of mapping/recording the surface of an arm in response to muscle activity.

1.10.2 Original Work Contribution

Comprehensive contour mapping of the MES has never been undertaken before and the results will generate a database from which hypotheses can be tested. The equipment utilised was selected using the criteria laid out in Chapter 2. Full consideration was made from a physiological, anatomical and electronics perspective**(114)**. The historical description of a stochastic, non-deterministic MES has been shown by this research to be incomplete. This research has used an **original** controlled mapping technique for surface MES's that has revealed unique spectral features for various muscle actions that cannot be

accounted for by the Tissue Filter Function (TFF) alone. It is these unique features, plus the use of the TFF, that is intended for an **original** approach proposed using 3 to 4 distinct very narrow band pass channels in the frequency-domain, signal transient-region as detected by multiple site electrodes (4 sites proposed). The intention is then for the signal to be presented to a Neural Network (NN) pattern recognition tool. This research has shown that the probability is high that the cross coupling between a multiple set (4) of surface electrodes will detect these frequency shifted signals throughout the 3 dimensional medium of an amputee upper forearm. Here the use of a "weighting factor" can be applied to represent the spatial distances of these signals.

An **original** simplified geometry model of the hand has been devised which greatly improves prosthesis dexterity while minimising the requirement for the many degrees of freedom of the human hand. A **novel** approach to fabricating a multi electrode pickup has been suggested to enable the mapping techniques to be fully utilised for multifunctional control of a prosthesis. An **original** updated model of the MES, based upon a more in depth consideration of the physiology of muscles and the nervous system, is presented.

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Chapter 2: Myoelectric Signals

2.1 Hand Actions

To appreciate the physiology of the hand, it may ***first*** be helpful to consider the dexterity of the human hand and how we can describe its basic operational geometry. As mentioned in section 1.3.5, the hand can be shown to act with over 25 degrees of freedom.

Consider the following:

If a "robot" designer were to start from a set of specifications that required a compact, lightweight, manipulator with the same levels of portability, operational conditions, dexterity and longevity/maintenance, (as the human hand) then, inevitably, that design would supersede a purely hi-tech, material/mechanistic approach. It would converge upon a hauntingly close, quasi-biological copy of what nature has produced over the millennia.

To provide these functions, the author decided that the basic movement geometry of the hand could be simplified into the following diagram (*see Figure 2.1*). Using this basic geometry it will be possible to construct a hand with the essential hand movements.

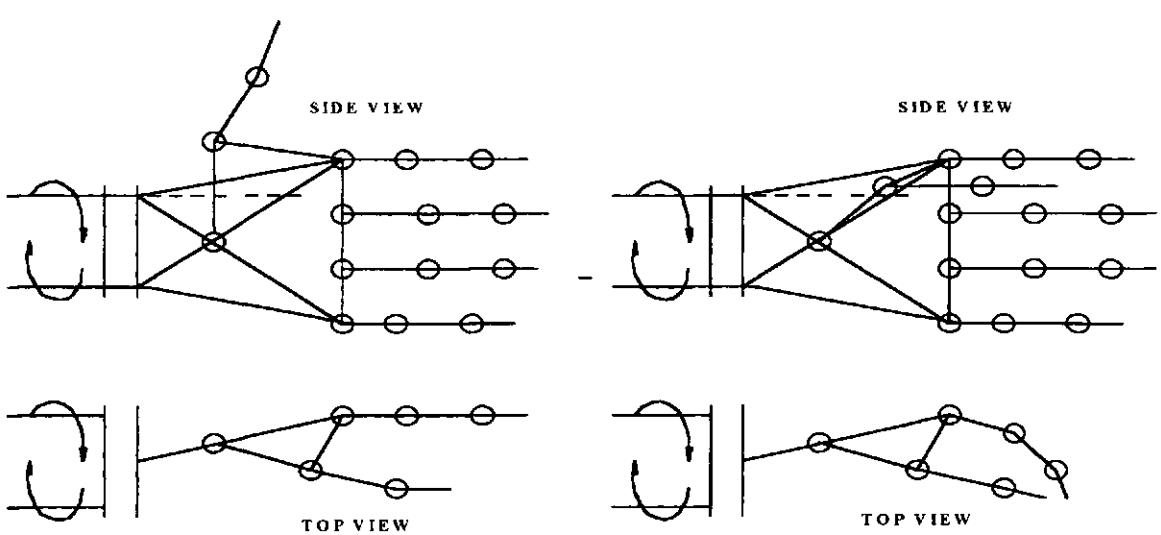


FIG. 2.1 Basic Hand Movement Geometry as an operational and constructional principle.

The assignment of a binary value to each of the actions made available to the thumb and first two digits can be seen to produce a basic range of grasp actions. Intermediate states can be reached by the application of force-sensing limiters that limit progress between states.

As long as a control action can be maintained by the amputee, the movement of the wrist and digits, limited to the 10 actions (*Figure.2.2*), should cover a range of practical yet feasible hand functions. The functional classification of hand grasp types (see Appendix) can be reduced to a much smaller number of actions from which the major and minor subdivisions can still be effectively produced. The limits placed upon the mechanical design, in terms of dimensional flexibility, (no travel outside the confined angular settings) are a necessary design compromise. Further increases in a closer approximation to the human level of dexterity would exact an additional cost in; control lines, mechanical parts, increased weight, computational time and complexity, and power requirements. The basic range of grasp actions can be seen below in *Figure 2.2 (see also Appendices p.237)*

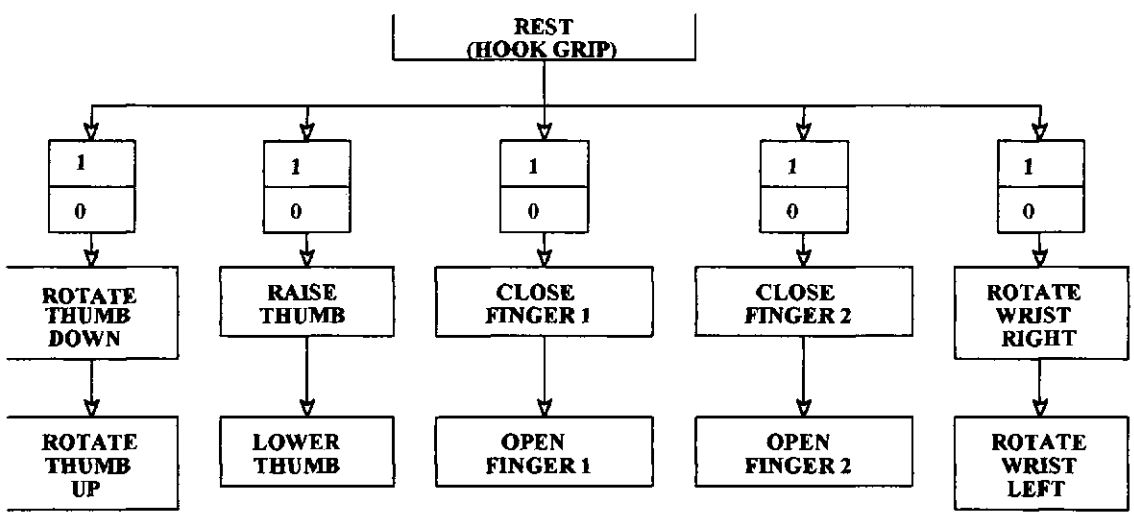


Figure 2.2 Simplified range of grasp actions for a myoelectric prosthesis

2.2. Forearm Muscle Anatomy and Physiology

How is the MES produced and What does it represent?

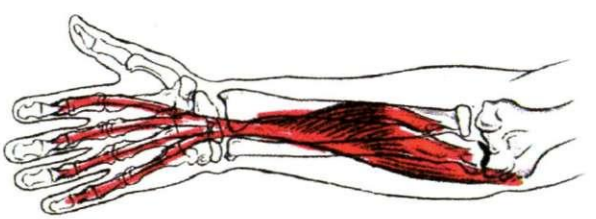
Definition: MES: Myo**E**lectric Signal

From a functional perspective, the action produced by a normal arm is not the result of a single muscle action but is rather a combination of muscle actions, with major and minor players taking part. **[1,2,3]**

In order to decipher the MES signal, we need first to know the extent and limitations of the muscles available in the forearm and to know how those muscles contribute to the action of both wrist and digits.

An example shown (*Figure 2.3*) **(4, page 315)** here is of the muscles that play a part in the closing (flexion) and opening (extension) of the ringfinger What can also be seen is how these muscles have a common origin in the elbow region. With an amputation occurring in the mid forearm region, it can be seen that a large part of the muscle still remains and, (assuming competent surgical methods were used to anchor the muscles), can be activated by the amputee, producing detectable myoelectric signals (MES

The **flexion** (closing) of the ring finger (annularis) is brought about through the innervation



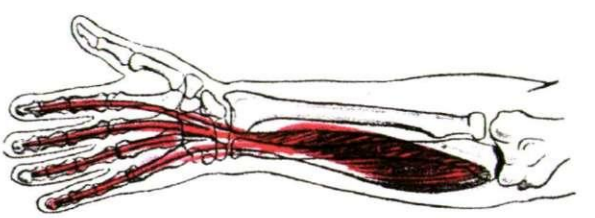


Figure 2.3Flexor digitorum superficialis. Figure 2.4 Flexor digitorum profundus
Adapted from 'Human Anatomy and Physiology' by D. Shier and J. Lewis, 8th edition, McGraw Hill, 1999.

of both the flexor digitorum superficialis muscle (FDSm) and the flexor digitorum profundus muscle (FDPm) (*see Figure 2.3 a and 2.3b*). Ring finger **extension** (opening) is the result of the Extensor Digitorum muscle (*see Figure 2.9, page 62*)

Note: for a helpful Latin/English translation of the muscle names see appendix page235

Apart from ring finger flexion the FDSm and FDPm also assist in wrist flexion (closing). The FDSm is a muscle that overlies the FDPm (like the layers of a sandwich). The FDSm is closer to the skin surface than the FDPm, but is itself overlain (*see Figure 2.9, page 62*) by the flexor carpi radialis (a powerful flexor of the wrist) and flexor carpi ulnaris (a powerful flexor of the wrist) muscles.

Note: It is an acknowledged, but habitually continued misnomer to classify the FDSm as a superficial (surface) muscle). The FDSm flexes the middle phalange of the finger (proximal interphalangeal joint), while the FDPm flexes the distal phalange. The FDPm, supplied by the median and ulnar nerve, acts in gentle flexion and the FDSm, supplied by the median nerve, comes into play for greater force or acceleration.

The wrist extension action (opening) is generally triggered from the site of the superficial extensor group of muscles. This group comprises:

- the extensor digitorum (posterior interosseous nerve supply)
- the extensor carpi radialis brevis (posterior interosseous nerve supply which is a branch of radial nerve) more involved in wrist extension than the longus
- and the extensor carpi radialis longus (radial nerve supply) more involved in the releasing actions than brevis.

The above mentioned wrist flexion and extension actions have been introduced because they are the muscles, above which are the surface electrode sites commonly chosen for the

extraction of the two MES actions, (extension) open and (flexion) close, that typify the commercially available myoelectrically operated prosthesis.

The following section on muscles and their action is a compilation from more than ten separately authored texts on anatomy and physiology, plus the unabridged version of Gray's anatomy. It is as complete a classification as was possible to construct, yet some areas of disagreement exist. This research thesis has revealed that a less than complete picture is available.

The forearm muscles are divided into two compartments (the ANTERIOR and the POSTERIOR) by fascia sheets, and each compartment has 'superficial' (near to surface) and 'deep' (below the superficial) layers. The compartmental muscles differ in both location and function. The Anterior contains mostly wrist and finger flexors plus wrist pronators and largely supplied by the median nerve. The Posterior contains wrist and finger extensors along with wrist supinators, all supplied by the radial nerve. The forearm muscles are referred to as the 'extrinsic' muscles of the hand, as they are behind the coarse movements of the hand. The muscles that give the fine movement of the hand are in the hand itself and are called the 'intrinsic' muscles of the hand.

2.2.1: Anterior Flexors. These are involved in flexion of the fingers and wrist. The two pronators of the wrist are the exceptions, still physically contained, in this anterior compartment.

Superficial Muscles

- **The flexor digitorum superficialis (FDSm):** Actually forms an intermediate layer. FDSm flexes the wrist (carpal), and proximal and middle phalanges of the fingers 2 to 5

(proximal interphalangeal joint). Comes into play for acceleration or greater force against resistance (not in gentle flexion). Its precise action varies according to what other muscles are activated. The muscle has four independently active muscle slips to operate the four fingers.

- **The** (overlying) **palmaris longus:** (missing in 10% of the population) also assists in wrist (carpal) flexion and is involved as an anchor in tension of the palm fascia.
- **The flexor carpi ulnaris:** (also overlying the FDSm), when used along with the palmaris longus, and FDSm, is a strong flexor of the wrist and when used with the extensor carpi ulnaris is an adductor of the hand. The flexor and extensor carpi ulnaris work as synergists to prevent the hand abducting when the thumb is extended. It also tenses/stabilizes the wrist in (minimus) little finger flexion.
- **The flexor carpi radialis**: (also overlying the FDSm) when used with flexor carpi ulnaris and FDSm is a strong wrist flexor. When used with the radial extensors it is an abductor of the hand.
- **Pronator teres**: acts with the Pronator Quadratus to pronate the forearm (by rotating the radius on the ulna) and helps to flex the elbow. Acts only in rapid or forcible pronation.

Deep Muscles (profund=deep)

- **The Flexor Digitorum Profundus (FDPm)**: Overlain entirely by FDSm. The only muscle that flexes the distal phalange of the finger. Assists in wrist (carpal) flexion. The tendon to the index finger is usually capable of independent action whereas the other three tendons act together. Acts alone in gentle digital flexion but works with FDSm for greater force /acceleration requirements.

- **The Flexor Pollicis longus:** a weak flexor of wrist and flexes the distal phalanx of the thumb (pollex/pollicis). Partly overlain by the FDSm.
- **The Pronator Quadratus:** is the main pronator of the forearm, supplemented by the pronator teres when there is a need for rapid or forceful pronation. Opposes the separation of the distal ends of the radius and ulna when subject to external thrust through the carpus.

The Median nerve supplies all these above-mentioned muscles. The only exceptions being the Flexor Carpi Ulnaris supplied by the Ulnar nerve and the FDSm, which has the lateral half served by the Median nerve but the medial half served by the Ulnar nerve.

This Anterior Flexor compartment is that group which is commercially chosen as a site for extracting one of the two actions, (open and close) that typify the commercially available, myoelectrically-operated prosthesis. The flexor signal is used to trigger one action (close) of a myoelectric prosthesis.

2.2.2 . Posterior Extensors:

The other action (open) is generally triggered from the site of the posterior extensor compartment of muscles. (*see Figure 2.2*) This group comprises:

Superficial muscles

- **Brachioradialis** is the *most* superficial muscle on the radial side of the forearm. Most active during rapid flexion and extension of the elbow/forearm.
- **The extensor digitorum** (divided into 4 tendons) extends the wrist and extends and flares (abducts) the fingers. Opens hand to relax or prepare a grip. The extensor digitorum extends any single or all joints over which it passes i.e. wrist through to distal

interphalangeal joints. The extensor digitorum includes **the extensor digiti(orum) minimi(us)** which extends the little finger (minimus) and the wrist (carpus) along with the extensor digitorum and also includes the **extensor (digitorum) indic(us)es**, a small muscle near the wrist which helps to extend the index finger and the wrist.

- **The extensor carpi radialis longus:** (in co-operation with the **brevis**) extends and abducts the wrist. The **longus** is more active than the **brevis** when grasping or clenching
- **The extensor carpi radialis brevis:** is shorter than and covered by the **extensor carpi radialis longus.** The **brevis** with the **extensor carpi ulnaris** extends the wrist. With the **flexor carpi radialis** it abducts the wrist. Along with the **longus** steadies the wrist during finger flexion.
- **The extensor carpi ulnaris** adducts the wrist along with (see) the flexor carpi ulnaris. With the extensor carpi radialis longus and brevis and the digital flexors it acts to extend and fix the wrist in gripping or clenching the fist.
- **The anchoneous** assists the tricepts muscle in elbow extension. May be responsible for movement (abduction) of the ulna during pronation. *N.B. This latter action has not been adequately confirmed as stated in 38th ed. 1995 Grays Anatomy P. 624. This should be assessable using the results from mapping*

Deep muscles

These muscles are generally covered by the superficial group although certain of their tendons and parts of the muscle outcrop *just above* the wrist.

- **The Extensor Indices**: a small muscle arising near the wrist that helps to extend the index finger and the wrist.

- **The Abductor Pollicis Longus:** acts with the abductor pollicis brevis to abduct the thumb radially in the plane of the palm and extend the thumb at the carpometacarpal joint.
- **The Extensor Pollicis Brevis:** extends the proximal phalanx and metacarpal of the thumb.
- **The Extensor Pollicis Longus:** extends the distal phalanx of the thumb. Along with the extensor pollicis brevis it extends the metacarpal and proximal phalanx. Further movement results in adduction of the thumb and its lateral rotation.

The Supinator: which rotates the radius and works with the biceps brachii to supinate the forearm. For slow unopposed supination it acts alone. For fast or forceful supination it acts together with the biceps brachii. A heavy object, when lifted with the forearm pronated, will use the powerful supinators, along with elbow flexion, to lift and rotate the object along.

These are the 19 muscles to be found in the forearm, and many more again are found in the hand. Together they produce 28 plus degrees of freedom in the hand and wrist.

The mechanical "Pulley Action" of the finger, as a result of the some of these muscles, can be seen in *Figure* 2.5 [**5**]

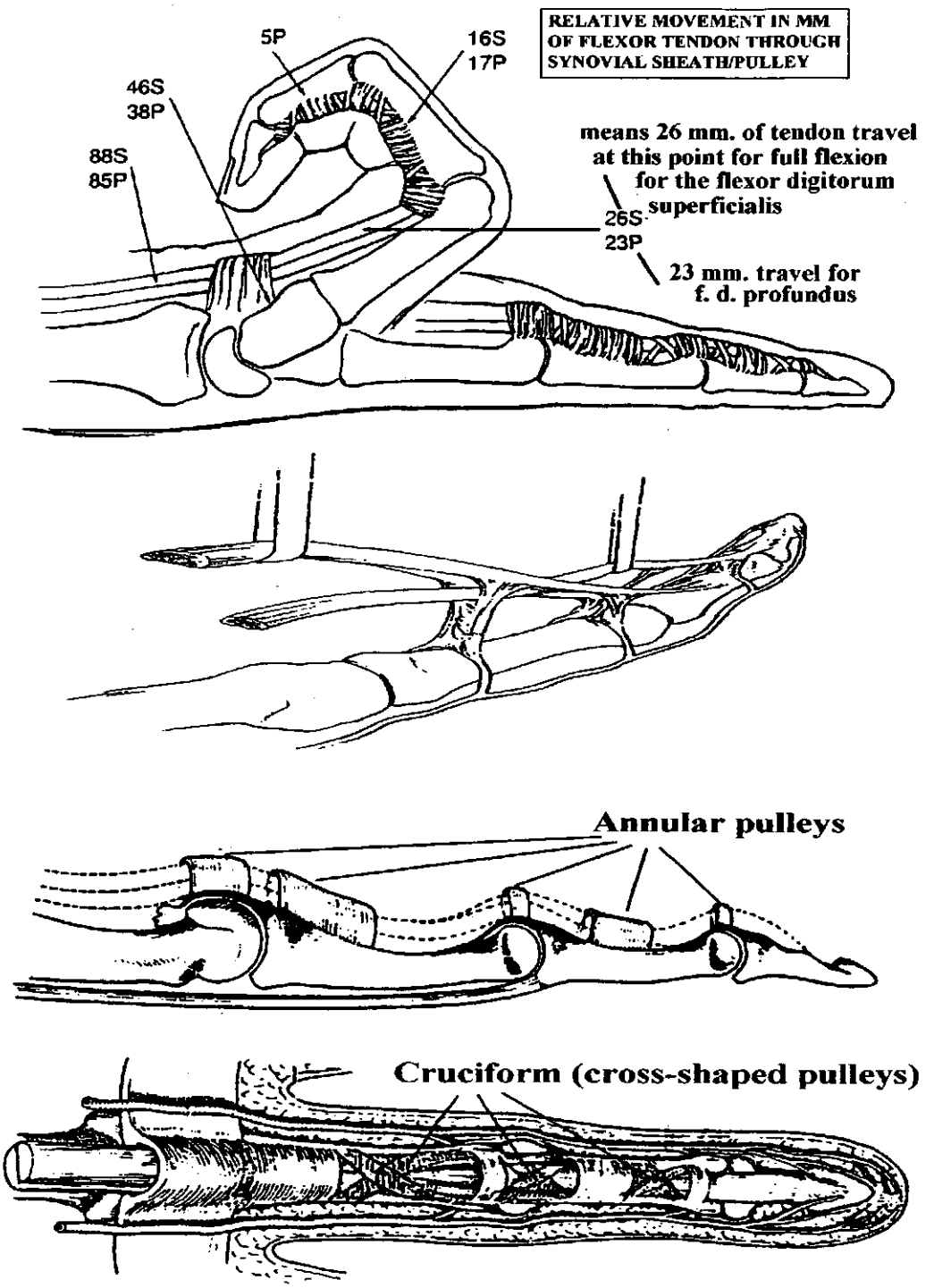


Figure. 2.5 The 4 figures above show how the finger tendons slide within the pulleys and produce the finger bending action.
From: Grays Anatomy, 38th. ed., 1995.

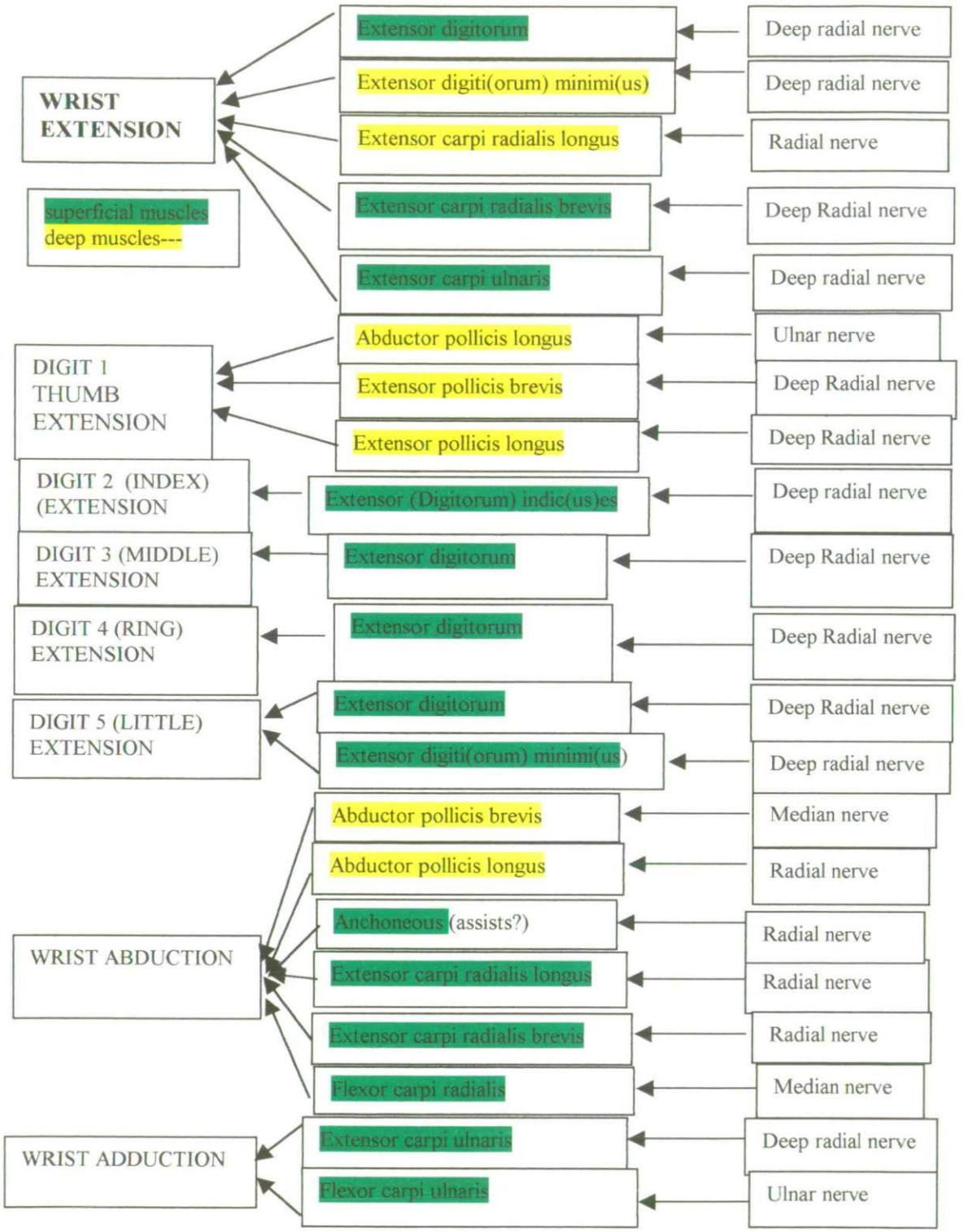


Figure 2.6 Extensor muscles of the forearm. The muscles in the centre column above, are those that are found within the forearm (elbow to wrist) and involved in the extension or wrist actions (seen in the column on the left). The colour code applies to those muscles normally assigned as sited either superficial or deep.

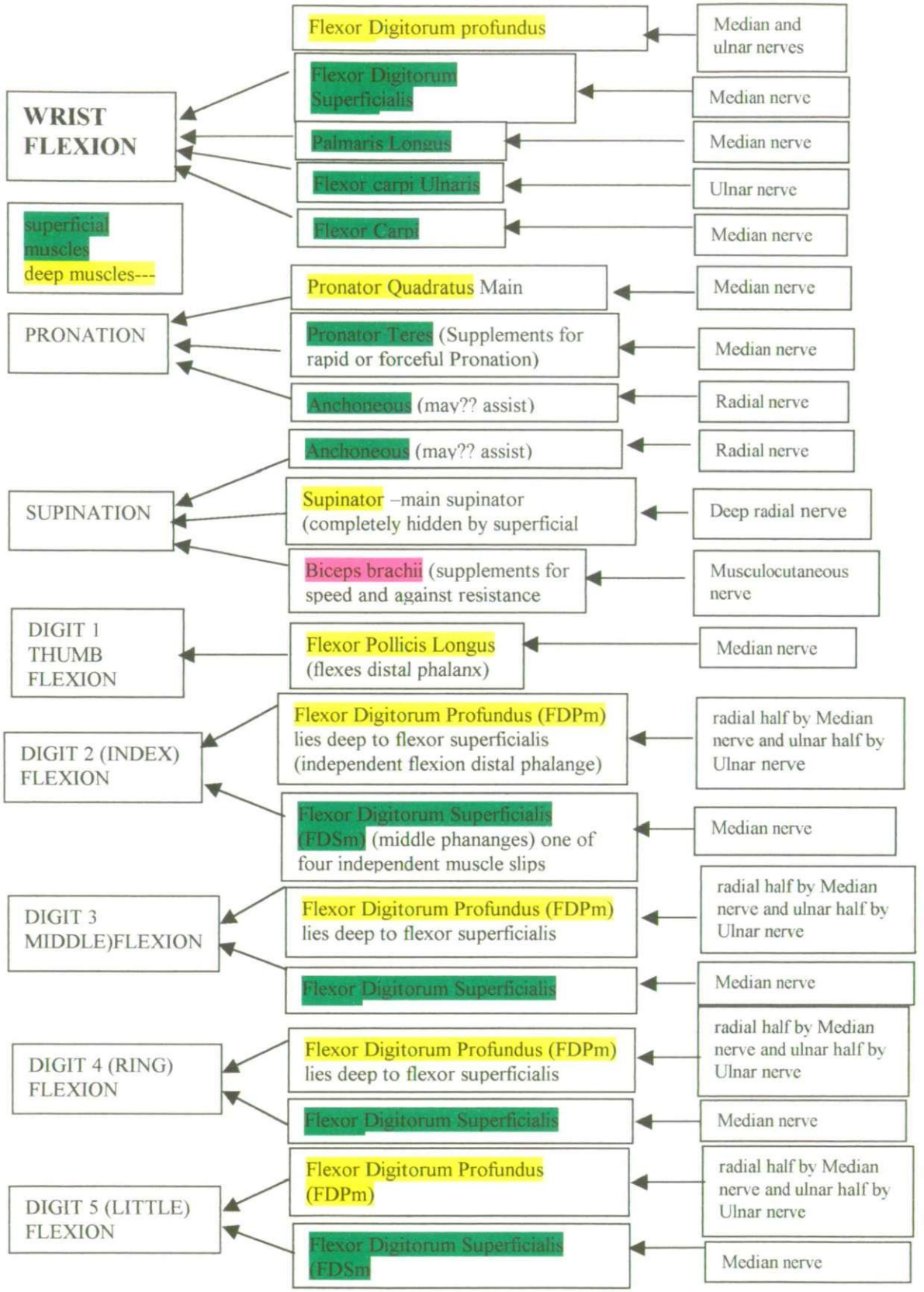


Figure 2.7 Flexor muscles of the forearm. The muscles in the centre column above, are those that are found within the forearm (elbow to wrist) and involved in the flexion actions. The colour code applies to those muscles normally assigned as sited either superficial or deep. The differing nerve sources are seen in the right hand column.

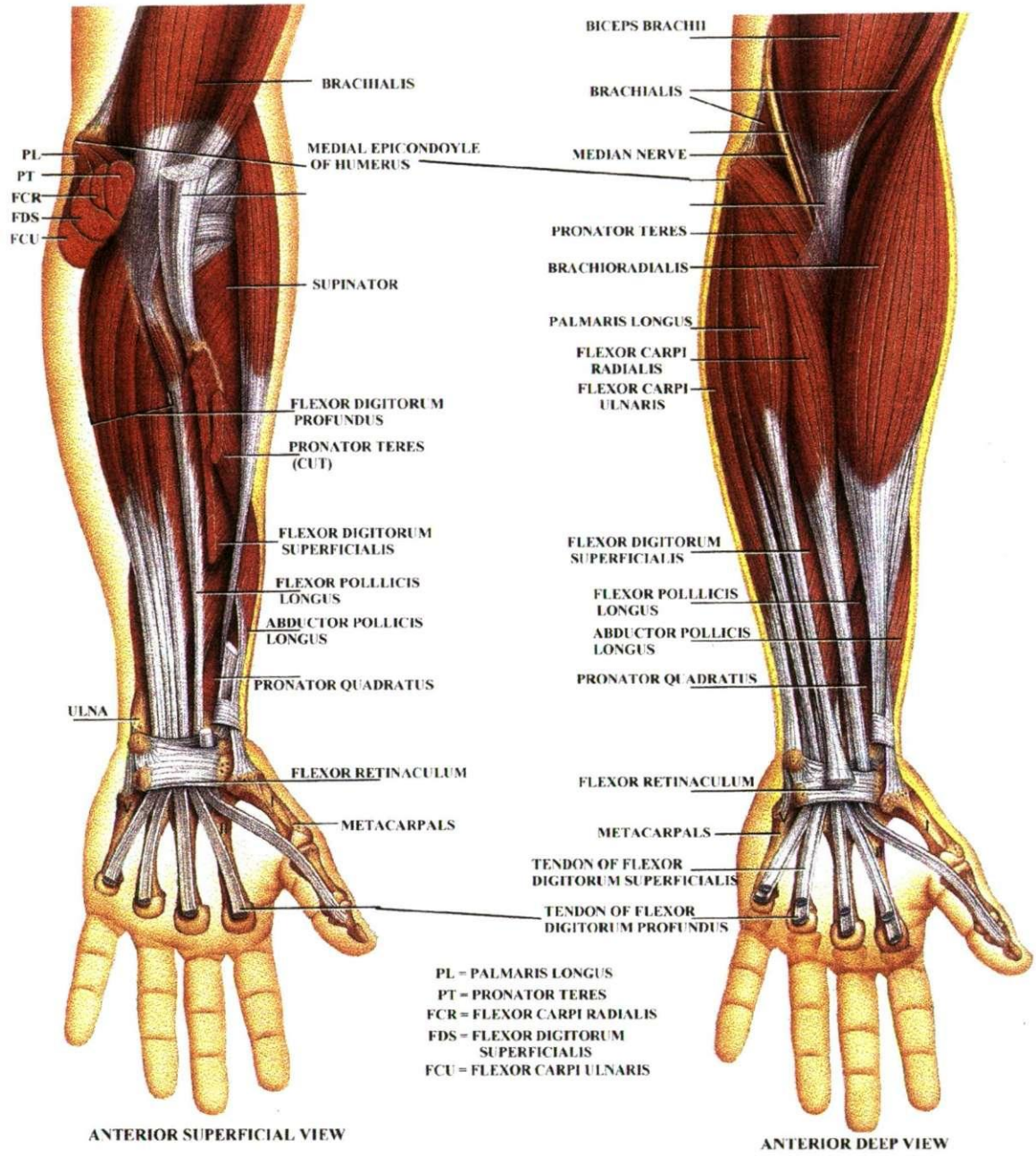


Figure 2.8 Muscles of the forearm involved in wrist, hand, and digit action. View (a) shows the deeper muscles, while View (b) shows the overlying superficial muscles.
Adapted from "Principles of Anatomy and Physiology" by Tortora and Grabowski, Wiley and Sons, 9th edition, 2000. ISBN 0-471-36692-7

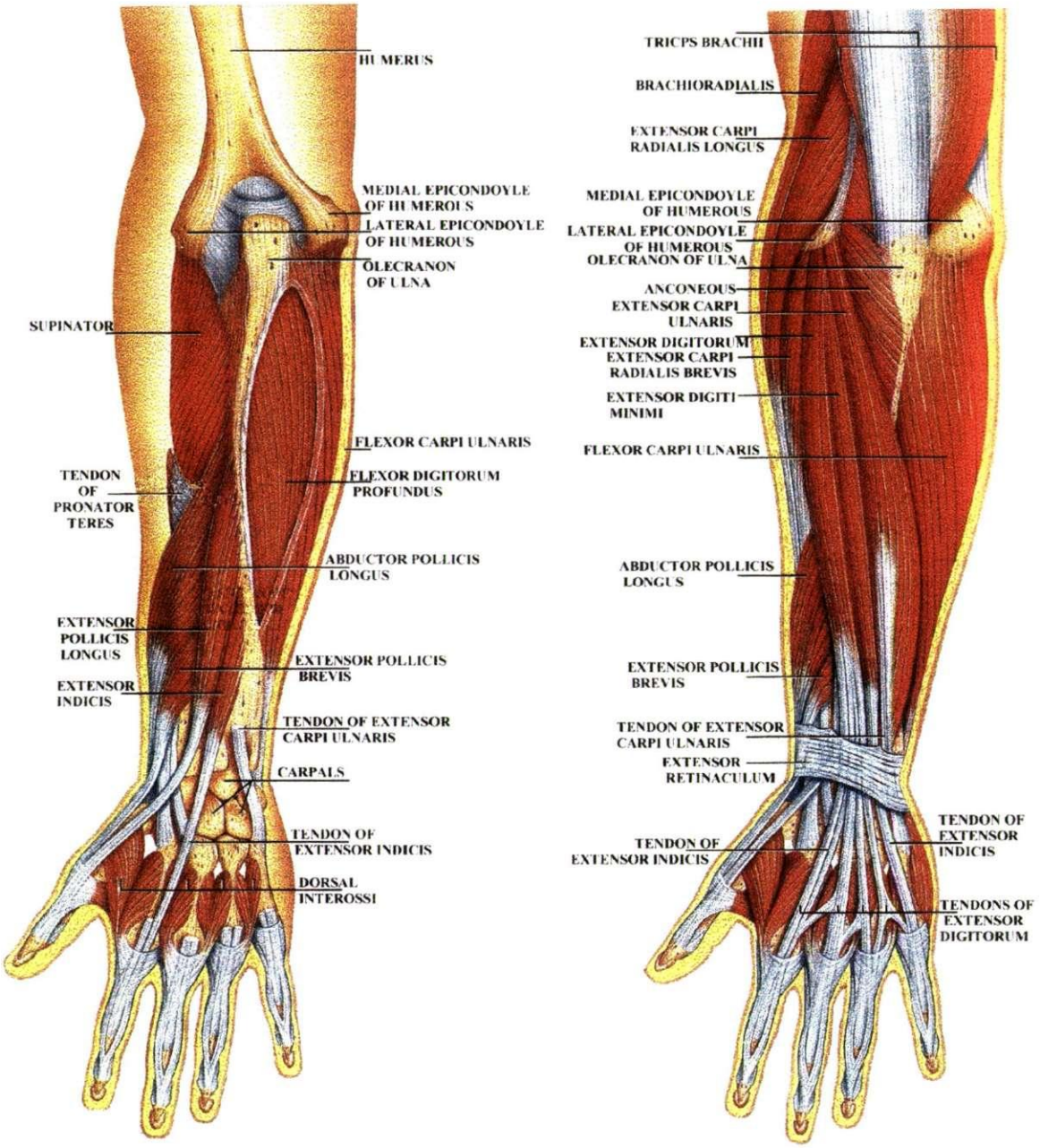


Figure 2.9 Muscles of the forearm involved in wrist, hand, and digit action. View (a) shows the deeper muscles, while View (b) shows the overlying superficial muscles.
Adapted from "Principles of Anatomy and Physiology" by Tortora and Grabowski, Wiley and Sons, 9th edition, 2000. ISBN 0-471-36692-7

2.3 Myoelectric Signal (MES) Generation

The muscle fibres (innervated by the spinal cord motor nerves that carry the commands from the brain), generate the surface MES signals that are detected. The surface EMS is the electrical manifestation of the neuromuscular activation associated with the contracting muscle. The signal represents the potential generated by the ionic flow across the membrane of the muscle fibres, which passes through the intervening tissues to reach the detection surface of the electrode [**6**].

The muscle fibre (cell) is like a very fine thread of diameter 0.01 to 0.1 millimetres and a length from a few millimetres to 30 centimetres. When innervated it will contract to about 2/3 of its length. These muscle fibres do not contract in isolation and one nerve fibre will branch and innervate a group of muscle fibres within the muscle. This group of fibres is called a "motor unit".

Even within one motor unit the moment in time at which fibre activation actually occurs varies (minutely) due to the different individual lengths of the nerve fibre branches within that group (motor unit). This is in addition to the **random rate of release** [7] within the motor unit group, of the chemical transmitters (e.g. acetylcholine) at the individual nerve/muscle-fibre (neuromuscular) junctions (synapses). It is the release of these transmitters that 'fires' the neuron [**8,7**].

The "InterPulse Interval" (IPI) refers to these 'firing' differences in the propagation potentials separated in time among the muscle fibres of a motor unit. [**9,7**].

The IPI varies from discharge to discharge due to variations in synaptic delay (accounted for by: (a) the amount of neurotransmitter released, (b) rise time and excitability of the end plate potential, and (c) the random nature of acetylcholine release). This variability in

firing response is known as "Jitter". Jitter has a standard deviation of about 20 μs. Jitter is usually expressed as either the mean of consecutive differences (MCD) of the IPI which minimises the influence of slow trends, or as the mean sorted difference (MSD) which eliminates the influence of the firing rate. Firing rate (or interdischarge interval (IDI)) is a parameter that represents the inverse value of the InterPulse Interval (IPI) [*see Figure 2.9*]. The size of a motor unit, as a rule, is proportional to the "fineness" of the control action. For a fine action such as eye movement the motor unit size is small, around 10 fibres /unit; while for the larger lower limb muscles the motor unit size can be in the thousands of - fibres/unit. To further complicate the matter the fibres of up to 30 different motor units may occupy/interpenetrate the same region encompassed by one motor unit [7]. Buchthal, using a 12 lead, multielectrode technique, looked at the human biceps brachii. He was able to show that the fibres of each motor unit were localized in an approximately circular region with an average diameter of 5 mm.; with some reaching a spread of 20 mm.**[10]**. The rate at which the motor units are recruited (recruitment strategy) for use also varies. As a muscle is further brought into action, (e.g. more strength is demanded in lifting an increasing load), then more motor units are increasingly recruited for use. The smallest motor units are controlled by the most easily excitable (i.e. lowest stimulus threshold) motor neurons. The neurons that activate the motor unit fibres do not transmit just a single impulse with its twitch only response, but rather the neurons emit volleys or streams of these impulses to the fibres. These volleys are composed of closely spaced impulses and as a consequence the fibres are stimulated repeatedly before each one has time to fully relax. This produces a "wave summation" that appears as a sustained state of muscle contraction (tetanus).

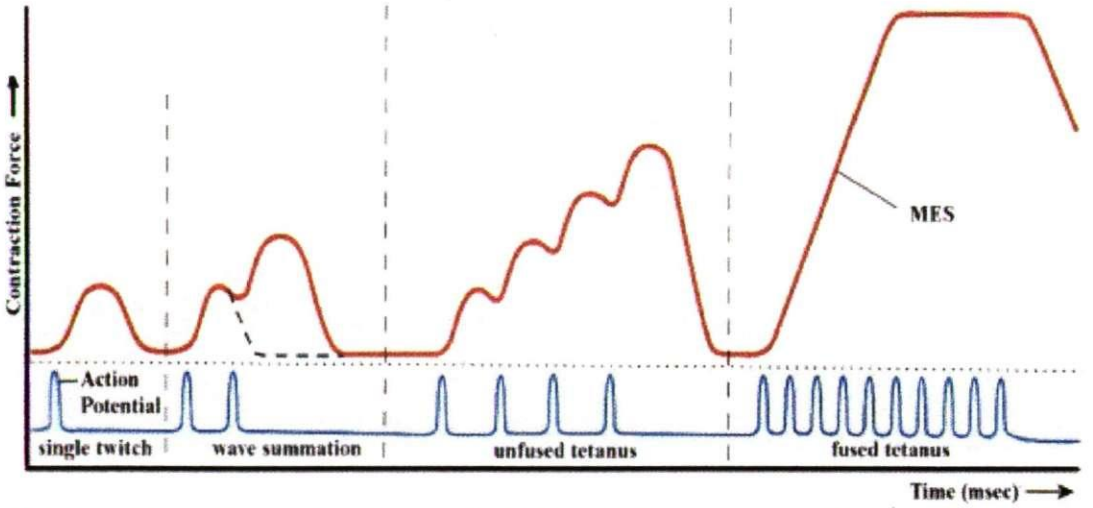


Figure 2.10 Shown here is a single twitch and its corresponding contractile force response. When a second action potential follows on quickly, before the muscle has relaxed, the result is a wave summation in which the overall contraction response is greater. As more action potentials arrive, the result is a wave summation called 'unfused tetanus'. As the frequency of the action potentials increases, the wave summation becomes much smoother and is called a 'fused tetanus.' In a fused tetanus, stimuli are of the order of 80 to 100 action pps, and the contraction is steady and sustained.

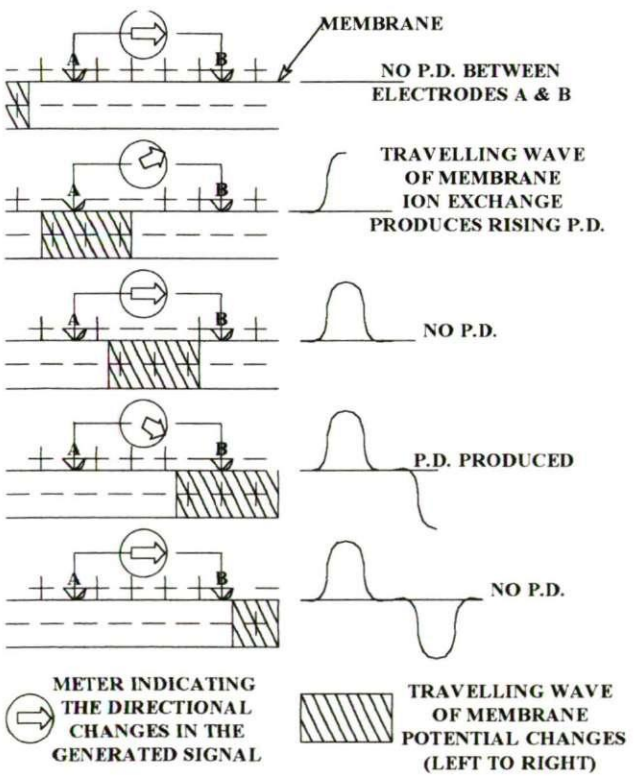


Figure 2.11 Muscle fibre electrical activity.

Thus, one way to increase the strength of contraction is to increase the frequency of the exciting stimuli (*see Figure 2.10*). This wave summation has other considerations. When a muscle has been at rest for an extended period the characteristic activity will be slightly different until the muscle has been warmed up by activation. As the muscle warms up (over a period of several contractile responses) it works more efficiently. A slightly stronger

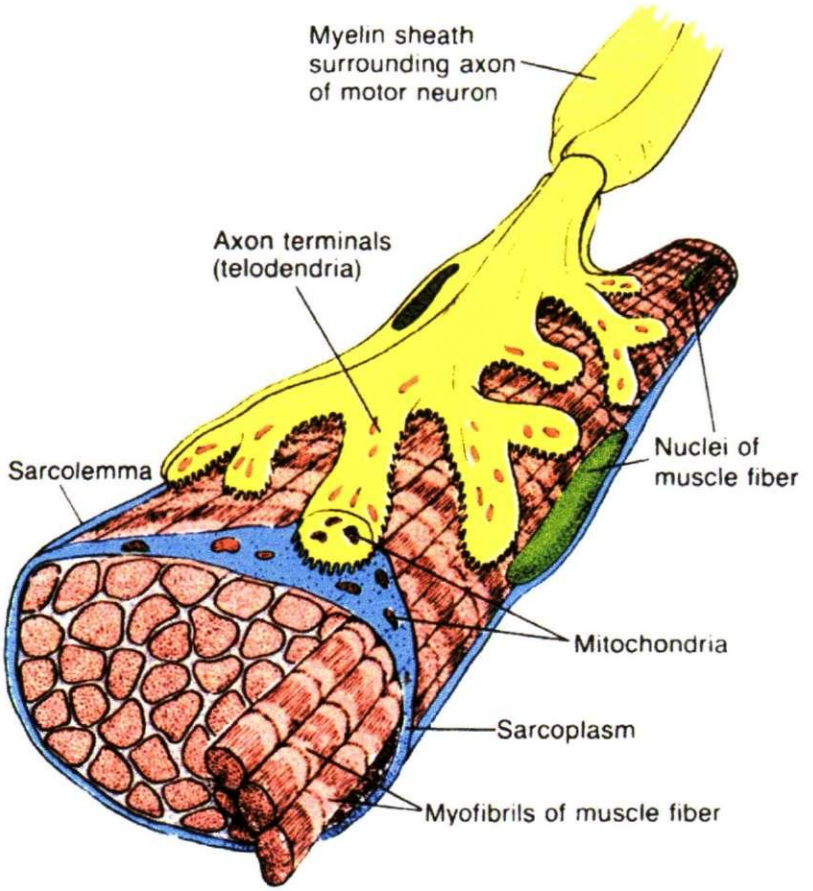


Figure 2.12 Neuromuscular junction (motor end plate Diagram based on a 400x micrograph. From 'Introduction to the Musculoskeletal System' by Rosse and Clawson, Harper and Row, New York, 1970

reaction is produced in each subsequent contraction (over that period of several contractile responses) in response to an otherwise equally applied stimulus. This is called "Treppe" or the staircase effect. All of these characteristics surrounding the firing action of the muscle fibres are detectable as features of the myoelectric signal (MES).

Once the actual fibre has been innervated the response of the fibre and its representation as a detected MES is shown in *Figure 2.11*. The point on the fibre, at which the neuromuscular junction occurs, known as the endplate region, is usually found near to the middle of the muscle fibres. It is at this point where the fibre response spreads in opposite directions along the length of the fibre (*see Figure 2.12*).

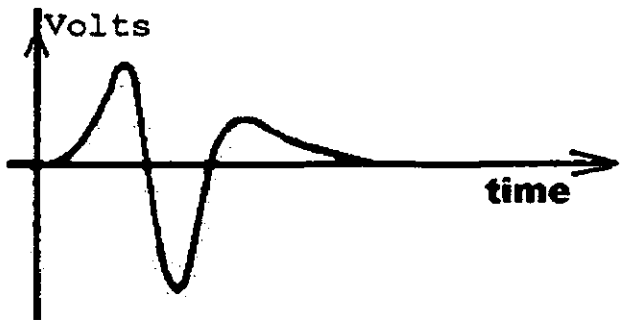


Figure 2.13 motor unit action potential (MUAP)

2.4 Myoelectric Signal (MES) Investigation

Only the action potential of individual muscle fibres has been considered in *Figure 2.11*. In fact the motor unit as a whole is triggered into action and the depolarisations, of the individual motor unit fibres, overlap in time. The result is an overall space-time superimposition of the individual fibre Action Potentials (AP) (*see Figure 2.13*) combined into one Motor Unit Action Potential (MUAP) [**11**]. The MUAP time duration varies between 1 to 13 ms. In order to sustain a muscle contraction the motor unit must be repeatedly fired. The resulting sequence of MUAP's is called a Motor Unit Action Potential Train (MUAPT) (*seeFigure 2.14*). Many different and intermingled MUAP's are fired to bring about an intended muscle activity with the resultant space-time superimposition of a number of MUAP's seen by the electrodes at the surface.

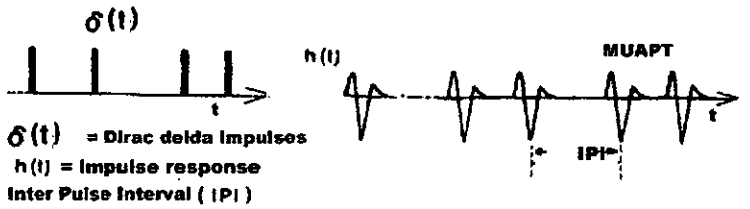


Figure 2.14 MUAPT as pulses with Interpulse Intervals (IPI's)

At each increment in time, there occurs a summation effect as the result of these many changing variables. The MES at the surface is the "blended" sum of the individual MUAP trains (*see Figure 2.15 and 2.16*) [**7**].

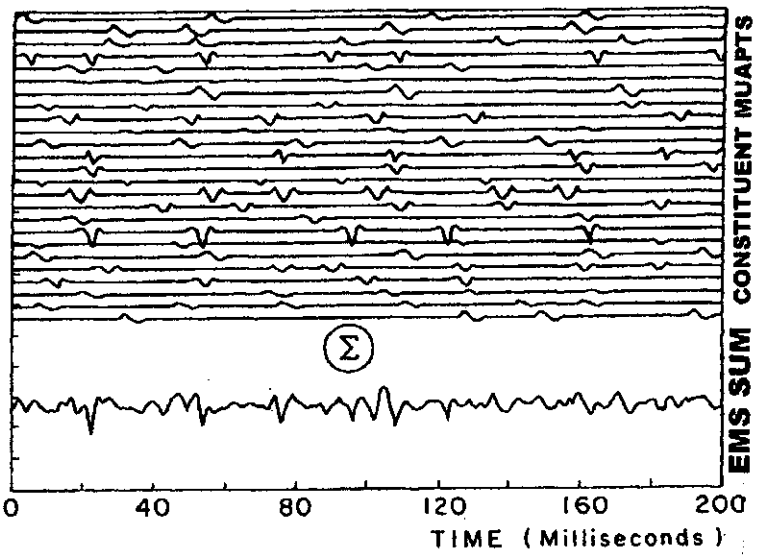


Figure 2.15 MES signal resulting from summation of 25 MUAPT's. Redrawn from 'Muscles Alive' by Basmajian and De Luca, Williams and Wilkins, 1985.

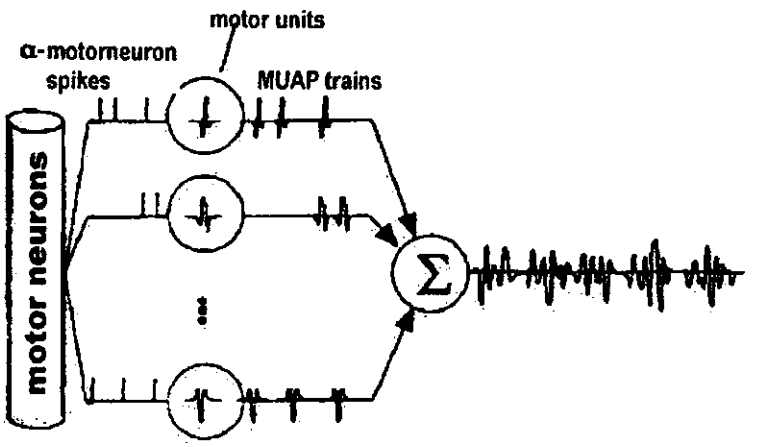


Figure 2.16 MES construction from MUAP trains (MUAPT's). Redrawn from 'Muscles Alive' by Basmajian and De Luca, Williams and Wilkins, 1985.

Investigators **[12]** have determined that *the surface MES appears to be a band limited stochastic process with a Gaussian amplitude distribution* (with a bandwidth from D.C. to about 500 Hz). Different models of the MES have come up with variations on this "random signal" theme. A model by Deluca and Stulen describes the MES as white Gaussian noise passing through a linear filter (signals representative of MES spectrum are synthesised by varying the gain and filter coefficients

[13,14].

2.5 Muscle Fibre Types

Fibres Are Categorised Into Three Types: [15]

Type 1: The red (red in appearance) slow-twitch fibres. These are slow contracting oxidative fibres with large amounts of myoglobin using **aerobic** pathways with fat as the primary fuel. They split ATP at a slow rate and as a result the 'contraction velocity' is slow. They are extremely fatigue resistant and can contract for prolonged periods. As they are thin fibres, they produce less power than the thicker white fast-twitch fibres.

Type 2: The red fast-twitch fibres. These are intermediate in size between types 1 and 2, and contain large amounts of myoglobin, and very many blood capillaries. They split ATP at a fast rate and as a result, contraction velocity is fast. They are fatigue resistant but less so than type 1 fibres. **Aerobic** capacity is the fibre capacity to do work in short bursts using oxygen as a fuel.

Type 3: The white (white in appearance) fast-twitch fibres. These are double the diameter of the red slow-twitch fibre, are fast contracting, and contract much more powerfully than the red slow-twitch fibres. They have a low myoglobin content and few blood capillaries They do however contain large amounts of glycogen using **anaerobic** pathways to split ATP at a fast rate so that they have a fast contraction velocity. As glycogen reserves deplete rapidly followed by a lactic acid build-up these fibres have poor endurance and fatigue easily. Note: **Anaerobic** capacity is the fibre capacity to do work in short bursts in the absence of oxygen.

In each particular motor unit the fibres are all of the same type. Most muscles are of mixed fibre types and some muscles are dominantly, but not exclusively, of one fibre type. Some

people will have more of one type in some muscles than other persons might have and this difference is genetically determined.

The contribution of the frequencies of these three fibre types to the overall MES has yet to be determined. The pinkish or reddish appearance of the fibres is due to relatively large amount of myoglobin and blood supplied to them by their extensive vascularization

The white fibres have a paler colour and are less vascularised.

2.6 Electrode Signal Detection Method

How Completely Can The MES Be Captured?

Electrodes used on the skin surface can be broadly classified as wet or dry electrodes. Wet electrodes are fixed into place by a temporary sticky gel that has good electrical conduction properties. Dry electrodes have inferior stability for MES detection (see motion artefact) and sensitivity to weak signals is slightly less. The great advantage to dry electrodes is their use in locating the best location for a particular MES and their use in this research in exploring and mapping the arm MES.

2.6.1 Electrode Materials

Silver-Silver-Chloride Electrodes: Used with a 0.9% saline solution these electrodes have **very low noise** voltages developed between the pair of electrodes (half-cell potential) and as a consequence are used by choice as reference electrodes in electrochemistry.

Platinum-Black Electrode: A heavily chlorided silver-silver chloride electrode followed by platinum deposition followed by chloriding once again results in an electrode

with the combined best properties of the (low impedance of a few ohms at 20 Hz) platinum-black (platinum on platinum) electrode and the (low equilibrium potential) chlorided silver electrode.

The Silver-Black Electrode: If the silver chloride surface coating is then treated with photographic developer for 3 minutes, a dramatic reduction (to levels between 1/20th and 1/60th) in impedance, at all frequencies, is seen. The magnitude of the deposit will vary with the required end use.

Bare metals and polished metals in particular, have the lowest electrode-electrolyte (EE) series-equivalent capacitances. Thus roughened surfaces, an increase in the concentration of the electrolyte (skin-salts, moisture) and an increase in temperature, all increase the series-equivalent EE capacitance.

2.6.2 Interfaces in the Signal Path

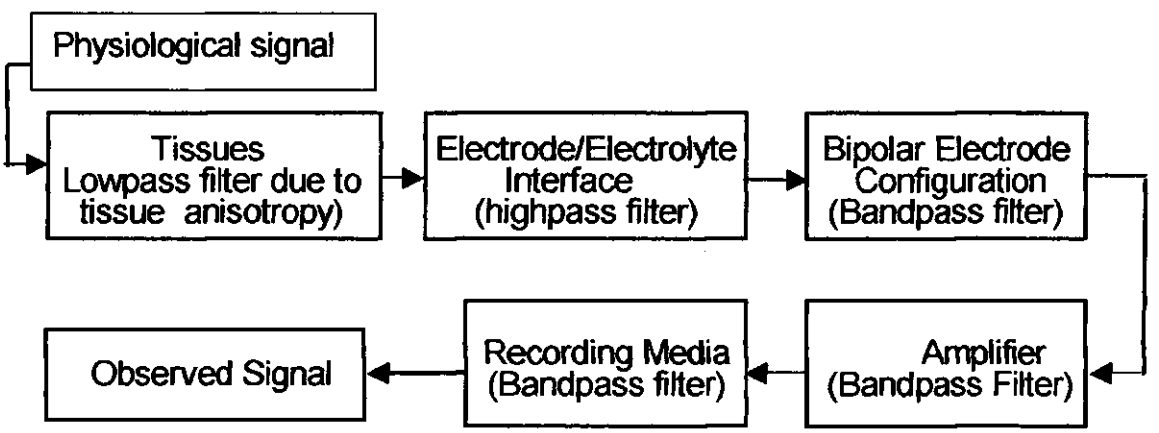


Figure 2.17 Filter effects from signal source to observed MES).
Redrawn from 'Muscles Alive' by Basmajian and De Luca, Williams and Wilkins, 1985.

Both the tissue and the electrode (*see Figure 2.17*) filter the EMS while in the process of being detected. The characteristics of the observed EMS are a function of the apparatus used to acquire the signal as well as the electrical current (signal) generated by the membrane of the muscle fibres. When using surface electrodes the thickness of the fatty and skin tissues behaves as a low-pass filter, with gain and bandwidth decreasing approximately inversely proportional **[11,16]** to the distance between signal source and detection surface (*see Figure 2.18*). For maximum signal information, the detection materials and technology need to be at their optimum. The orientation of the detection surfaces with the length of the fibres is critical in order to avoid signal loss.

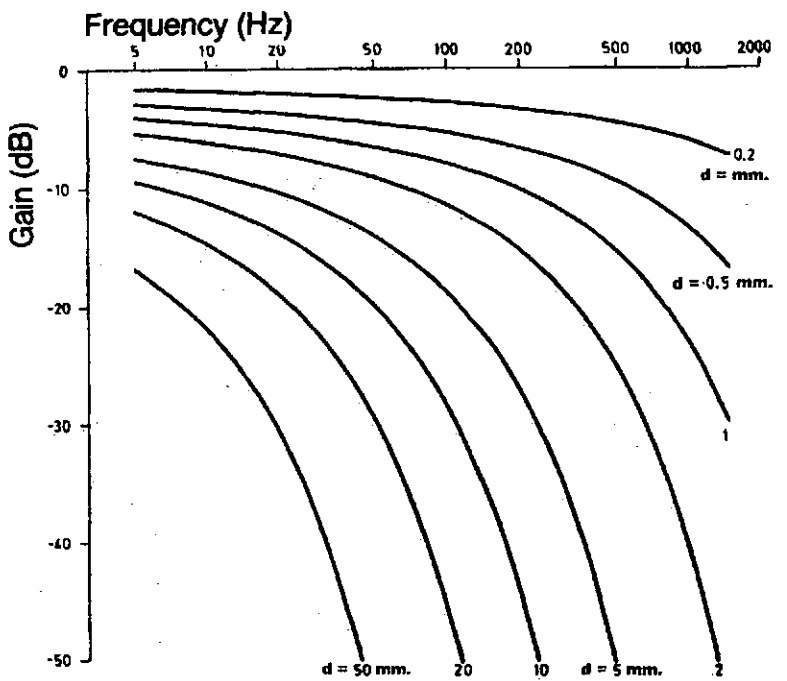


Figure 2.18 The Tissue Filter Function (TFF) is represented here as a decrease in the detected gain (in dB) of higher frequencies (over the range of 0-2000 Hz) as 'd' increases (distance in mm. from active fibre to detection electrode). Redrawn from 'Muscles Alive' by Basmajian and De Luca, Williams and Wilkins, 1985

A bipolar (differential) amplifier configuration (when not D.C. coupled) behaves as a band-pass filter. Note however that this is only if the differential inputs are balanced and the filter characteristics of the electrode/electrolyte junction are equivalent (*see Figure 2.19*).

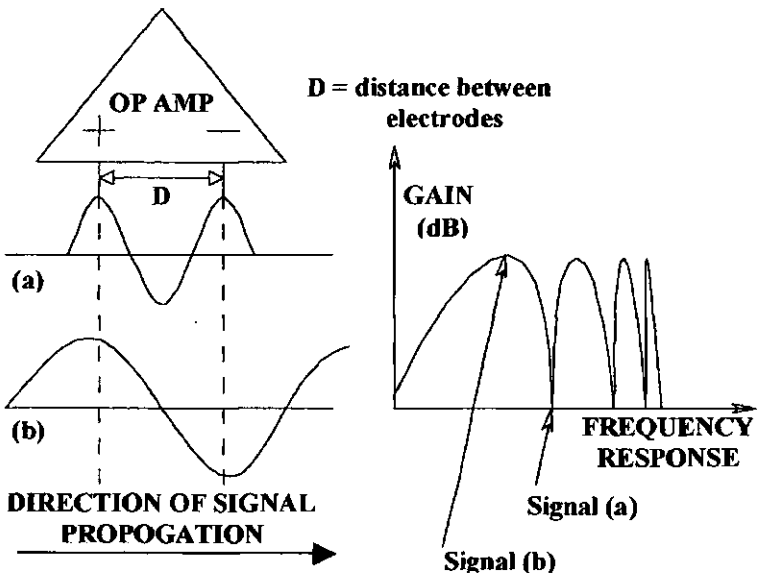


FIGURE 2.19 Amplifier/electrodes filter function. As an op amp amplifies the difference in signal magnitude between the + and – electrodes, no signal gain (a) will result when the situation 'D' occurs. All multiples of 'D' will also be affected. Greatest gain will occur at (b). *(For explanation see Section 2.6.7)* Redrawn from 'Muscles Alive' by Basmajian and De Luca, Williams and Wilkins, 1985.

Bandwidth: The window of interest in the frequency domain determines the type of amplifier to be used, i.e. A.C. or D.C. coupled amplifier. Amplifiers designed for D.C. signals are required to minimise "drift" as a function of temperature.

The "voltage decrement function" describes how the amplitude of action potentials decreases **rapidly** with distance e.g. the signal amplitude decreases by 75% at only 100 micrometres from the signal-generating source.

2.6.3 Electrolytes

Human sweat composition is more than 99% water (99.2 %- 99.7 %) and can be considered to be a weak saline solution of concentration between 0.1% and 0.7%.

The surface of the skin, where an electrode is placed, is coated by a weak saline (sweat) solution mixed with the oily secretion from the sebaceous glands. The sebaceous glands

produce an oily substance that passes up the hair follicle to protectively coat the surface hairs. These secretions coat the layer of dead cells (which is the point on the signal pathway that gives the highest resistance to the signal).

2.6.4 Noise Problems: Corruption Of the MES by Noise

The myoelectric signal sample looks very much like electrical noise with the greatest peaks relating to strong muscle force exertions. The most useful range of strong surface detectable MES activity is from 20 HZ to 500 Hz. The MES detected is of the order of 1 microvolts to 100 microvolts peak to peak. Amplification of this very small signal is necessarily required and it is of the utmost importance to avoid introducing electrical noise into the amplification process [17,7,8]

Note: The RMS (root mean square) commonly used as a method of measuring a detected signal, seriously accentuates the peak values at the expense of the lesser values: e.g. the result of squaring a value of 2 is a doubling while squaring a value of 3 is a tripling. A common solution is to find the mean absolute value by using a full-wave rectifier circuit [18].

Mains noise: is the most intrusive noise source (50 Hz east of the Atlantic or 60 Hz west of the Atlantic). This noise is generally the mains signal radiating throughout the environment, emitted by domestic supplies from embedded or equipment wiring sources. When using unshielded signal cables and/or imbalanced input impedances, these unwanted mains signals might need to be removed with a notch filter.

Thermal noise: is generated by electrodes. This property is proportional to the square root of the resistance of the detection surface. The problem may be reduced by cleaning the electrode contacts and by using a large surface to minimise the resistance.

Motion-Artifact noise: can produce signal bursts much greater in amplitude than the MES (with subsequent malfunction of the prosthesis) [19].

Motion-artefact noise occurs in two locations:

1) At the electrode-tissue interface i.e. "relative movement" between the tissue and the electrode. A lack of chemical equilibrium exists between any two differing materials (each having dissimilar electrical properties) in contact with each other. This inequilibrium generates a polarisation potential. Relative movement at the interface of these materials will modulate the polarisation potential that produces an A.C. waveform, though of a low frequency nature (less than 30 Hz). Another variation is "skin potential". Normally a voltage of about 20 millivolts exists across the layers of skin (believed to be a result of the dead skin cells migrating towards the surface). This voltage varies as the skin is stretched, such as when the limb is moved and the muscles contract beneath the skin. Abrasion of the skin surface reduces this effect as the voltage across the skin layers is shorted out [7,17].

2). Induced Leads Noise: is also generated at the leads coming off the electrodes as the wire (lead) is moved through a magnetic field, such as the 50 Hz fields that permeate rooms. The voltages generated can be of the order of several millivolts and can thus seriously contaminate the MES. When the input impedance of the amplifier is very high, this small, induced current can produce a high voltage across the amplifier-input terminals [7]. Lead length must be kept as short as possible (located within 10 cm. of the electrode) and not subject to movement. The necessity of this precaution is increased when using amplifiers of input impedance greater than 10 megohm.

Seebeck (thermoelectric) noise: When a closed conducting circuit comprised of two conductors of dissimilar metals has a temperature difference between the metal junctions, a thermocouple is created with high thermoelectric potential of about 35 microvolts /degree C. Such a condition exists in a typical integrated circuit, with **kovar** (the standard IC lead material), and copper tracks. Thus care must be taken to ensure that all connections remain isothermal.

2.6.5 MES Signal Amplifier Selection

It is **not** recommended to use D.C. amplifiers for the following reasons:

1) The D.C. polarisation potential, found at the skin/electrode junction, might be greater than or equal to the detected MES signal.

2) The lead wire may generate motion signals of low frequency, less than 20 Hz, and present these for amplification.

3) Signal content below 20 Hz is unstable, highly variable, and not necessarily related to desired signal activity.

Rau (1974) [7] reported that in order to improve MES signal detection, the suppression of the influence of skin impedance is necessary. Variations in skin resistance and signal pathways result in a decrease in the result of the recorded lower frequencies. In order to decrease the inaccuracy of skin resistance variations to about 5 per cent, the input impedance of the amplifier needs to be a minimum of 10 times the maximum skin impedance.

2.6.5.1 CMRR (Common Mode Rejection Ratio)

In the real world, perfect noise cancellation does not occur due to both imperfect subtraction in the amplifier (gain imbalance and non-linearities) and to the noise signal, not necessarily being applied as common mode. The latter failure in noise reduction could be the result of a non-uniform, physical structure (anisotropic or non-isotropic) in the signal pathways or impedance characteristics of the pathways to each of the inputs.

CMRR: This is the ratio of the common-mode **voltage** gain to the common-mode **error voltage** gain. Common-mode gain (A_{cm}) is the ratio of the change in output voltage to the change in common-mode input voltage (i.e. the input to output gain for voltages common to both inputs). The differential gain, i.e. normal-mode gain (A_d), is the gain between input and output for voltages applied across the two inputs (differentially). Thus CMRR is the ratio of (A_d) to (A_{cm}). CMR is the logarithmic expression of the CMRR.

i.e. CMR = 20 CMMR. e.g. a CMRR of 10,000 yields a CMR of 80 dB

As the CMR increases, the common-mode output error signal does not increase with gain. This does **not** also mean that the error signal decreases with gain.

In án ideal set up, a high value of CMRR would produce a cancellation of noise signals imposed upon the bipolar inputs of a differential amplifier **[20]**.

i.e. Amplified signal: = GAIN (signal A - noise) - (signal B + noise)

= GAIN (signal (A-B))

In an instrumentation amplifier, degradation of common-mode rejection is caused by a differential phase-shift due to differences in distributed stray capacitances. Shielded cables are commonly used to minimise the pickup of noise, but the shielding increases input capacitance. This in turn degrades the settling-time for signal changes. Any imbalance in

the source resistance between the inverting and non-inverting inputs, when capacitively loaded converts the common-mode voltage into a differential voltage. This can create common-mode errors unless the shield is properly "driven". A.C. common-mode rejection deterioration can be improved by "bootstrapping" the capacitances of the input cabling thus minimising differential phase shift.

To preserve the high CMRR it is necessary to use the first stage of amplification as a unity amplifier.

Note: Skin-electrode impedance ranges from 200 ohms to 2 Megohms (Rau, 1974) [7].

In order to decrease the inaccuracy of the measurements to 1% or less, the input impedance of the amplifier needs to be at least 50 times greater than the skin-electrode impedance. This will assist in the flat measurement of the frequency response, at least from 10HZ to 100 HZ.

An electrode-electrolyte interface can be equated to a series resistance and capacitance circuit, the values of which vary inversely with the square root of the frequency. i.e.

$$Z_s \propto \frac{1}{\sqrt{f}}$$

Comparing the resistance to the overall reactance shows them to be very nearly equal and varying inversely with the square root of the frequency.

2.6.6 Signal Reliability

The reliability of the detected MES as a repeatable phenomenon is dependent upon a number of factors. If the muscle is small and close to the surface, the electrodes may need to be sited accurately to within a few millimetres. If the muscle is large or deep, then electrode placement may vary by a few centimetres without affecting the MES. Amplitude

variations in the MES may result due to skin impedance changes. Frequency shifts may occur due to fatigue, amplifier bandwidth, timing of MES sampling, and the physiological and anatomical differences between individuals.

2.6.7 Bipolar Filter Function (*see Figure 2.19*)

When an MES is generated, it passes through the skin layers. When detected at the skin surface there is a different frequency response by the differential amplifier inputs according to the actual distance between the surface electrodes. When the distance D (*see Figure 2.19*) that separates the electrodes is the same as the wavelength of the myoelectric signal, the response of the amplifier is at its minimum. This is because each of the op-amp inputs experiences the same amplitude and thus acts as in common mode to the signal and the signals cancel out. When the signal wavelengths are 2D, the signals at the two op amp inputs are at opposite signs, and are thus at a maximal difference. The amplifier then gives maximum amplification to such a signal. The resulting response of a differential amplifier is thus clearly also a function of the physical distance between the two input electrodes. Surface size of electrodes should be made ideally as large as possible, but advantages of large size diminish with diameters of greater than 5 mm. due to the loss of muscle selectivity and an increase in crosstalk (i.e. the swept region may encompass more muscles). A major question with respect to selectivity is how far apart to place the electrodes i.e. the detection surfaces? The standard spacing recommended is 1.0 cm. for surface electrodes. This is a compromise to ensure adequate high frequency response without loss of selectivity of swept muscle area.

The bandwidth (bw) of the detected MES signal increases as interdetection surface (D) decreases. i.e. $\text{bw} \propto \frac{1}{D}$

An increase in interelectrode spacing and the associated reduced bandwidth results in an increase in the signal-to-noise ratio. With increases in interdetection surface spacing comes a greater susceptibility by the electrode to detecting measurable EMS amplitudes of adjacent and/or deep muscles.

A rule of thumb for surface electrodes is that the electrodes will detect measurable signals from a distance equal to the interdetection surface spacing **[7].** Note however, that the anisotropy of the tissues beneath the electrode may produce signal cross-coupling at the electrodes.

From the previous discussion we have now some recommendations for:

Desirable Amplifier Characteristics

- Output gain of approx. 500 to 1000
- Input impedance >10 Megohms in parallel with 5pf. capacitance.
- CMRR >130dB
- Less than 20 pA input bias current
- Less than 5 μv (RMS) noise floor. Valid EMS signals start at 10 μv to 20 μv
- 3dB Bandwidth (for *surface* electrodes): from 20 to 500 HZ

For general purposes the low frequency 3dB point should be set to 20 HZ and the high frequency point should be set slightly higher than the highest frequency of interest.

2.7 Analysing the Detected MES

2.7.1 Time Domain Analysis (TDA)

In the time domain the MES can be approached as:

- a specific deterministic signal [21]
- a deterministic signal with random noise disturbances
- a stochastic signal
- a stochastic signal with trends e.g. transients, biases

2.7.2 Frequency Domain Analysis (FDA)

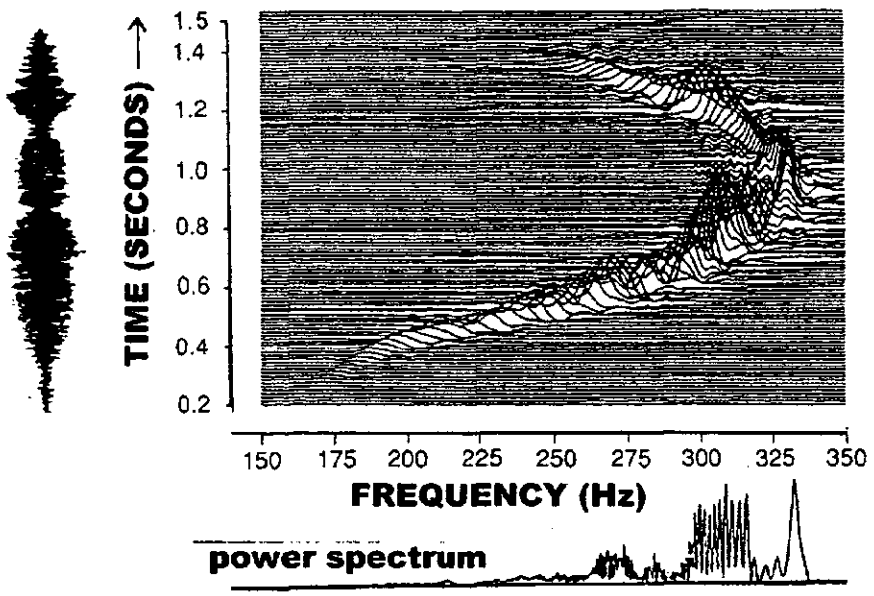
In the frequency domain, the MES can be seen as a power density frequency spectrum drawn from the time domain characteristics.

2.7.3 Time-Frequency Analysis (T-FA)

The most common signal analysis method, Time Domain Analysis (TDA), e.g. the oscilloscope, provides a measure of the signal **amplitude** as it changes in time.

This is a different story from the Frequency Domain Analysis (FDA) commonly encountered where a signal is captured over a period of time and the (FDA) provides a measure of the **power** contained in the frequencies that existed for the whole duration of measurement. So time and frequency analysis do not fully describe what is happening in the signal.

With Time-Frequency Analysis (T-FA) the purpose is to understand and describe the "frequency content of a signal changing in time". With T-FA we learn of the frequencies that existed at each moment of time [22].



The common tool for frequency domain conversion, the Fourier Transform, tells of the frequencies that existed for the total duration of the signal and not the frequencies that exist at a particular time. This can be seen readily in *Figure 2.20*, which shows a representation of a 1.5 second duration sound produced by a whale over a spectrum of 150 Hz to 350 Hz [**22**].

Figure 2.20: The Time-Frequency distribution of a whale sound over a 1.5-second duration. The time-frequency plot shows how frequencies are 'changing' with time. The energy density (power) spectrum shows the total summation of the individual frequency components but doesn't tell you at what moment they were produced throughout the 1.5-second period. From: 'Time-frequency signal analysis', by B. Boashash, (1992) ISBN 0-582-71286-6.

Muscle fibre conduction velocity, muscle fibre size and type, and motor unit firing rate/recruitment strategy all influence the power spectral content of the MES.

During contractions of the muscle, as the force increases so does the recruitment of the larger motor units composed of larger fibres. It is the changes in strategy used by the central nervous system to recruit motor units that may be part of a detectable process that can be used in feedback control of applied force in a myoelectric prosthesis. One method used is the decomposition of the Interference Pattern (IP). The IP is the sum of the action potentials produced by each active motor unit.

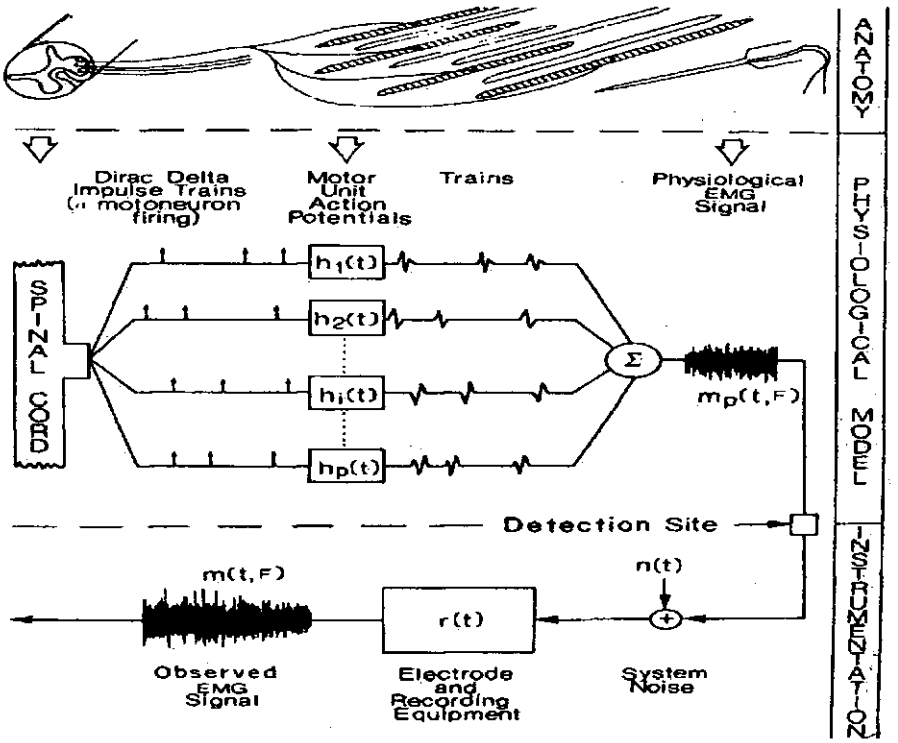


Figure 2.21 De Luca's model of the MES signal as a summation of MUAPT's as detected by an electrode. Adapted from 'Muscles Alive' by Basmajian and De Luca, Williams and Wilkins, 1985.

One well-known observation with regards to the spectral content of the MES is that of the shift toward lower frequencies during a sustained contraction. This frequency shift may be a result of the widening of the time domain shapes of the MUAP's. Laboratory experiments have also noted a reduction in overall signal amplitude during a sustained contraction (fatigue).

2.7.4 Modelling the MUAPT

De Luca, [**7,11**] modelled the MES signal as a linear, spatial, and temporal, summation of the MUAPT's, as detected by the electrode (*see Figure 2.21*). Figure 2.21 can now be seen as a combining of the concepts introduced in Figures 2.12, 2.13, 2.14, 2.15, and 2.16. In *Figure 2.16* the MUAPT is decomposed into a sequence of Dirac delta impulses δ (t), which are then passed through a filter with impulse response $h_i(t)$ Each impulse marks the

time occurrence of a MUAPT with filter output $u_i(t)$ where i indicates a particular MUAPT.

As mentioned the **random** character of the MES has been observed and so we need to consider this feature in any model.

2.7.5 Mathematical Analysis

Using DeLuca's [**7,11**] notation we have:

a **firing rate** for a motor unit denoted as λ(t, F)

where: t= time and F=force.

Thus the firing rate is considered to be a function of time and force.

Given an **InterPulse Interval (IPI)** histogram with a probability distribution function:

p_x (x,t,F)

the inverse of which will be the firing rate, we have: $\lambda(t,F) = [\int_{-\infty}^{+\infty} x p_x (x,t,F)\, dx]^{-1}$ (Equ. 1)

Now if we describe the (Filter Input) Dirac impulse train as: $\delta_i(t) = \sum_{k=1}^{n} \delta(t - t_k)$ (Equ. 2)

where integer i denotes a particular MUAPT

Then we can describe the (Filter Output) MUAPT $u_i(t)$ as: $u_i(t) = \sum_{k=1}^{n} h_i(t - t_k)$ (Equ. 3)

where $t_k = \sum_{l=1}^{k} x_l$ for $l = 1,2,3,\ldots\ n$

t_k represents the time locations of the MUAP's,

t is a real continuous **random** variable,

n the total number. of IPI's in a MUAPT,

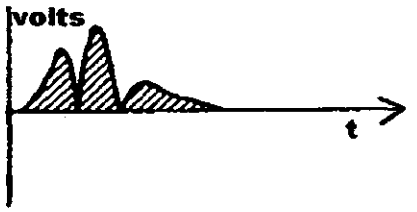


Figure 2.22 The signal in figure 2.13, is here rectified, to be shown as the area under the motor unit action potential

x represents the IPI's,

and i, k, l are integers which denote specific events.

From this we can write an expression for the MUAPT Mean rectified value: (E)

$$E\{|u_i(t,F)|\} = \int_0^{\infty} \lambda_i(\hat{t},F)\,|h_i(t-\hat{t})|\,d\hat{t} \qquad \text{(Equ. 4)}$$

This value denotes **force output** of the muscle. where $\hat{t}$ is a dummy variable,

and Mean-Squared value :

$$MS\,|u_i(t,F)| = \int_0^{\infty} \lambda_i(\hat{t},F)h_i^2(t-\hat{t})d\hat{t} \qquad \text{(Equ. 5)}$$

Figure 2.23 The signal in figure 2.13 is here shown as the area under the square (whose square root is the RMS

De Luca suggests that since λ(t, F) is slowly time varying the above expressions can be reduced to:

$$E\{|u_i(t,F)|\} = \int_0^{\infty} |h_i(t)|\lambda_i(t,F)\;dt \qquad \text{(Equ. 6)}$$

and: $$MS\,|u_i(t,F)| = \int_0^{\infty} |h_i^2(t)\lambda_i(t,F).dt \qquad \text{(Equ. 7)}$$

In (Equ. 4) the term: $|h_i(t-\hat{t})|\,\hat{}$ is dropped out and reduced to (t) in (Equ. 7)

In each of the last two expressions the first term on the right side of the equation has become a scaling value and is time independent. **Thus we have a model of the MUAPT reduced to an expression of the firing rate multiplied by a scaling factor (h_i^2).**

De Luca presented the Mean Rectified and the RMS model expressions particularly well, as shown in *Figure 2.24*

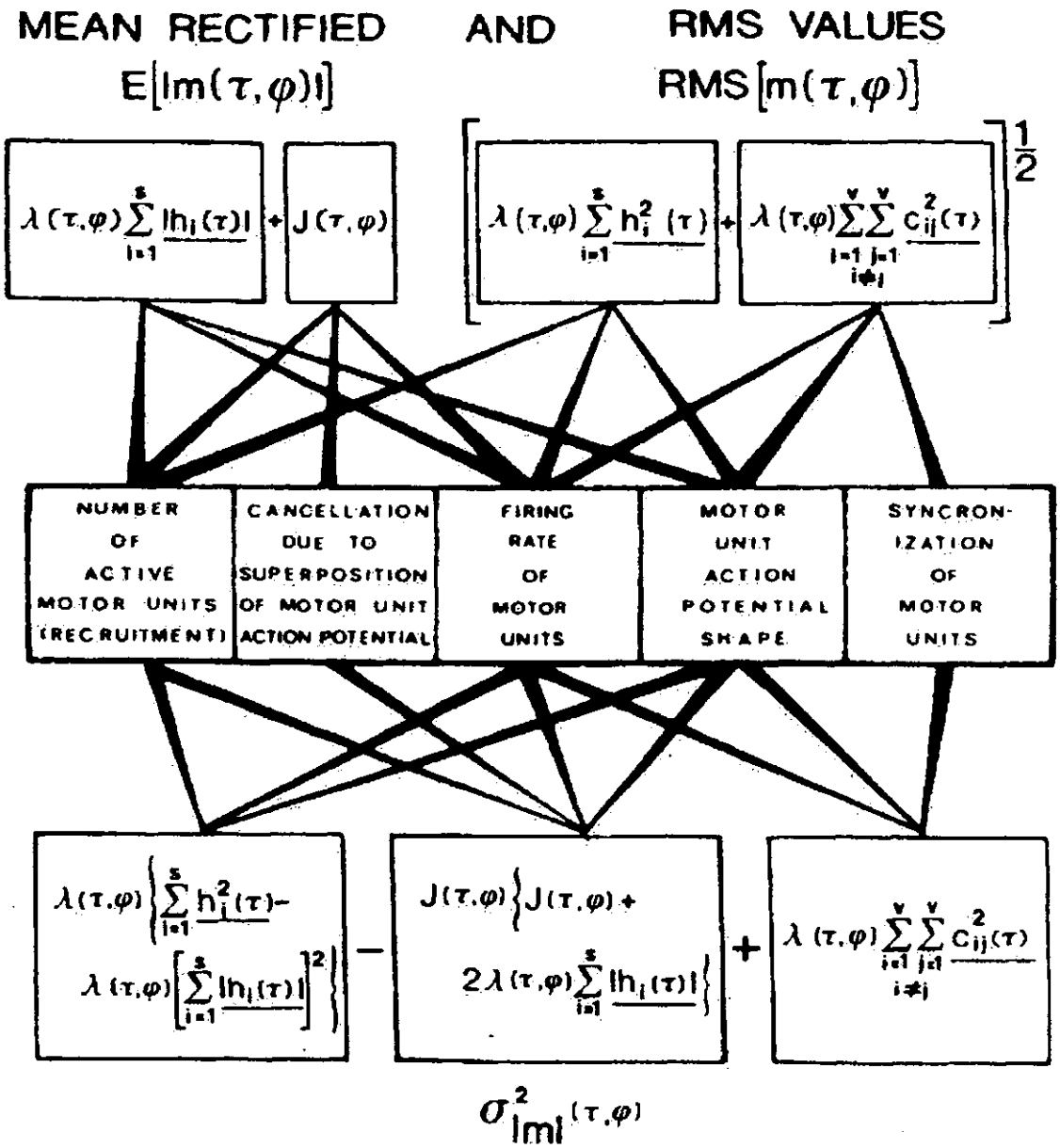


Figure 2.24 Parameters of the summed |MUAPT's as seen as mean rectified and RMS expressions and the relationship to their generated physiological origins. Note: no inclusion for filter effects and dynamic changes has been introduced. From 'Muscles Alive' by Basmajian and De Luca, Williams and Wilkins, 1985

where: Synchronisation is represented by the $c_{ij}^2(\tau)$ term

m (t,F) refers to the observable EMG signal

v denotes the Number of MUAPT's that are cross-correlated

τ the normalised contraction time

φ the normalised force

$\lambda(\tau;\varphi)$ generalised firing rate

$h_i(\tau)$ mean rectified filter impulse response (see also Equ. 6)

$h_i^2(\tau)$ mean squared filter impulse response (see also Equ. 7)

J (t, F) a non-positive term for cancellation due to superposition of opposite phases

The MUAPT model cannot be directly observed (except for using decomposition techniques, great difficulty is encountered in observing the individual fibre potentials within the MUAPT) as every motor unit is interwoven in the muscle region with many other motor units. Any portion of the muscle may contain fibres belonging to 20 to 50 motor units!! The situation at the surface recording site just gets more complex as superposition of MUAPTS occurs; along with signal cancellation at points where opposite phases (positive and negative signal excursions) occur, encroaching cross-talk of muscles, filter effects of tissue, electrodes, instrumentation and extraneous noise sources. It is after this journey that we finally observe what we refer to as the MyoElectric Signal (MES).

This mathematical model is a crude simplification of the generation of an MES and no spectral qualities can be fully described. No provision has been made for fibre type. Other much less well-detailed mathematical descriptions have been presented by other authors and as such have practical shortcomings.

2.8 What Can We Do With the MES after Detection?

2.8.1 Recognition of Signals / Software Dependency

The random element of the MES necessitates that, for signal recognition to be successful, some intelligence (expert knowledge) and probabilistic processes are incorporated into the

recognition algorithm. It is the apparently non-deterministic appearance of the surface MES that, in the past, has restricted the MES to its common Mean-Rectified-only usage.

2.8.2 Software Methods for User Acceptability

It will be necessary to detect the onset of an intended MES and then quickly sample the signal using the exponential averaging process (or a modified version). To miss the onset or transient of the signal, will record a signal of less-well defined frequency and of lower amplitude.

The basis for transient detection will require a continuous sampling process of at least 1 KHz (assuming a 450 Hz maximum bandwidth), with sampled data continuously being updated in a small memory block and retrieved for further processing when an MES (signal strength threshold) is detected. At this stage, the sampled data is passed on for digital filtering, followed by presentation to a Neural Network. There a decision is made as the probability of an intended user action and the consequent execution of that action by the prosthesis.

2.8.3 Time Constraints for User Acceptability

2.8.4 The 200 ms. MES Signal Generation Period

This 200 milliseconds (ms.) time slot is the window in time in which all user generated MES information/frequencies (that are to be utilised to direct a user intended prosthetic action) must be produced. This allows any slow moving frequencies, down to 5 Hz, (200 ms. duration), to be captured for feature purposes.

2.8.5 The 300 ms. Capture Period

Research has determined that a 300 ms delay (where: delay = measurement + processing + action) between user muscle action and prosthetic response is acceptable for a practical sampled data system. With only a few averages of the continuously sampled signal a small delay in response to the user action occurs. This delay will be well within a 200 ms delay period. The task will be to keep all computing time before response, to within the acceptable range.

2.8.6 The 500 ms. Response Limit

Prosthesis reaction times have been shown to be very important if the amputee is to successfully adopt the usage of any prosthesis. Too slow a response and the amputee will abandon the prosthesis in frustration. A half second (500 ms.) maximum has been observed by the prosthetics community as the user acceptable limit for a delay between muscle activation and prosthesis activation. The inertia of the mechanical prosthesis must then be included in the delay calculations.

2.9 Summary

As stated in Chapter 1 the objectives of the research are:

- 1)-to investigate the information content of a MES.
- 2)-to study the nature of the Tissue Filter Function (TFF)
- 3)-to map and identify optimum upper limb (forearm) myoelectric sites
- 4)-to analyse the mapped data for frequency content and other unique identifiers

- 5)-to recommend the practical application of the MES analysis for control purposes
- 6)-to provide a greater range of user-generated control signals.

This chapter has made progress on objective:

- 1)-to investigate the information content of a MES: The physiology of muscle activity has been introduced and the Motor Unit Action Potential (MUAP) can be seen as a unit of measure used in past research along with its stochastic description. The importance of accurate and optimal capture of the MES has been emphasised. The pathway of the MES and its interface with recording/detection instruments is examined and conditions defined. Noise problems are identified for consideration. The useable bandwidth is identified from past research and will be checked in chapter 3. The limitations of separate Time and Frequency analysis are presented and the preference indicated for a combined Time-Frequency approach *(Figure 2.20)*. The most common mathematical model description is introduced and its weaknesses pointed out. The anatomical examination explains how the two fundamental actions of the forearm muscles (flexion or extension) can be grouped within a superficial layer (sited just below the skin surface) or a deep layer (sited below the superficial layer). The taxonomy tends to further describe the flexors (flexion) as contained in the anterior compartment of the lower limb and the extensors extension) as contained in the posterior compartment of the lower limb. This compartmentalisation is for convenience only, and should not be assumed as exclusive; as the detected surface MES from both flexion and extension activity

can be found to overlap and interpermeate the other 'compartment' surface regions. Muscles are not exclusively all superficial or all deep, but are proportionally so. *See Figures 2.6-2.7 pages 59-60 for a helpful classification of all upper limb actions.* This list was put together by the author from a number of sources (all experts but not all in expert agreement) and represents the generally agreed upon functions. The juxtaposition of the muscles within the forearm is important in determining the MES pathway to the surface detection-electrodes. The critical question of complete detection of the MES so that all information can be gathered for analysis is dealt with in depth. Electrode technology for optimal sensitivity is explained and the need for vigilance and design for minimising the intrusion of unwanted signal noise is detailed. The design criteria for an appropriate detection amplifier are specified. (This will be seen to be met in chapter 3). The MES generation was described from the scale of the individual muscle fibre and the action potential (AP) generated when fired by the arrival of a nerve impulse to the collected mass of these fibres into what we call the muscle. The motor units are seen to innervate varying sized groups of fibres, according to the needs and demands placed on the muscle, at any particular point in time. The nature of the neurotransmitter activity is seen as a random process, as is the firing of the fibres, because of the varying signal pathway lengths within the motor units. Invasive signal detection at the muscle fibre site is seen as highly complex but limited in perspective. A large number of invasive electrodes would be needed to gather a full picture of the signal activity in any muscle at any one time (due to rapid signal loss over short distances, (i.e. one cannot see the forest for the trees).

However, it is also shown through the summing action of the Motor unit Action potential Train (MUAPT), how the detailed information about the small-scale signal generation is lost.

- 2)-to study the nature of the Tissue Filter Function (TFF). The TFF is expanded upon and graphically represented in *Figure 2.18.*

- 3)-to map and identify optimum upper limb (forearm) myoelectric sites: by breaking down the actions of the hand into a basic simplified structure from which a practical range of useful hand actions can be established and those actions and associated MES explored on the arm surface. A simplified geometry of hand movements was developed with a feasible range of 12 hand actions that could cover most manipulative needs. With this as a control signal target, the discussion moved on to see the human hand action, through the muscles of the upper limb, could provide an anatomical parallel to the simplified geometry and actions.

- 4)-to analyse the mapped data for frequency content and other unique identifiers: The three types of muscle fibres are described. These fibres have different contraction rates and different muscles have different 'mixes' of these fibre types, according to the 'type' of activity expected of the muscle, either in stamina, power, or speed. The relationship between the detected MES and the fibre types has been undeveloped in the literature and will be later developed by the author. Time-domain, frequency-domain, and time-frequency-domain analysis are briefly examined for their merits. The relatively long duration of the MES window (from a few hundred milliseconds to several seconds) is compared to that of a whale

sound over a similar interval. This is intended to illustrate the problem with assuming the adequate capture of sufficient signal information that would lead to the full reconstruction of the original signal. Time domain is seen to be two-dimensional, and power spectrum also, a two dimensional measure. It is only when seen as time-frequency that the full dimensionality of the signal can be appreciated. Anything less is at best only a partial capture and the whale sound would never be known. A gathering together of the fibre action potential and its transformation into a MUAPT and finally the detected surface MES is given a mathematical synthesis (model). The necessary simplicity of the model is mentioned and improvements are seen within the constraints of timing, detectability, cross talk, filter effects and instrumentation.

- 5)-to recommend the practical application of the MES analysis for control purposes: The MES is presented as a candidate for pattern recognition by a neural network. Practical time constraints for determining the user (amputee) take-up requirements for a functional prosthesis, is seen against the summed time constant of, signal generation (200 ms.), capture (300 ms.), and mechanical inertia response (500 ms.).

- 6)-to provide a greater range of user-generated control signals: A simplified geometry of hand movements was developed with a feasible range of 12 hand actions that could cover most manipulative needs.

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Chapter 3: Experimental Method

3.1 Methods used to examine the Surface MES

There are few clearly distinguishable features to be seen when recording the EMS over an active muscle for a random 1-second (1000ms.) period.

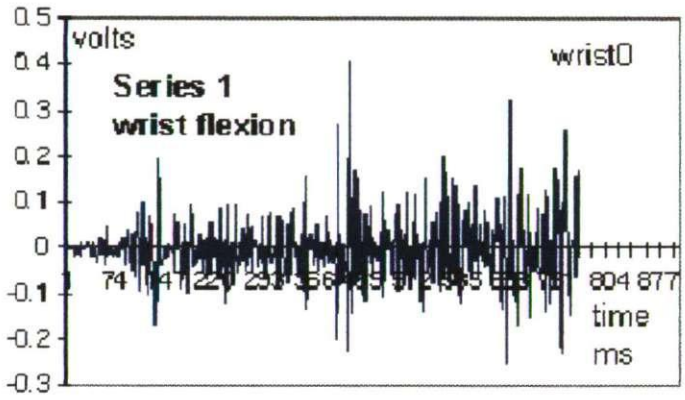


Figure 3.1 MES time-domain recording of a flexion of the wrist taken over a period of 800 ms.

Figure 3.1 shows the MES **time-domain** response recording of a flexion of the wrist. The recording was taken over a period of 800 ms. The wrist flexion MES is the most common signal-source used to trigger/drive commercial myoelectric prostheses.

Figure 3.2 shows the MES time-domain response to flexion of the ring finger taken over a period of 150 ms.

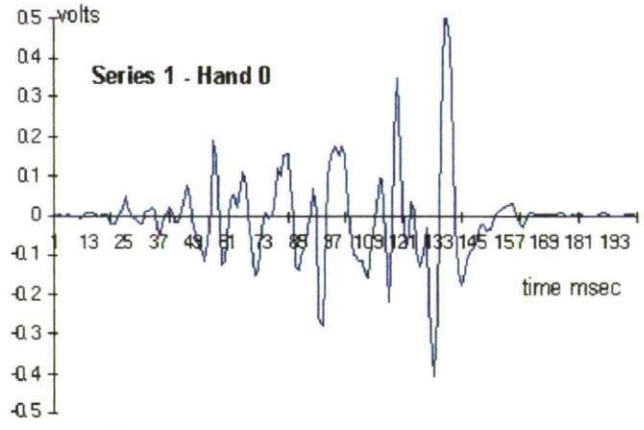


Figure 3.2 MES time-domain recording of a flexion of the ring finger taken over 150 ms.

Time-domain *Figures 3.1 and 3.2* were recorded by the author using the Liberty Electrode MYO115, general-purpose a/d converter, DADiSP software, and presented using Excel 5.0. Sampling rate was 1 KHz.

3.2 Time-Domain Analysis of MES signals

The commercially available prosthetic hands are only set to look at the gross muscle activity as seen in *Figure 3.1*. The signal is bridge rectified to change the alternating components into a D.C. signal, and then integrated (summed) to produce a gross signal voltage. All frequency information is thus lost.

3.3 Frequency-Domain analysis of MES signals

The surface *working* MES frequency range, for skeletal muscle such as that found in the forearm, is from 30 to 500 Hz. Generated activity at less than 30 Hz does exist but tends to be obscured by movement-artefact signals **[1]** and is best left out of the spectrum. Movement-artefact occurs when the electrodes move relative to the skin surface. The rapid loss of contact followed by a reestablishment of contact induces an extremely large signal at the electrodes that swamps the actual MES. The frequency induced is quite low i.e. in the 10 to 30 HZ range. As mentioned in Chapter 2 the unwanted mains frequency at 50 Hz (UK) may be readily picked up by the MES transducer. MES surface activity above 500 Hz also exists, but due to the filter action of the tissue (see Chapter 2), is of rapidly declining amplitude. Hence, it may be ignored for most practical investigations that relate to surface MES. In accordance with accepted Nyquist rate sampling requirements for the accurate capture and digitally reconstruction of an analogue signal, the higher bandwidth frequency of 450 Hz was always set at a sampling rate of no less than 1KHz. on the HP 3566A analyser.

3.4 Selecting a Suitable MES Source

For convenience, the signals off a non-amputee arm were examined. Past research suggests the results should be as equally valid as if an amputee were used [2].

Before applying the electrodes to the surface (of the skin), the skin was thoroughly cleaned of oils, dirt, and loose, dead skin. An alcohol swab was followed by a proprietary skin cleaner/abrasive.

3.5 Equipment used to detect the MES

For these MES investigations, frequency analysis equipment from the following manufacturer was used.

Hewlett Packard, 3566A Low-Frequency Spectrum Analyser

For these investigations, EMG equipment from the following two different manufacturers was used.

1.) **Digitimer Ltd.**, Neurolog NL180 isolator and NL 125 filter [3] (See manufacturer for details)

2.) **Vickers Medical,** Medelec Sapphire (See manufacturer for details)[4]

For these investigations, detection electrodes of two types were utilised (from two different suppliers).

1.) Dry-Type

Liberty Mutual: MYO115 with 54dB gain, (See Appendices p. 244 for details [5]).

2.) Wet- Type

Nicolet: (019-400400) disposable silver/silver-chloride electrodes

Note: other suppliers of wet type electrodes were tested at a later period (as they became available) but no differences in frequency response were found. Final choice of wet type suppliers came down to the following differences:

cost, size, flexibility, durability, reusability and skin-reaction (allergy).

3.6 The Hewlett Packard (HP) 3566A

Low Frequency Spectrum Analyser

The Hewlett Packard 3566A Low-Frequency Spectrum Analyser comes with a Windows-based software interface running on a 486 DX33 PC through an IEEE communications bus. The following two types of electrodes (commercial products) were tested with the HP 3566A

- Disposable silver/silver chloride electrodes (Nicolet -019-400400)
- Liberty Electrode MYO115

After activation of the flexor muscle group, subsequent signal pickup, amplification by the Liberty electrodes, frequency analysis and video presentation, the visual appearance of the myoelectric signal (MES) in its real-time spectral response appears to be devoid of clearly defined and repeatable spectral characteristics. In fact, the same muscle activity appears to elicit a different frequency response each time over the given range

However, by using the HP 3566A/3567A software averaging (Exponential or Peak Hold) on the MES, a definite difference between two activities, ring finger action and wrist flexion, can be detected at the same electrode site (*see Figure 3.6*).

Note: Exponential or Peak Hold averaging are two types of 'window' function that analyse the MES time slice in different ways. It was the exponential averaging that was chosen as a basis for the later mapping of the arms.

For a discussion on the HP 3566A/3567A methods of averaging, see Appendices page 240.

There is an upward shift in the frequency response – i.e. an increase in the high frequency response along with a decrease in the low frequency response, – for wrist flexion versus ring finger flexion, showing clearly different and repeatable frequency peaks (*Figure 3.6*). These peaks can be used with digital filters to identify the different actions.

3.7 Using the Digitimer Ltd., Neurolog NL180 Isolator Amplifier and NL 125 Filter

The Neurolog equipment uses the standard Nicolet EMG silver-chloride stick-on electrodes using an approximately consistent electrodes spacing of 1 to 2 cm. As mentioned in Chapter 2 the ideal spacing is approx. 1 cm for the greatest bandwidth detection. Considerable experimentation over a range of sites on the arms using different muscles, showed measured bandwidth variations such as:

- No discernible difference with up to 5cm separation at some sites on the arm (associated with the thicker, fatty areas of the arm)
- Significant bandwidth variations according to the orientation of the electrodes (i.e. a 90 degree change in orientation of the electrodes) with respect to the axis of the arm (observable as the electrodes moved away from the source)
- Significant bandwidth variations according to orientation of the muscle fibres with respect to the axis of the arm and electrodes e.g. the wrist contains a muscle (quadratus) that is oriented 90 degrees to the long axis of the arm (unlike the more typical orientation of muscles that run very nearly parallel to the long axis of the arm)

Note: These variations were also found on all subsequent combinations of EMG equipment and electrodes.

These variations lend support to the view that a considerable loss of any generated higher-frequency signal takes place, prior to electrode detection, due to the tissue filter effect.

3.8 The Vickers Medical: Medelec Saphire

The Medelec equipment has potentially very low noise levels (*see Figure 3.3 above*) as shown on two separate test files that shows basic S/N levels superior to both the MYO115

and Neurolog equipment. The noise that did appear was due to the proximity of the mains power leads to local equipment. Care had to be taken, when setting up a signal detection environment, to optimise the position of signal wires (relative to mains and noise sources). Without this extra care, the noise levels were of the same order as the MYO115. Theoretically, the lower noise levels may be a result of the superior noise characteristics of silver chloride versus stainless steel electrodes.

The Medelec equipment produced an observed frequency bandwidth slightly wider than the MYO115. This is probably due to an improved (flatter) Medelec amplifier response (operational over a 0.1 Hz to 10 kHz bandwidth) rather than due to the sensitivity of the silver chloride electrodes. Neurolog also used the silver chloride electrodes but did not show a significant improvement in bandwidth. Due to the impossibility of generating **identical** signals (to be seen by the different equipment) it was not possible to exactly quantify the bandwidth improvement, but a slight improvement in response (between the Medelec and the Liberty), in the range 450 Hz to 600 Hz, of up to 50% was seen. It needs to be noted that this gives only a marginal, overall, frequency-improvement due to the very low energy content in this region of the spectrum i.e. 50% more of a small amount overall is still a small amount. Once again, experiments in changing the inter-electrode distance over a range up 5cm. did not produce an improvement in bandwidth and again suggests that the loss of generated bandwidth takes place prior to detection at the electrode/skin interface

3.9 Establishing the Frequency Range of the MES as measured by the Test equipment

The Neurolog equipment has a stated bandwidth of DC to 20 kHz. Using Nicolet electrodes, the Neurolog produced a response that, over the entire measured bandwidth, was no better than the Liberty MYO115 (the Liberty was observed to be less than the Medelec). Without the built-in 50HZ filter switched on, the Neurolog response was noisy around 50 Hz and was noticeably noisier than the Medelec and Liberty, (though at a diminishing rate with increasing harmonic multiples of 50 Hz). The noise plots in *Figure 3.3 below* show these levels. The higher noise level near 40 mv. would seriously contaminate the overall detected MES, but the lower level of 6 mv. would not intrude significantly.

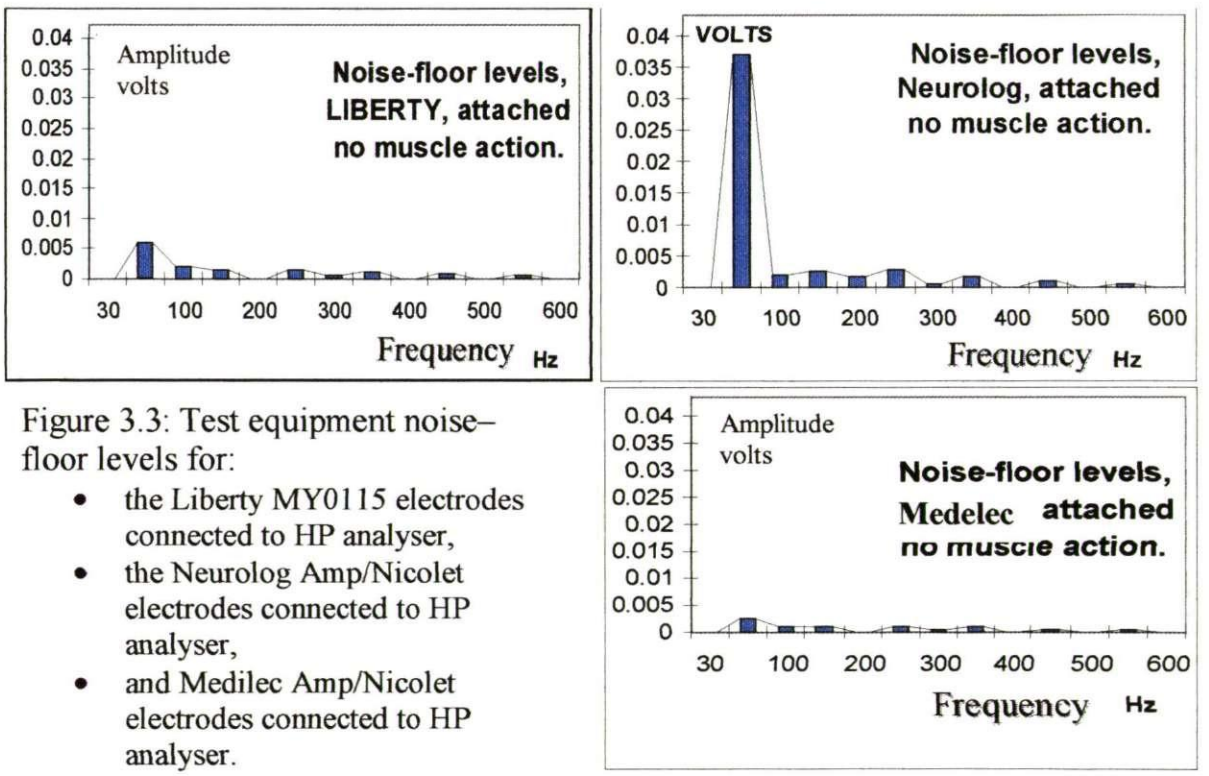


Figure 3.3: Test equipment noise–floor levels for:

- the Liberty MY0115 electrodes connected to HP analyser,
- the Neurolog Amp/Nicolet electrodes connected to HP analyser,
- and Medilec Amp/Nicolet electrodes connected to HP analyser.

3.10 The Liberty Mutual MYO115 Electrodes

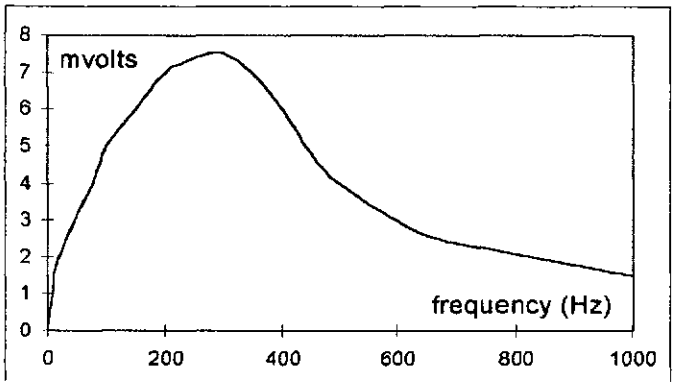


Figure 3.4 MYO115 amplifier test plot. The response of the amplifier can be seen to be non-linear but emphasizes the important 20-450 Hz range. Test results were obtained using a signal generator with fixed output level applied to the MYO115 over the 0 to 1KHz range

The importance of establishing experimentally just what frequencies are available to be picked up at the skin surface, requires a close look at the frequency response capabilities of both the interface and the amplifier response capability. To investigate this a variable frequency generator with a fixed output voltage was applied, via a potential divider, to the inputs of the MYO115 to mimic the low voltage (50 to 1000 microvolts) [**6**] of the expected skin surface MES. The output signal was logged and graphically shown in *Figure 3.4.*

The Liberty electrodes, with its built-in amplifier, can be seen to have a non-ideal (non-flat) amplifier frequency-response, which fades away rapidly after peaking at 300 Hz, thus frequencies less than 500 Hz are proportionally lost in practical terms. The design of the MYO115 is a compromise: trading a completely flat response for range-specific, reduced-noise, and sensitivity. The MYO115 has an electrode spacing of 1.5 cm. (centre to centre) and dome shaped electrode diameters of 4mm. (of which 2mm. to 3mm.of the dome diameter can be assumed as the effective surface to skin contact area). The bipolar filter function as mentioned on page 58, chapter2, can be estimated to produce a drop-off in the detected frequencies beginning at approximately 350 to 400 Hz. This estimate is extrapolated from theoretical values taken from De Luca [**6**] showing a drop-off at 5 KHz at a spacing of 0.5 cm., and a drop-off at 500 Hz for a spacing of 1 cm and Lindstrom [**7**] showing a drop-off at 175 Hz for a 2 cm. spacing. This 350 400 Hz limit is an acceptable

limitation as the experiments done with the other electrode types at close spacing still showed the actual detectable signal to be far too low to be of use as the 400 Hz mark was reached.

The frequency response of the Liberty electrode was found to be however only marginally less effective than systems with the more ideal silver chloride electrodes and stand-alone amplifiers. As the amplifiers for MES detection are capacitively coupled to the electrode surfaces, there is an inherent filtering effect; decoupling any D.C. signals that develop on the skin surface (thus removing any problems of signal baseline drift). Capacitive coupling also reduces the lower frequency signals (movement artefact and 50 Hz mains noise). If the design specifications are set for an amplifier to respond minimally to the frequencies below 60Hz and tail off response above 400 Hz, then you have a MYO115! This is a practical design for the surface electrode environment and general frequency demands placed upon it.

3.11 Bandwidth Comparison between the Liberty the Neurolog and the Medelec

Figure 3.5: shows the results of a test to compare the bandwidth variation between the Liberty (dry) electrodes (channel 1) VS the Digitimer Neurolog with Nicolet wet electrodes (channel 2). Bandwidth is measured in 10 Hz increments from 30 to 400 Hz. The test input signal chosen was a live 'wrist flexion' action, due to its previously determined occupation of the higher frequencies region of the overall MES bandwidth. Due to the impossibility of placing both sets of electrodes in exactly the same position for exactly the same live signal, the wet electrodes were placed in line with, but just outside of, the liberty dry electrodes (see diagram). The intermediate amplification of the surface MES

signal occurred separately in the Liberty and in the Neurolog amplifiers before presentation to the HP analyser. It must be assumed that a slight difference in position will give a slightly altered result. As mentioned earlier the author detected far less bandwidth change when varying the spacing of the wet electrodes than expected from the reports of other researchers and from electrode theory. The slight variation between tests is a normal result of variation over time in any selected muscle action. The signal was transformed into the frequency domain using a 'Hanning Window' on the HP 3566A and two types of averaging techniques were applied. The Peak Hold averaging used 40 sample blocks, and the Exponential averaging used 4 sample blocks. A series of additional, (16 in all) repeated tests were performed, yielding confirming results. The similarity in the results, suggest the onset of the transient signal is most probably the important area of interest in the detected signal. **See Appendix (page 240) for explanation on averaging techniques for the HP 3566A**. Given the closeness in the results from the two detection methods, (when simultaneously detecting a similar signal), combined with the ease of use in a practical environment, a preference for the Liberty (dry) electrodes was indicated for a lengthy mapping research program. Note: The amplifier output of the Liberty is double that of the Neurolog.

It should be realised that the Medelec equipment was on loan from the company and has its own internal wiring and did not allow its amplifier output to be directly presented to the HP analyser for comparison with the Liberty and Neurolog amplifiers. It did however allow for data files to be stored on floppy disk and these are shown in *Figures 3.7 and 3.8*

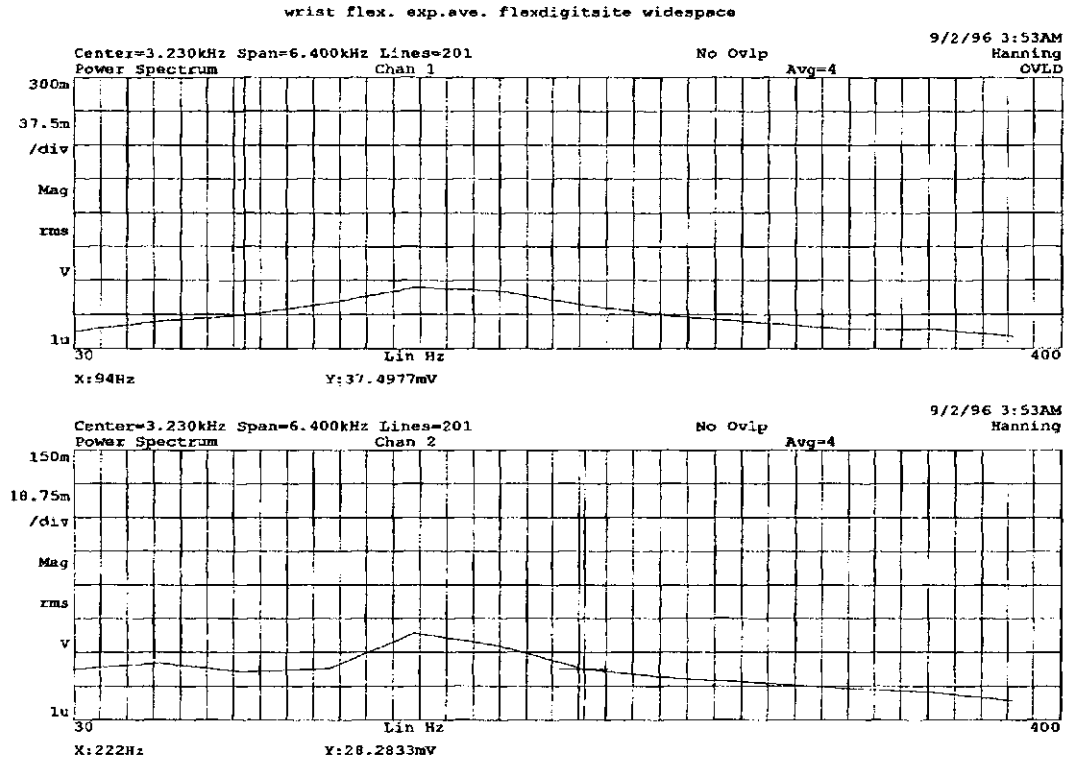
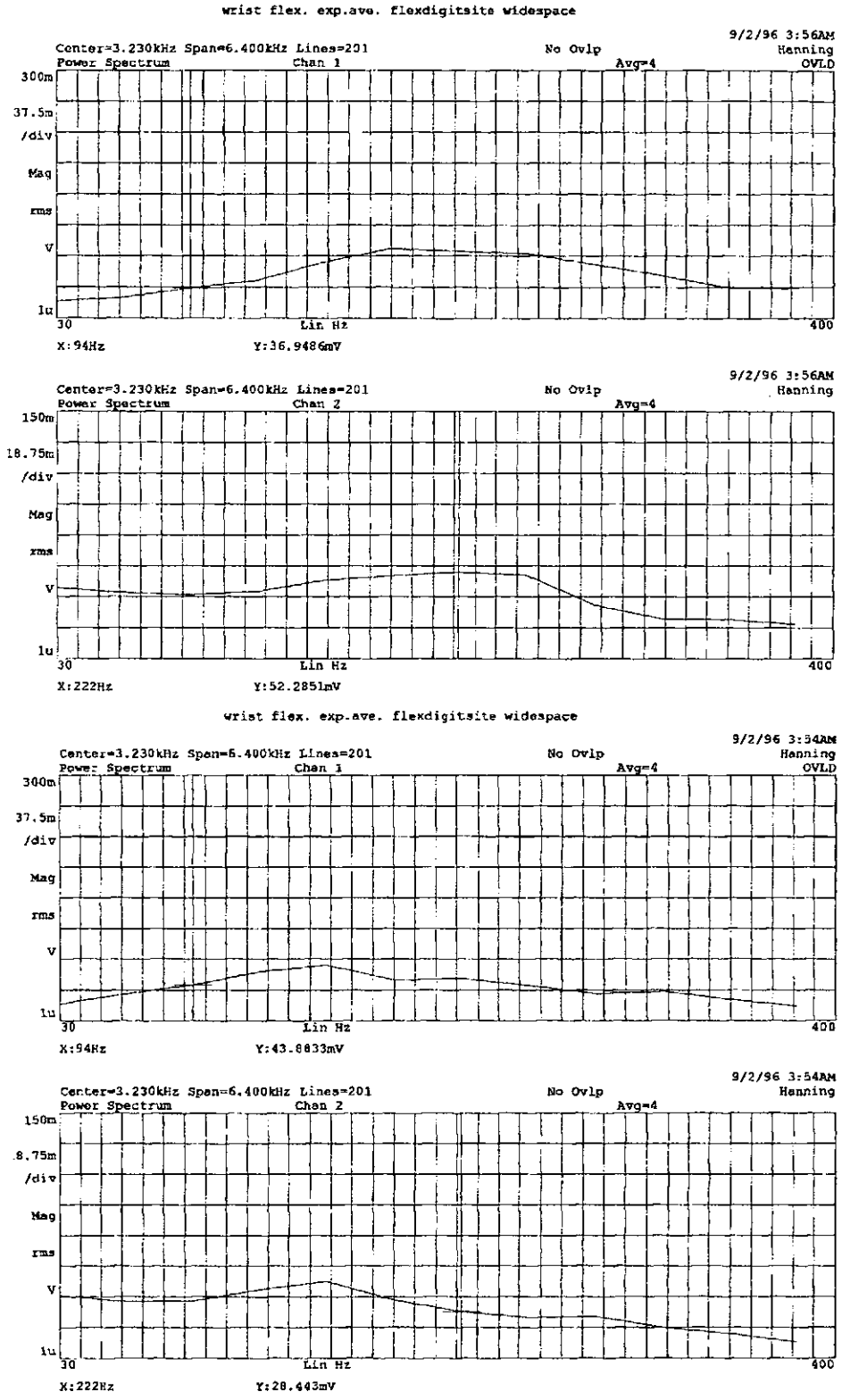
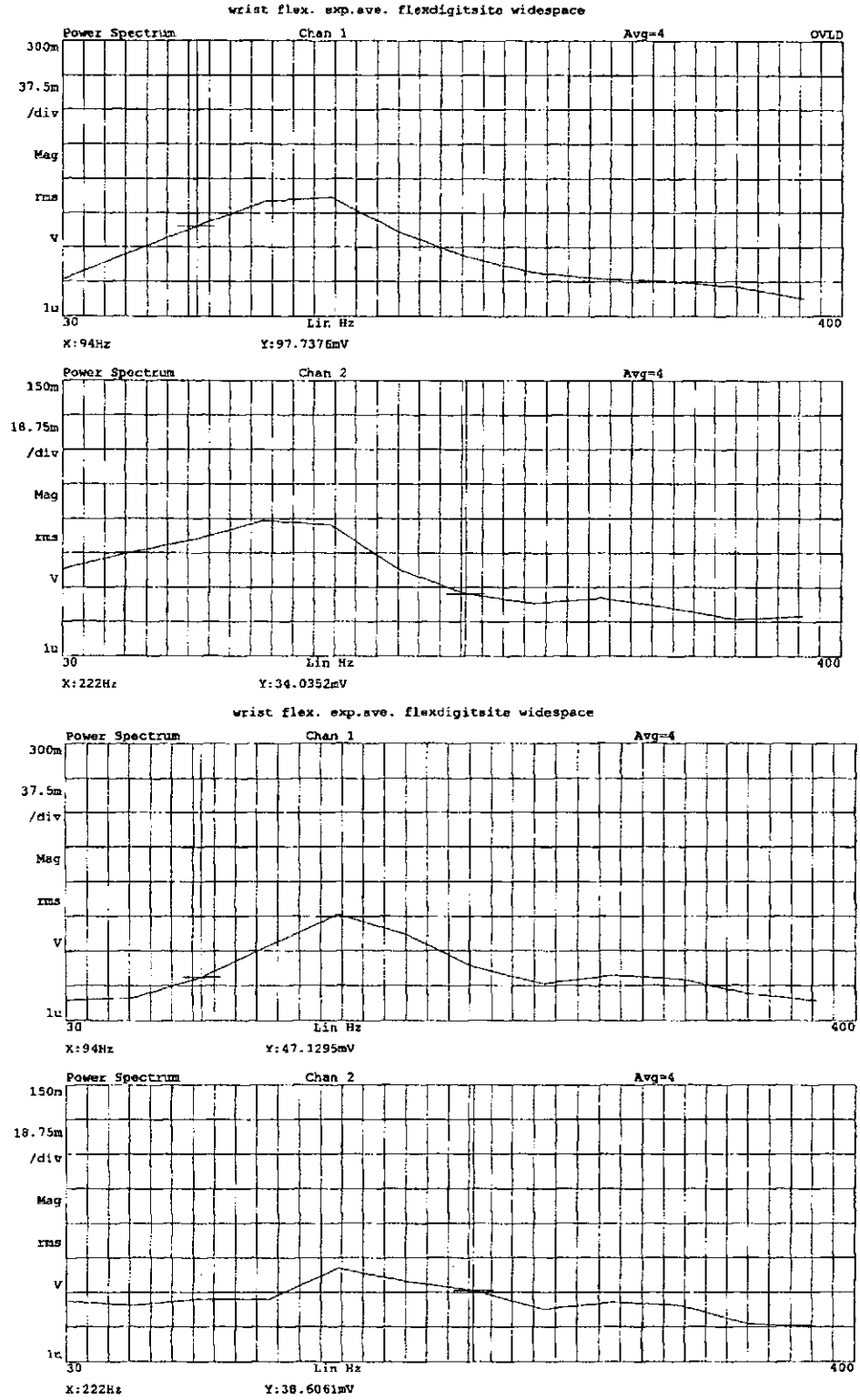


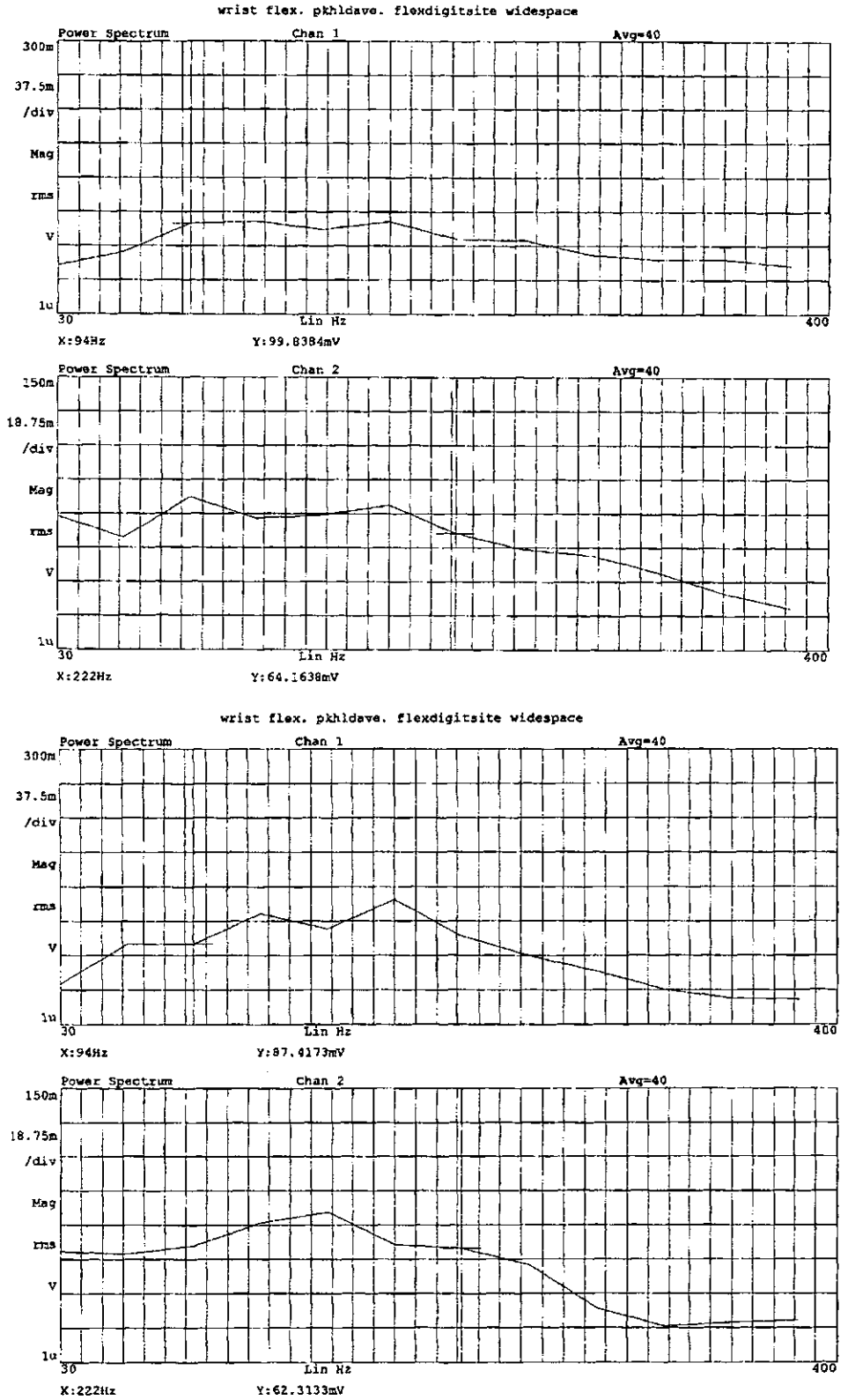
Figure 3.5: Test to compare the bandwidth variation between the Liberty (dry) electrodes (channel 1) VS the Digitimer Neurolog with Nicolet wet electrodes (channel 2).
Bandwidth is measured in 10 Hz increments from 30 to 400 Hz. Shown above is the output using the HP3566A Spectrum Analyser.
The following Figures 3.4 b,c,d,e,f,g, are further tests for bandwidth using different Window averaging techniques.



Figures 3.5. b and 3.5 c Test for bandwidth using Liberty (dry) and Neurolog (wet) electrodes.



Figures 3.5 d and 3.5 e Test for bandwidth using Liberty (dry) and Neurolog (wet) electrodes.



Figures 3.5 f and 3.5 g Test for bandwidth using Liberty (dry) and Neurolog (wet) electrodes.

3.12 Does the equipment used show the True MES Frequency Range?

Whatever the frequency content of a signal generated at the actual muscle site, by the time that signal passes through the varying thickness of tissue en route to the skin surface, a loss of frequency content is inevitable. The experimental work undertaken here has shown the extremes of the available MES bandwidth available for detection at the skin surface are from 10 Hz to 800 Hz. The potentially useable bandwidth is however from 30 Hz to 500 Hz. The region from 350 Hz to 500 Hz can be very marginal with respect to useable information due to the very low energy content of the signal. As a result, the range for useable MES frequency detection is focused within the 30 Hz to 350 Hz frequency range. These results obtained by the author for bandwidth are in full agreement with previous findings in the research literature.

There is an upward shift in the frequency response (*Figure 3.5*) for wrist flexion versus ring finger flexion, showing clearly different and repeatable frequency peaks. These peaks can be used with digital filters to identify the different actions.

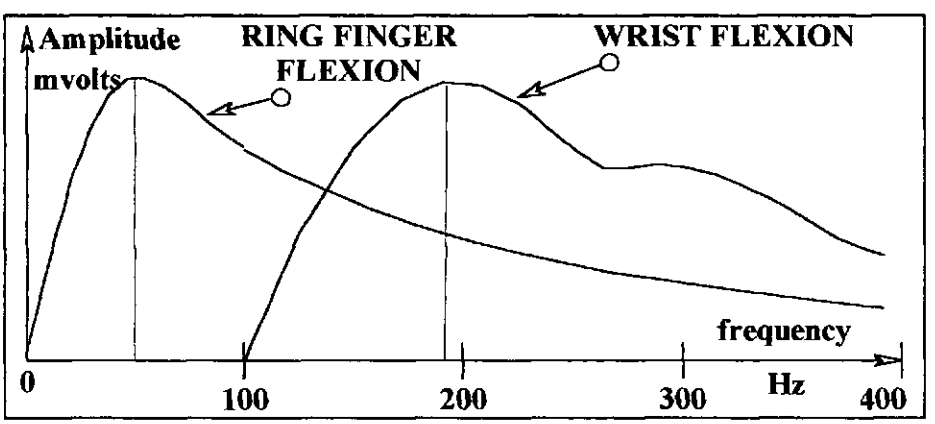


Figure 3.6 Average MES range (spectral shape) for both wrist and ring-finger flexion, showing the distinct differences in the occupied frequency spectrum for the actions.

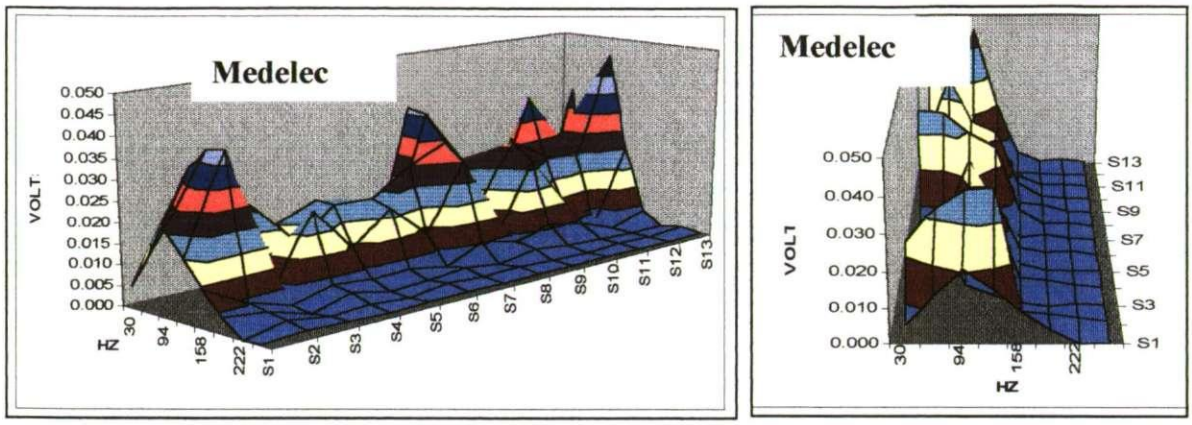


Figure 3.7 above shows the ring finger flexion bandwidth using data recorded by the Medelec Saphire. Data is clustered from 30 Hz to 158 Hz at varying amplitudes from 20 to 45 mv.

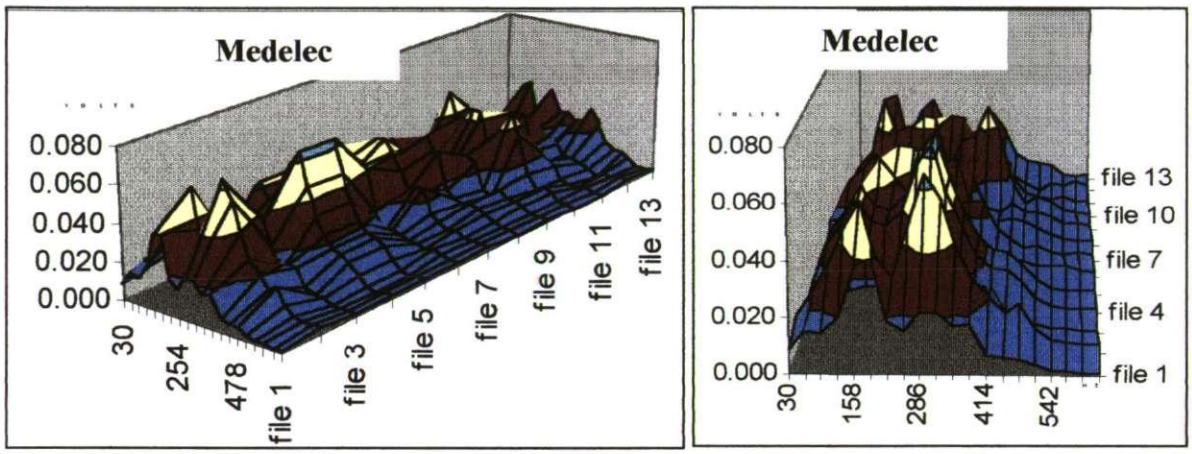


Figure 3.8 above shows the wrist flexion bandwidth using data recorded by the Medelec Saphire. Data is clustered from 90 Hz to 400 Hz at varying amplitudes from 40 to 65 mv. Contour mapping was chosen to best represent the changing frequency and voltage values. The ring finger action is clearly represented by a different portion of the frequency spectrum.

The above *Figures 3.7 and 3.8* show a group of 13 wrist flexion actions and 13 ring finger flexion actions recorded by the Medelec Saphire using the Nicolet (wet) electrodes. The two different actions were recorded at the same site on the arm of the author. Contour mapping was chosen to best represent the changing frequency and voltage values. The ring finger action (compared to the wrist flexion action) is clearly represented by a different portion of the frequency spectrum. The Nicolet (wet) electrodes, in combination with the Medelec amplifier, pushes the useable bandwidth response to approximately 450 Hz

compared to the approximate 375 Hz of the MYO115 (dry) electrodes. This represents an improvement of between 50 to 75 Hz. What must be realised however is the extra 75 HZ is not representing a significant energy portion of the detected spectrum and is significant in only approximately 10% to 20% of detected actions. This should however not underrate the importance of a optimising the detection capabilities of the EMG equipment available for research and medical uses. The MYO115 has great versatility but improvements could be made to its amplifier response by pushing the gain at higher frequencies and cutting back the gain at middle frequencies while retaining the existing response at lower frequencies.

3.13 Summary

.As stated in chapter 1, the objectives of the research are:

- 1)-to investigate the information content of a MES.
- 2)-to study the nature of the Tissue Filter Function (TFF)
- 3)-to map and identify optimum upper limb (forearm) myoelectric sites
- 4)-to analyse the mapped data for frequency content and other unique identifiers
- 5)-to recommend the practical application of MES analysis for control purposes
- 6)-to provide a greater range of user-generated control signals

This chapter has made progress on the following 3 objectives:

- 1)-to investigate the information content of a MES:
- 4)-to analyse the mapped data for frequency content and other unique identifiers:
- 5)-to recommend the practical application of the MES analysis for control purposes.

And is summarised as follows:

The useable bandwidth for MES detection can now be confirmed from 30 to 350 Hz. Out side of this range the signals are too weak to contribute any practical information. This is however not a fixed barrier but rather a compromise by the equipment manufacturers chosen (MYO115) and high end bandwidth (>350 Hz) extensions of 20% could be seen with improved design. The lower bandwidth (<30Hz) limitations are also due to amplifier design but also would probably suffer from 'movement artefact' and become prone to false signals.

MES-detection equipment artefacts/shortcomings, and their use in various environments, are very important in MES analysis and conclusions.

The setting up and testing of the different sources of MES equipment in the experimental lab environment suggests that without due care it is easily possible to encounter serious noise problems that will corrupt the MES. Bringing a Nicolet electrode lead near a computer monitor, results in a sudden influx of noise superimposed onto the detected signal. When trailing the leads too closely to a mains-lead source the 50Hz noise will often appear. The use of a frequency analyser was found to be essential to monitor for mains and other noise encroachment while making data recordings and testing for true MES detection. Shielding the electrode wires from noise pickup and the proximity to and between electronic equipment (monitors are especially included) are the minimum standard procedures.

Signal-amplifier equipment needs to be appropriate to the task: and should be matched to the intended bandwidth response.

Electrodes must also be suitable and matched to the frequency requirements. The choice of wet or dry electrodes will be based upon maximising either frequency response (wet) or the ability to be easily adjusted (dry).

If an extended session is undertaken with a volunteer for mapping large areas of the skin surface, then the use of dry electrodes will be the serious choice for the following reasons:

- The wet-type of electrode has only a limited number of times that it can be applied to the skin surface before the adhesive becomes ineffective and the signal detection quality is compromised (usually no more than 5 to 8 uses)
- The skin surface must be cleaned of natural oils and sweat before applying the wet lead to prevent rapid contamination of the adhesive surface and subsequent loss of adhesion. The loss of adhesion and subsequent signal loss may be further complicated if the skin is covered with dense or thick hair.
- The volunteer will be unhappy with the hairs from their skin being ripped out (still stuck to the wet-electrodes) while the adhesive is fresh. The alternative is to shave the arm of the volunteer (which may well be met with equal resentment or refusal). The author kept his own left arm shaved and marked with indelible ink for 6 months (*see Figure5.1, page 139*) while undergoing extended exploratory work.
- The wet electrode approach is arduously slow compared to the easy movement of the dry electrodes. The cost of time and patience to volunteers is much higher than with the dry-type. The dry types are much more suited to exploring the skin surface for subtle changes.
- The actual resultant frequency response achieved from using the wet type is only marginally better (approx. 10 to 15 % extension with the higher frequency range), but most importantly, is of equal performance over the range common to both types of electrode.
- Noise-floor levels are very low with the dry-type (*see Figure 3.3*), due to the shorter lead length. To achieve the same noise-floor levels with the wet-type with the associated long leads, is much more demanding of the equipment proximity in

the experimental environment. The "twisted-pair" design of the dry-type leads (between the MYO115 and the signal processor) reduces the tendency to mains noise pickup. The wet-types are not set-up to be used as a "twisted pair".

- The dry-type electrodes have a much higher initial financial cost (approx. $300. U.S.), but over the course of testing (mapping) a few patients/volunteers this extra cost would be recouped, due to the short lifetime of the wet-types set against the long lifetime of the dry types.

3.14 References:

[1] Geddes LA and Baker LE, (1975). "Principles of Applied Biomedical Instrumentation", J.Wiley& Sons, ISBN 0-471-29496-9.

[2] O'Neill, P.A.Morin, E.L.Scott, R.N. (1994)."Myoelectric Signal Characteristics from Muscles in Residual Upper Limbs." IEEE Trans. on Rehab. Eng. Vol. 2, No. 4, Dec. pp.266-270.

[3] Neurolog System, Digitimer Ltd., Welwyn Garden City, Hertfordshire, U.K., AL73BE

[4] Medilec Saphire[II] Medelec Ltd., Manor Way, Old Woking, Surrey, U.K. GU229JU

[5] Liberty MYO115 Electrode, Liberty Mutual Research Centre, Prosthetics Group, 71 Frankland Rd., Hopkinton, MA., 01748, USA.

[6] Basmajian, J and DeLuca, C. (1985). 'Muscles Alive, ,Their Functions Revealed by Electromyography', 5th Edition. Baltimore: Williams & Wilkins, pp 49.

[7] L H..Lindstrom, R. I. Magnusson, (1977). 'Interpretation of Myoelectric Power Spectra: A model and its applications', Proc.of IEEE, Vol 65, No. 5, May, pp 656.

CHAPTER 4

Experimental Determination of the Relationship between Muscle Action and Frequency

What different frequency characteristics for differing muscle-actions are observed at one site?

4.1 Test Procedure Used to Search for a Site with Widely Separated Frequency Characteristics

For reasons discussed in Chapter 3 the author decided to use the MYO115 (dry) as the standard electrodes for the remainder of the research activity. The MYO115 electrodes were connected to the HP frequency analyser and applied to the left forearm of the author. The left arm was selected based on convenience as the author is right-handed and having the right hand/arm free to write etc. while the left is connected up has obvious practical merits. All subsequent volunteers were tested using the left arms for the sake of consistency. Using the known anatomical location of muscles of the forearm,the electrodes were placed first directly over the site of the strongest signal corresponding to a particular muscle-action. The same muscle action was repeated and the electrodes were moved radially away from the site centre until the detected signal reduced to a negligible value. The values were noted and another muscle that had produced a strong signal source close to the previous muscle action was activated, followed by moving the electrodes radially away until, once again, reduced to a negligible value. An examination of all possible

below-elbow and above wrist, muscle actions was undertaken and the following basic list of hand and wrist control actions was derived (see list below).

4.2 List of 20 different control actions

1. wrist rotation (counter clockwise) left
2. wrist rotation (clockwise) right
3. thumb extension
4. thumb flexion
5. index finger extension
6. index finger flexion
7. middle finger extension
8. middle finger flexion
9. ring finger extension
10. ring finger flexion
11. little finger extension
12. little finger flexion
13. wrist extension
14. wrist flexion
15. wrist abduction
16. wrist adduction
17. hand grasp (clenched fist)
18. relax hand (rest position)
19. hand fully open (all fingers extended)
20. 3-finger chuck grasp

The spectrum was observed for each of the above actions.

The observed signal spectrum for each action varied according to source (muscle) proximity and no one site was suitable to detect a response from all 20 actions on the list. This methodical approach identified an initial, though of limited potential, area of promise for single site detection of multiple actions. In the area of promise it was found that two different muscle actions (wrist flexion and ring finger flexion), occupied (visually) different portions of the selected (30 Hz to 350 Hz) spectrum

(*see Chapter 3 Figures 3.5,3.6,3.7*).

See Chapter 5 page 132 for test results

The above range, of 20 possible actions, requires that each unit of surface area on the forearm be tested 20 times for all 20 actions, in order to determine if any other multiple

muscle action detection sites were to be found. The preferred alternative approach would be to test the entire forearm for one action followed by another full arm test for each of the remaining actions. This allows a standardised position for both volunteer and test set up. The action to be repeated can be predetermined and practised by the volunteer (subject) for velocity, acceleration and duration. This will prove to be an important methodology when considering the physiological basis of muscle action (motor unit recruitment procedures). As previously mentioned in Chapter 2, the fatigue effect begins to shift the MES (towards the lower frequencies but with an increase in gain in those lower frequencies) after approximately 2 seconds of sustained hard contraction. The early indicators suggest that the most significant, muscle identifying characteristics, are to be found in the transient (initial portion) of the MES. This will be considered later, in some depth, in the analysis in Chapter 6.

4.3 Active (Isometric) Grasp (Loading) Vs Passive (Isotonic) Movement Test Results

(for definition of Isometric vs Isotonic see Appendix List of definitions)

Some early exploration (by the author) into the comparison between the surface detected MES of a finger flexion in both unloaded and loaded conditions, showed the MES *magnitude* to be greater under loaded conditions but the associated *spectrum* to be largely unchanged despite the loading. Muscle actions were not required to be sustained for long periods during data collection. No muscle fatigue was observed due to the nature of the test procedure. This 'muscle fatigue' issue was not exhaustively searched over a varying range of loads and could be an associated factor in the commonly reported observation with past researchers of a "fatigue effect" [1,2] i.e. changing spectral characteristics over time with a shift toward lower frequencies accompanied by an increase in amplitude of the MES. As

the muscles used by an amputee are indirectly involved in generating the prosthesis control signals, the amputee need only vary the muscle tension over a given (small) range for the prosthesis to vary the (amplified) grip strength. As long as the muscle contraction is retained above a preset level the desired hand position or "state" of the prosthesis could be retained for a sustained action. As the 'fatigue effect' starts, and shifts toward a lower frequency, the control action could be retained as long as the MES summation contains the same spectral energy. The same threshold triggering circuit (a simple peak detector can be modified to have an additional summing action) that monitors the MES for an intended control action (by ignoring sub-threshold MES levels) can be used to retain the control action. This area could be further investigated as an additional control action to be included in any MES detection algorithm.

4.4 Results of Testing of Other Males at the Same Site

The test site results of the ring finger and wrist flexion could have been specific to the test person involved and not apply in general to any other person. To check for this possibility a further 3 adult male staff volunteers, and the author, were tested under the same conditions i.e. same site, equipment, and same actions. A quick search of the same forearm area on each volunteer located an optimum site. Careful but not precise positioning was adequate. All four men showed the same separation and spectral range as in the first experiment. A slight modification was introduced to this test. The ring finger was flexed but brought to rest against the thumb. The thumb was not used in the earlier tests in Chapter 3 and the implications of the co-activity of the thumb was not apparent at the time as no thumb MES activity was detected at the site. The thumb did introduce an apparent enhanced spectrum selectivity (more *detailed* repeatability in the results). The results are shown for wrist flexion in *Figure 4.1* with a centre peak frequency of 160 Hz and for ring finger flexion with centre peak frequency of 95 Hz in *Figure 4.2*. The data on these male

volunteers is clear and unambiguous and suggests peer group replication would quickly confirm these observations. No reference has been found in the literature with regards to this observation.

The following three possibilities exist regards the anatomical and physiological structure of the four test males.

- **(1)** The test males differ significantly in anatomical layout. This would not lead to a site of common response, not yield the observed results as mentioned above, and would not lead to any deterministic features in the detected MES.
- **(2)** The test males do not differ significantly in anatomical layout The qualitative and quantitative location, layout, and proximity of the two different muscle actions (wrist flexion and ring finger flexion), for all the individual test males are approximately the same. This anatomical sameness, along with a concession to a deterministic, non-random contribution to the outcome of the MES, would yield the observed results as mentioned above
- **(3)** The anatomical sameness of option (2) is further refined by the Tissue Filter Function (TFF) and all muscles involved in the two actions, contribute (summate) proportionally to the MES outcome.

The similarity in results, by the four male volunteers, suggests further questions regards determinism and universality need to be posed and answered. What, if any, differences in anatomical structure, contribute to the explanation for the spectral similarities and differences between the muscle actions (wrist flexion and ring finger flexion) for the group of test males?

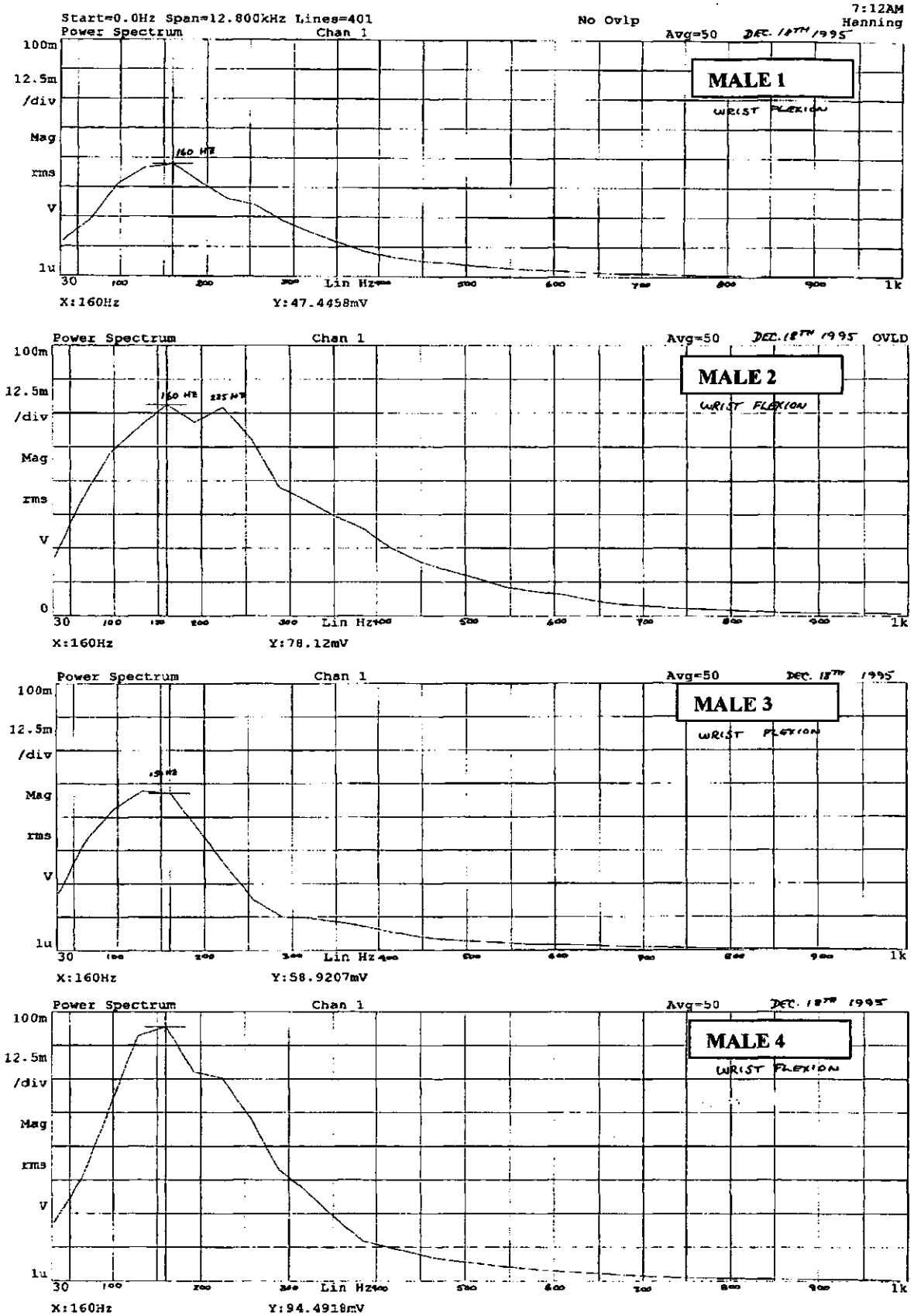


Figure 4.1 (a),(b),(c),(d); the four figures above are the test for wrist flexion on 4 male volunteers. The ability of the 4 males to cluster around a centre frequency of approximately 160 Hz is remarkable.

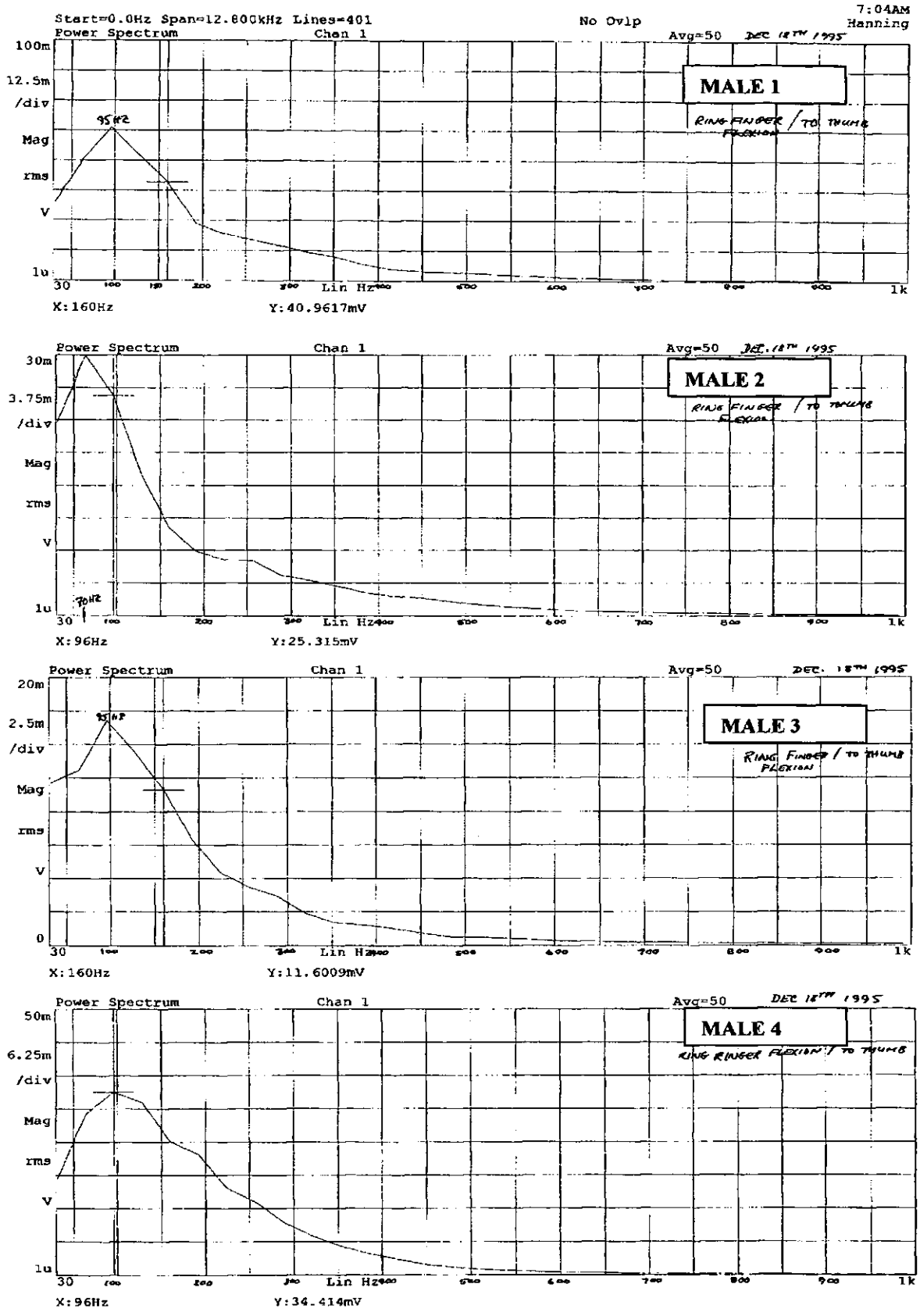


Figure 4.2 (a),(b),(c),(d); The four figures above are the test for ring finger flexion on 4 male volunteers. The centre frequency @ approximately 95 Hz is again closely followed.

4.5 Results and the Need for a Theoretical Explanation

Implications for Universality

The results of the four test males were a possible indicator of a deterministic element (at least seen at the level of the surface MES) that was not just local (to one person), but extended to include another level (the class of adult males). Once again, the tests were not exhaustive across a large population but further work with other males failed to refute the phenomenon.

The following questions arise:

'A*t what point, on its journey to the surface, does the initial random nature of the muscle fibre Action Potential (AP) convert to an apparent determinism in the surface MES*'?

'*Is the precise activity of the hand, the result of a feedback loop established by the neuromuscular motor control system, to overcome and compensate for, the random firing of muscle fibres at its most basic level*?

- If so then the motor control system has evolved without a firing pattern/plan directed to its motor unit recruitment requirements and is functioning on an extension of a continuous low level feedback compensation (such as our 'upright balance' control system) on a millisecond by millisecond decision basis. This would then imply that the deterministic pattern seen at the surface MES is an illusion'. (But a nonetheless, potentially-useful, illusion!!) To resolve this issue requires further research and a full mapping and juxtaposition of signals, muscles and actions.

Are the test results indicators of deterministic behaviour (i.e. are the muscles producing a spectral response different in composition from that of adjacent or other muscles.)?

- From the known anatomical structure of the forearm, the presumption is that, unless the MES is derived from a single muscle source, the MES is a composite signal and comes from a combination of surface muscles and deep muscles. This is true for only some muscles however. Referring back to Chapter 2 Figure 2.6 and 2.7, (the chart on all known forearm muscles and their actions within the forearm) we find that for some actions (5 out of the 16 actions) there is only a superficial muscle or group of muscles involved and for some actions (4 out of the 16 actions) there is only a deep muscle or group of muscles involved. This has implications for one of the explanatory candidates: the 'Tissue Filter Function' (TFF).

The results of the male tests raise two scenarios regarding spectral signatures:

1. If the surface detected MES **shows** a constant and broad bandwidth:

A spectral change would be seen only as the tissue thickness to source distance was varied. This would demonstrate a common "tissue filter effect" generating consistent and repeatable spectral results. This change would manifest as a loss of high frequency information at the detection site.

2. If the surface detected MES **does not show** a constant and broad bandwidth:

In addition to the "tissue filter effect," any observed spectral differences would be the result of the muscles generating significantly different (and thus unique) spectral signatures. This would indicate an element of deterministic behaviour in addition to the tissue filter effect.

With these two unresolved scenarios in mind, *Figure 4.3* illustrates the range of logical possibilities offered by two signal sources.

Figures 4.3 (a)(b)(c) show how two MES sources can be seen at the skin surface of the arm by a MYO115. The doubled ended arrow above the MYO115 represents its movement between surface sites C and D for detecting the source signal from either site A or site B.

These spectrum sources, As and Bs, are shown at three different possible sites and depths, i.e. (a)(b)(c), relative to the detecting surfaces C and D. Comparison of these three figures shows how caution needs to be applied when making assumptions, about a detected MES spectrum, at sites C and D. After examining the effects of different pathways we are left with the following two outcomes:

- The various locations within the arm can yield **similar** surface spectral results at C and D, despite actual spectral differences at sources A and B
- The various locations within the arm can yield **different** surface spectral results at C and D, despite actual spectral similarities at sources A and B.

The large range of logical possibilities shown at the right of the figures suggests the need for further research into a more definitive theoretical explanation.

Note: For simplicity, the pathways from sources A and B to detectors B and D are shown as straight lines. It is not known however, just to what extent in each particular event, the pathway is an actual straight line. It is the varying conductivity of the pathway, i.e. through the varying tissues layers, that determines the attenuation and phase lead or phase lag of the signals as they arrive and converge at any point of detection.

Additionally, in an actual muscle the signal source would not be a single point source as shown but would be more diffuse, due to the anatomical spread of the motor units when activated.

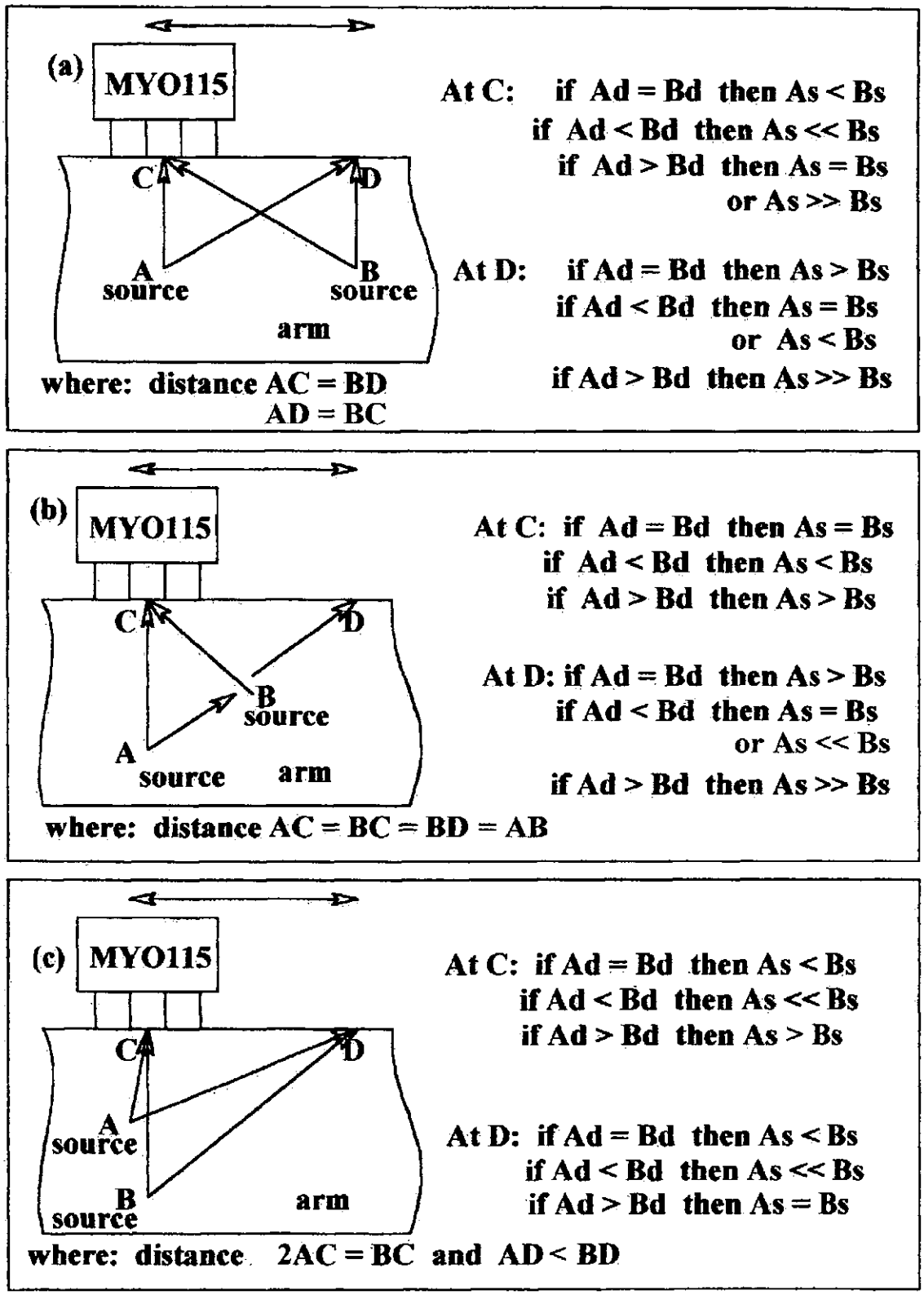


Figure 4.3(a), (b), (c): Sources A and B represent two separate muscles/sites in the arm. The arrows show the 'direct line' signal pathways through the tissue en route to the MYO115 detector.
As, Bs = generated spectral source Ad, Bd, = detected (measured) signal

4.6 Summary

This chapter posed the question: ***What different frequency characteristics for differing muscle-actions are observed at one site?***

This chapter has only been able to open the can of worms, but not analyse the details of the contents as yet.

Chapter 1 posed the following objectives of the research

- 1)-to investigate the information content of a MES.
- 2)-to study the nature of the Tissue Filter Function (TTF)
- 3)-to map and identify optimum upper limb (forearm) myoelectric sites
- 4)-to analyse the mapped data for frequency content and other unique identifiers

Objective 1)- has been tackled but has introduced more questions than answers. The information is there and the author has brought some to the surface with the revealed differences in the wrist and ring finger response at one site. The author has not yet defined the breadth of that information nor detailed the source.

Objective 2)- the Tissue Filter Function (TFF) has been suggested as an explanation for the results described with Objective 1) but uncertainty prevails as to what extent the TFF can be applied as an explanation. A logical structure for the TFF has been developed to describe the full range of complex pathways (*see Figure 4.3*) and the proportional contribution of varying path lengths. If further research, of specific control commands, reveals pathway details of the different muscles involved, actual path lengths, the tissue layers involved, the surface MES detected, and the source MES given a probable value, then the TFF contribution can be determined and separated from any deterministic element in the surface MES.

Objective 3)-to map and identify optimum upper limb (forearm) myoelectric sites

Some progress has been made here with the detection of the one site offering two well-defined unique muscle actions and the discovery of a corresponding site with replicability of function on other males. The author's refinement of all hand activity into 16 individual and 4 combined muscle commands is presented as a target for mapping the surface MES. The technique for mapping is established and ready for full implementation.

Objective 4)-to analyse the mapped data for frequency content and other unique identifiers

The limited data gathering has supplied more questions than answers and different Window averaging techniques have suggested the important information is found early in the transient signal. More work on the transient is required along with the full implementation of the mapping.

4.7 References:

[1] Basmajian, J and DeLuca, C. (1985). Muscles Alive, Their Functions Revealed by Electromyography, 5th Edition. Baltimore: Williams & Wilkins, pp 204

[2] H..Lindstrom, R. I. Magnusson, (1977). 'Interpretation of Myoelectric Power Spectra: A model and its applications', Proc.of IEEE, Vol 65, No. 5, May, pp 656.

CHAPTER 5: MES Site-Mapping

5.1 Frequency Response for Muscle /Site Actions

Can we determine a common frequency response for muscle /site actions?

The previous chapter introduced the possibility of an element of deterministic behaviour in the detected MES. To investigate this possibility, further detailed measurements were required.

This Chapter describes the method used to determine how to extract a "map" of the MES available on the arm of a user of prosthetics. The use of a non-amputee can be validated (see Chapter 3 page 113) and predicated upon the following:

- past myoelectric research that has been carried out has rarely required the use of an actual amputee. This has been due to the practical availability of amputees and the ethical issues involved.
- an amputee may well have a residual limb in which the original muscles may be in a different state of completeness compared to another amputee. Many amputees in the past have not been subject to a standardised type of surgical amputation technique that results in the muscles being attached in a manner in order to maintain their optimal activity and muscle tone. This situation has now been changed and standard methods introduced.
- except for the shortening of certain muscles in the arm, there is no difference in the physiological function of the detected MES, thus a non amputee, in principle, can provide a signal that is appropriate for research purposes
- the use of a non amputee establishes a baseline standard of all possible muscle actions that can be detected by the MES equipment. This is the most crucial issue in

the authors opinion, in order to proceed with the search for improved MES control signals.

5.2 Selection of Core of Muscle Actions Used for Mapping

The following list (also in chapter 4, page 116) was used by all volunteers to generate the recorded MES database.

5.2.1 List of 20 different control actions

1. wrist rotation (counter clockwise) left
2. wrist rotation (clockwise) right
3. thumb extension
4. thumb flexion
5. index finger extension
6. index finger flexion
7. middle finger extension
8. middle finger flexion
9. ring finger extension
10. ring finger flexion
11. little finger extension
12. little finger flexion
13. wrist extension
14. wrist flexion
15. wrist abduction
16. wrist adduction
17. 3-finger chuck grasp
18. relax hand (rest position)
19. hand fully open (all fingers extended)
20. hand grasp (clenched fist)

5.2.2 Core Of Actions As Applied To Geometry Model

The above list can be seen to be longer than the basic geometry model (*chapter 2, page 50, Figure 2.1*). If the commands can be extracted from the MES, the resulting control action will far exceed the minimum requirements for an advanced prosthetic hand (*Chapter 2, page 50, Figure 2.2*).

5.3 Method of Mapping: Constant Technique

An extensive mapping of the arm of a team member (the author) was undertaken for 20 distinctive (see above list) muscle actions that could be used for control purposes. For purposes of consistent and controllable access to measuring corresponding areas across the range of team members, a standard-unit grid-section was drawn (non-washable ink) upon the skin surface of the arm. A photo showing the grid on the author can be seen in Chapter 5, 5.1, page 139.

Method:

- All 20 actions were separately mapped.
- One action was repeated over the entire surface as the electrodes were moved methodically over a "grid pattern" marked on the arm surface. The grid-pattern divided each forearm view into one medial (midline) plane with five transverse subdivisions. The resulting grid created a total of 20 grid-sectors over the complete forearm.
- The view of the arm was divided (on paper) into four separate overlapping view positions.
- The data was recorded (written) directly onto the paper image corresponding to the recorded position on the arm.
- For every grid position, a particular action was repeated and observed at least 5 times before the value was recorded. Each action, e.g. ring finger flexion, was recorded by an observer, ***visually*** determining the 3dB bandwidth of the spectrum and the amplitude of the MES at the lower 3dB point.
- This ***visual*** method was necessary (the functional shortcomings of the HP spectrum analyser necessitated this procedure) due both to:

1. The stochastic and thus imprecise influences in the generated MES

and 2. The timing difficulties in synchronising the generated MES with the sampling rate and screen update rate of the HP analyser.

- The signal noise floor was consistently excluded as a significant contribution to the observations, by being directly observable, and thus controllable at all times.

The following four arm views can be seen on *Figure 5.2 (page 140)*

View 1:Superior (lateral) View of Pronated Forearm

View 2:Superior View of Supinated Forearm (Volar Aspect)

View 3:Medial View of Flexed Forearm

View 4:Lateral View of Pronated Forearm (elbow flexed at 90 degrees)

All four views were mapped/determined for the author (male 1). In the interests of efficiency and keeping the collected data to a more manageable and compact form the other 3 volunteers were mapped using only Views 1 and 2. This did not result in any significant loss of data as views 3 and 4 have overlapping elements with views 1 and 2.

5.4 Reference Site Selection

On the four views, it will be seen that there are reference areas given alphabetical tags. These are the initial areas that were determined on the author (male 1) to be sites of particular MES interest. These sites were strong signal areas for one of the 20 core actions, were a site for showing exclusivity between core actions, or were of notable spectral distinction. These sites were also marked on the author using indelible ink as the mapping and investigation took place over a period of many months. The marked sites allowed recording activity to be carried over between research/recording sessions. Factors such as daily temperature variations, fatigue, environmental changes could also be given some consideration with respect to the consistency (over time) of muscle action versus recorded

data. These sites were also included as marker areas in mapping all four volunteers to act as both a comparative site between all four subjects and to facilitative the taking of readings and subsequent locating of them on the paper-based grid.

A breakdown of the initial reference sites and their particular meaning with respect to the author only can be seen on the following "Site reference list."

5.5 Site Reference List

Note: Low, Medium, and High "Shift": refers to the mid point of a power spectrum measured over a bandwidth from 30 Hz to 500 Hz, corresponding to an occupation by the power spectrum of a predominantly Lower, Middle, or Higher proportion of that bandwidth. The observable 3dB bandwidth "shifts" up and down (along) the baseline bandwidth. The following labelled sites in Table 5.1 can be seen on *Figure 5.2.*

	Table 5.1	
Site	**Action**	**Spectrum Result**
A	wrist extension	Low shift
A	index finger extension	Low shift
A	thumb flexion	Medium shift
B	Index finger flexion:	Medium shift: 70 to 158 Hz peak @ 110 Hz
B:	Middle finger flexion	Low shift50 to 90 Hz peak @ 78 Hz
B	Ring finger flexion	peak @ 48 Hz
C	Index finger flexion	Low shift
D	Index finger flexion	High Shift
E	Thumb extension	Low shift: peak @ 90 Hz
E	Thumb flexion	High shift: 174 to 230 Hz
F	Wrist rotation left (counter clockwise)	High shift: 86 to 270 Hz
$\mathbf{F_1}$	Wrist rotation (left **and** right)	same frequencies (54 to 110 Hz)
$\mathbf{F_1}$	See diagram/notes	on wrist rotation!!
$\mathbf{F_1}$	Middle finger extension	54 to 110 Hz
F2	Wrist rotation left (counter clockwise)	54 to 110 Hz
F2	Middle finger extension	62 to 166 Hz
G	Wrist rotation left (counter clockwise)	High shift: 62 to 294 Hz
$\mathbf{G_2}$	Middle finger extension	86 to 198 Hz
H	Wrist rotation left (counter clockwise)	Medium shift: 62 to 246 Hz

	Table 5.1 continued	
H	Middle finger extension	High shift peak: 62 to 206 Hz
J	Thumb flexion	High shift
K	Thumb flexion	Low shift
M	Thumb flexion	High shift peak 174 to 230 Hz
M	Thumb extension	Low shift peak @ 90 Hz
	Note: As thumb extension action goes from proximal to distal (i.e. the result of an increase in muscle force). The frequency increases	from medium to high shift. This could give a direct correlation of user fine thumb muscle control to the prosthetic thumb action control.
N	Thumb extension	Medium shift
N	Index finger extension	Low shift
O	Wrist rotation right (clockwise)	High shift
P	Wrist rotation right (clockwise)	Low shift
P	Middle finger flexion	Low to Medium shift peak @ 110Hz
P	Thumb flexion	Medium shift: 94 to 206 Hz
Q	Thumb flexion	Low shift (weak signal)
R	Thumb extension	Low shift: 54 to 150 Hz
R	Index finger extension	Low shift: 54 to 206 Hz
S	Thumb extension	Low shift
S	Index finger extension	High shift
T	Thumb extension	High shift
U=M	Thumb flexion	High shift: 174 to 230 Hz
U=M	Thumb extension	Low shift peak @ 90 Hz
W	Middle finger flexion	Low shift: 90 to 166 Hz
W	Index finger flexion	Medium/High shift: 90 to 174 Hz
W	Thumb flexion	Low shift: 54 110 Hz
X	Wrist flexion	Medium/High shift: 86 to 238 Hz
Y	Wrist flexion	High shift: 126 to 326 Hz
Z	Wrist flexion	Low shift: 86 to 206 Hz
5	Ring finger flexion	Low shift: 38 to 78 Hz
1	Ring finger flexion	Low shift: 46 to 86 Hz
2	Ring finger flexion	Medium shift: 54 to 126 Hz
3	Ring finger flexion	Low shift: 38 to 94 Hz
4	Ring finger flexion	High shift: 54 to 198 Hz
6	Ring finger flexion	Medium shift: 78 to 182 Hz

Note: Sites 5,1,2,3,4,6 are in a line along the arm axis and show a clear downward shift in frequency for the same muscle action as distance increases from 6 to 4 ,3,2,1,5,

Patterns of spectrum shifts began to emerge. The data was then rearranged to emphasize those shifts and to see what else emerged (see Table 5.1). The author's markings and arm (*seen in Table 5.1 and Figure 5.2*) are shown in photos *Figure 5.1. views 1,2 and 3).*

	Table 5.2	
Site	**Action**	**Spectrum Result**
B	Ring finger flexion	peak @ 48 Hz
5	Ring finger flexion	Low shift: 38 to 78 Hz
1	Ring finger flexion	Low shift: 46 to 86 Hz
3	Ring finger flexion	Low shift: 38 to 94 Hz
2	Ring finger flexion	Medium shift: 54 to 126 Hz
6	Ring finger flexion	Medium shift: 78 to 182 Hz
4	Ring finger flexion	High shift: 54 to 198 Hz
	Ring finger extension	(none located)
B	Middle finger flexion	Low shift: 50 to 90 Hz, peak @ 78 Hz
W	Middle finger flexion	Low shift: 90 to 166 Hz
P	Middle finger flexion	Low to Medium shift, peak @ 110Hz
F_1	Middle finger extension	54 to 110 Hz
F2	Middle finger extension	62 to 166 Hz
G_2	Middle finger extension	86 to 198 Hz
H	Middle finger extension	High shift: 62 to 206 Hz
C	Index finger flexion	Low shift
B	Index finger flexion	Medium shift: 70 to 158 Hz, peak @ 110 Hz
W	Index finger flexion	Medium to High shift: 90 to 174 Hz
D	Index finger flexion	High Shift
A	Index finger extension	Low shift
N	Index finger extension	Low shift
R	Index finger extension	Low shift: 54 to 206 Hz
S	Index finger extension	High shift
Q	Thumb flexion	Low shift (weak signal)
K	Thumb flexion	Low shift
W	Thumb flexion	Low shift: 54 to 110 Hz
A	Thumb flexion	Medium shift
P	Thumb flexion	Medium shift: 94 to 206 Hz
E	Thumb flexion	High shift 174 to 230 Hz
J	Thumb flexion	High shift
M	Thumb flexion	High shift peak @ 174 to 230 Hz
U=M	Thumb flexion	High shift: 174 to 230 Hz

	Table 5.2 continued	
E	Thumb extension	Low shift: peak @ 90 Hz
R	Thumb extension	Low shift: 54 to 150 Hz
S	Thumb extension	Low shift
U=M	Thumb extension	Low shift peak @ 90 Hz
M	Thumb extension	Low shift, peak @ 90 Hz
	Note: As thumb extension action goes from proximal to distal (i.e. the result of an increase in muscle force). The	frequency increases from medium to high shift. This could give a direct correlation of user fine thumb muscle control to the prosthetic thumb action control.
N	Thumb extension	Medium shift
T	Thumb extension	High shift
Z	Wrist flexion	Low shift: 86 to 206 Hz
X	Wrist flexion	Medium to high shift: 86 to 238 Hz
Y	Wrist flexion	High shift: 126 to 326 Hz
A	Wrist extension,	Low shift
F	Wrist rotation left (counter clockwise)	High shift: 86 to 270 Hz
F2	Wrist rotation left (counter clockwise)	54 to 110 Hz
G	Wrist rotation left (counter clockwise)	High shift: 62 to 294 Hz
H	Wrist rotation left (counter clockwise)	Medium shift: 62 to 246 Hz
F_1	Wrist rotation (left **and** right)	same frequencies (54 to 110 Hz)
F_1	See diagram/notes on wrist rotation!!	
P	Wrist rotation right (clockwise)	Low shift
O	Wrist rotation right (clockwise)	High shift

5.6 Determination of Candidates

The decision to use non-amputee candidates arose due to practical considerations. The ready availability of adult volunteers within the University compared to accessing, organizing, and sorting the suitable amputees over a wide local catchment area. The decision was made to bring in amputee volunteers only at a much later period in order to test the research results. Two male and two female volunteers were decided upon as an initial test group.

5.7 Volunteers used in the MES research

Male 1 (author): Description: musculature, age, fitness

Medium height (5ft. 10 in), light-build, 47 years of age, muscular but not athletic, no adverse physical health problems

Male 2: Description: musculature, age, fitness

Medium height (6ft.), medium build, 29 years of age, athletic-build, no adverse physical health problems

Female 1: Description: musculature, age, fitness

Medium height (5 ft.5 in.), light build, 32 years of age, light-build (non-active non-sportsperson), no adverse physical health problems

Female 2: Description: musculature, age, fitness

Medium height (5 ft. 8 in.), light/medium-build, 38 years of age, athletic-build (active sportsperson), no adverse physical health problems

5.8 Summary

. As stated in chapter 1, the objectives of the research are:

- 1)-to investigate the information content of a MES.
- 2)-to study the nature of the Tissue Filter Function (TFF)
- 3)-to map and identify optimum upper limb (forearm) myoelectric sites
- 4)-to analyse the mapped data for frequency content and other unique identifiers
- 5)-to recommend the practical application of MES analysis for control purposes
- 6)-to provide a greater range of user-generated control signals.

- 1)-to investigate the information content of a MES: see objective (4) below
- 2)-to study the nature of the Tissue Filter Function (TFF): The data shows clear spectral shifts for each muscle action category and suggests a spectral link with muscle action and distance from a reference point. This may be a result of the Tissue Filter Function (TFF) and/or it may be a unique signature of the muscle or a part of that muscle. Not all digits functions were located on the forearm so the need for a completely methodical mapping and filling in of the database was the next candidate for action. The early stages of this site reference list were the forerunner to the later implemented arm 'site mapping'
- 3)-to map and identify optimum upper limb (forearm) myoelectric sites: A standard method of mapping by grid was established. The 20 actions were mapped onto a grid of 20 sections. Those 20 sections are spread over 4 arm views (*see Figure 5.2*) author mapped his arm according to that standard. The HP spectrum analyser was able to display the MES spectrum as the signals arrived to its inputs but was not up to the demands of capturing the MES onset, simultaneously record the 3dB bandwidth and save the sample to file in any reliable process. So for expedience the author chose to use a visual method of recognising the MES bandwidth and manually recording the results on the grid views. This proved successful in the limited mapping of the arms but the full detailed data would have allowed further analysis of the signals with respect to bandwidth, slope, shape, zero crossings etc. (see chapter 6 section 6.7 page 152). An example of the mapping method grid results can be seen in *Figure 5.3.*
- 4)-to analyse the mapped data for frequency content and other unique identifiers: Table 5.2 shows the 20 muscle actions and the shifts in frequency content as the detection electrodes are moved in the local 'hot spots' associated with each action.

The clearest example of frequency signature selectivity was position 'M', with a very finely varying signal available for thumb control. Three additional volunteers for arm mapping were identified and the same mapping method was applied to 3 further volunteers to ascertain the extent of similarity or differences within and across gender.

- 5)-to recommend the practical application of MES analysis for control purpose: The case for using a non-amputee was presented and considered sound. A core of 20 basic muscle actions was decided as control signal actions. An initial exploratory investigation followed on the arm of the author. Results of the site reference list are presented in tables 5.1 and 5.2.
- 6)-to provide a greater range of user-generated control signals: The list of 20 different control actions was shown to provide one or more unique sites on the arm for MES detection purposes. This verifies a feasible supply of an extensive range of control signals for a multi-function prosthetic arm. The signals are there; only a practical collection method needs to be developed.

The results have been further developed into a more readily assessable form, with the data entered into a database (Microsoft Excel) and presented in a visual 3-dimensional format. See Chapter 6 "Second Moment of Area".

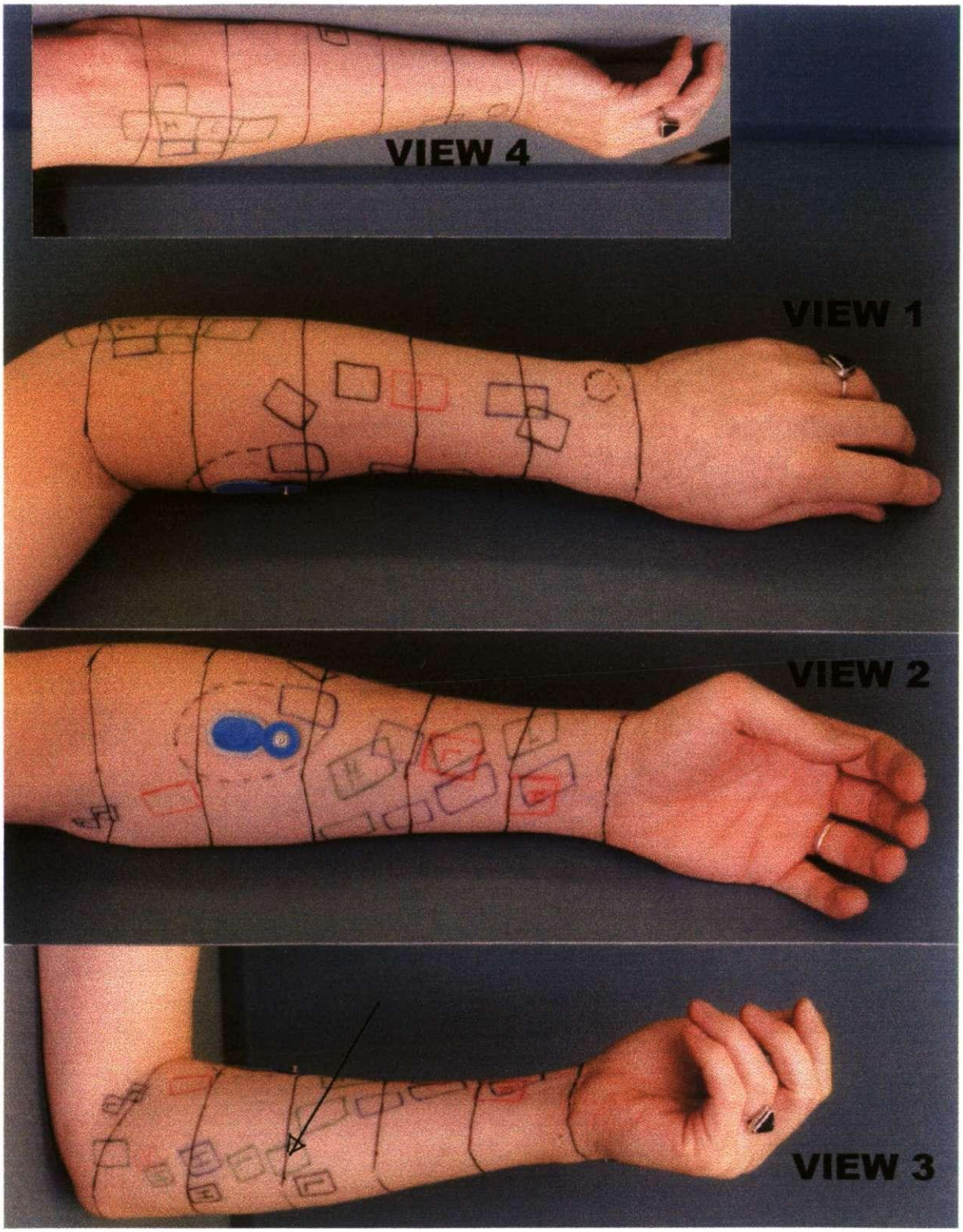


Figure 5.1 The arm of the author (male 1) showing all 4 views and detected sites of interest. The H and L markings show sites of High and Low frequency shifts and the colour code is a marker for a particular muscle action. The initial site found for wrist and ring finger flexion is arrowed on View 3.

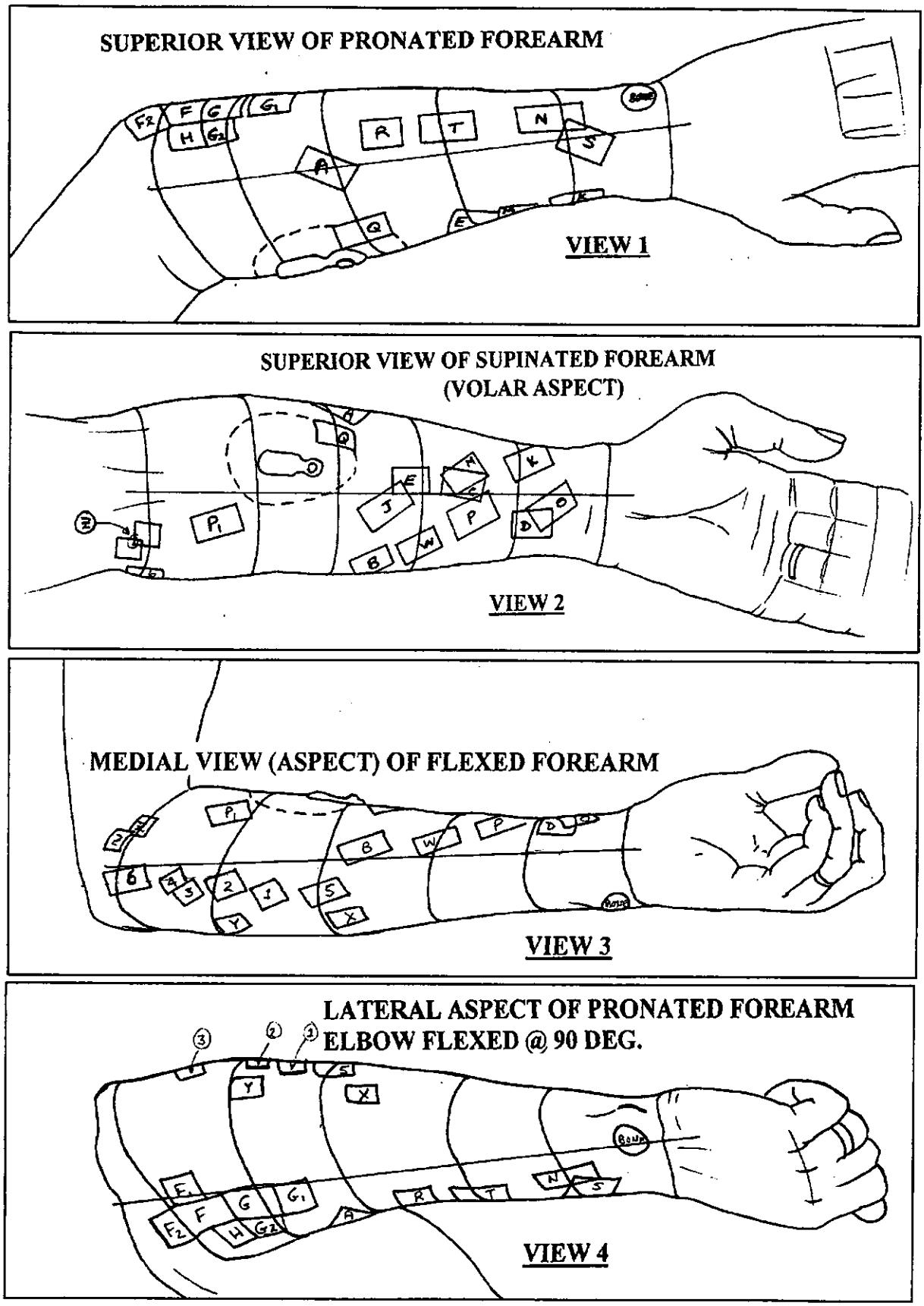
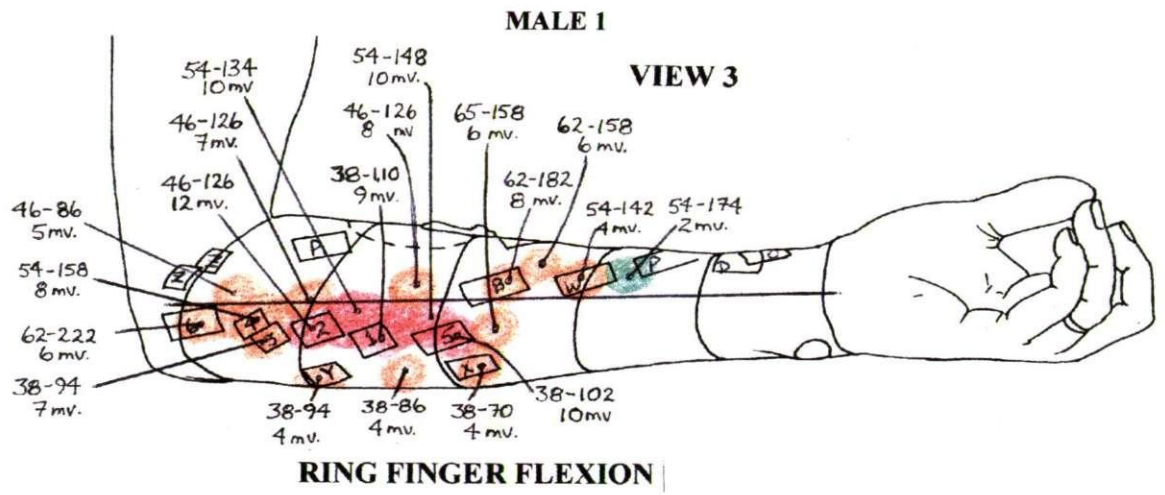


Figure 5.2: The grid pattern of the 4 views of the arm showing detected muscle action

VIEW 3

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM



VIEW 3

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

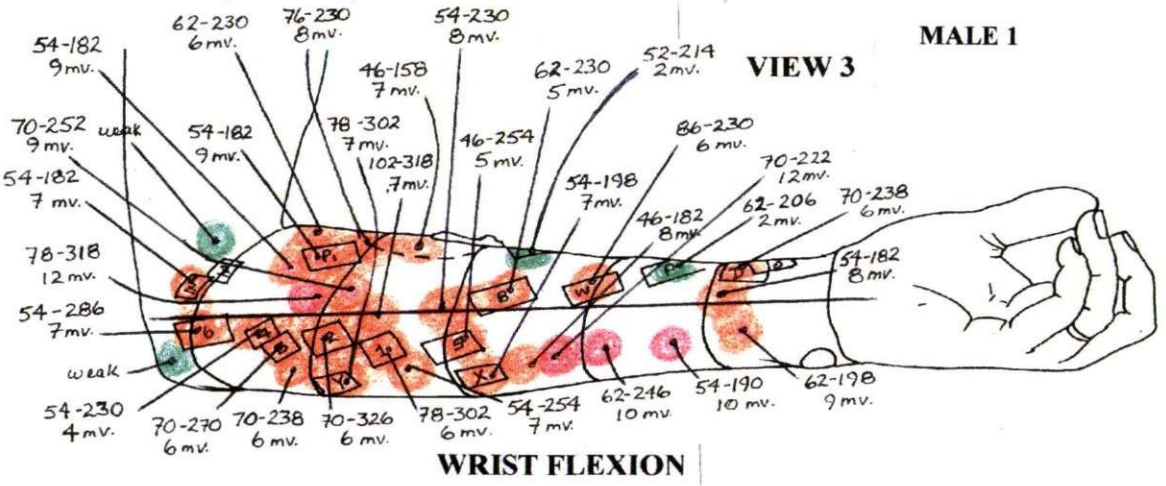


Figure 5.3 An example of 'mapping' the arm for a single muscle action. In this case the ring finger flexion and wrist flexion action have been mapped.

Legend: Violet = strong signal, Brown= medium signal, Green = weak signal

CHAPTER 6: Analyses of Results

6.1 Muscle Action VS Frequency

What relationship can be drawn between frequency and muscle action?

6.1.1 Test results for sites

The results of the first male generating all 20 actions, show, for each action a clearly defined strongest MES (Hot Spot) region in close proximity to the muscles associated with the MES source. The strongest region has a gradual reduction in signal strength as the electrodes are moved further away from the strongest point. The detected MES undergoes a shift in frequency content that appears both representative of a loss of frequency as distance increases (filter effect) and also shows a different "Hot Spot" spectrum starting point.

If the MES source showed a different, "Hot Spot " spectrum (assuming same source tissue-depth) for each of the different muscle actions then the results would show a strong support for declaring an at least partly deterministic MES source.

If the MES source showed the same, "Hot Spot " spectrum (assuming same source tissue-depth) for each of the different muscle actions then the results would show a strong support for declaring a non-deterministic, stochastic MES source.

A preliminary assessment of the results does not support a non-deterministic conclusion. The frequency spectrum does not fully undergo the expected "filter effect" with distance but shows an initial high frequency loss from the hot spot epicentre but retains the same frequency spread as the overall MES amplitude decreases.

Consider the comparison of two separate muscles, one overlying the other. (*see Figures 6.1a and 6.1b*). The (superficial muscle), the extensor digitorum (used for middle digit

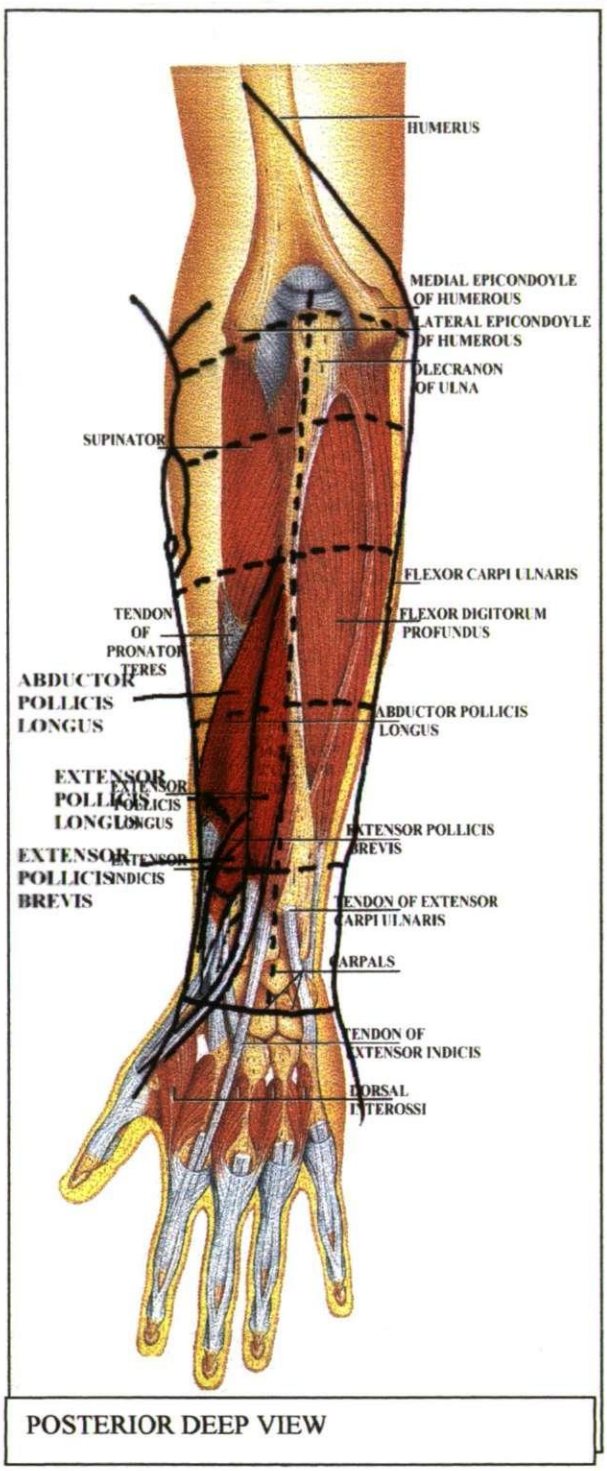


Figure 6.1a (above) shows the deeper laying muscles. The transparency shows the selected muscles involved in the thumb extension action

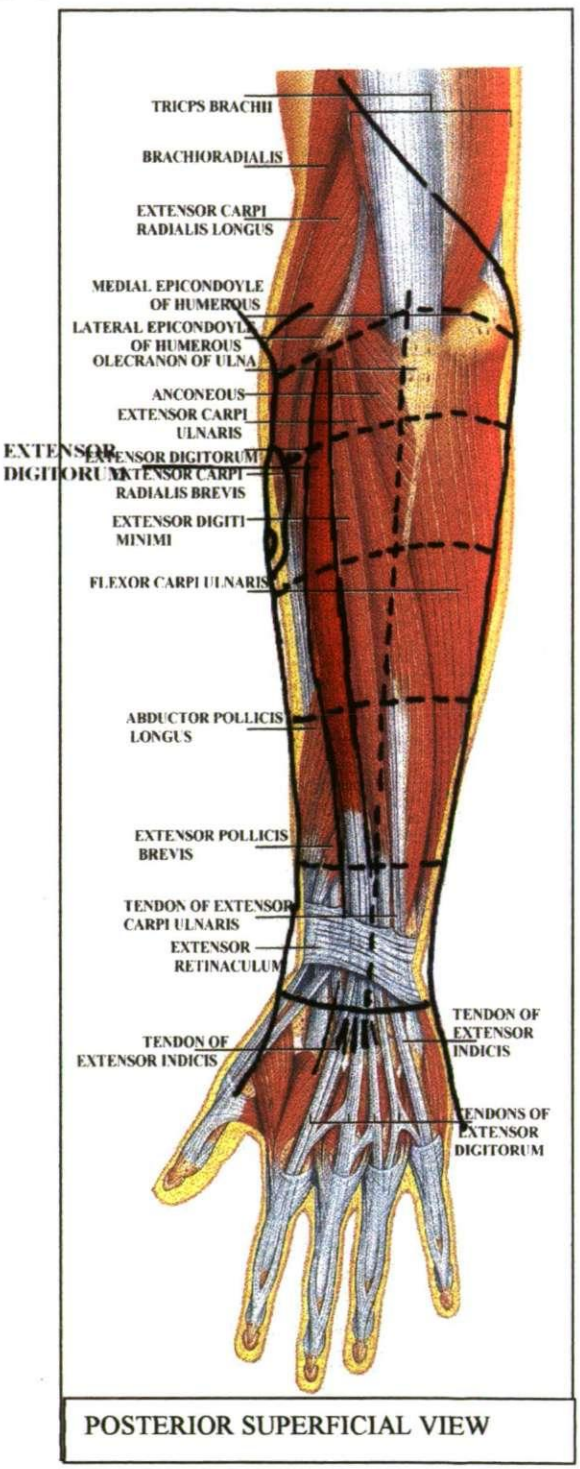


Figure 6.1b (above) shows the muscles closer to the surface. The transparency shows the selected muscle involved in middle digit extension.

Figure 6.1 adapted and redrawn from 'Principles of Anatomy and Physiology' by Tortora and Grabowski, Wiley & Sons, ninth edition, page 349, 2000.

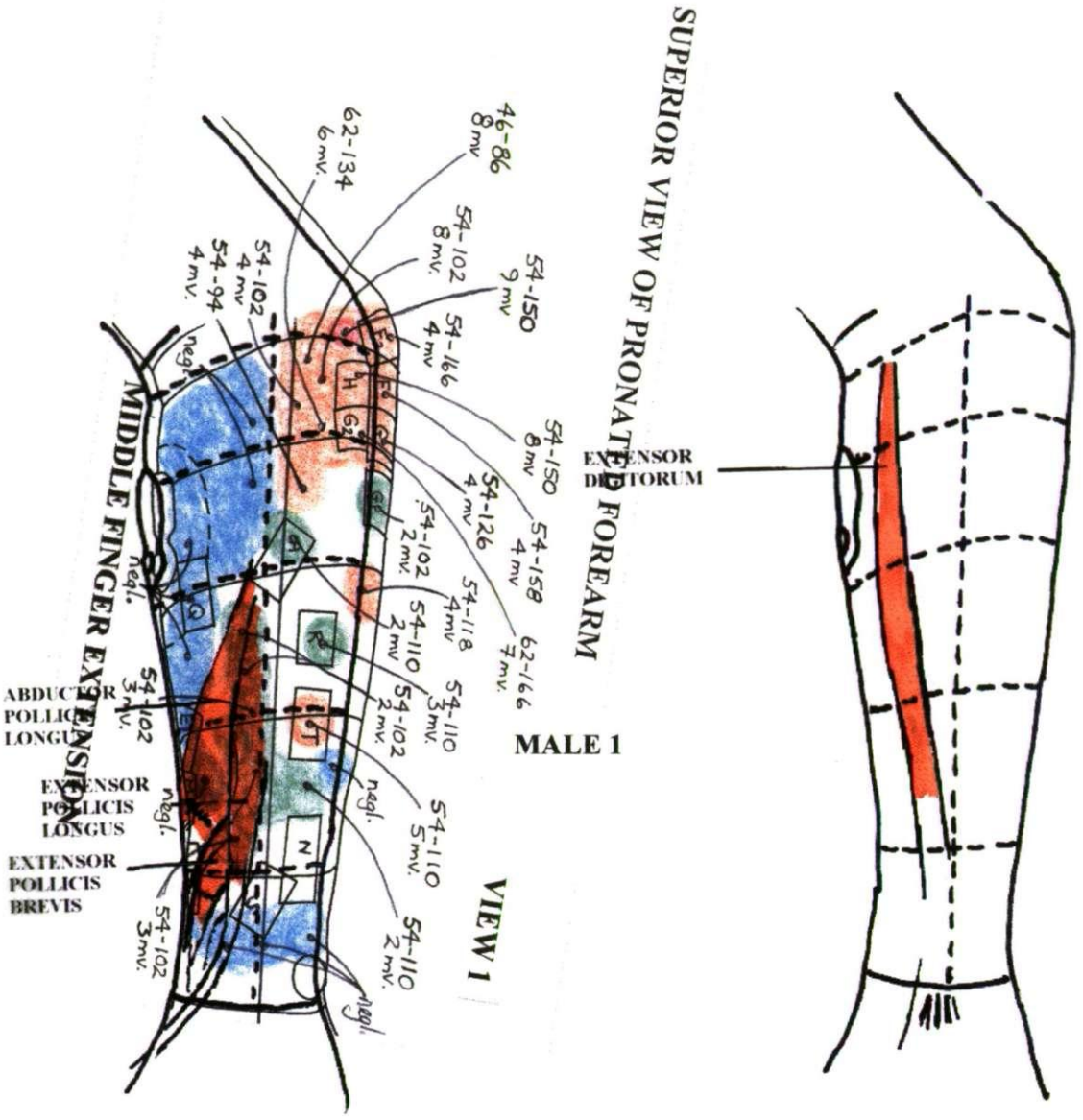


Figure 6.2a (above) shows the mapped arm 4for the middle finger extension action. The transparency superimposes the extensor digitorum muscle normally assigned as responsible. The author cannot reconcile the position of the extensor digitorum according to the textbooks, with the activity areas detected on the maps! The same areas however were seen also to be active on the other three volunteers. See appendix.

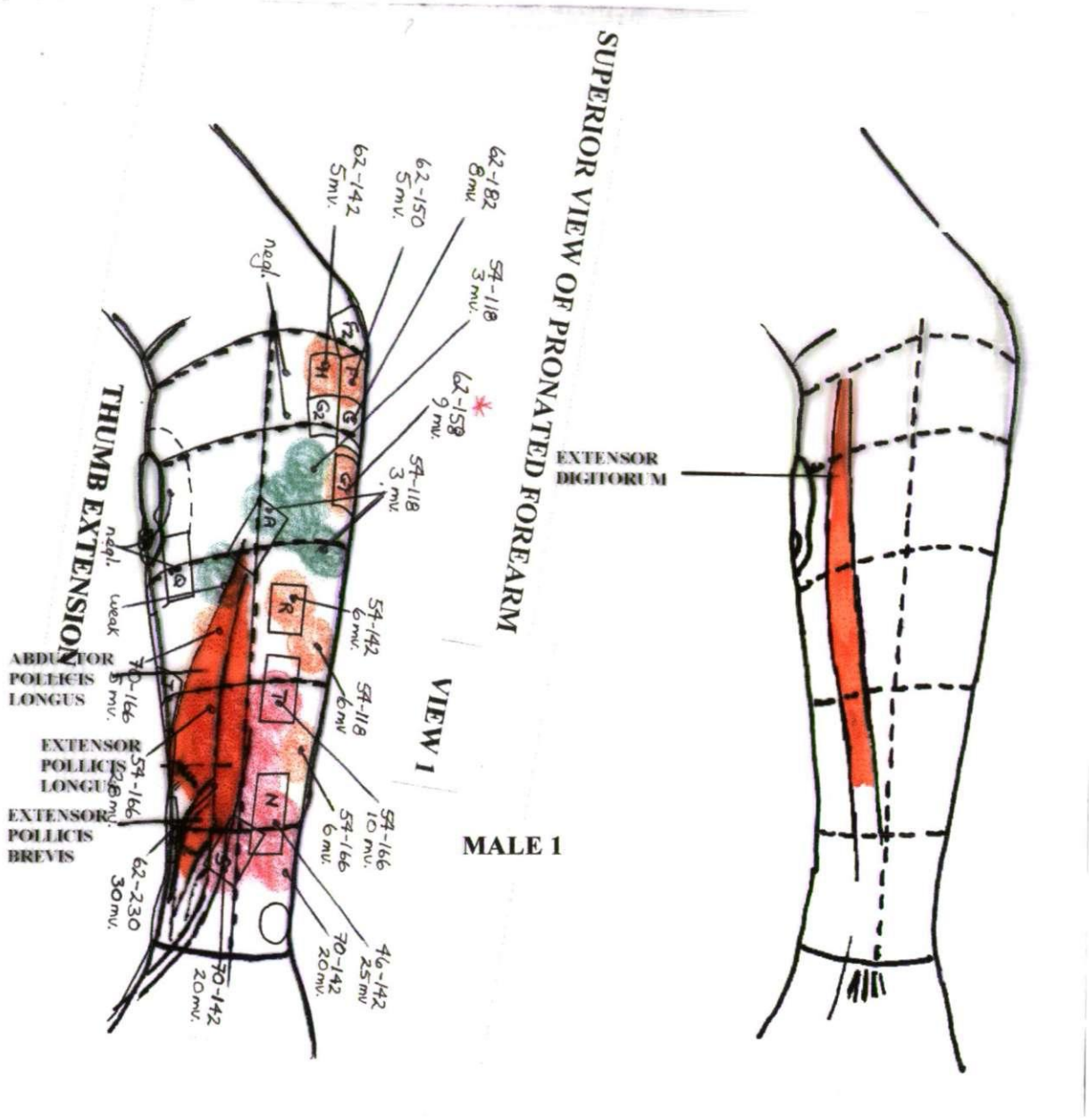


Figure 6.2b (above) shows the mapped arm areas for the thumb extension action. Much closer agreement with textbook muscle positions drawn on the overlaid transparency can be seen. The brown regions (F2, F, G, G2, H) are seen as active yet do not correspond to the formally assigned region for middle finger extension, but do correspond to the flexor carpi ulnaris and flexor digitorum profundus which are both involved in wrist flexion, or in this case, wrist stabilization. Thus the wrist has been stabilized while the middle finger is extended. This same supportive action is also found in the middle finger extension views for the other three volunteers (see appendix). There appears to be more muscles involved in a supportive role (synergists and fixators) in any desired action than has formally been assigned in the textbooks. The arm mapping shows itself to be invaluable in determining the contributions made by various complementary muscles in achieving a desired muscle action. Further extensive analysis of the mapped areas would reveal complex interdependency of the muscles in order to achieve desired actions.

extension) overlying the (deep muscle) the extensor pollicis longus (used for thumb extension). The superficial muscle is seen to have a spectrum of 54 to 110 Hz while the deeper to have a 54 to 142 Hz at the same surface grid site. If the theory of a constant (non deterministic) muscle spectrum were the whole picture then the inverse of these spectral-comparison figures should be the case (i.e. the underlying muscle should show a *reduced* high frequency component compared to the overlying muscle).

It was stated that for a non-deterministic signal the "average" spectrum should be approximately uniform for all MES sources. Therefore the average spectral signal loss for a deeper muscle should lose proportionally more of its higher frequencies as it passes through a greater thickness of tissue than the overlying muscle, yet the spectrum actually shows the inverse situation to be the case. There is necessarily a degree of uncertainty as to the exact details of the signal path, but in principle, these results show a strong suggestion for a differing spectral signature being available for control action by selected muscles. The selective nature of Neural Networks certainly offers a tantalising option.

6.2 SITE MAPPING

"What common MES features or repeatability, if any, can be found between samples from the general population?"

This question of repeatability introduces what has been given only minimal attention by past researchers: "How thoroughly do we need to look at the distribution of the surface MES over the arm?"

The repeatability issue was confronted with the "site mapping" of the three additional volunteers (one male and two female) and a comparison of their results.

6.2.1 MES Zones: Features, Overlap, and Significance

For each muscle action, the MES (as detected on the surface) shows a strong "Hot Spot" with a trend to a radial reduction in amplitude as distance increases. The radial reduction in

spectral content is less predictable and the effect is more the result of a combination of the length, size and shape of the muscle used, the varying consistency of the intervening tissue, and the source MES spectrum.

When looking at each grid area that was mapped, the overlap of MES generated by the 20 different muscle actions varies from no interactive overlap to a complex interaction depending upon the muscles used. As a single muscle action (e.g. finger movement) is increased to a hand grasp or fully-open action the number of muscles brought into play increases, with a resultant expansion of the areas of surface activity and a blending/complexity of the detected MES.

6.3 Gender differences

6.3.1 Male-Male

Given a similar musculature and fat thickness/density, the MES comparisons between the two tested males gave a broad agreement in principle. Enough differences were shown to conclude that training a general Neural Network (NN) to be applied to a class of "all males"- would not produce an optimal result. For a practical application, a NN training should take place for each user. A general NN for the single electrode/single site can be used to detect the wrist/ring finger actions with good success but reliability decreases rapidly as demands for additional actions are applied.

6.3.2 Female-Female

The 2 females tested were of quite different muscular development. One was an active sportsperson (squash etc.) and the other a comparatively less active, non-sportsperson. This is a significant consideration when discussing these females but also applies across gender as well. One female had developed or utilised certain muscles that can be used for an action in preference to others that also could have been used. Consequently when comparing the amplitude peaks between the 2 females there was a significant difference

between some actions regarding the site amplitudes observed, rather than the sites as such. This is a further consideration against attempting to develop a general NN program.

6.3.3 Male-Female

The 2 females chosen probably gave a good span of the female range in general but still show a strong similarity between their general sites and features and those of the males.

As a demonstration of both gender similarities and an indication of a deterministic element to the detected muscle MES, the "thumb extension" MES of all four volunteers was compared (Table 6.1). There are two widely separated muscles involved in the action (*see Figures 6.1 and 6.2*). Corresponding sites (on all four adults) show similar spectral features for the one muscle site but different spectral features for the other site.

Site 2 shows a higher frequency component over Site 1 for both males and females. This is an early indicator of both gender similarities and of a non-random deterministic element in the MES.

TABLE 6.1 Spectrum (in Hz) for 'thumb extension' MES comparison of all 4 volunteers. Comparison of the two sites are shown on *Figure 6.3.*

	Site 1	Site 2
(female 1)	62-150	78-182
(male 2)	54-166	46-182
(female 2)	86-174,	70-214
(male 1)	62-182,	62-230

The female sportsperson was so similar to the male pair that arguments for a physiological difference between males and females regards general structure of muscle layout were without basis. Differences detected seem to be derived from individual muscle developmental skills. Of course, these tests were not exhaustive and make no claim for statistical significance. The author would welcome the resources to undertake such an exhaustive study.

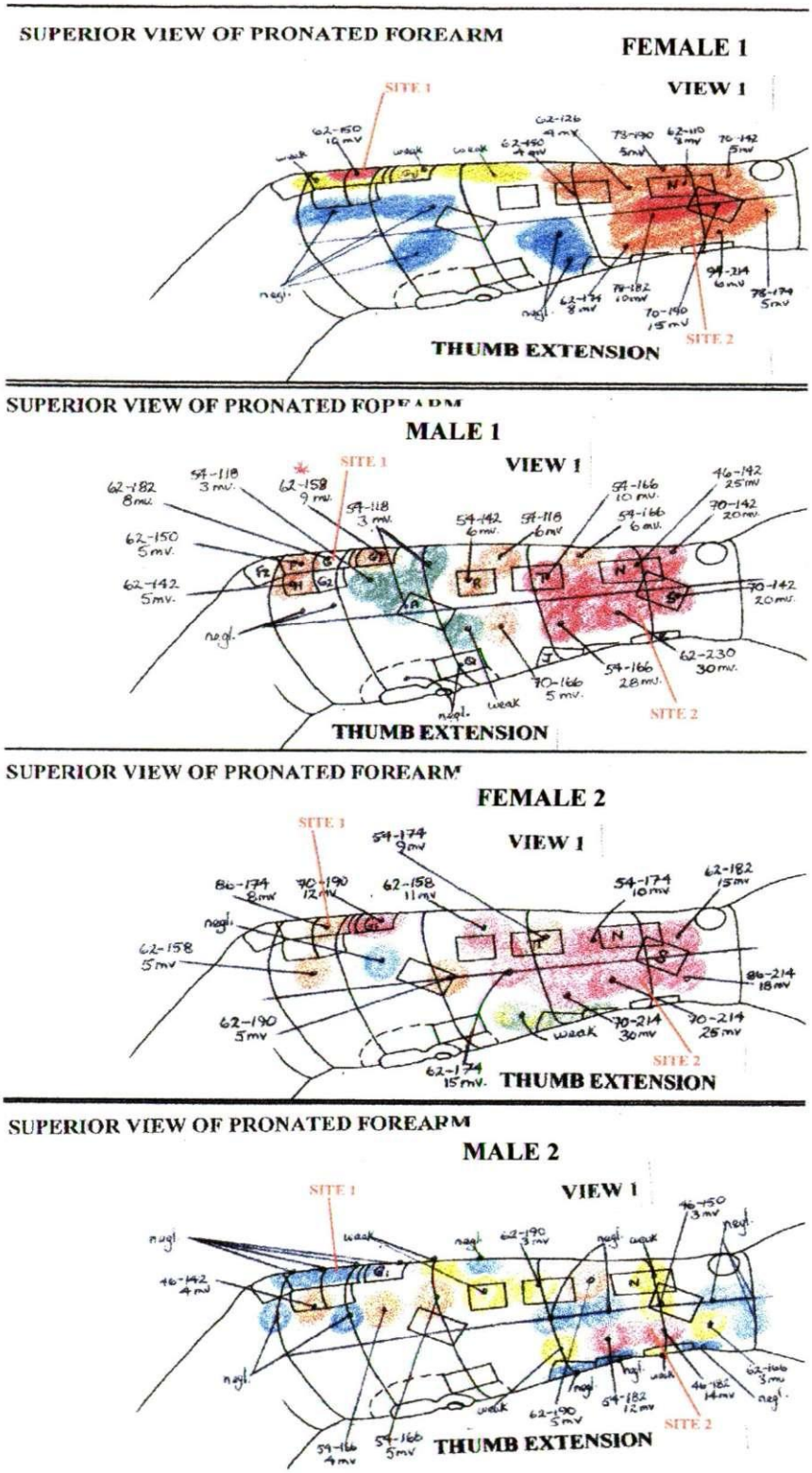


Figure 6.3: Thumb extension action

Table 6.1 refers to these 4 diagrams. Site 1 shows a similar spectral range for all 4 volunteers. Site 2 also shows a similar spectral range for all 4 volunteers.
The spectral ranges for sites 1 and 2 are distinctly different however, and suggests a different spectral characteristic for sites 1 and 2.

6.4 Techniques for Bandwidth and Central-Frequency Representation

6.4.1 Feature assignment

How do the 4 MES signal characteristics of: (1) Amplitude, (2) Central Frequency, (3) Bandwidth, and (4) Spectral Shape, combine as a unique MES label?

The spectral shape (e.g. the peak frequency, "q" (or sharpness), and slope variations)) was also seen to be a very distinctive characteristic and would have required very data intensive, time consuming, averaging and recording for each observation. Time considerations did not allow for this but with appropriate equipment should prove a fruitful research activity that would complement the current research. Neural Networks (NN) can be employed to recognise that part of the MES spectrum that corresponds to the "shape " without actually doing a lengthy analysis. This would be intended for practical applications and the theoretical origin of the "shape" would not be revealed but rather embedded in the hidden layers of the NN structure

6.5 Using the Second Moment of Area as a Unique Combining Method

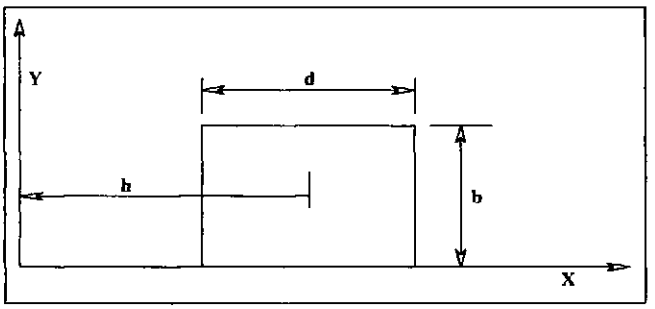
The results of the site mapping needed to be entered into a database and analysed. The normal 3-dimensional representations could not account for the 4 variables [(1) Amplitude, (2) Central Frequency, (3) Bandwidth, and (4) Spectral Shape], obtained as the data results. A method was required to compress the 4 variables into 3 variables for graphical representation. The Second Moment of Area using the Parallel Axis Theorem was chosen as a medium to represent a frequency bandwidth envelope shifting along an X-(frequency) axis. For simplicity the 4^{th} variable (Spectral shape) is considered here as symmetrical and set to unity (as data for this variable was not recorded) It can be considered as asymmetrical by multiplying by a plus or a minus factor. The following diagram *(Figure*

6.4) shows a box along an X-axis. This box represents a frequency bandwidth along a frequency X-axis with magnitude represented by the Y-axis:

(**1**) b = Amplitude, (**2**) h = Central Frequency,

(**3**) d = Bandwidth, (**4**) +/-= Spectral Shape]

6.6: Using Second Moment of Area to represent Bandwidth Shift along x-axis



Where: $A = b \times d$

$b = v$ = voltage

d = bandwidth = (high-low)

= v (high-low)

$$h = \left[\frac{(high - low)}{2} + low\right]$$

N.B. x-axis viewed as frequency

y-axis viewed as voltage

Figure 6.4 Using second moment of area to represent bandwidth shift along x-axis

Formula: Parallel Axis Theorem

$$I\,yy = \frac{bd^3}{12} + Ah^2 = A\left(\frac{d^2}{12} + h^2\right)$$

$I\,yy$ is a value that represents:

the signal bandwidth plus its combined Y axis voltage and position along the X axis

$$I\,yy = \left[\frac{v(high - low)^3}{12}\right] + \left[v(high - low) \times \left(\frac{high + low}{2} + low\right)^2\right] \quad \text{equation (6.1)}$$

Observations of influences (changing values of variables) inherent in the formula need to be considered as limiting the absolute reliability as a measure of the 3 variables of:

Central frequency, Amplitude, and Bandwidth

along the X-axis

Consider the following note re: equation (6.1)

Note: The value Iyy increases as bandwidth (d) increases: Iyy α d^3

: The value Iyy increases as amplitude (b) increases: Iyy α b

The value Iyy increases as central frequency (h) increases: Iyy α h^2

The value Iyy increases as area (A) increases: iyy α b x d

Hence Iyy is very sensitive to changes in d and h and relatively insensitive to changes in b.

The shortcomings of the formula given in equation (6.1) occurs when:

As amplitude (b) increases and drives output value Iyy upwards

so can the distance (h) increase and drive value Iyy upwards

so can the bandwidth (d) increase and drive the value Iyy upwards

We then have the situation where:

A **large** change in amplitude (b) yields an output Iyy that: -

Is equal to a **small** change in bandwidth (d)

Is equal to a **small** change in central frequency (h)

This degrades the 'absolute value' merit of the Parallel Axis Theorem in establishing a single value that represents the 3 variables of:

Central frequency, Amplitude, and Bandwidth

along the X-axis

And we are left with a generalized representation that is, still however, a valuable indicator for our purposes.

6.7 Alternative Method: Assigning A Code To Each Feature

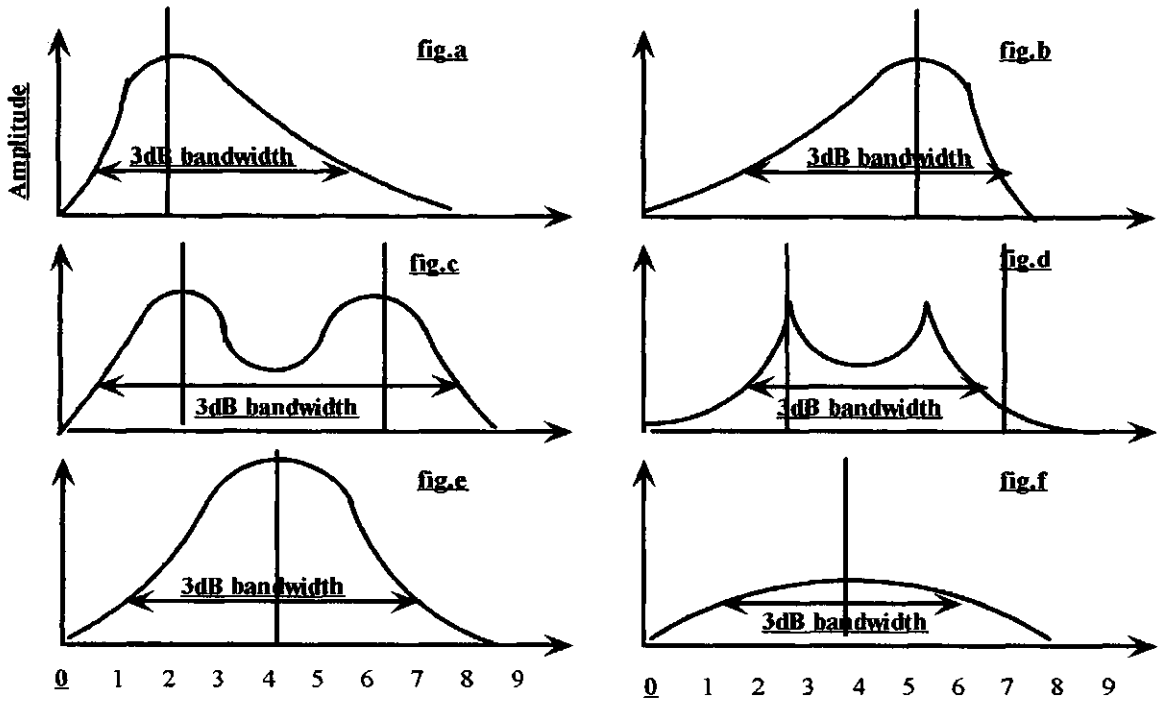


Figure 6.5 'Spectral Shapes' a selected few of the many possible 'spectral shapes' that can be measured as an MES response

The above (*Figure 6.5*) shows a selected few of the many possible 'Spectral shapes' that can be measured as an MES response. The following descriptors can be used to apply a unique identifying code number to the detected MES. These codes can be used as input numbers to the inputs of a Neural Network

e.g. 1: **trigger threshold value** = 0 to 9

2: **peak amplitude** (@central frequency of peak 1) = 0 to 9

3: **central frequency** (@ peak amplitude of peak 1) = 0 to 9

4: **bandwidth** $= [3dB(high) - 3dB(low)]$ = 0 to 9

5: **slopes ratio** (length of slopes: as ratio of slope 1 to slope2)

$$\left[\frac{F_1}{F_2}\right]$$ = 0 to 9

where: F_1 = slope 1 = frequency change from threshold trigger to peak amplitude

F_2 = slope 2 =frequency change from peak amplitude to below threshold trigger

Thus an MES with:- **trigger threshold value = 3**

peak amplitude = 7

central frequency = 3

bandwidth = 7

slopes ratio = 1

could be represented as being of coded value = 3 7 3 7 1

This 5 digit input code, (representing identifiable characteristics of the generated MES), could then be presented to the 5 input nodes of the Neural Network. The output nodes would be coded to trigger the desired hand actions.

6.8 The Relationship between the Separated Individual finger MES actions and that of Two or more combined MES finger actions.

The hand fully open action activates (extends) all five digits on the hand. The use of all five extension actions i.e. thumb extension, index finger extension, middle finger extension, ring finger extension, and little finger extension should produce an overall result that closely approximates the summing of all five actions. As the second moment of area is a description of the bandwidth and its position along the frequency axis, we would expect to see a summing action of the second moments where the individual finger actions overlap. *Figures 6.7 (7,3,5,9,11)(on page 157)* are the individual finger actions involved in extending the hand (wrist), and are summed below (*Figure 6.6b)* to become the figure 'Cumulative Result of Test'. Compare that with *Figure 6.6a* (19: Hand fully open). A close correlation with proportional distribution over the mapped surface can be seen between

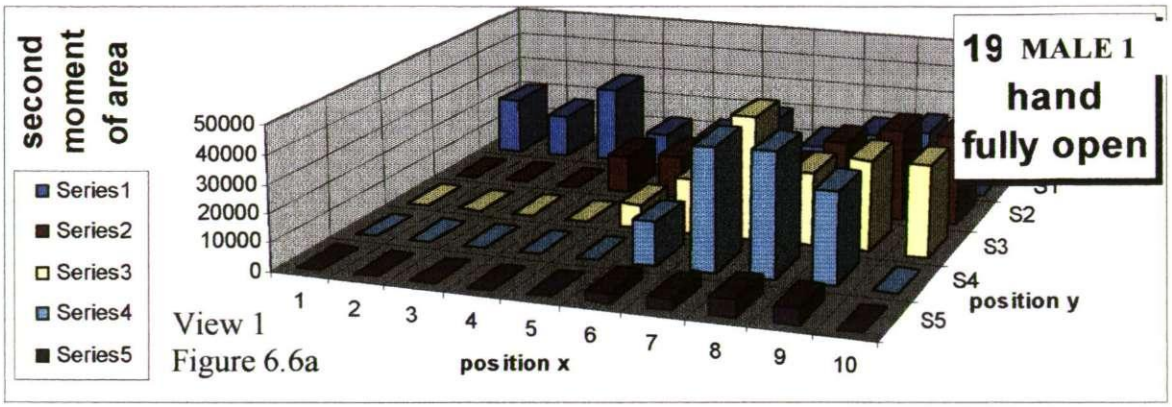


Figure 6.6a

Figures 6.6a and 6.6b. As can be seen, compared with the 'hand fully open' data, the scale of values (magnitude) along the vertical Z-axis is greatest with the cumulative results

Any true additive or subtractive frequency interaction requires that the phase of the signal be taken into account. If two specific frequencies were 'exactly in-phase' we would get a wholly summing action at the amplifier terminals. If the specific frequency were wholly 'out-of-phase' we would get a nulling action at the amplifier terminals. Due to the varying pathways that the signals take from their sources to the point of measure (and thus a different time taken for each signal action) we cannot expect to see a pure summing action. Rather we should expect an overall unique interaction that yields a portion of the interacting MES regions.

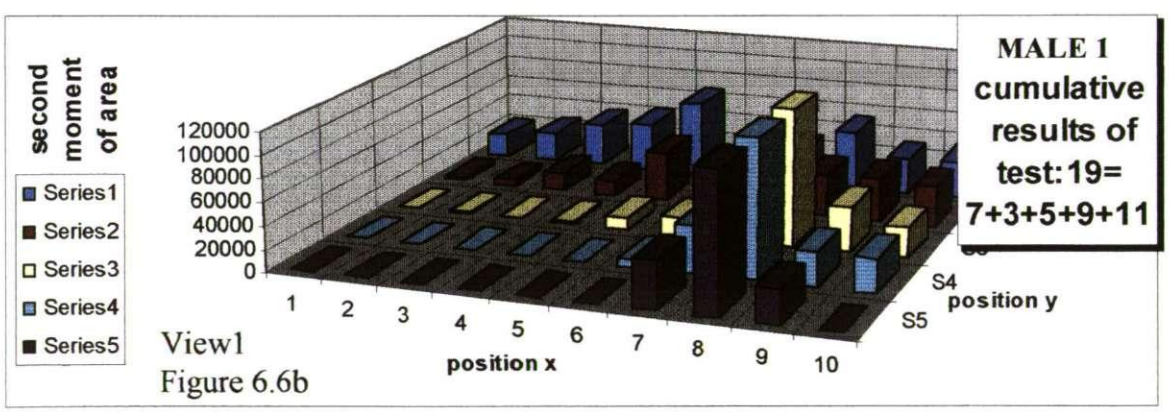
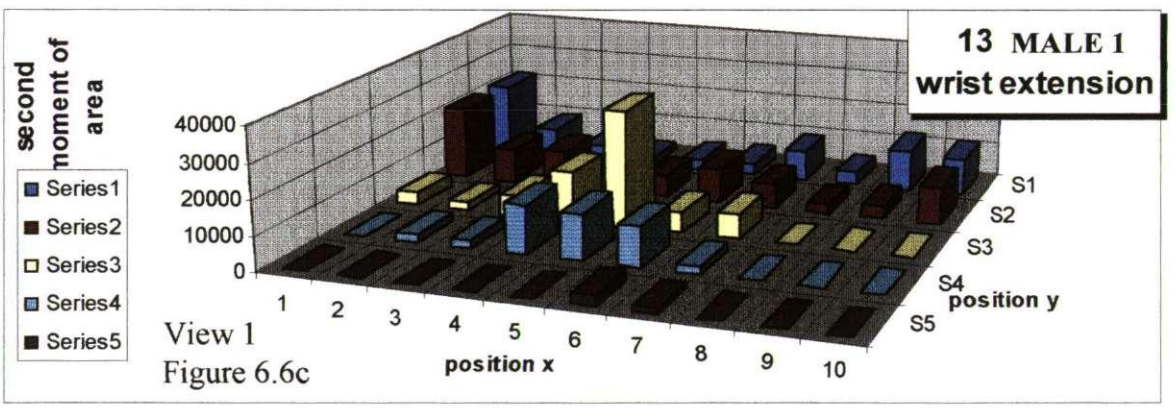


Figure 6.6b

The diagram labelled 'cumulative result of tests' in *Figure 6.6b* shows such a result. What does stand out as different is the S5 (purple) row of data as generated in *Figure 6.7* (3: thumb extension).

Note how the region of the thumb extension has lower recorded strengths on *Figure 6.6a* (hand fully open) compared to *Figure 6.7*('3:thumb extension'). This discrepancy appears, to have three possible sources (1) different muscle actions involved in thumb abduction and that involved in thumb extension (2) due to the cumulative results action having less vigour applied to the thumb (no data is available as separately recorded thumb abduction) and, (3) as we have seen in *Figure 6.2b* how the action for thumb extension involves a synergist and/or fixator contribution by other muscles to restrain the wrist region. The contribution of these other muscles may well be diminished for the hand to be fully open.

As long as the amputee (source of the MES) can reproduce this unique pattern consistently, then for practical purposes the pattern will be a useful control signal.



View 1
Figure 6.6c

The wrist extension figure above (*Figure 6.6c*) shows how different are the mapped MES features generally utilised as an 'open' trigger-signal for the commonly available prostheses. *Figures 6.6 (a,b,c)* show how the action of wrist, hand, and finger extension, offer such a rich and varied range of detectable features.

The relationship between the unified muscle action and the summed constituent muscle actions was explored for further clarification.

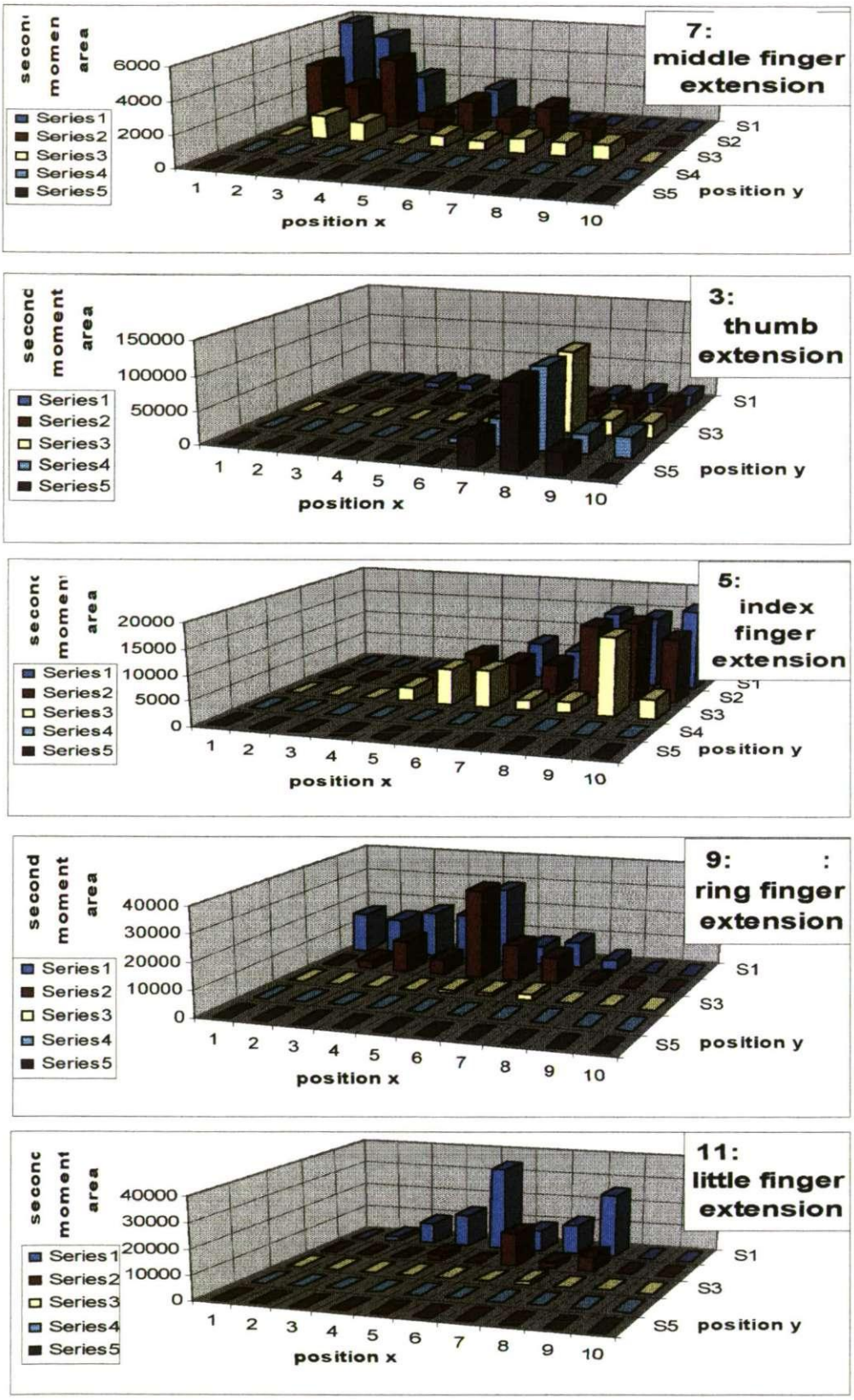


Figure 6.7 (**male 1**) encompasses the above sub-figures 7,3,5,9,11 The z-axis has been standardized at a common value.

The following figures (*Figure 6.8 to 6.35*) show the results from all 4 volunteers for 2 separate actions covering both 'View 1' and 'View 2',

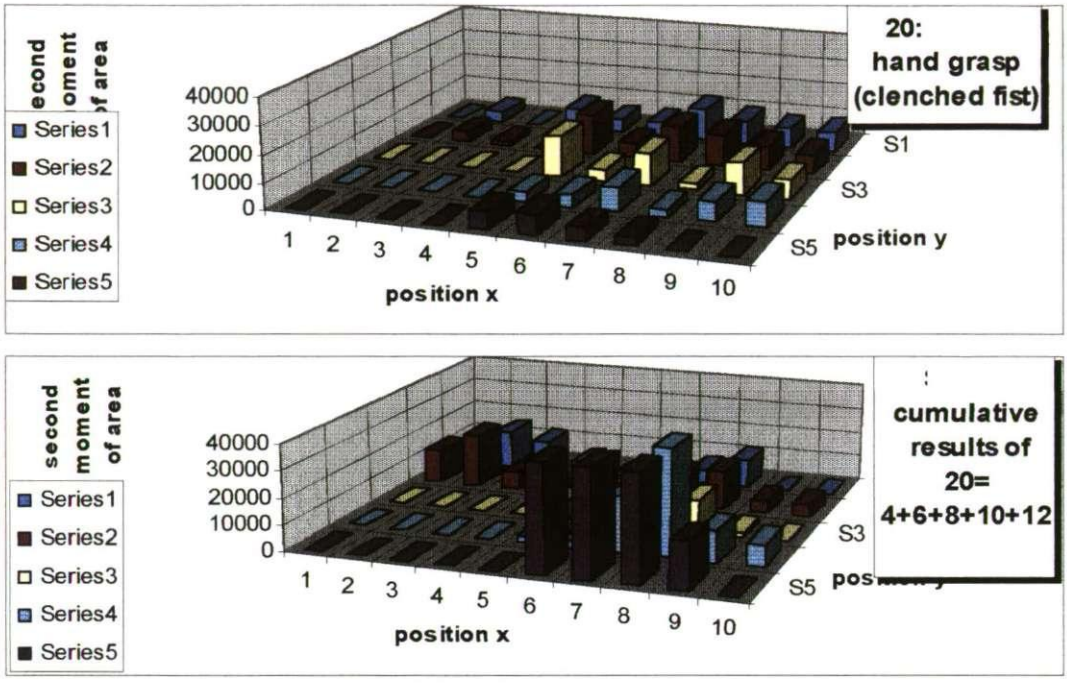
1) hand fully open' was set against both the action of wrist extension and the 'cumulative results' of the constituent actions.

2) 'hand grasp' (clenched fist) was set against both the action of wrist flexion and the 'cumulative results' of the constituent actions

6.9 Decomposition of the MES

Decomposition (using invasive needle electrodes, see chapter 1,page 26) of the MES has been undertaken with respect to the time and morphological aspects of the individual MUAP's, and the result of the decompositions has proven of benefit to the diagnosis and clinical assessment of neurological disorders. The control by the central nervous system of the motor units, (and the peripheral nervous system) can be assessed, and used to clinically quantify upper motor neuron diseases [1]. This approach by De Luca does not attempt to examine the surface spectral composition. The actual success of decomposing the frequency content of the surface detected MES can only be of very limited scope. As mentioned in the previous section (6.8) the surface electrodes cannot extract the phase relationship of the individual sources of any given detected frequency over the working bandwidth due to the varying distance and consequent time origins of the muscles sites. If examining the surface MES gives any indication of a particular muscle being activated, it will be from indirect methods in most cases and not those from the MUAP analysis of traditional decomposition techniques.

Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand and are summed below to become the Cumulative Result figure. Compare that with figure 20 (clenched fist). A close correlation with proportional distribution over the mapped surface can be seen between the two latter figures. As will be seen the scale of values (magnitude) along the Z-axis is greater with the cumulative results compared with the clenched fist).



What does stand out as different is the S5 (purple) row of data as generated in the figure '4: thumb flexion'.). This discrepancy appears, to have three possible sources (1) different muscle actions involved in thumb/little finger opposition and that involved in thumb flexion (2) due to the cumulative results action having less vigour applied to the thumb (no data is available as separately recorded thumb and thumb/little finger opposition, (3) as we have seen in figure 6.2b how the action for thumb flexion involves a synergist and/or fixator contribution by other muscles to restrain the wrist region. The contribution of these other muscles may well be diminished for the hand to be fully closed. The wrist flexion graph below shows how different are the mapped MES features generally utilised as an 'open', trigger-signal for the commonly available prostheses. These three figures show how the action of wrist, hand, and finger flexion, offer such a rich and varied range of detectable features.

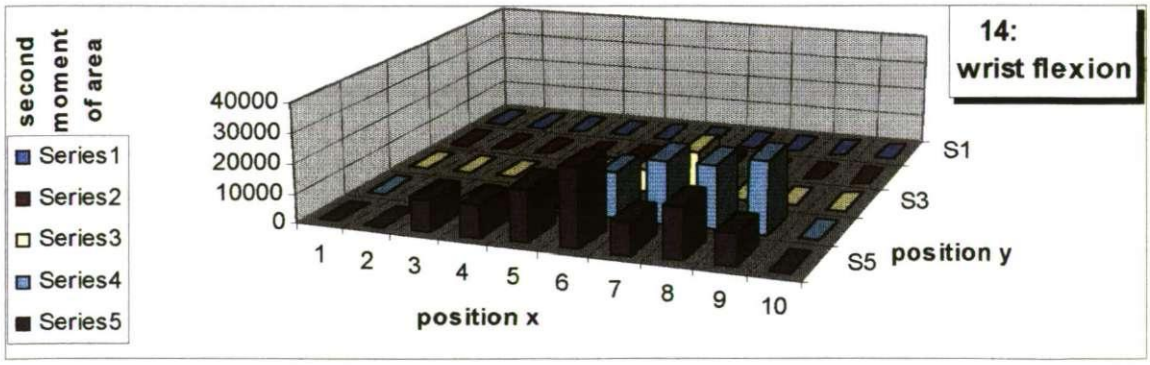


Figure 6.8 (**male 1**): The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions

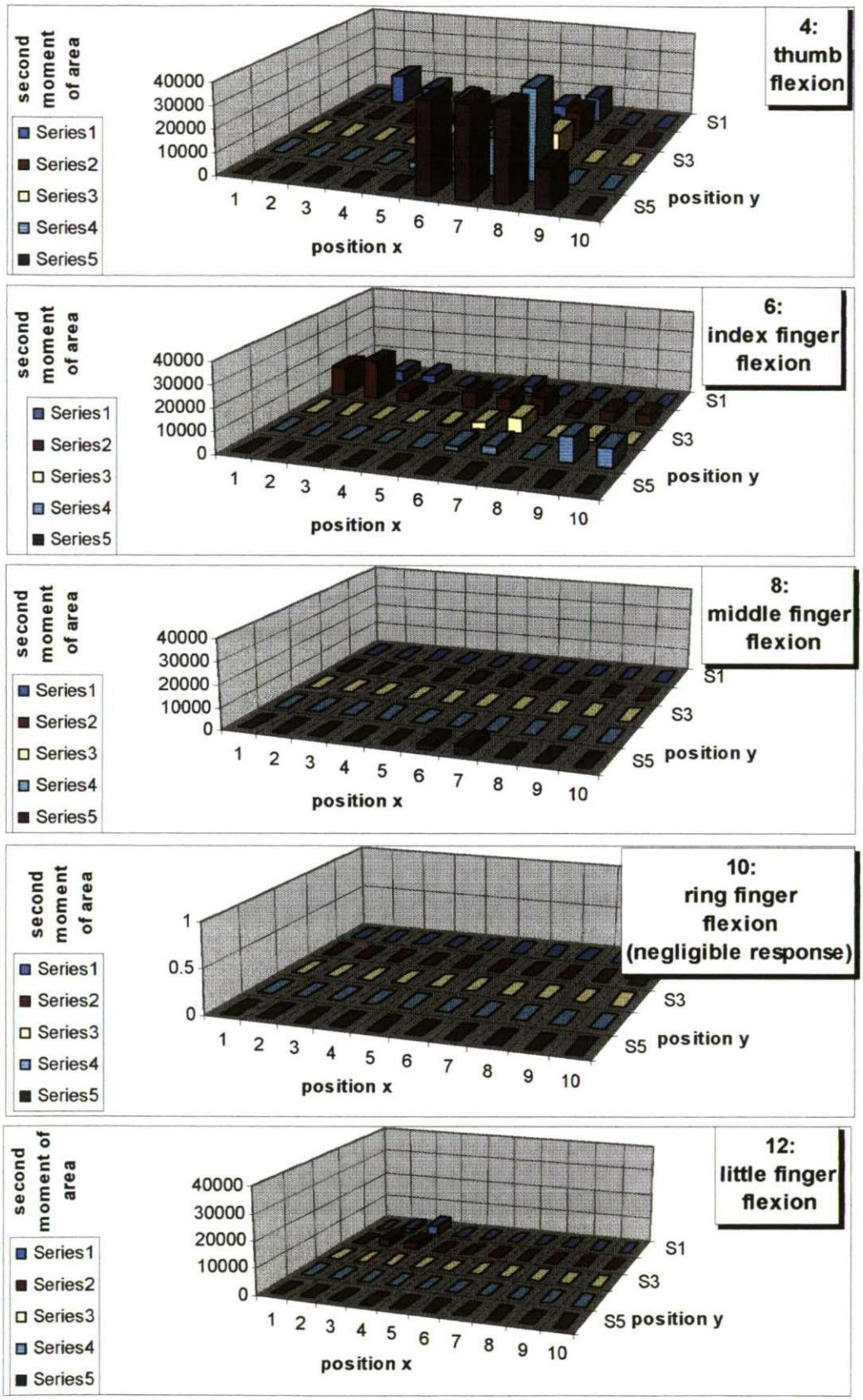
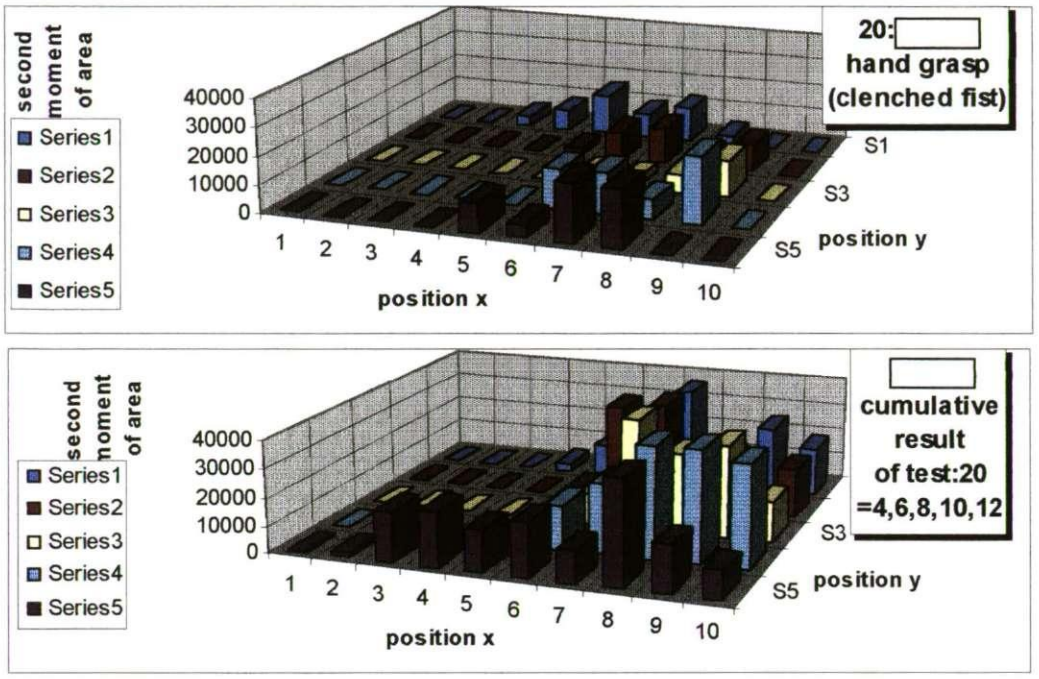


Figure 6.9 (male 1) encompasses the above sub-figures 7,3,5,9,11 .The z-axis has been standardized at a common value (except 10: ring finger flexion).View 1

Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand and are summed above to become the Cumulative Result Test figure. Compare that with figure 20 (clenched fist). A close correlation with proportional distribution over the mapped surface can be seen between the two figures. As will be seen the scale of values (magnitude) along the Z-axis is greater with the cumulative results compared with the clenched fist). '



Again as in View 1, what does stand out as different are the rows of data generated in the figure '4: thumb flexion', that are missing in the 'figure 20:(clenched fist)' This discrepancy appears to be (current hypothesis) an example of the different muscle actions involved in thumb/little finger opposition and that involved in thumb flexion. No data is available as separately recorded thumb/little finger opposition. More analysis may clarify this point.

The 'wrist flexion' graph below shows how different are the mapped MES features/regions (compared to the two figures above) generally utilised as an 'open', trigger-signal for the commonly available prostheses. These three figures show how the action of wrist, hand, and finger flexion, offer such a rich and varied range of detectable features.

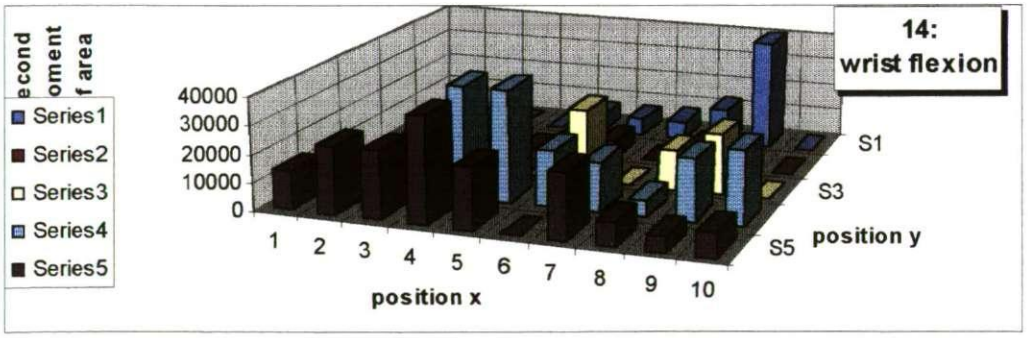


Figure 6.10 The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions **(male 1):View 2**

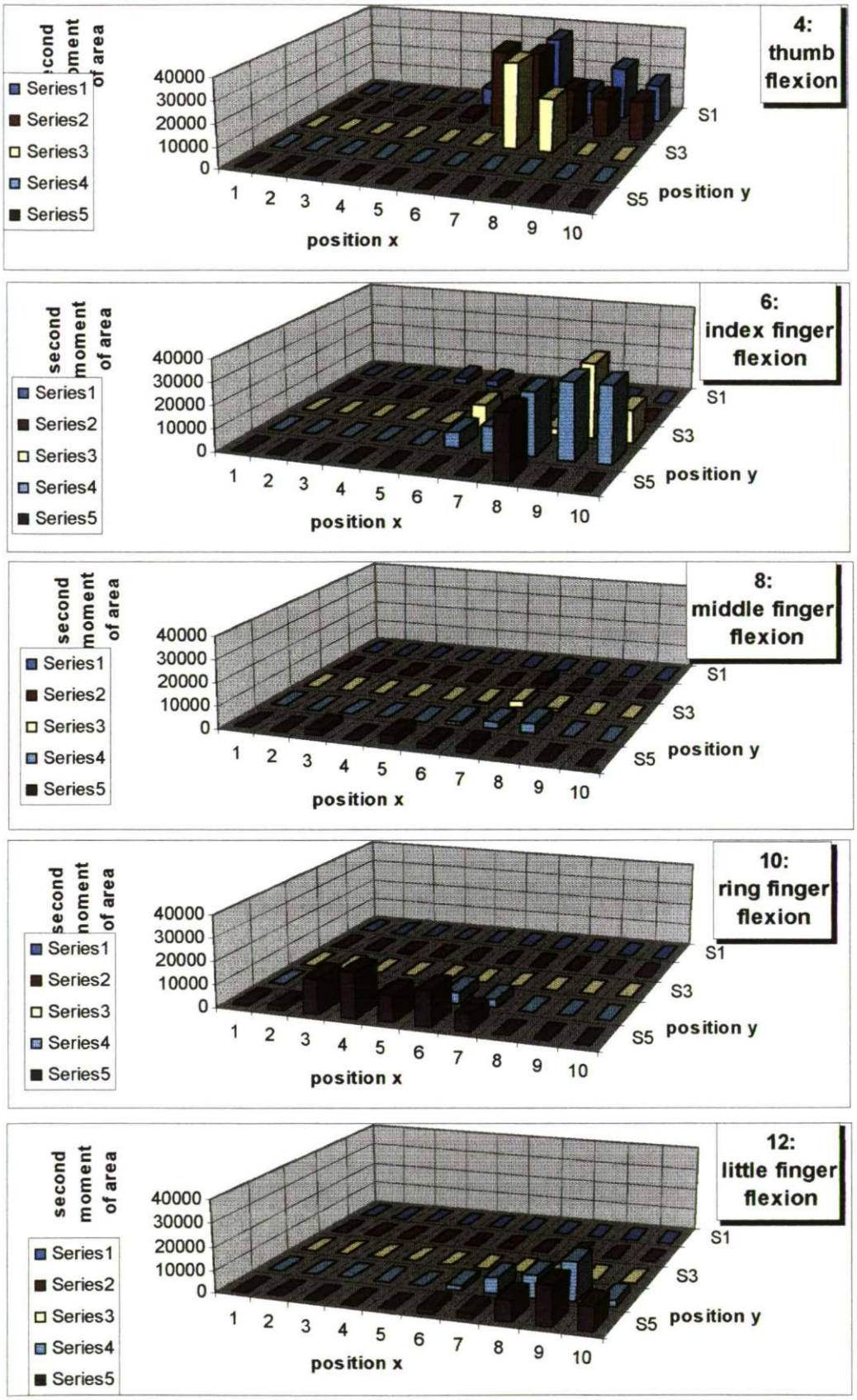


Figure 6.11 encompasses the above sub-figures 4,6,8,10,12 . The z-axis has been standardized at a common value (except 10: ring finger flexion): (**male 1) View 2**

Figures 7,3,5,9,11 are the individual finger actions involved in extending the hand and are summed below to become the Cumulative Result figure. Compare that with figure 19 (Hand fully open). A close correlation can be seen between the two upper figures.

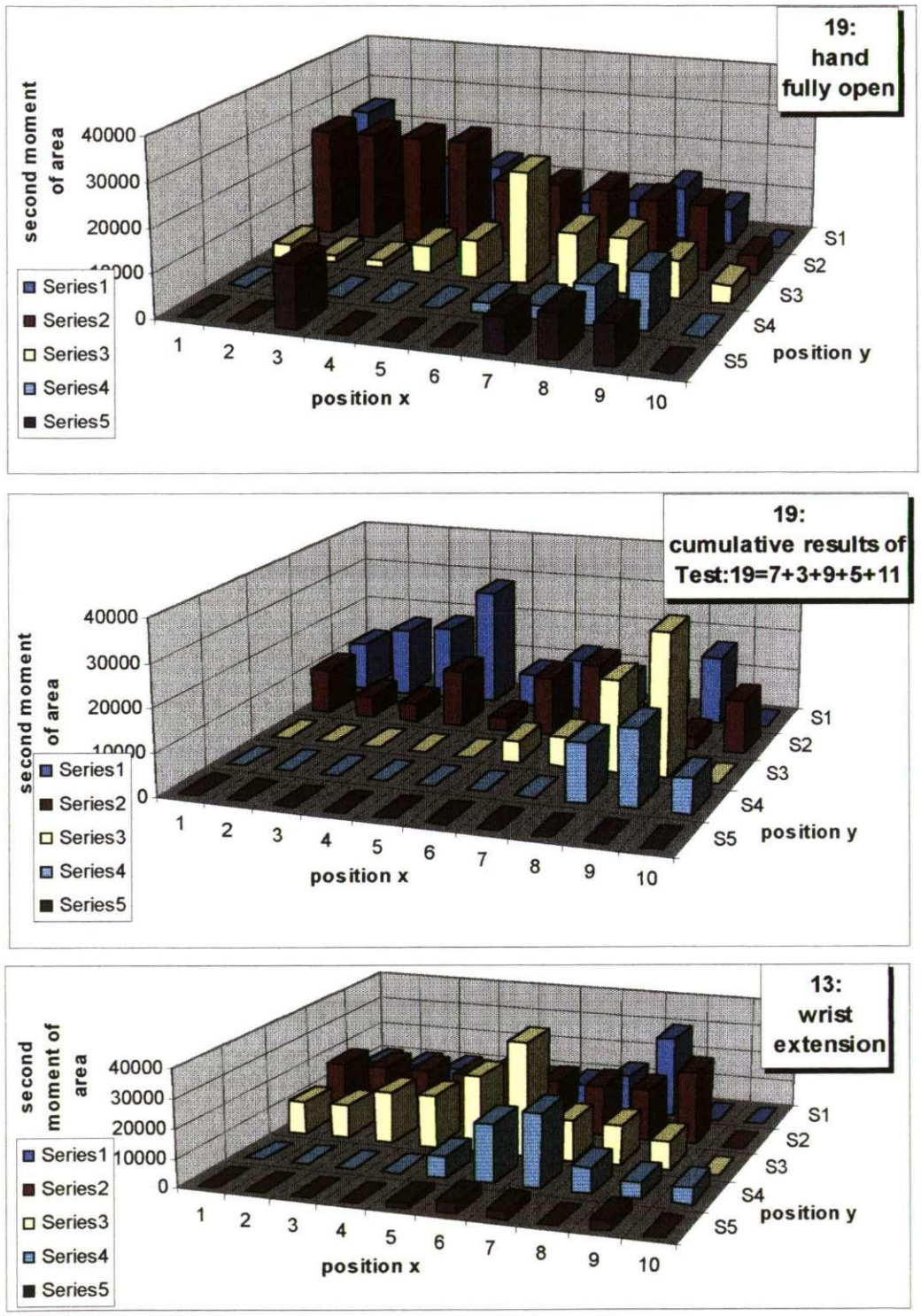


Figure 6.12 The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions **(female 1) View 1**

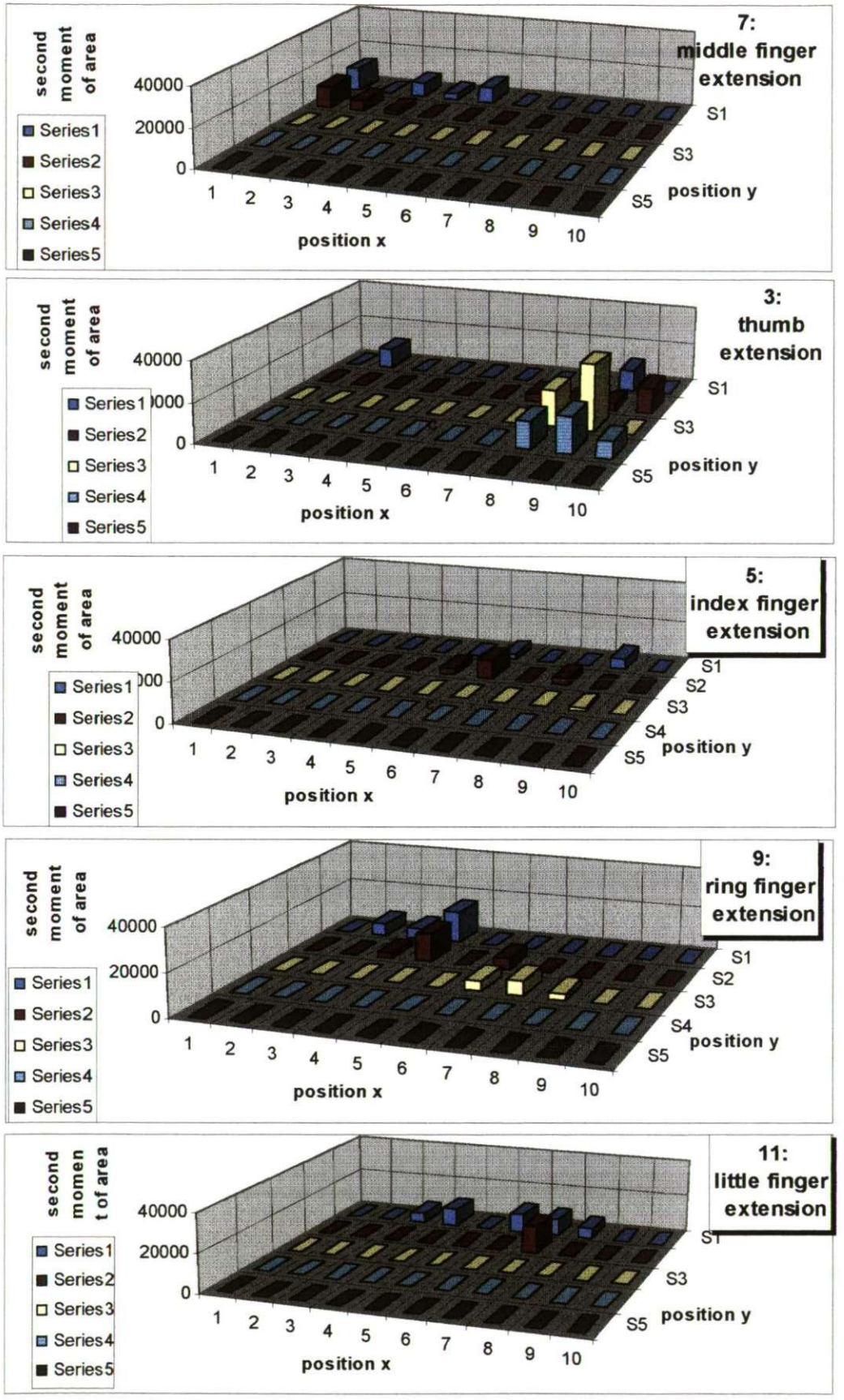
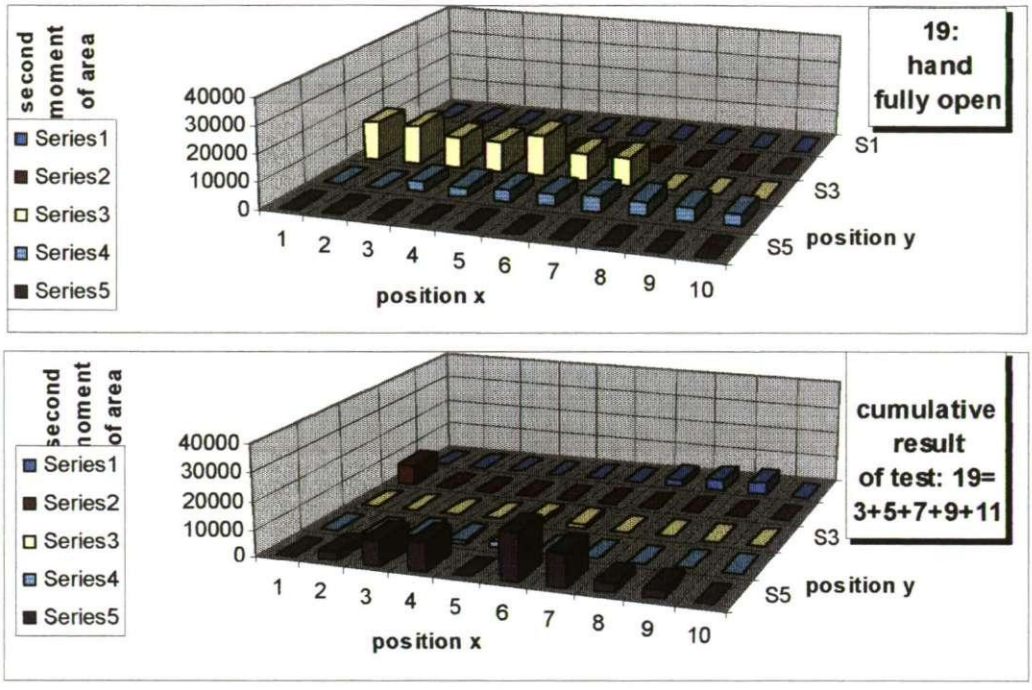


Figure 6.13 encompasses the above sub-figures 7,3,5,9,11 . The z-axis has been standardized at a common value (except 10: ring finger flexion)**(female 1) View 1**



The 'hand fully open' above includes all the digits; none of which are in contact opposition. No correlation on the surface plane can be seen between figures '19:hand fully open' and 'cumulative result of test 19 = 3+5+7+9+11'. It is possible that the missing data, (for 'figure 5:index finger extension), may fill in some of the open S3, S4 region in the cumulative result figure.

The 'wrist extension' action can be seen to be positionally unrelated to the other two figures above and supports the position shown on all other volunteers that the commonly used wrist action is unrelated to other actions detectable for MES control purposes.

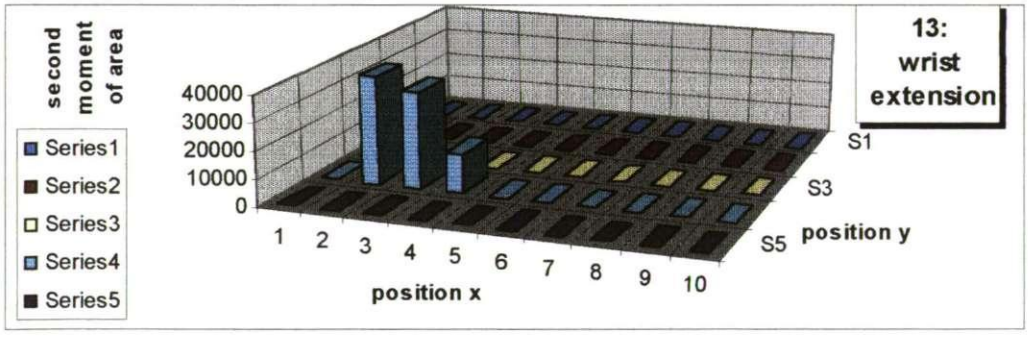


Figure 6. 14 The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions: Figures 3,5,7,9,11 are the individual finger actions involved in the hand **(female 1): View 2**

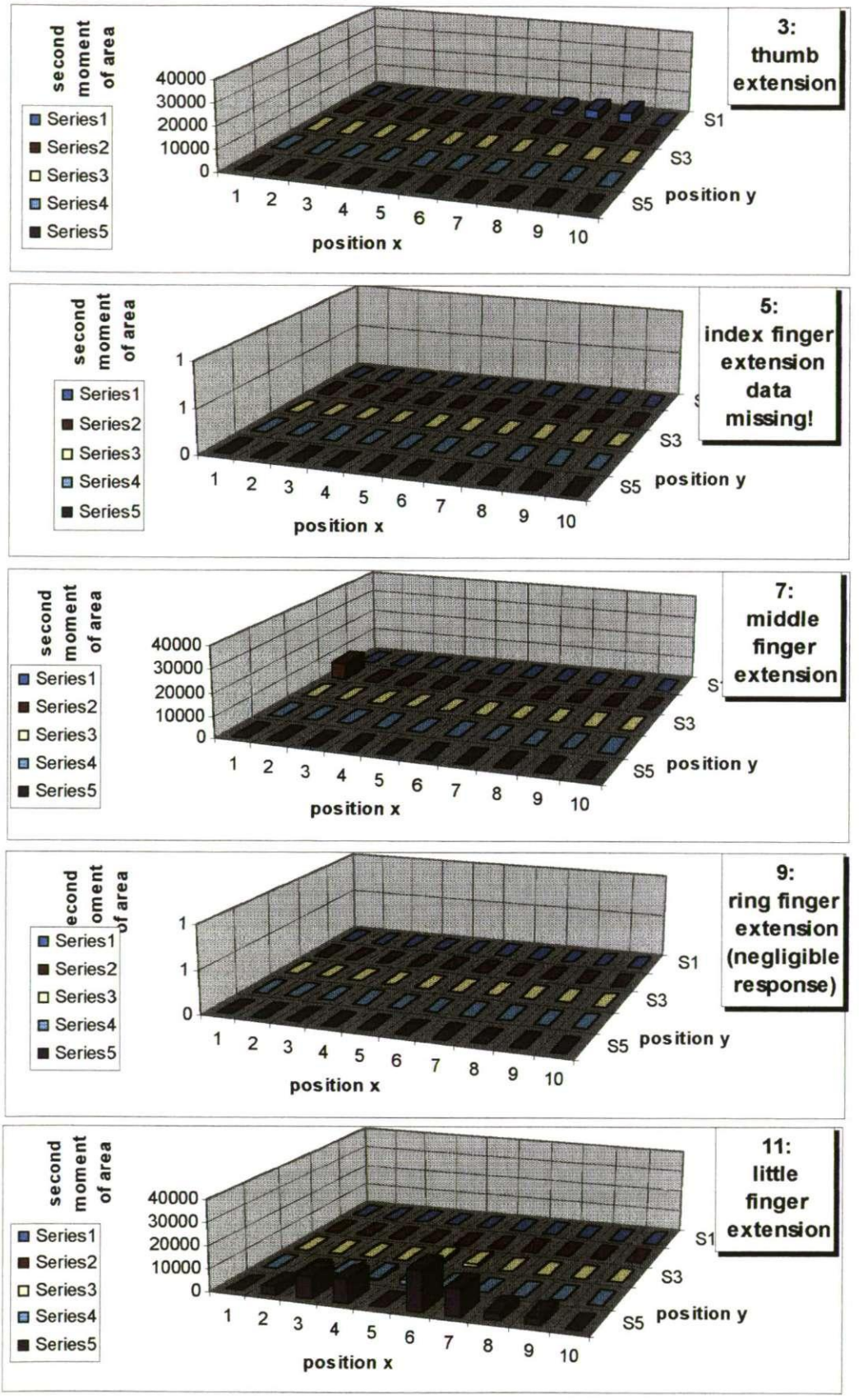
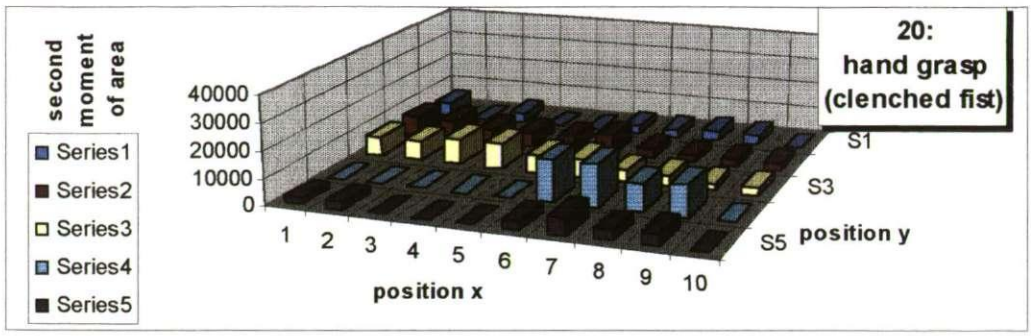
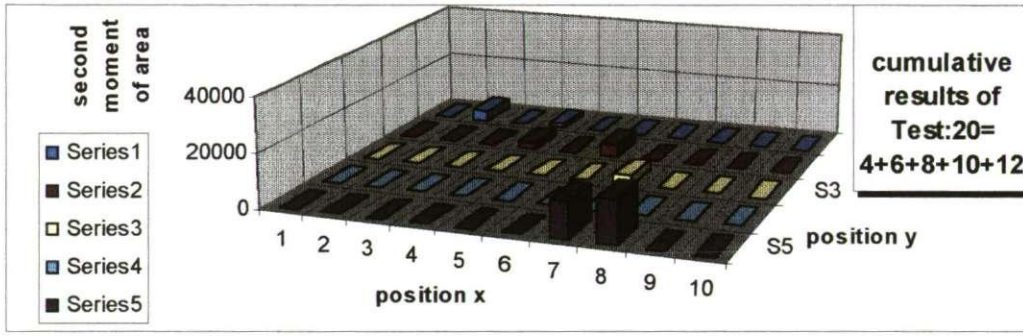


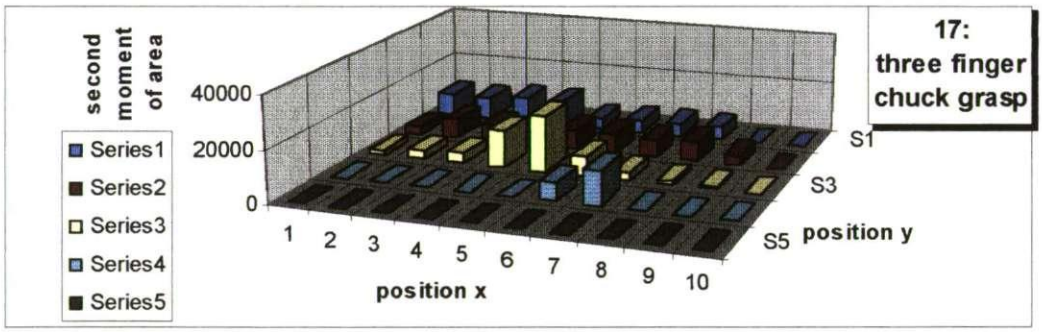
Figure 6.15 encompasses the above sub-figures 7,3,5,9,11 The z-axis has been standardized at a common value (except 10: ring finger flexion)**(female 1) View 2**



The 'clenched fist' above includes all the digits; of which none are in contact opposition. The 'three finger chuck grasp' below has the digits in contact opposition.

Test 20 = 4+6+8+10+12 is the sum of the thumb and finger flexion activities respectively. These three activities are those same digits as used in the 'hand grasp' above. No precision reconstruction of the composite action is achieved through comparison with the addition of the constituent elements. It was however noted that only figure 4 of the group 4+6+8 had any activity showing on the surface plane. Further examination of the opposite surface plane (View 2, Volar Aspect of supinated forearm) may show relevant activity.





The 'wrist flexion' action can be seen to be strong in contrast to other actions by this volunteer. This in accord with a generally weak grip and is in contrast to the other female volunteer. It does show how caution needs to be taken when setting up generalities about inner and cross gender MES's.

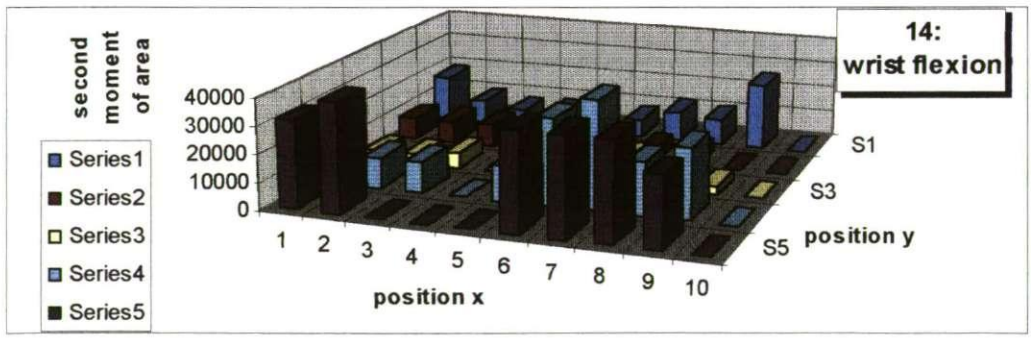


Figure 6. 16 : The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions. Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand **(female 1) View 1**

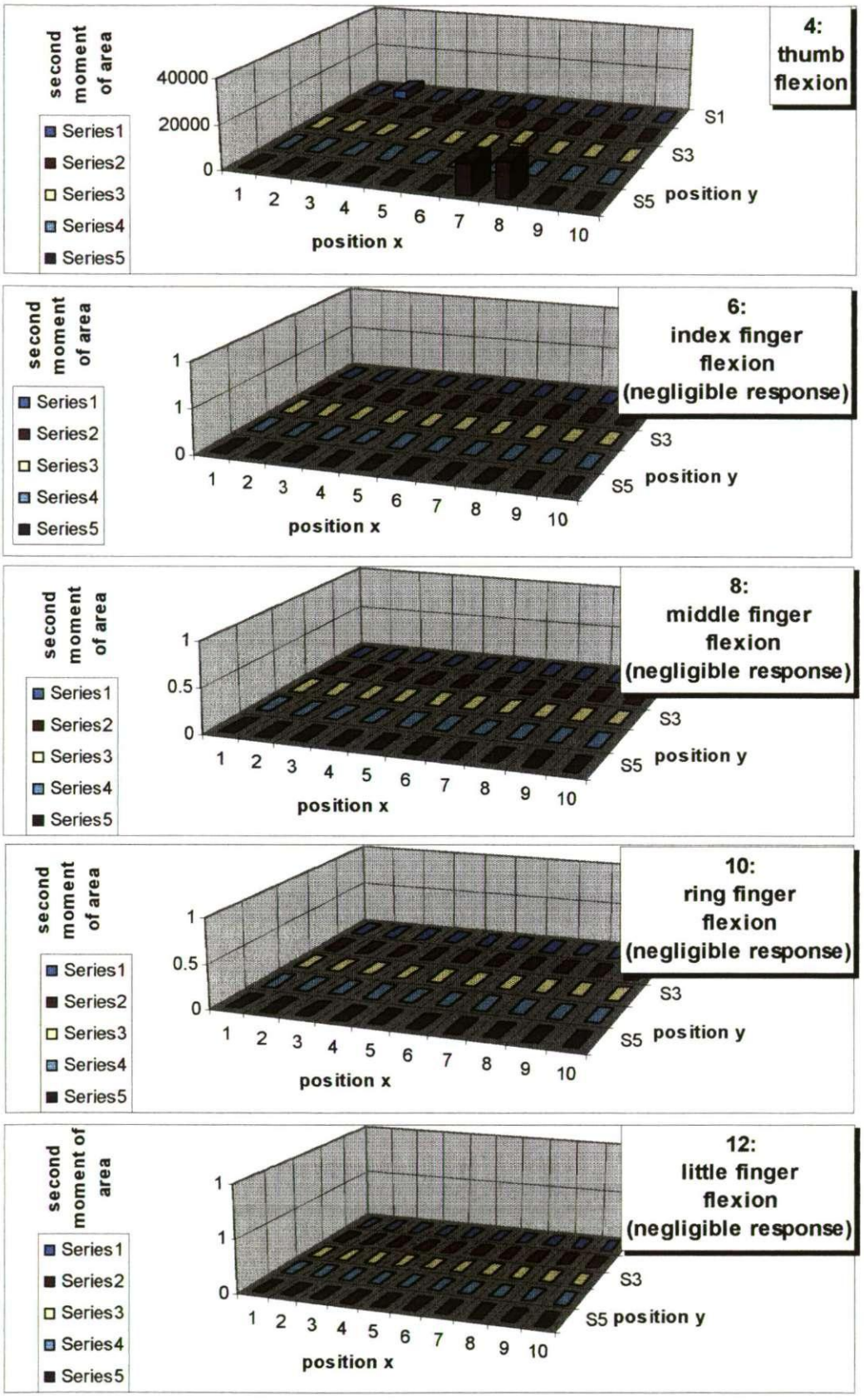
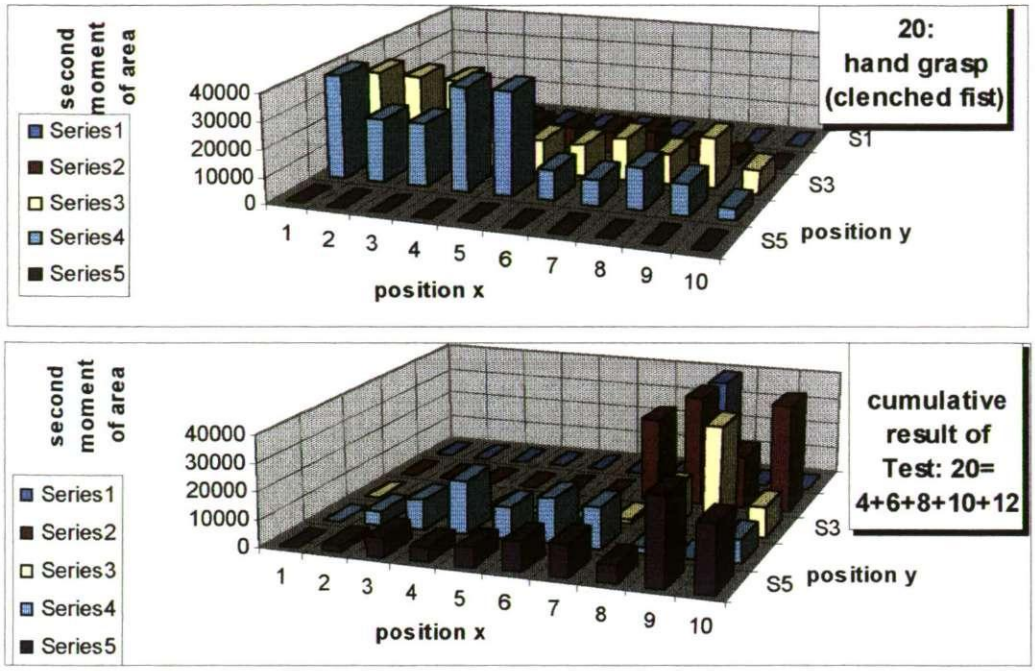


Figure 6.17 Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand **(female 1) View 1**



The 'clenched fist' above includes all the digits; of which none are in contact opposition. The 'three finger chuck grasp' below has the digits in contact opposition.

Test 20 = 4+6+8+10+12 are the sum of the thumb and finger flexion activities respectively. These activities are those same digits as used in the 'hand grasp' above. No reconstruction of the composite action is achieved through comparison with the addition of the constituent elements. There is a correlation for the constituent elements of the group figure 4+6+8 with the figure for the 'three-finger chuck grasp'.

The 'wrist flexion' action can be seen to be strong in contrast to other actions by this volunteer. This in accord with a generally weak grip and is in contrast to the other female volunteer (female 2). It does show how caution needs to be taken when setting up generalities about inner and cross gender MES's.

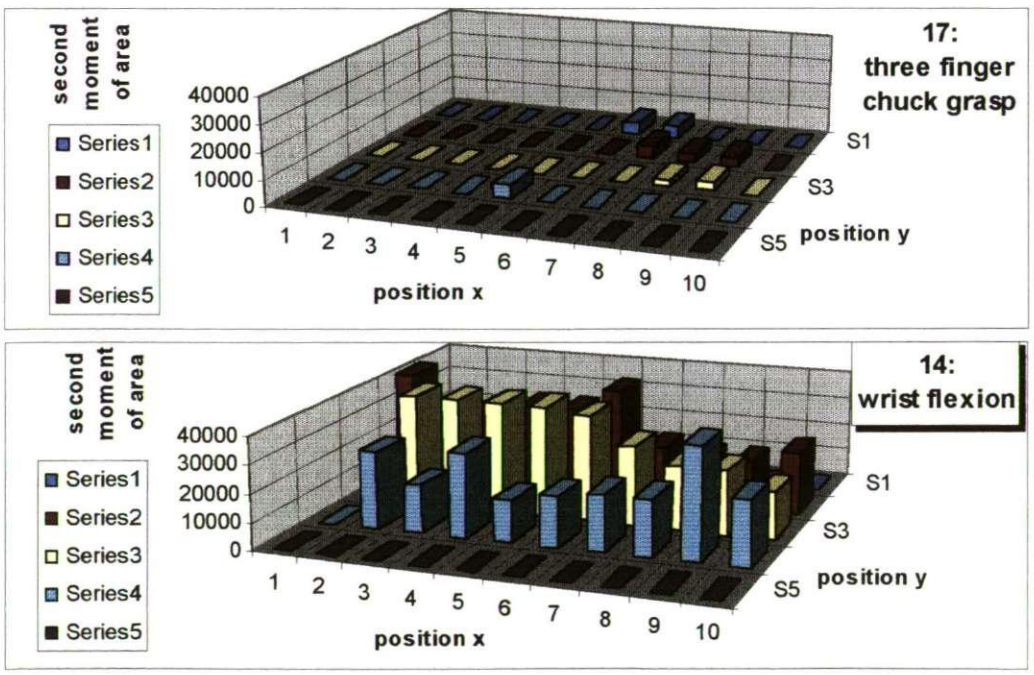


Figure 6.18 : The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions: Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand **(female 1) View 2**

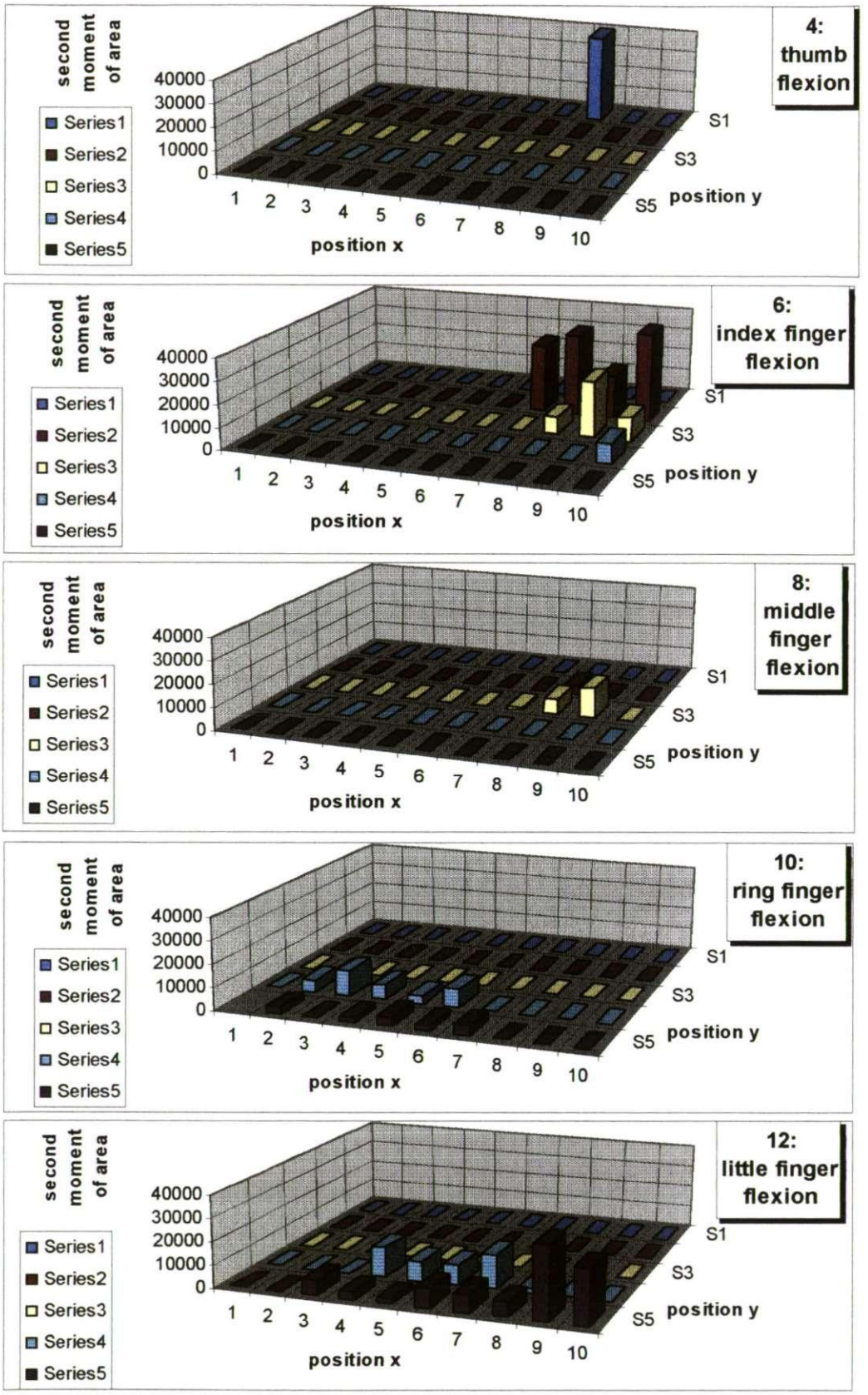


Figure 6.19 Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand **(female 1) View 2**

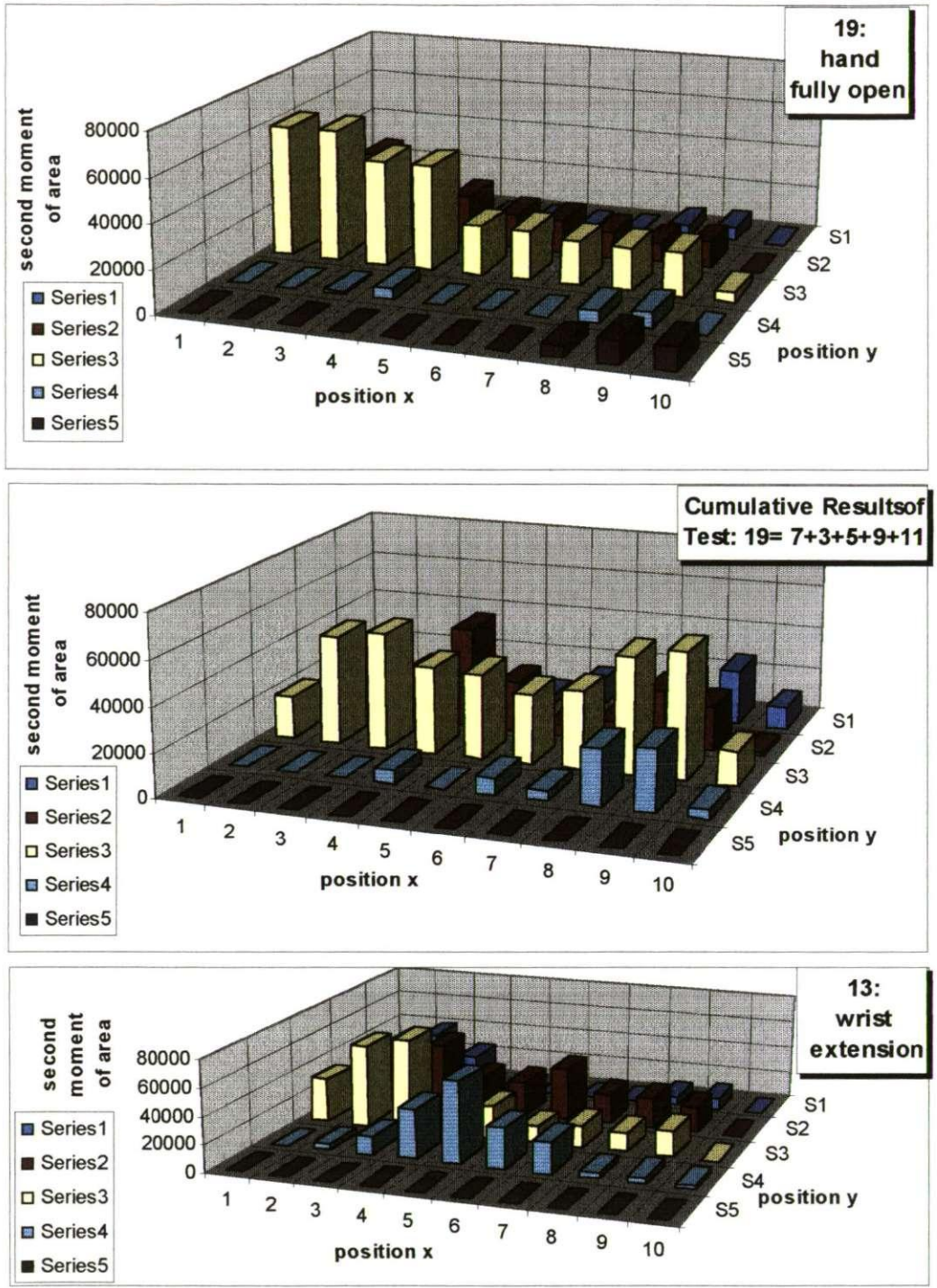


Figure 6.20 The relationship between the separated individual finger MES actions and that of two or more combined MES finger actions. Figures 7,3,5,9,11 are the individual finger actions involved in extending the hand and are summed above to become the 'Cumulative Result' figure. Compare that with figure 19 (Hand fully open). A close correlation can be seen between the two upper figures **(male 2)** **View 1**

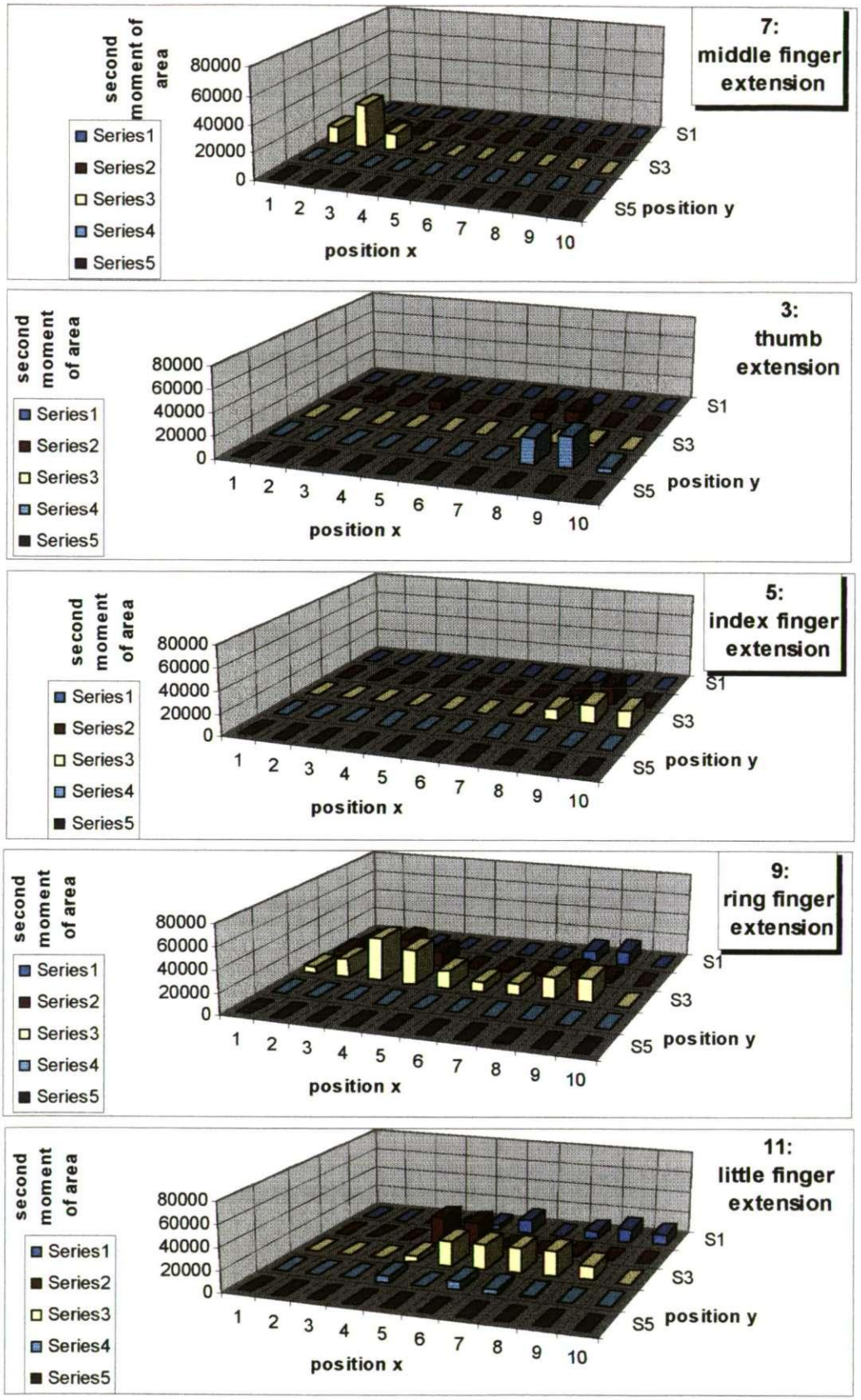
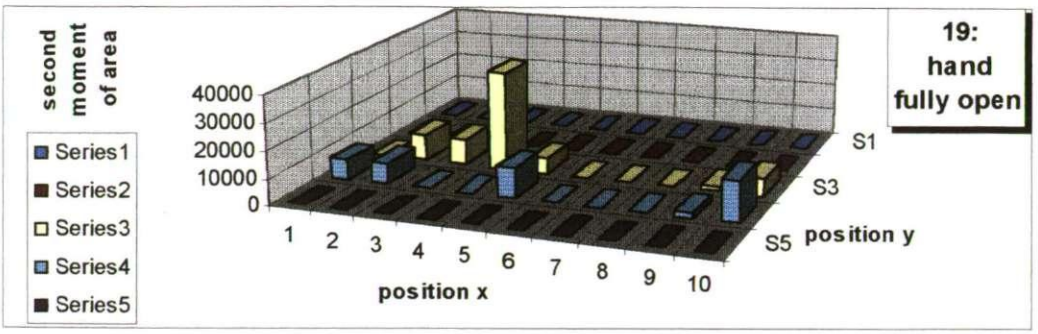
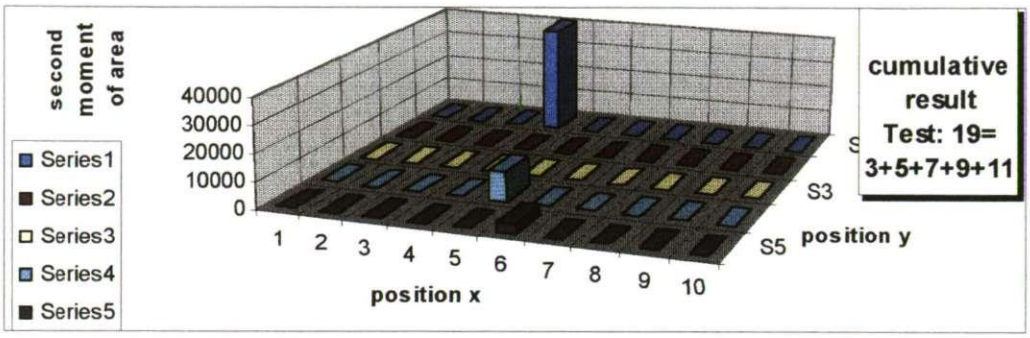


Figure 6.21: Figures 7,3,5,9,11 are the individual finger actions involved in extending the hand. **(male 2)** **View 1**





No correlation is shown between Figure 19:Hand fully open above and the cumulative test result.

A negligible response (below) for wrist extension suggests that separate muscles activity is involved w.r.t. hand fully open activity.

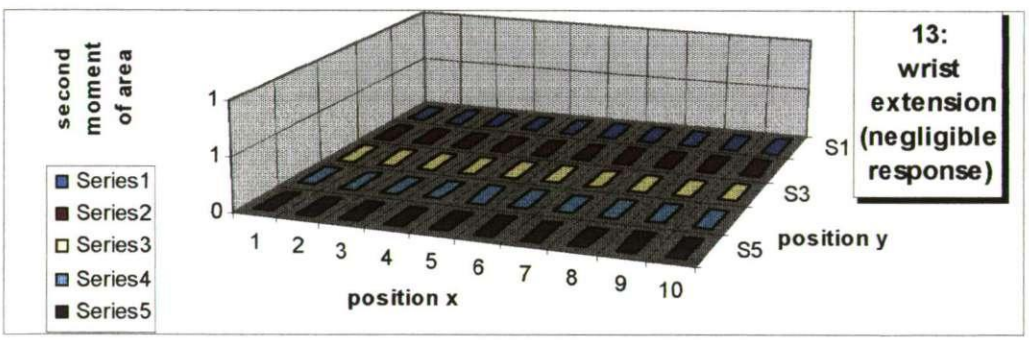


Figure 6.22 The relationship between the separated individual finger MES actions and that of two or more combined MES finger actions **(male 2)View 2**

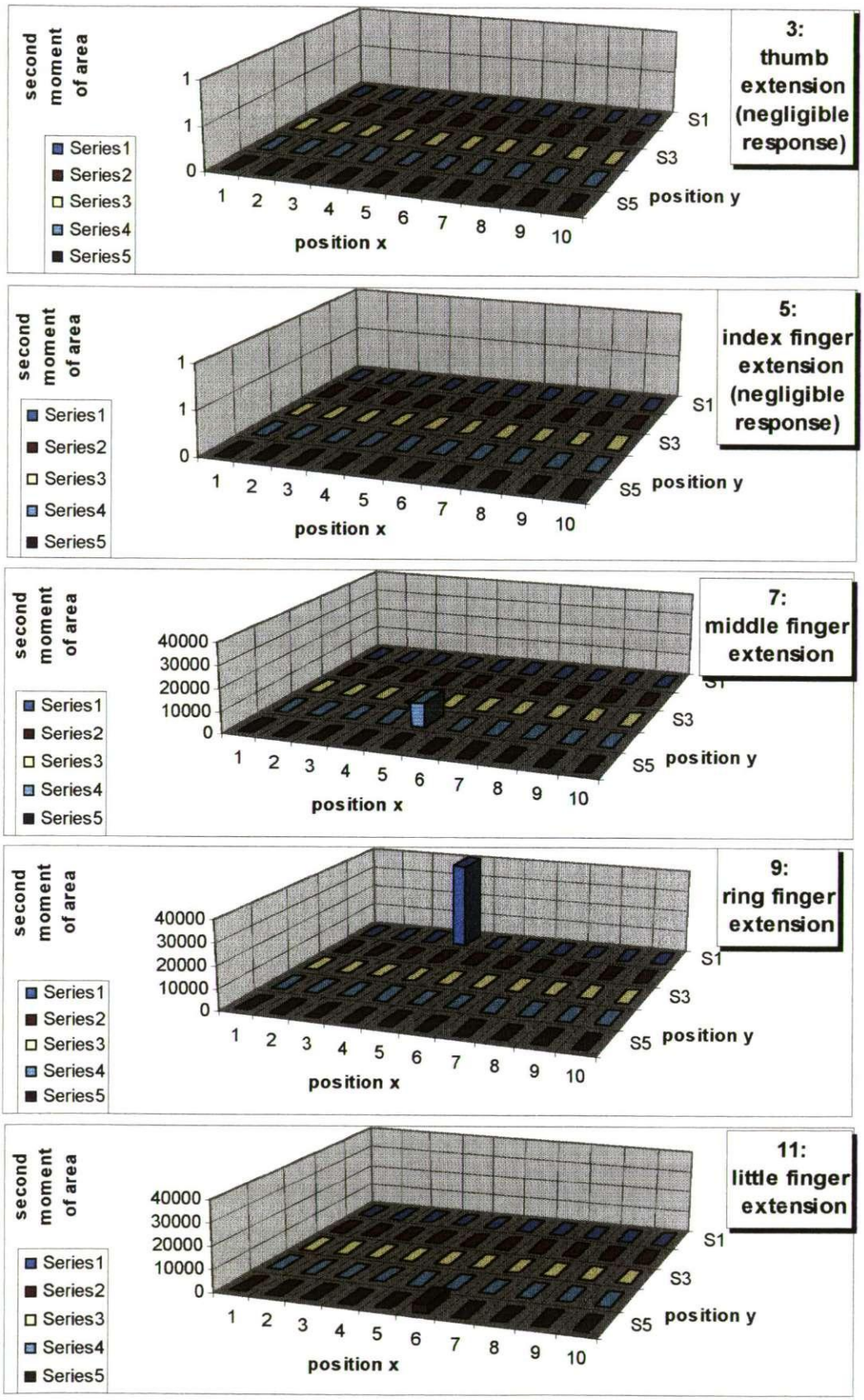
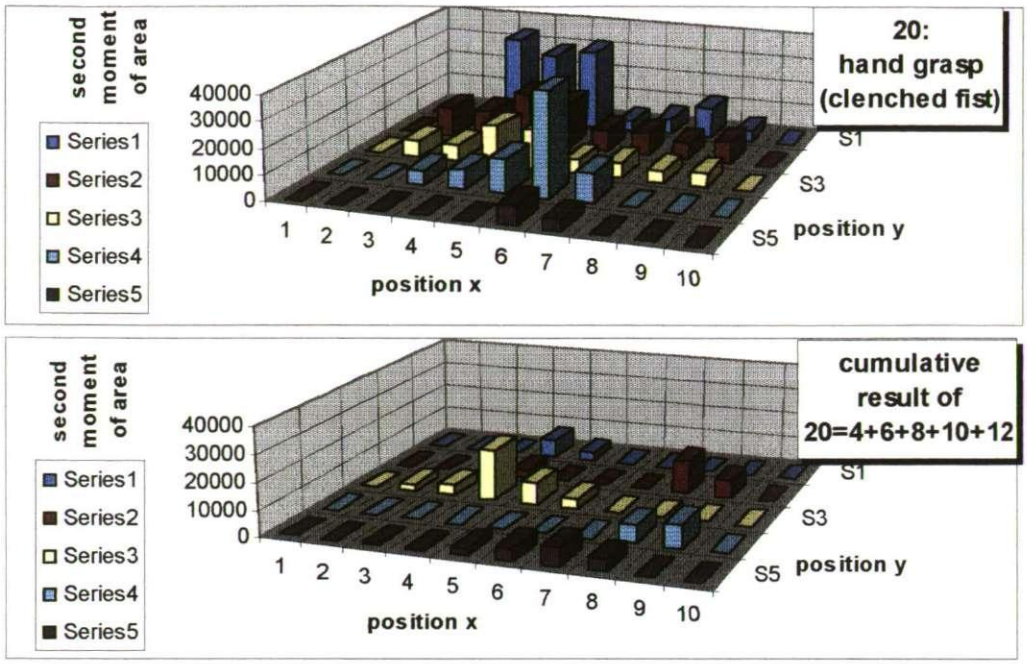


Figure 6.23: Figures 7,3,5,9,11 are the individual finger actions involved in extending the hand. **(male 2)** **View 2**



The clenched fist above shows a very strong response in two distinct regions (light and dark blue) that does not show up as expected in the cumulative result. Most notable is the missing thumb response shifted from position 8and 9, (light blue) into position 5,6,and 7. Little finger flexion shows a very much greater response when used in the clenched fist. These results suggest that the volunteer (male 2) has a strongly developed clenched fist response and has a thumb response that differs for the individual thumb flexion response from those found in the clenched fist and 3-finger chuck grasp. The volunteer (Jim) may well be using the thumb flexion and thumb/ little finger opposition actions (see figure in appendix) with fine discrimination. Comparison needs to be made against View 2 for the same responses!! Once again the graph, (cumulative result of 20 =4+6+8), has data missing from the' middle finger flexion' action.
It is possible that positions 3,4 in red and dark blue are representative of the missing data.

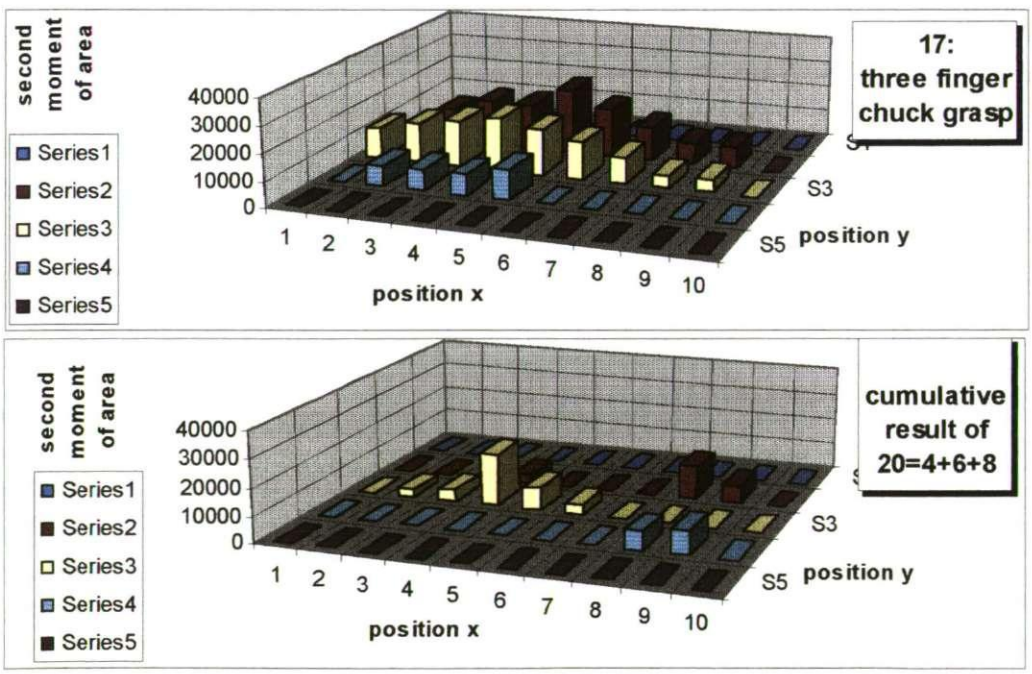


Figure 6.24: The relationship between the separated individual finger MES actions and that of two or more combined MES finger actions.**(male 2):View 1**

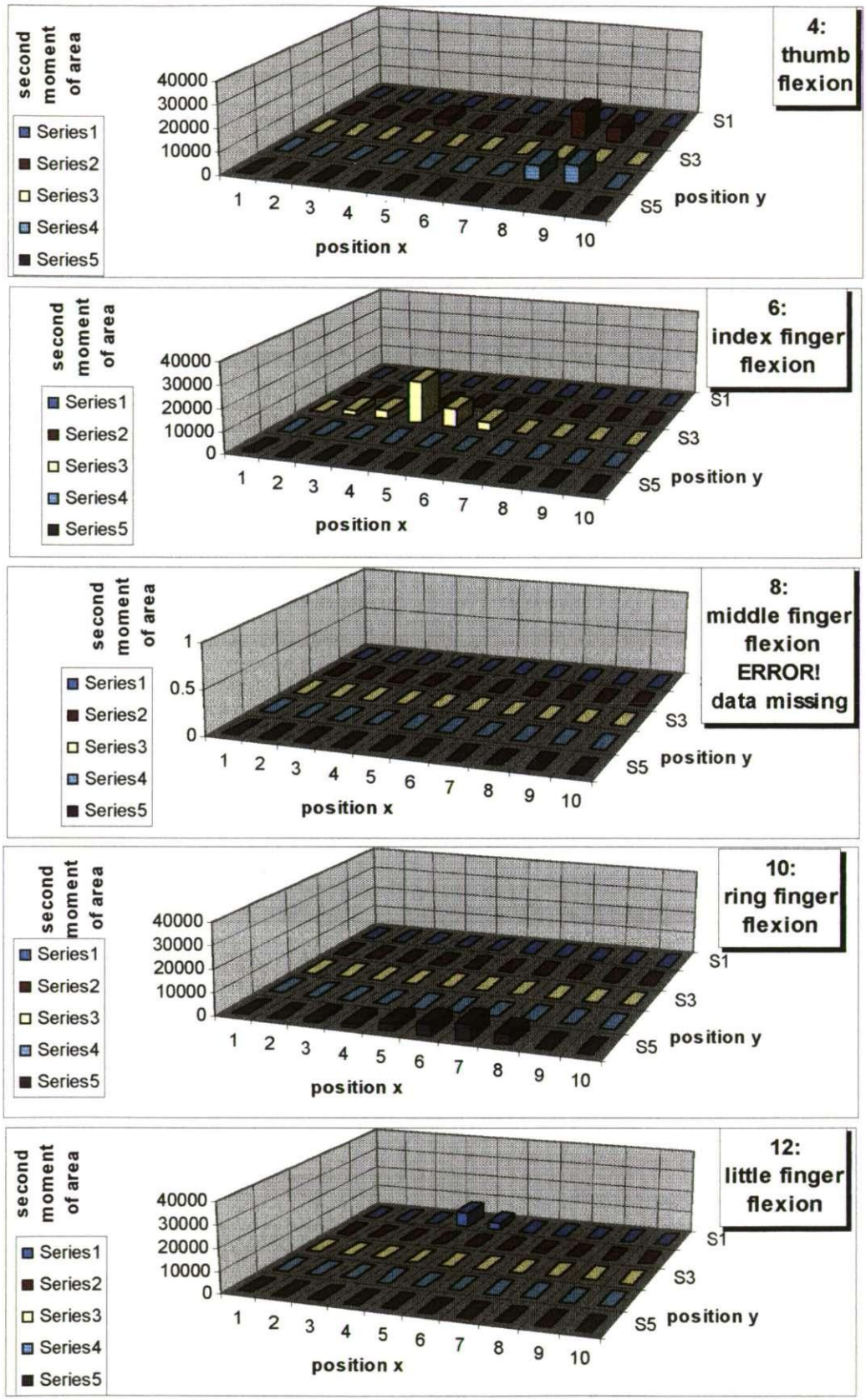
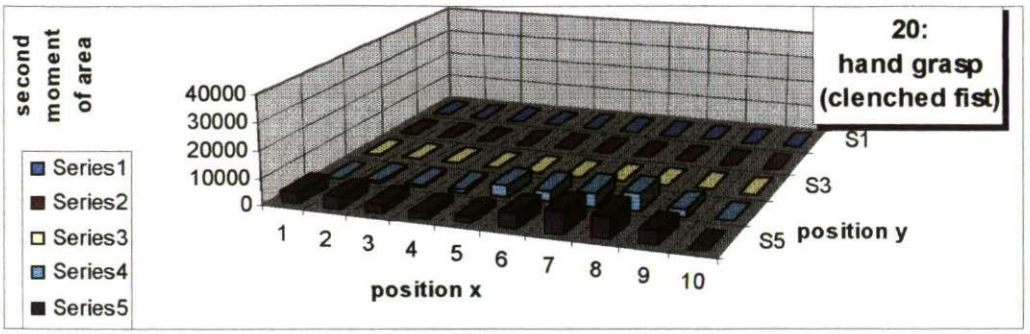
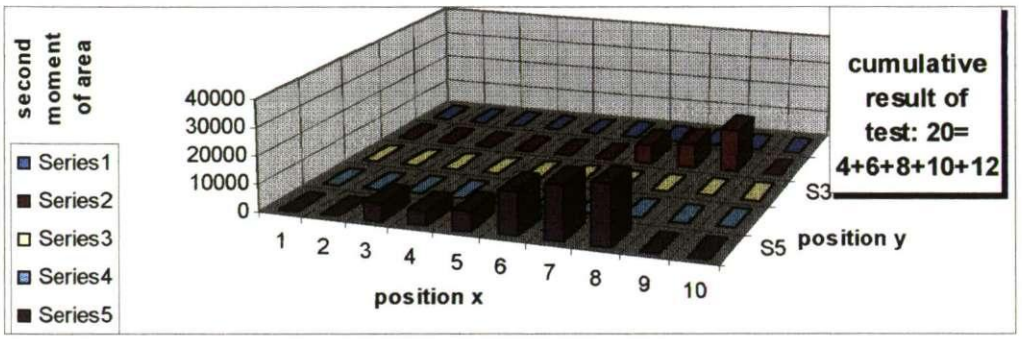
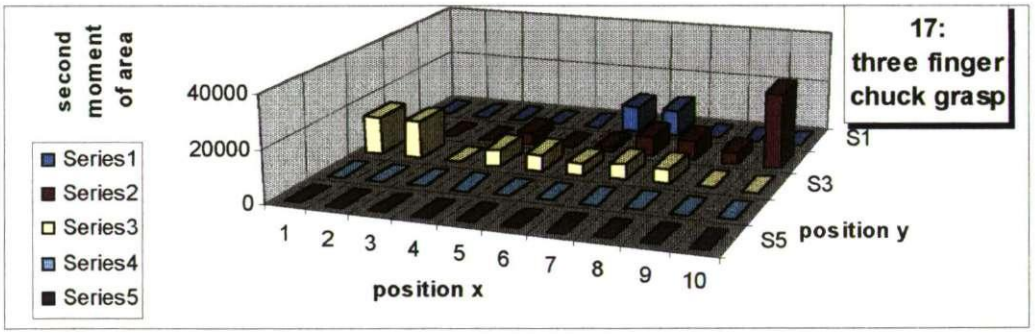


Figure 6.25 Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand **(male 2): View 1**





The clenched fist above shows a very strong response in purple regions 6,7,8. Little finger flexion shows strong response in these regions when used in the clenched fist. These results suggest that the volunteer (male 2) has a strongly developed clenched fist response. Compare with other volunteers.



Wrist flexion (Figure 14 below), shows a strong response overall and is by far the most powerful overall action on this planar surface.

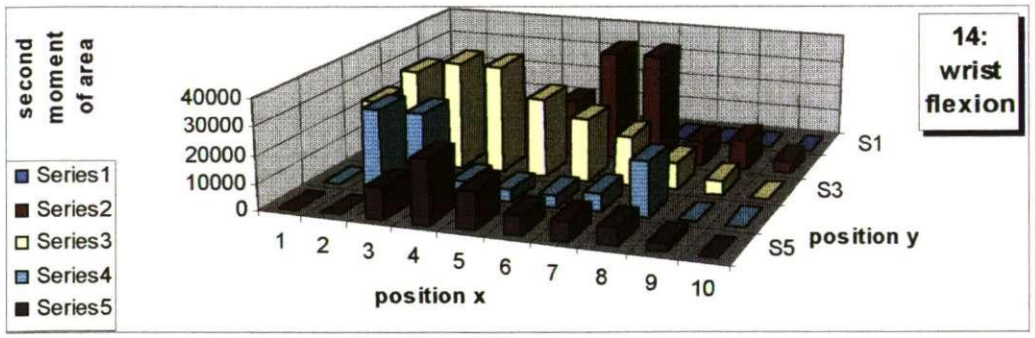


Figure 6.26 The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions **(male 2) View 2**

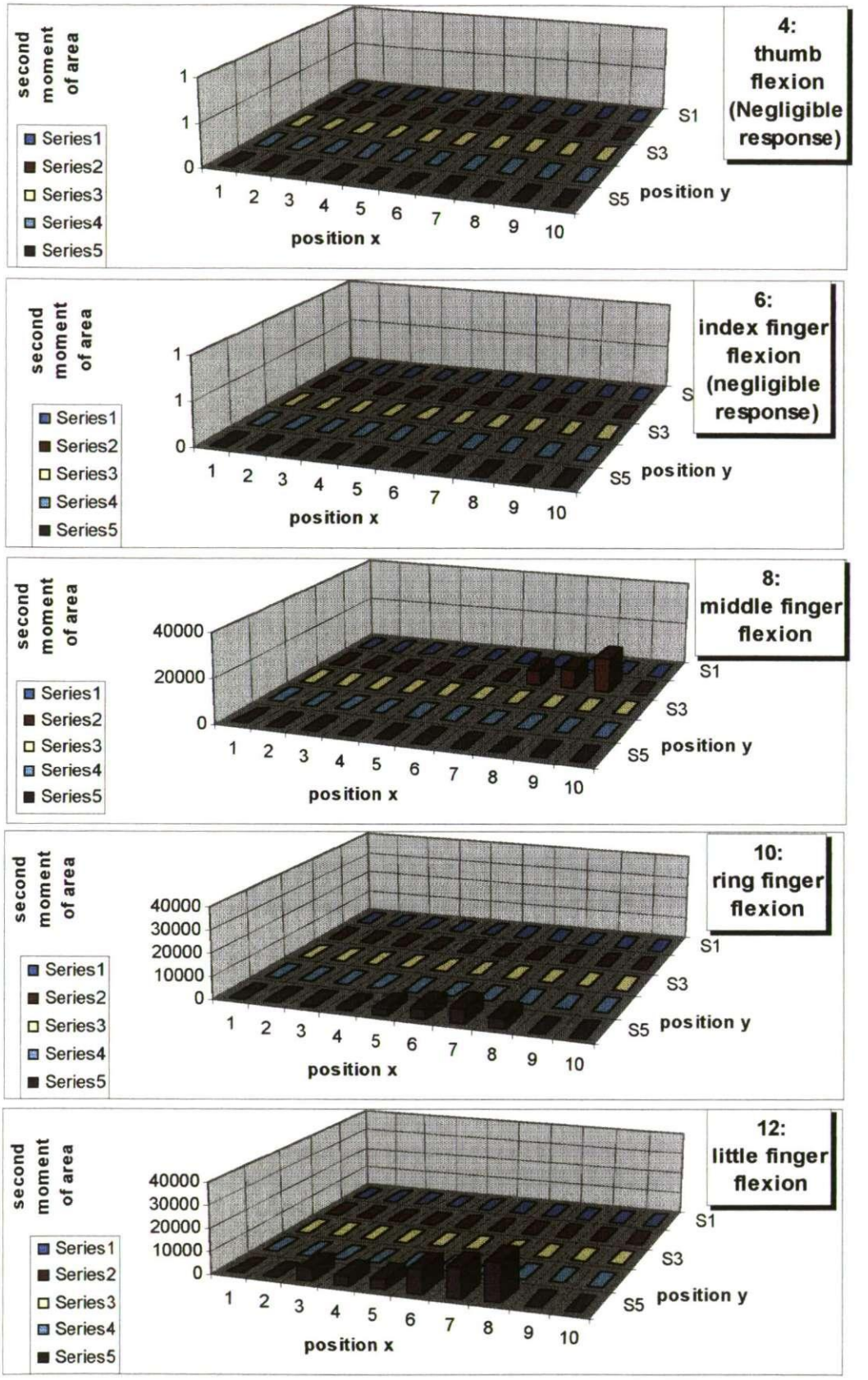
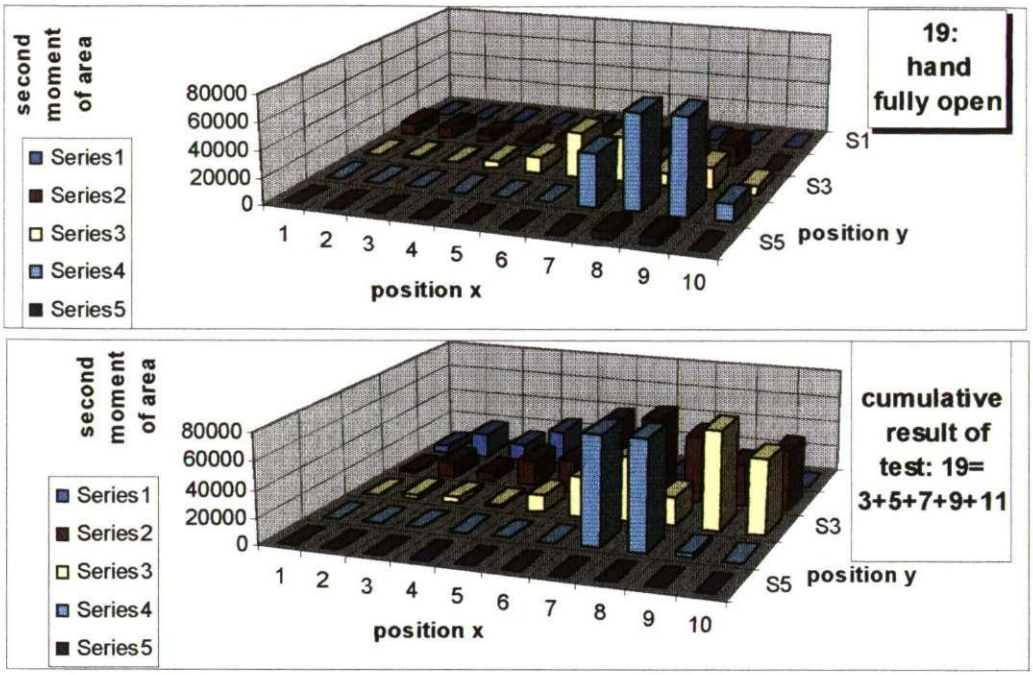


Figure 6.27 Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand **male 2**: **View 2**



The crude but commonly used wrist extension action is shown below for comparison with the above figures. The wrist extension clearly occupies a different planar region compared to the figure 'Hand Fully Open'. Comparison needs to be made with the 'View 2' results to see if there is any introduction of wrist extension activity into the above figures.

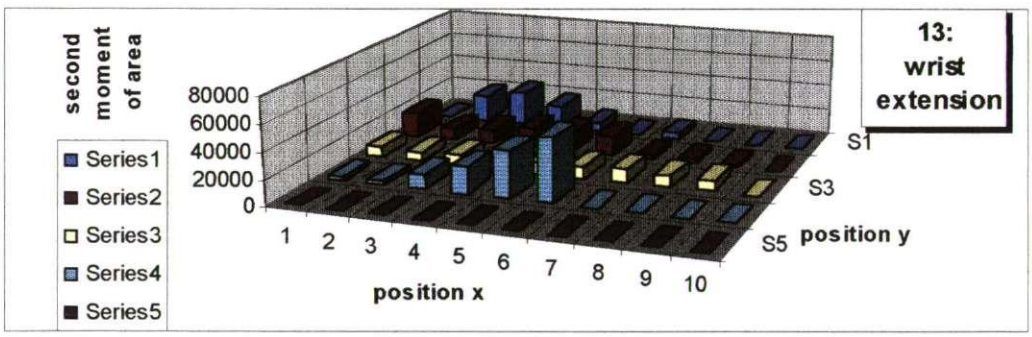


Figure 6.28 The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions
Figures 3,5,7,9,11 are the individual finger actions involved in extending the hand and are summed above to become the Cumulative Result figure. Compare that with figure 19 (Hand Fully Open). A close correlation can be seen between the two upper figures. **(female 2): View 1**

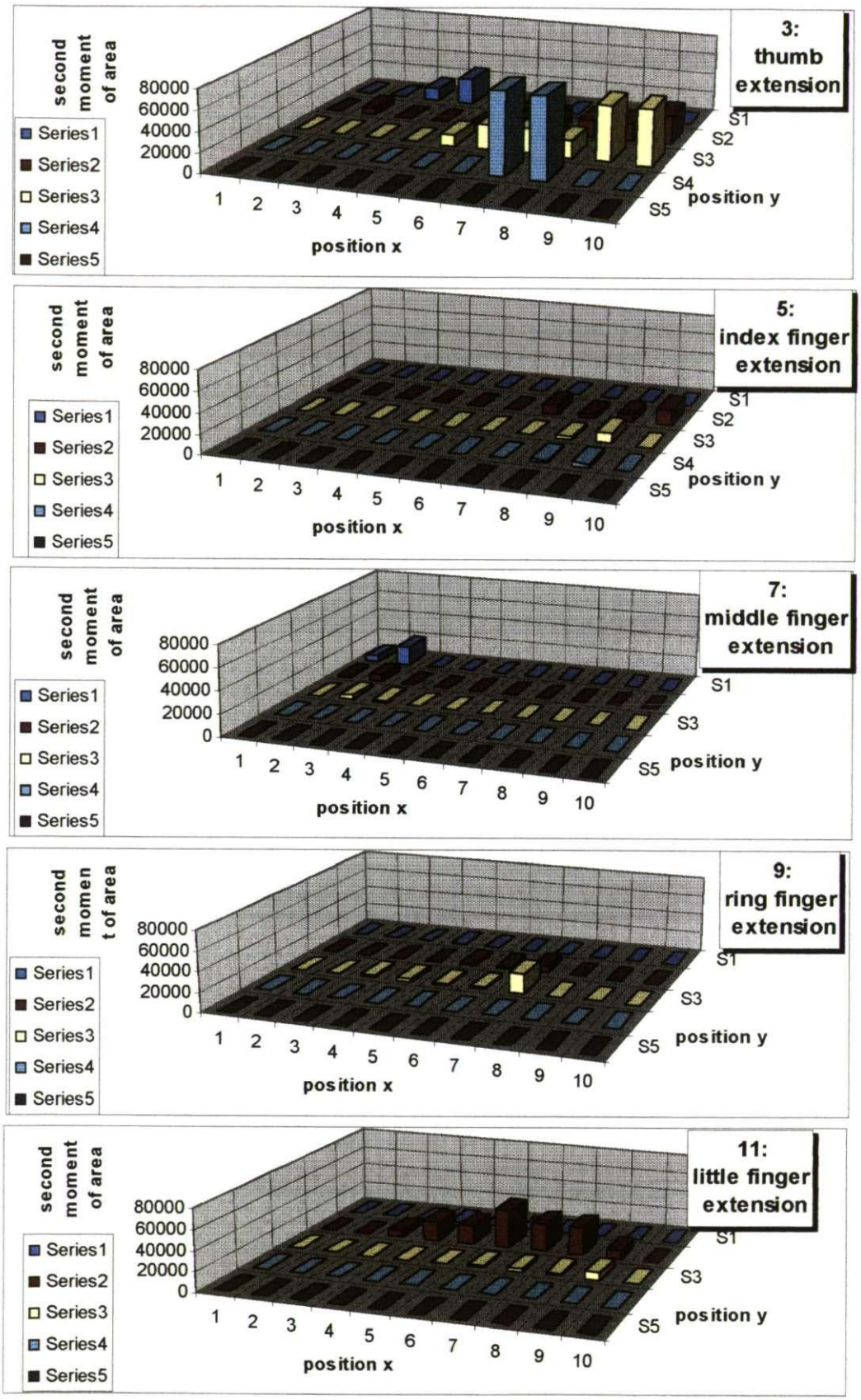
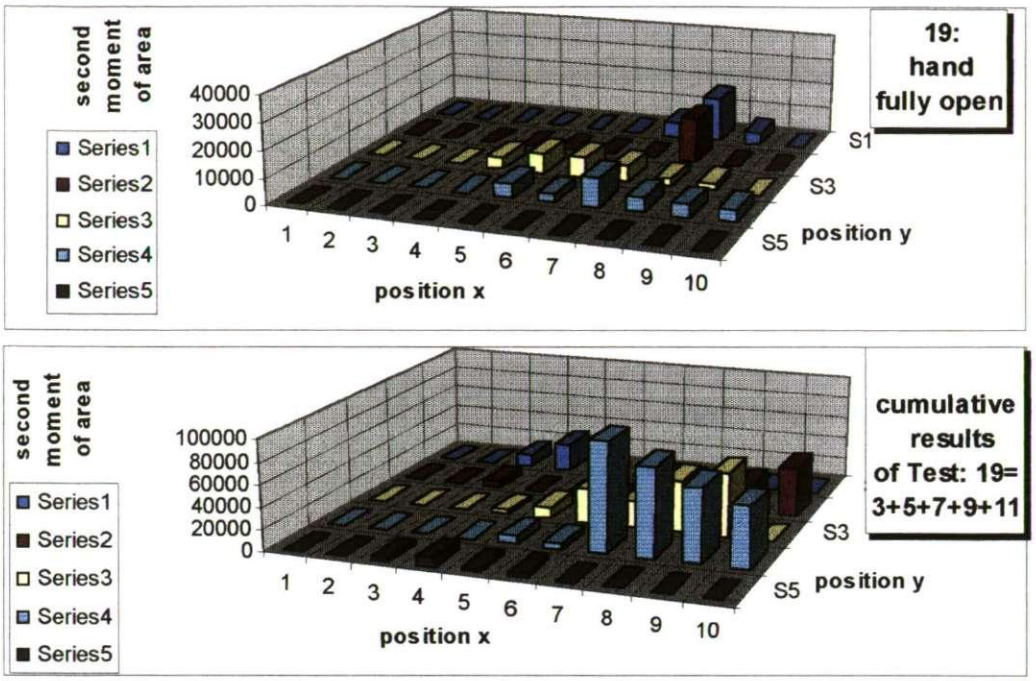


Figure 6.29 Figures 3,5,7,9,11 are the individual finger actions involved in extending the hand. **(female 2): View 1**



Test 19 = 3+5+7+9+11 is the sum of all thumb and finger extension actions respectively. No precision reconstruction of the composite action is achieved through the addition of the constituent elements. The same areas of activity can be seen to be involved. Thumb activity is the major constituent element.

The crude but commonly used wrist extension action can be seen below. There appears to be no contribution detected, on the measured plane, from any unintended wrist extension activity by the volunteer.

N.B. This clearly suggests that, for these thumb and finger actions, a unique muscle usage occurs that is unconnected to those of the wrist extension response.

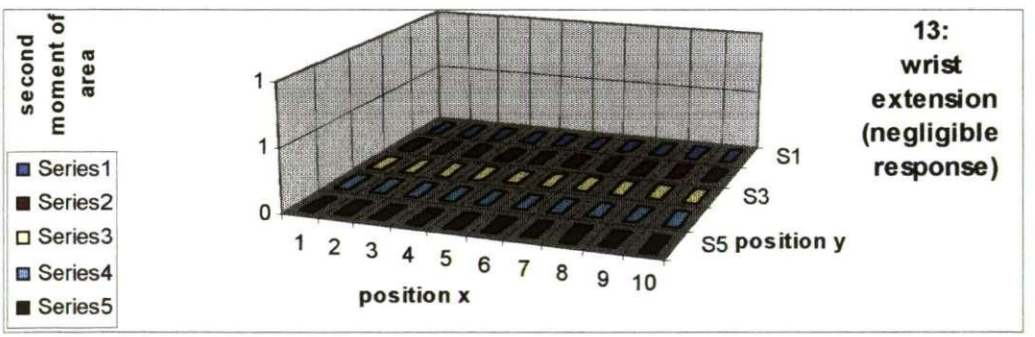


Figure 6.30: The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions **(female 2): View 2**

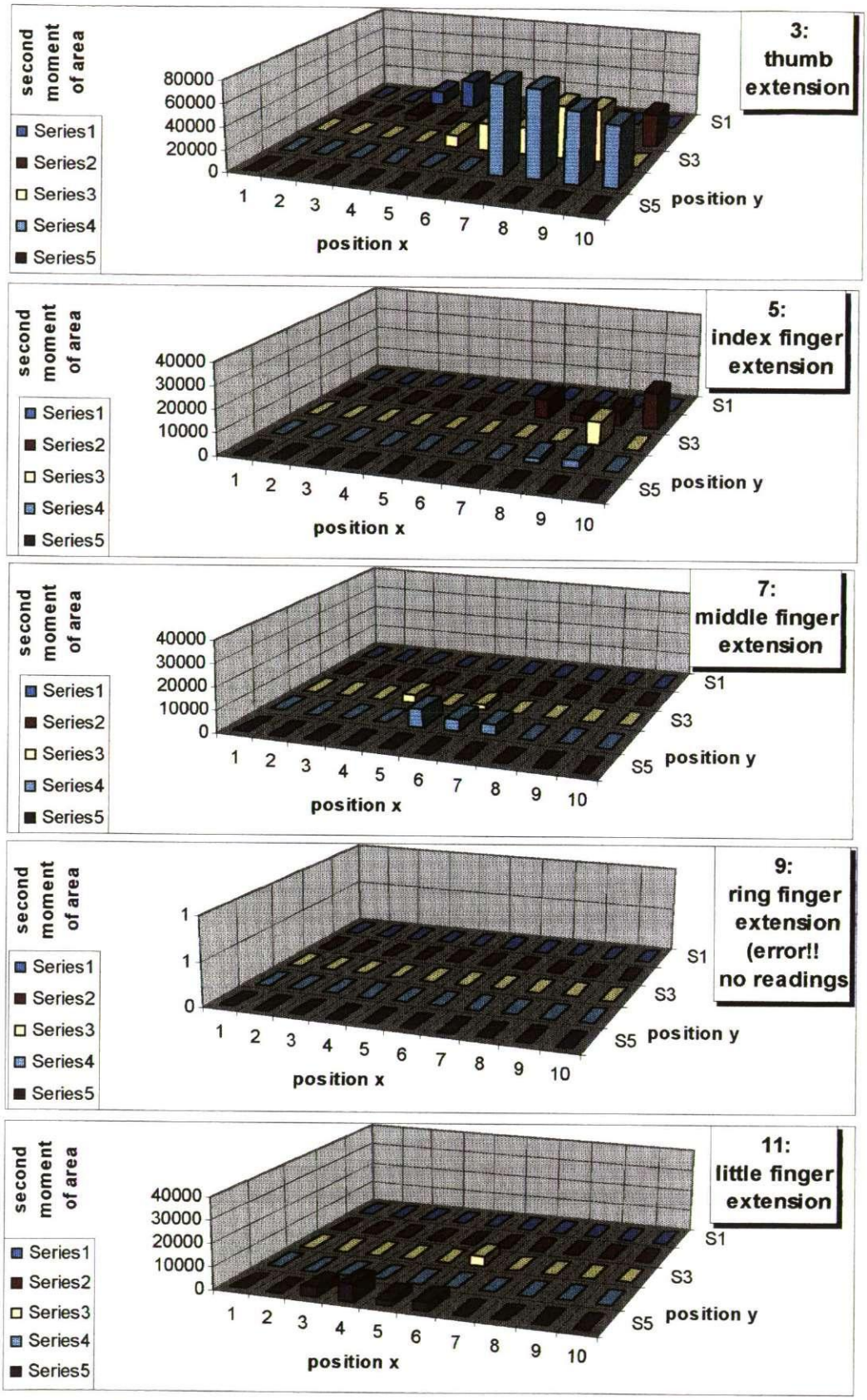
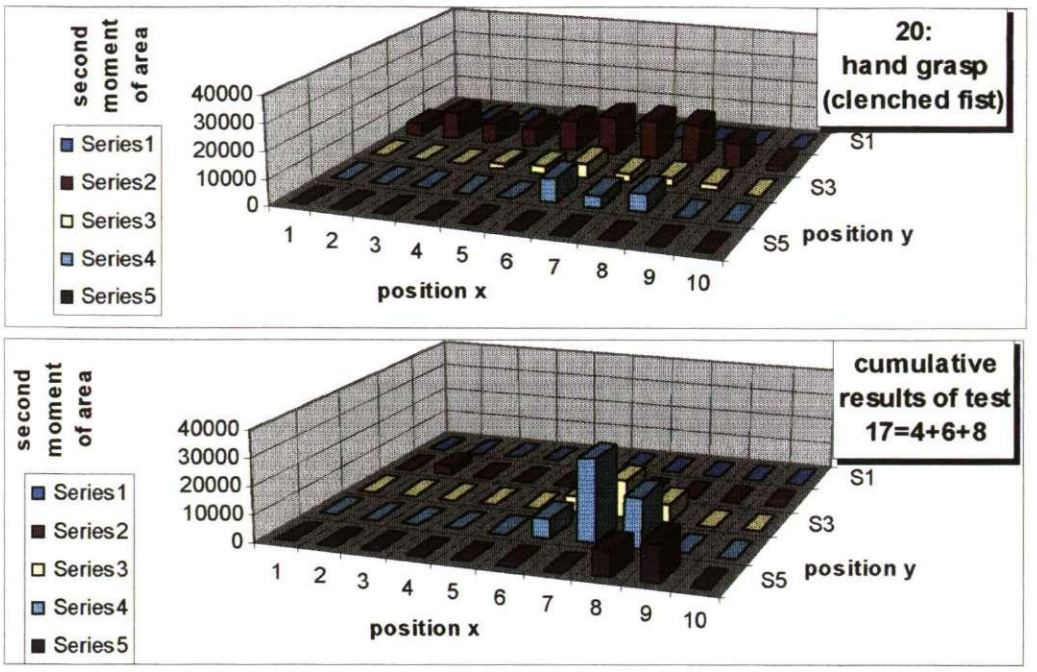


Figure 6.31 Figures 3,5,7,9,11 are the individual finger actions involved in extending the hand. **(female 2): View 2**



The 'clenched fist' above includes all the digits; of which none are in contact opposition.
Test 17 = 4+6+8 are the sum of the thumb, index, and middle finger flexion activities respectively. These three activities are those same digits as used in the 'three finger chuck grasp' below. No precision reconstruction of the composite action is achieved through the addition of the constituent elements. The same areas of activity can be seen to be involved. Though not intended the ring finger activity (intrudes into) i.e. is partially brought into play in the 'the finger chuck grasp' below and correlates closely to a partial activity of the 'ring finger flexion' in Figure 10 (page 184):This agrees with the observed difficulty of separating out the ring finger action by the volunteer. In this way, it can be seen how the constituent MES elements accumulate and can be used for fine control of a prosthesis.
The 'the finger chuck grasp' below has the digits in contact opposition.
The crude but commonly (commercially) used wrist flexion action can be seen below.

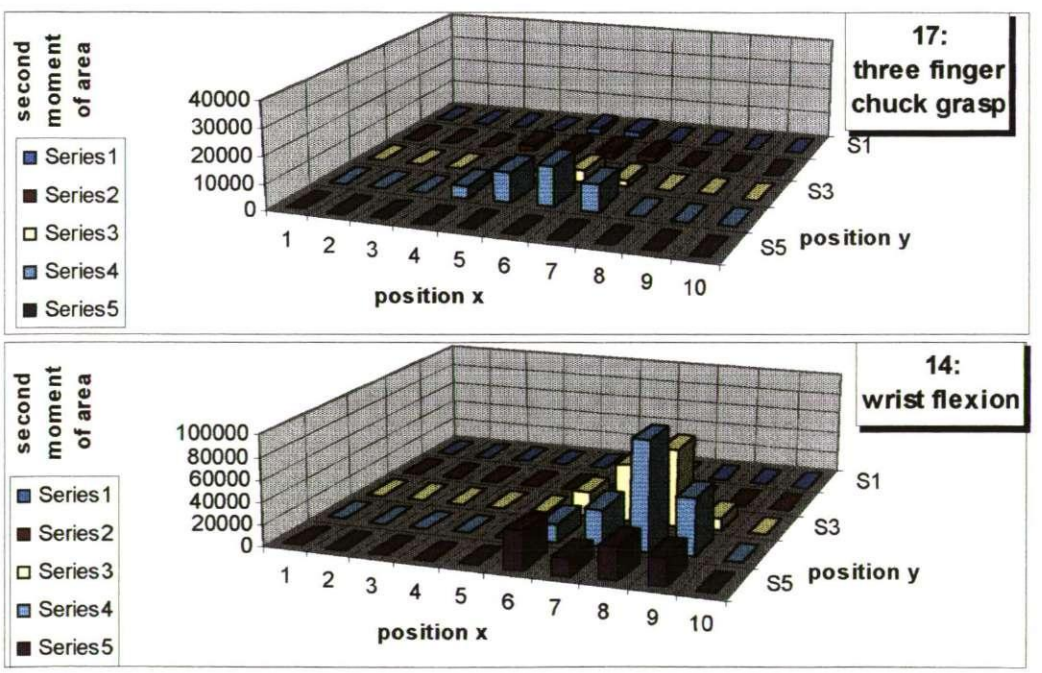


Figure 6.32: The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions. **(female 2): View 1**

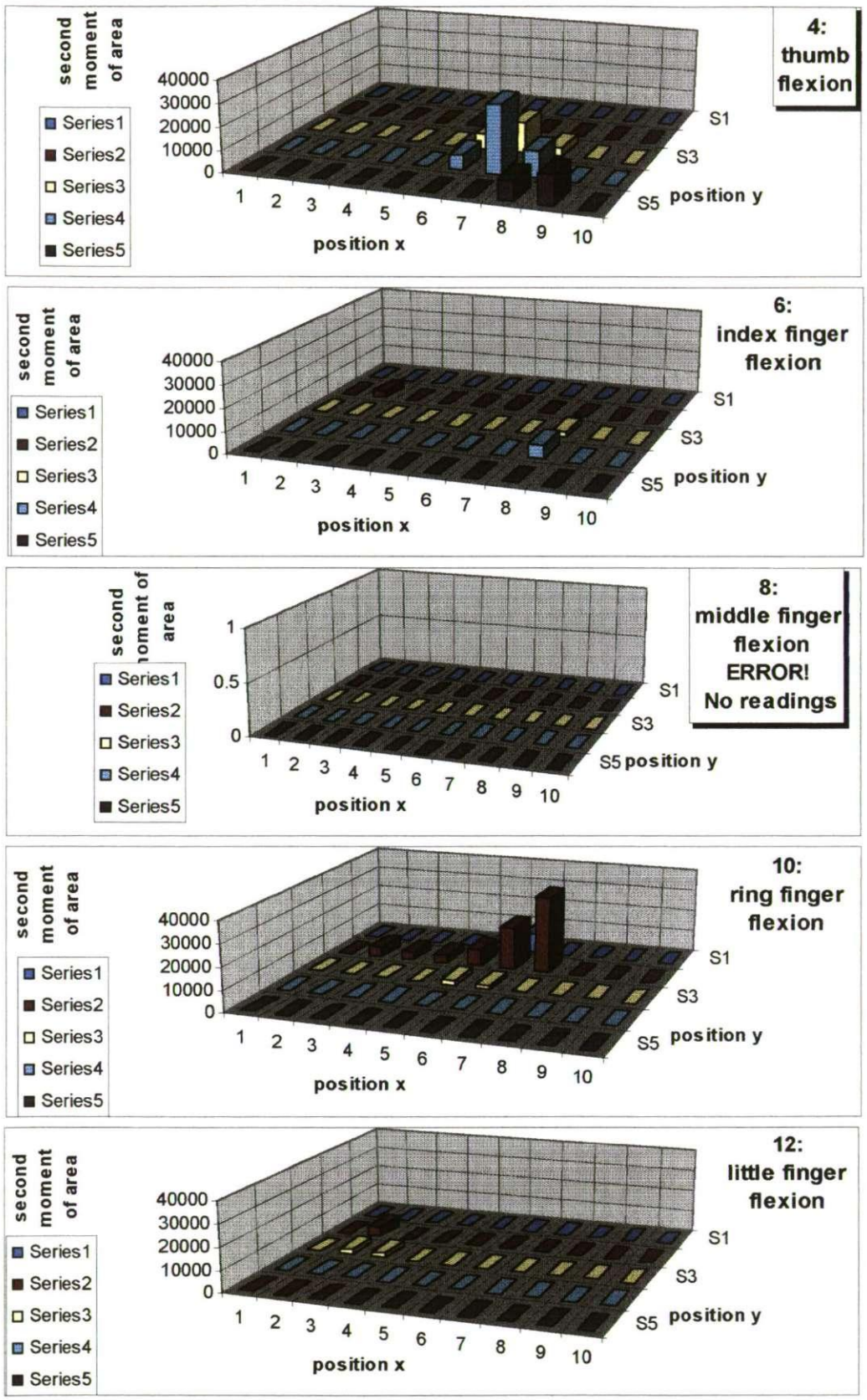
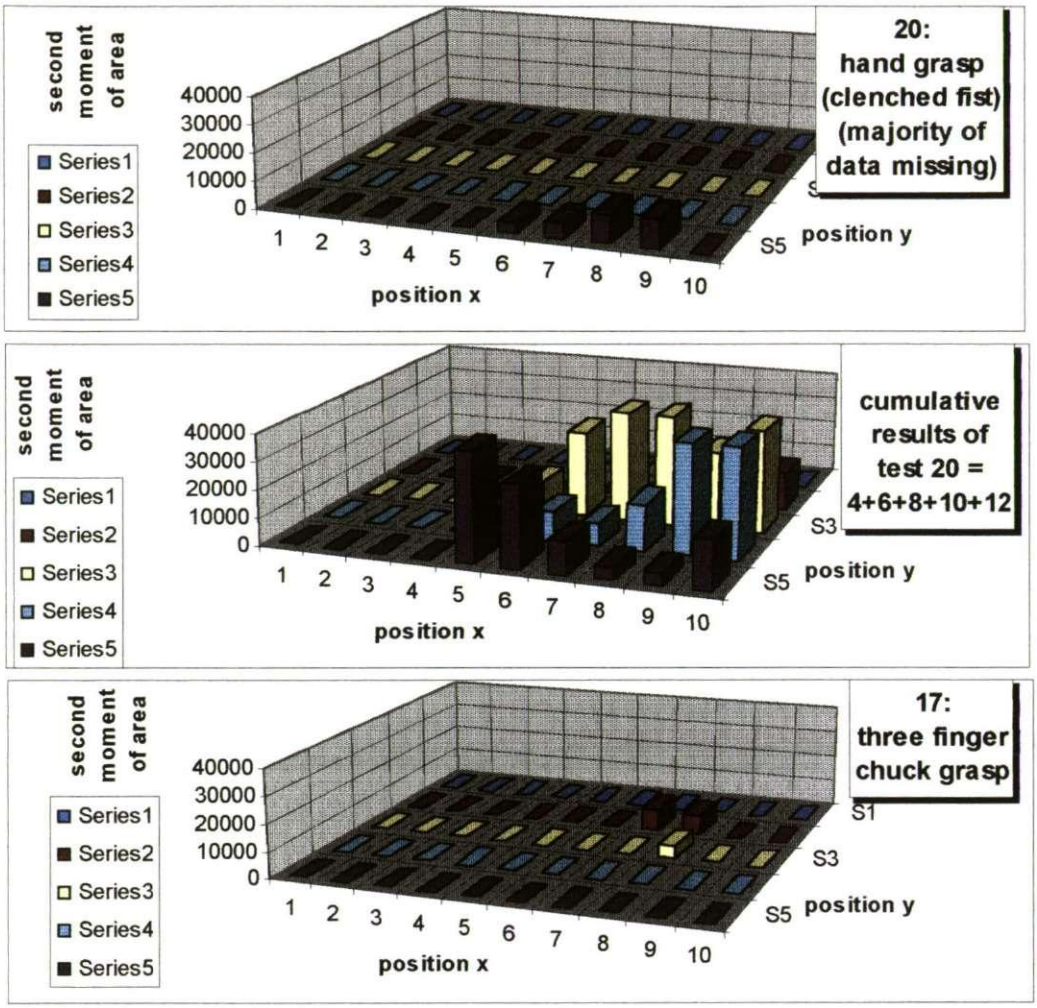


Figure 6.33 Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand. **(female 2): View 1**

Figures 4,6,8,10,12 (next page) are the individual finger actions involved in flexing the hand and are summed to become the Cumulative Result figure. Compare that with figure 20 (Hand Grasp (clenched fist)). No precise (or similar) reconstruction of the composite action is achieved through the addition of the constituent elements. This may be solely as a result of data missing for completing that region.



No conclusion with respect to additive actions can be assumed as a result of the missing data for figure 20.

The commonly used wrist flexion response below shows however as a completely separate region to the other 3 figures presented. This demonstrates how little of the available information is ever used with conventional prosthetic controllers.

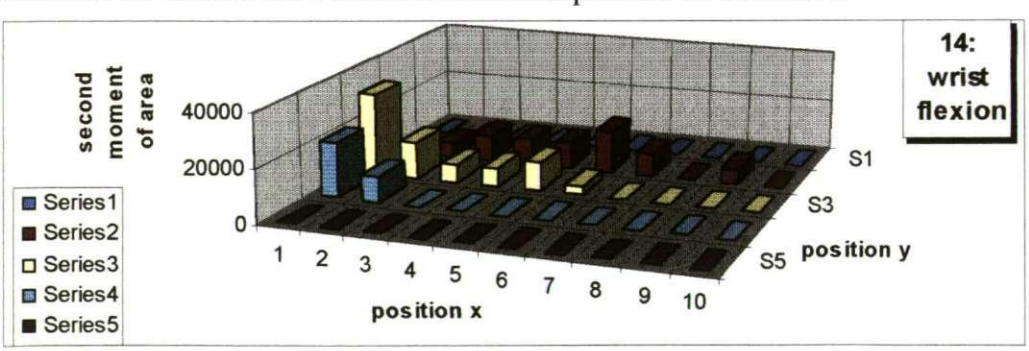


Figure 6.34: The Relationship between the Separated Individual finger MES actions and that of Two or More Combined MES finger Actions **(female 2)** **View 2**

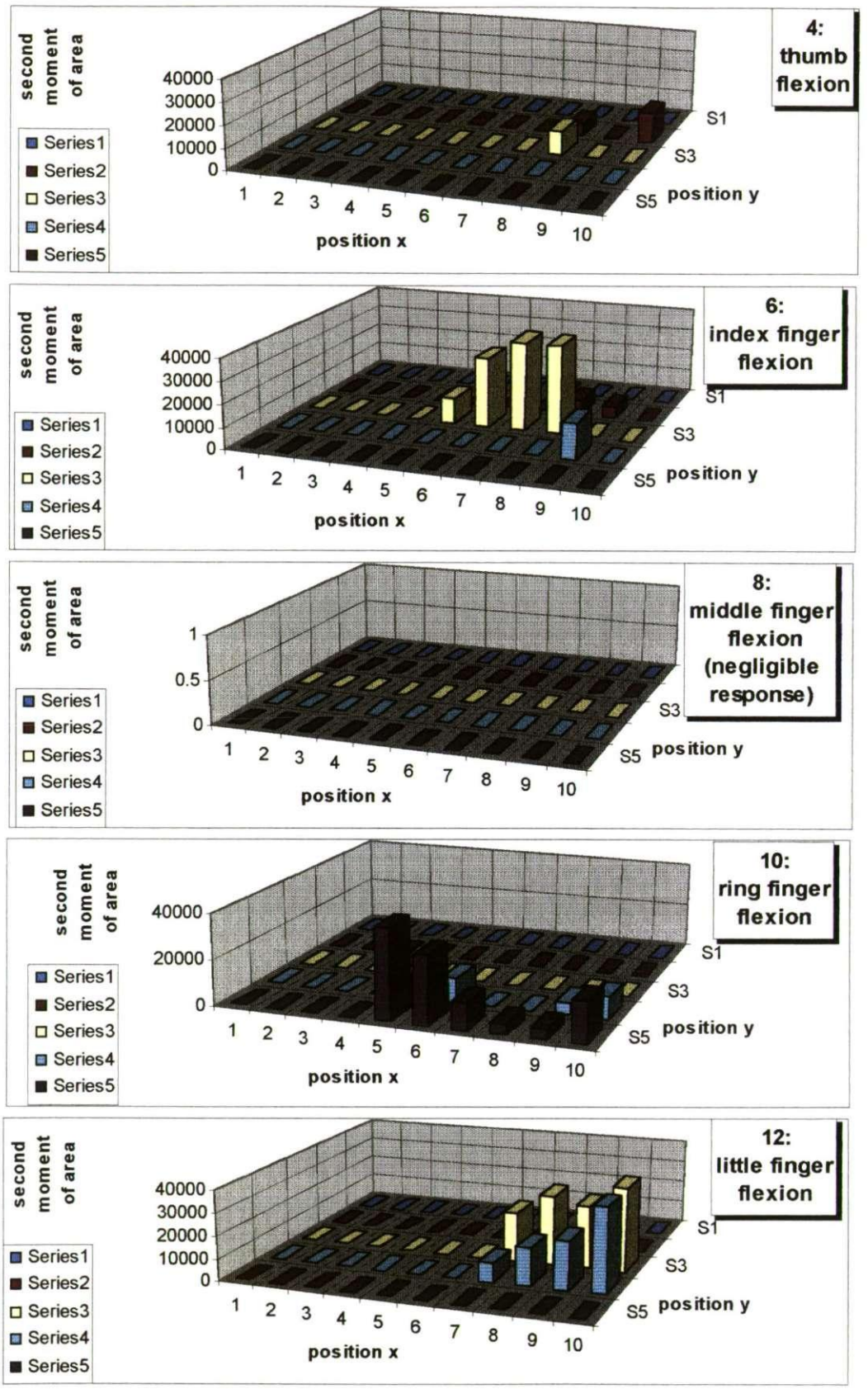


Figure 6.35 Figures 4,6,8,10,12 are the individual finger actions involved in flexing the hand. **(female 2) View 2**

Figures 6.6 to 6.35 examined the relationship between the addition of the individual digit actions and the combined hand actions. Following these studies it is clear that the overall interaction of individual muscle actions describes the combined effect. This demonstrates a deterministic nature in the observed results. The differences that do exist are largely due to the inclusion of synergistic muscles as they stabilize a joint. The most frequently encountered stabilizing action being around the wrist joint. Individual muscle action variations occur between various volunteers as a result of preferred techniques and developmental differences (sporting vs. non-sporting).

6.10 Standard Deviation Analysis To Determine 'Best' Location For An Electrode For Single And Multi Electrode Configurations

Extensive analysis has been done on the grid mapping results and the translations into an Excel database has allowed the standard deviation to be assessed. The results summary for the two male and two female volunteers can be seen on figures 6.36 and 6.37. The grid points with the tallest towers represent the most active grid points for all 20 mapped actions. The inclusion of composite actions such as 'clenched fist' in the standard deviation calculation tend to reduce the sharpness of the overall contour features. If desired the composite actions could be subtracted from the calculation in order to find sites for control signals that respond only to individual digit actions. The accuracy of response to user intended muscle activity would be directly proportional to the number of grid sites individually monitored by electrodes. The method can be incorporated into any future amputee mapping activity.

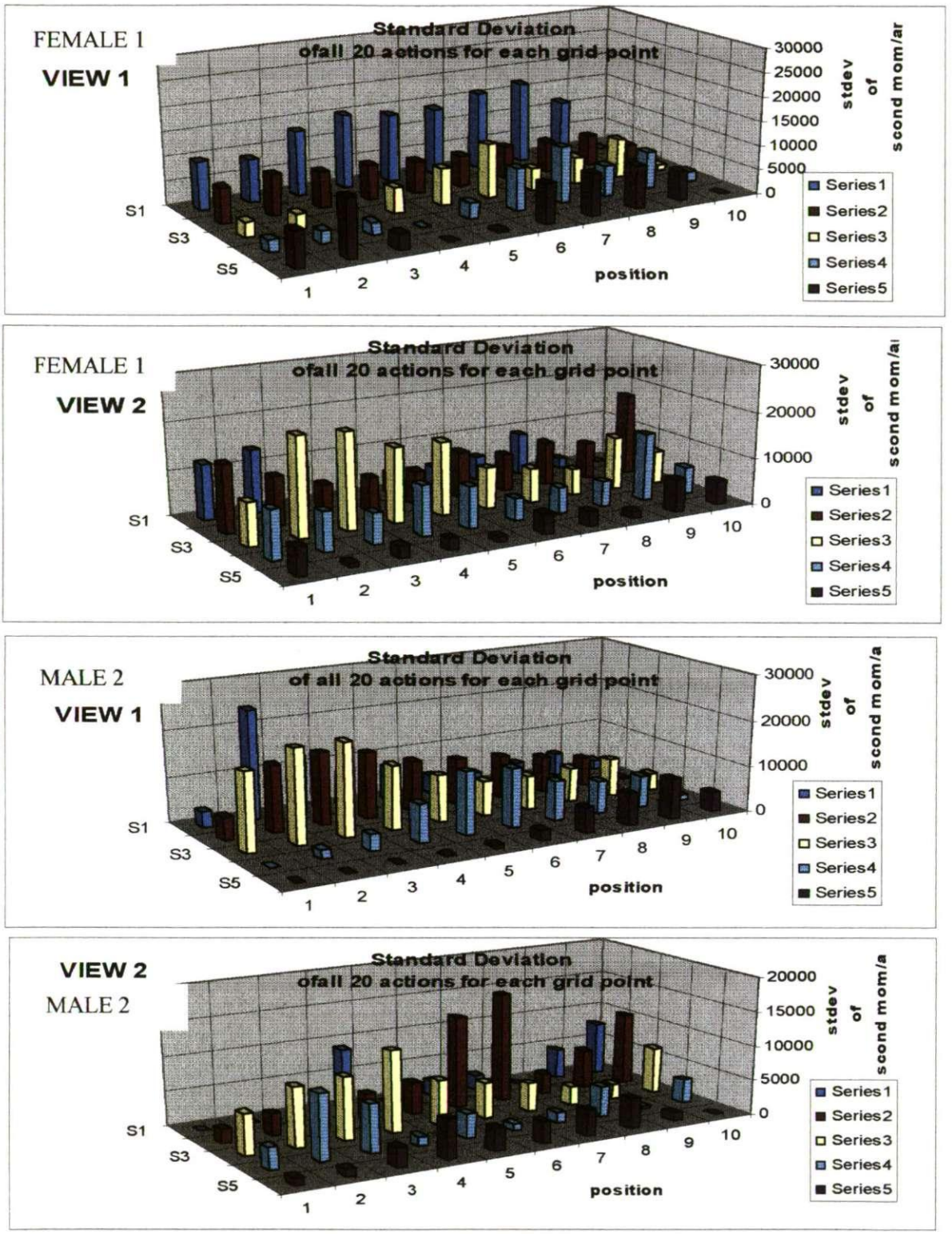


Figure 6.36 The above shows the standard deviation values for view1 and view 2 of volunteers female 1 and male 2 The grid points with the tallest towers represent the most active grid points for all 20 mapped actions. The accuracy of response to 'user intended muscle activity' would be directly proportional to the number of grid sites monitored by electrodes. It can be seen that individual electrode site selection would produce optimal results for each person.

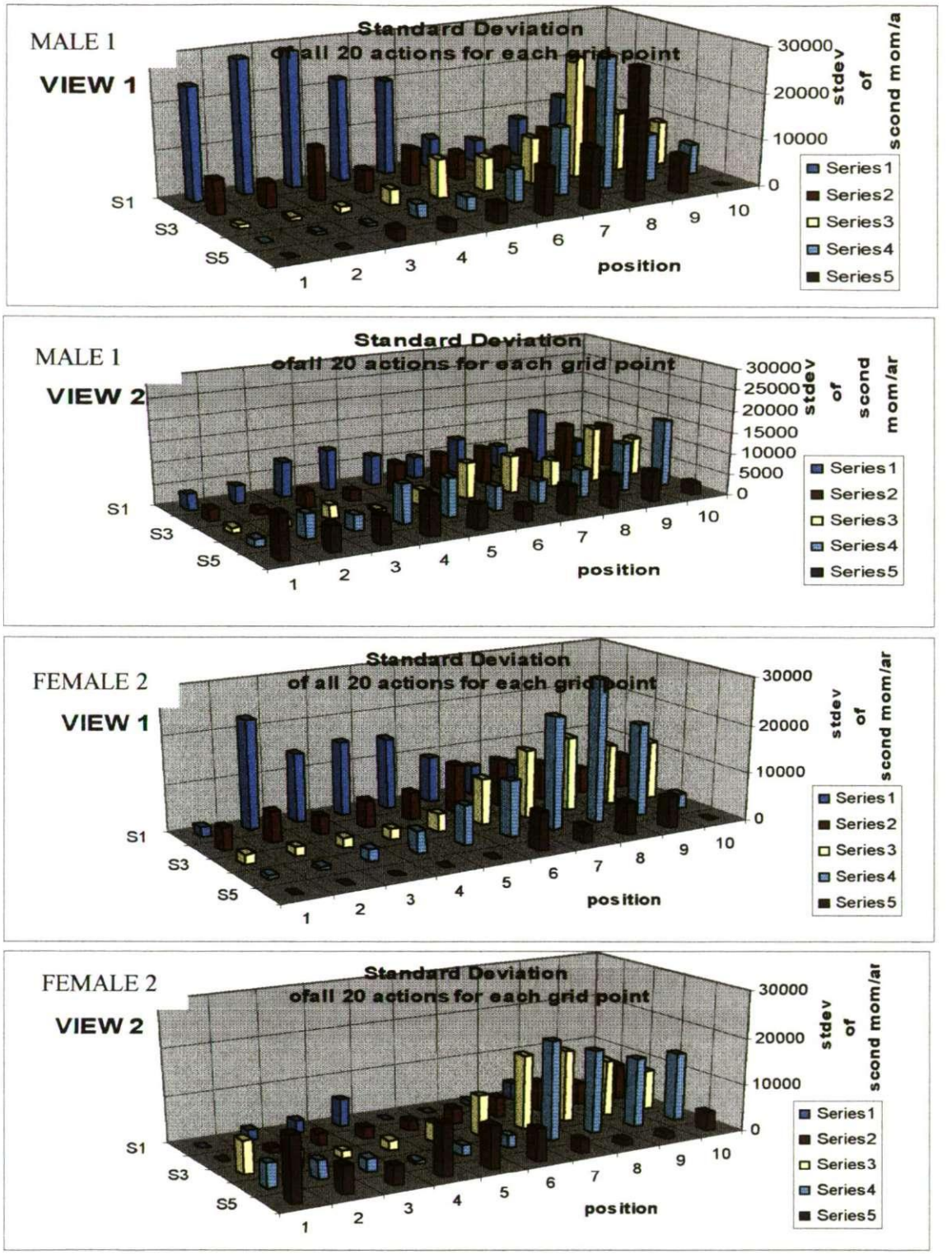


Figure 6.37 The above shows the standard deviation values for view1 and view 2 of volunteers male 1 and female 2. The grid points with the tallest towers represent the most active grid points for all 20 mapped actions. The accuracy of response to 'user intended muscle activity' would be directly proportional to the number of grid sites monitored by electrodes. It can be seen that individual electrode site selection would produce optimal results for each person.

6.11 Deterministic Vs Stochastic Content

The question as to whether the surface MES has a deterministic or stochastic content needs to be re-examined and rephrased as to whether it has ***both*** *a deterministic and a stochastic* content.

At the lowest level of the individual muscle motor units, the very nature of the firing signals along the neural pathway and varying branch lengths, fatigue, recruitment etc. (see chapter 2 on physiology of muscle and mathematical/theoretical description by De Luca) does not show promise of an isolatable deterministic frequency characteristic.

However, the investigation undertaken at the University of Plymouth by the author has revealed, at the level of the surface MES, an element of deterministic behaviour is detectable.

6.12 Summary

As stated in chapter 1, the objectives of the research are:

- 1)-to investigate the information content of a MES.
- 2)-to study the nature of the Tissue Filter Function (TFF)
- 3)-to map and identify optimum upper limb (forearm) myoelectric sites
- 4)-to analyse the mapped data for frequency content and other unique identifiers
- 5)-to recommend the practical application of MES analysis for control purposes
- 6)-to provide a greater range of user-generated control signals

This chapter has made progress on objectives:

1)-to investigate the information content of a MES.

For a non-deterministic signal the "average" spectrum should be approximately uniform for all MES sources yet this has not been the observed result.

If the MES source showed a different, "Hot Spot " spectrum (assuming same source tissue-depth) for each of the different muscle actions then the results would show a strong support for declaring an at least partly deterministic MES source. Results do show a different "Hot Spot" spectrum starting point for different muscles.

2)-to study the nature of the Tissue Filter Function (TFF)
In Section 6.1.2 the results of the first male (male 1) generating all 20 actions, show, for each action the detected MES undergoes a shift in frequency content that appears representative of a loss of frequency as distance increases (filter effect). The frequency spectrum does not fully undergo the expected "filter effect" with distance but shows an initial high frequency loss from the hot spot epicentre but retains the same frequency spread as the overall MES amplitude decreases.

Therefore the average spectral signal loss for a deeper muscle should lose proportionally more of its higher frequencies as it passes through a greater thickness of tissue than the overlying muscle,

3)-to map and identify optimum upper limb (forearm) myoelectric sites

The appendix contains the mapped results for all 4 volunteers

The optimum sites have been selected for electrode placement using standard deviation results. These values can be used to improve the multifunctionality of a prosthesis by simply increasing the number of detection electrodes applied to the hierarchy of preferred sites.

4)-to analyse the mapped data for frequency content and other unique identifiers

As a demonstration of both gender similarities and an indication of a deterministic element to the detected muscle MES, the "thumb extension" MES of all four volunteers was compared (Table 6.1). There are two widely separated muscles involved in the action (*see figures 6.1 and 6.2*). Corresponding sites (on all four adults) show similar spectral features for the one muscle site but different spectral features for the other site.

5)-to recommend the practical application of MES analysis for control purposes: Using Second Moment of Area to represent Bandwidth Shift along x-axis allowed for the use of the 4 variables [(1) Amplitude, (2) Central Frequency, (3) Bandwidth, and (4) Bandwidth Shape to be represented as a value and to represent the surface of the arm as a grid of potential electrode sites. The use of standard deviation analysis allowed the final electrode site selection to be optimised. An alternative method of 'assigning a code to each feature' was also formalised for representing spectral features.

6)-to provide a greater range of user-generated control signals: Section 6.8 investigated the relationship between the separated individual finger MES actions and that of two or more combined MES finger actions. The examination of figures 6.6(a,b,c,), (page 155-156) show how the summing action of individual muscle actions is not necessarily likely to produce the same mapping feature as combined action requiring the simultaneous activation of the individual muscles. There are certainly some areas of commonality and in some instances the summing action is remarkably close to the expected combined result, but for control purposes, the nature of synergist and fixators muscles needs to be taken into account.

Finally, with the demonstration of a deterministic element in the MES, one might ask for an underlying explanation as to just how the different muscles might exhibit a variation in frequency spectrum. Chapter 7 brings together a list of variables that are involved in the creation of the spectral features of the MES. The variables outlined in Chapter 7 not only suggest an unique signature might be detected but actually argue, by the sheer number of variables, how could anything else but a variation be expected!

6.13 References:

1 De Luca. C. J., (1993). Precision Decomposition of EMG signals', Methods in Clinical Neurophysiology, Vol. 4, March, Page 15.

CHAPTER 7: Discussion

7.1 Deterministic or Stochastic Content?

What has been explained?

Historically the surface MES has been assumed to be of stochastic content (De Luca **[14]**). This has now been shown to be (only partially valid for the MES at the point of origin only (the level of the wire electrode detection of the action potential (MUAP of individual motor units), due to (a) the very nature of the synaptic crossing points along the neural pathway and (b) the varying motoneuron branch lengths).

The human neuromuscular system has been studied for more than a century and the following section will draw together past research and current research at the University of Plymouth to clarify the deterministic nature of the MES.

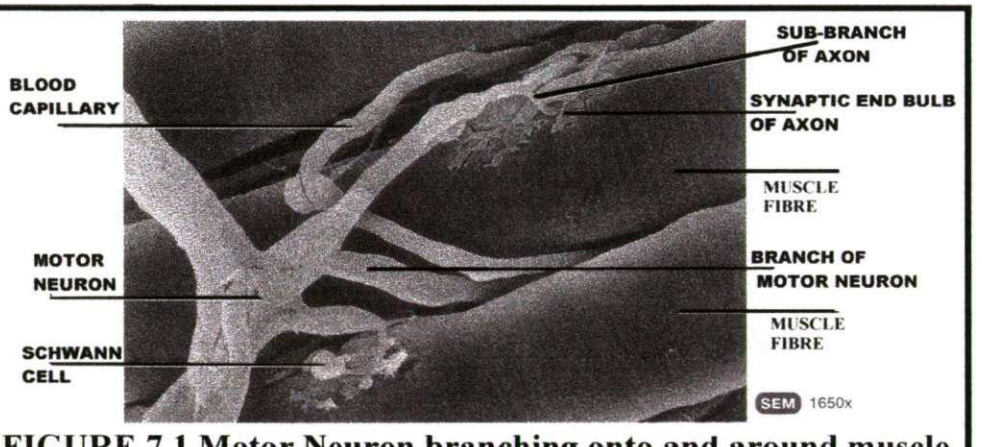


FIGURE 7.1 Motor Neuron branching onto and around muscle fibres. Diameter of fibres vary from 10 to 100 micrometres
Adapted from 'Principles of Anatomy and Physiology', Tortora and Grabowski, ninth edition, 2000

There has been an extensive volume of research literature in which MES detection has been undertaken using inserted needle/wire electrodes. These wire electrodes are often the equivalent of an extremely fine hypodermic needle. The full cross-sectional electrode diameter (of a 4 wire 3 channel discriminating electrode) would be approximately 300 to 400 micrometers (1). Finer wire electrodes are also used (25 to 75 micrometer diameter)

but they have limited discriminatory capabilities. Mature muscle fibres range from 10 to 100 micrometers in diameter (1 micrometer = 1 micron = 0.001 mm= 1/25000 inch) with a typical length of 100 mm. These fibres lie parallel to and very close to each other. At this point, it will be appropriate to look at a photomicrograph of a region of typical muscle fibres and the innervation by a motoneuron (*see Figure 7.1*).

The usual method, in using these wire electrodes, is to insert them directly into the central body of the particular muscle to be studied. As the fibre is often innervated by the nerve at the midpoint of the fibre, this would be the region of highest nerve fibre concentration amongst the muscle fibres. Remember, these are 'live' volunteers with no means for the researcher to 'see' the fibres at the end of the needle electrode. It is important to consider:

- the scale of movement of the electrode with respect to the fibre (300 to 400 micrometers electrode and 10 to 100 micrometer fibres),
- the interwoven network of the nerve fibres wandering throughout the central muscle fibres to create the dispersed territory of a single motor unit,
- the interwoven nature of the different motor units (with each other).

The likelihood of being able to tell the action potential of the nerve as it enters the fibre, from the action potential of the muscle fibre as it traverses the fibre length is called into question (*see Figure 7.2*). Considering that the shapes of the two action potentials are very similar and the resting membrane potential of a neuron fibre is (–90mv.increasing to +30 mv. at peak) versus (–70 mv. increasing to +30 mv. at peak) for a muscle fibre **(2)**, we see how difficult it will be:

a) To discriminate at the common signal feature boundary where nerve and muscle fibre potential have common appearances

b) To be sure of the electrode tip position, where the transition zone between the nerve and muscle fibre junction is an order of magnitude smaller than the electrode tip

c) To separate, (when seen as the surface detected MES), the muscle fibre action potential from the nerve fibre action potential (as they near to simultaneously, overlap, combine and pass through tissue layers).

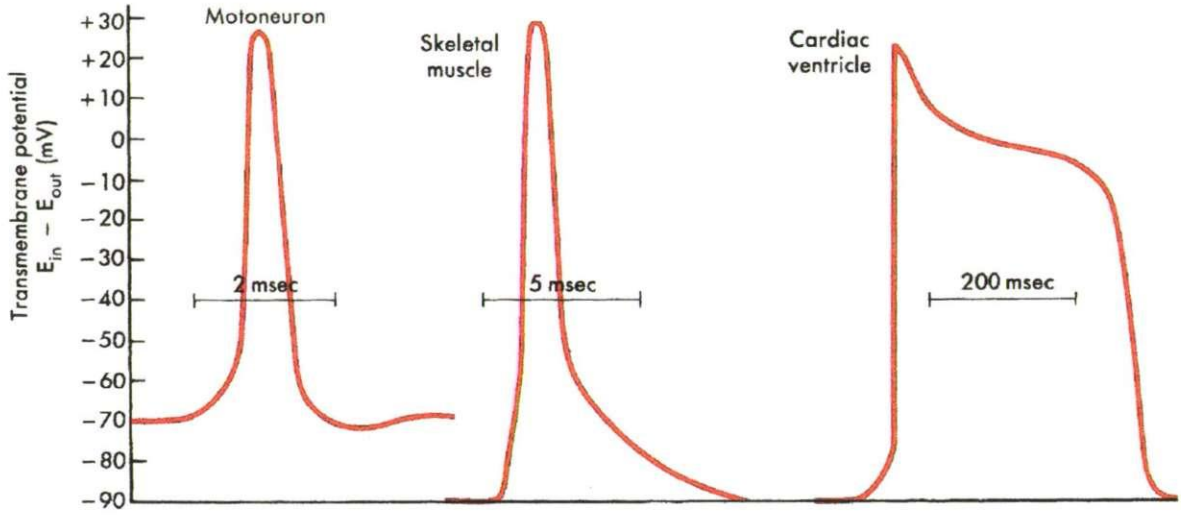


Figure 7.2 Typical action potential values. Note similarity of muscle and nerve fibre voltage ranges. Time scale differs by approximately 2:1.
Adapted from, 'Physiology', Berne and Levy, Mosby Year Book, 1993 edition.

For the requirements of research into motor units using needle electrodes, the points mentioned in a) and b) above will not be of crippling consequence as long as researchers use decomposition techniques to remove signals they deem not to be part of the motor unit. This can be done, but the options are:

- long and laborious human eye methods (99% success)
- or computationally expensive methods (only 80% success) (**1**).

For the sake of research into surface MES the consequences of (c) above are very significant. The surface MES is then a composite of **both** neuron and muscle fibre activity of similar AP magnitudes (for explanation see section 7.46, pages 209-211).

If we go back to the physiological/mathematical model of De Luca (chapter 2 page 83) we see a summing of the motor unit action potential trains (MUAPTS) as they approach the skin surface prior to electrode detection.

It is the summing and overlap in time of these MUAPTS according to De Luca that represent the MES at this stage.

The author proposes that the MUAPTS are only relevant and only have a 'reality' if detection is done by a needle electrode. The very nature of needle electrodes is to 'look for' MUAPTS as generated by close-proximity motor units. One needle electrode will see a small picture in the region of the muscle fibre. If we took a very large number of needle electrodes and evenly populated the gross muscle with them and were able to observe them as a decomposed (using decomposition techniques) instantaneous time slice, we would see a slice of the time-frequency graph. Combining these slices over the duration of a muscle action would give the complete time frequency graph of the muscle action.

We only ever see a small window on the skin surface using surface electrodes. All those action potentials (AP's) have interacted with other AP's locally and en route in a way very different from that seen at any needle electrode site. The AP's are not behaving as obedient members of a stationary MUAP. The AP's strike out on their radiative path and will combine with each other (*not with other needle detected MUAPTS*), interact with the tissue (TFF), and arrive with subtle differences (depending upon the path taken) at each surface point.

7.2 An Expanded Model of the Surface MES

It is the author's opinion that it is incorrect to describe the (needle-electrode detected) MUAPT's as the summed elements that comprise the surface MES. The story is much more complex.

De Luca **(1)**, **(pages 78-84)** proposed the power density spectrum for the MES, up to 40 Hz, could be accounted for by the motor unit Inter Pulse Intervals (IPI's) (see Chapter 2). Beyond 40 Hz, De Luca only describes the spectrum as the results (shape) of an impulse response through a black box filter. It should be noted here that De Luca used an

averaging/statistical assessment of the reciprocal of the IPI, to come up with a motor-unit firing rate **(1).**

7.3 An Extended Physiological description of the Surface MES

The following is the author's updated MES model using current knowledge of the physiological features that need to be an essential basis for incorporating into a description of the surface MES. The features are briefly stated, then given a short mathematical description. The mathematical statement is then developed into a flowchart (*see Figure 7.3*).

Muscle fibres are organised as Motor units

Let the force of the muscle contraction be (F_C)

Let motor unit firing rate be λ_r

(F_C) will determine the number of motor units brought into use (to achieve that composite force) As the force of the muscle contraction increases, the firing rate of the motor unit increases **(1)**

As F_C increases, λ_r increases

Small motor units are recruited first and largest motor units recruited last. **(2)**

The earliest recruited motor units also have the smallest nerve fibre diameters i.e. are recruited in order of increasing motor axon fibre size. **(2)(page 116)**

The higher the recruitment threshold of the motor unit, the less the motor unit increases its firing rate with increasing force **(3)**

Let motor unit recruitment threshold = τ_f

As F_C increases, τ_f increases and the rate of change of $\lambda_r \rightarrow 0$

Following recruitment a motor-unit firing-rate increases slightly with increasing force before levelling off (constant) at a 'preferred firing rate' (λ_p) **(4)**

As F_C increases, λ_r increases and $\lambda_r \rightarrow \lambda_p$

The 'preferred rate' increases slightly with increasing recruitment threshold.

As τ_f increases, λ_p increases

As force level decreases the firing rate decreases to 30 to 40 % of the preferred rate before becoming inactive **(4)**

As F_C decreases $\lambda_p \rightarrow 0.35\ \lambda_{p,init}$

At faster *rates* of force increase, motor units were recruited at lower force levels but with higher initial firing rates. **(5)**

There appears to be more variability in firing rate recruitment between different (named) muscles, than within the motor units in any particular muscle. **(1)(page 146)**

Let set of muscles = $\{M_1, M_2, M_3, ...\}$

variability of λ_r within M_1 ≠ variability of λ_r within M_2 etc. **(1)**

Motor units near the surface of the muscle have higher recruitment thresholds than those deeper in the muscle. **(6)**. The author considers this tends to suggest that the larger motor units are located at or near to the muscle surface. Relative location of fibre types throughout the muscle w.r.t. the recording electrodes i.e. surface, central, or deep, will affect the location of instantaneous centres of activity)

High threshold motor units tend to have shorter contraction times(T_C)

and twitch durations (t_D) **(2)**

Motor units are only of one type of fibre (i.e. not mixed) **(2)**

fibre types: (slow-twitch or fast-twitch type)

Note: It is not actually correct to state that fibres are of only the two types (see Chapter 2, page 68). There is a third intermediate (in both fatigue resistance and speed) type of fibre. For clarity, this intermediate type is omitted, (a reduction in terms) and does not affect the function of the model. Rather, it serves to facilitate understanding and emphasize the relationships

Mu_S = small motor unit= low threshold unit (long contraction times, long twitch)

Mu_L = large motor unit = high threshold unit (short contraction times, short twitch)

Fast twitch fibres are generally recruited at higher force levels. Fast-twitch fibres are larger in diameter and have higher amplitude AP's than slow-twitch fibres. Larger radius fibres have larger conduction velocities. A doubling of fibre radius will increase conduction velocity of by a factor $\sqrt{2}$. This should be reflected as an increase in detected MES frequency of $\approx\sqrt{2}$ **(2) (page 51)**.

i.e. λr of μ(fibF) $\approx \sqrt{2}$ [λr of μ(fibS)]

Where μ(fibF) = fast twitch fibre

Where μ(fibS) = slow twitch fibre

Decruitment of motor units: De Luca found force reversal not to be the orderly inverse activity of recruitment **(1)(page 154)**. Rather, with decruitment, the earlier recruited smaller, slow-twitch-fibre motor units decreased their firing rates before the latter-recruited larger, fast-twitch units. **(1)**

At decruitment, λr of μ(fibS) decreases before λr of μ(fibF)

Why this occurs is not well understood and conjecture by De Luca follows a selective sensitivity to excitation and inhibition in the motor neuron pool resulting in ordered firing rate reversals. **(1)**

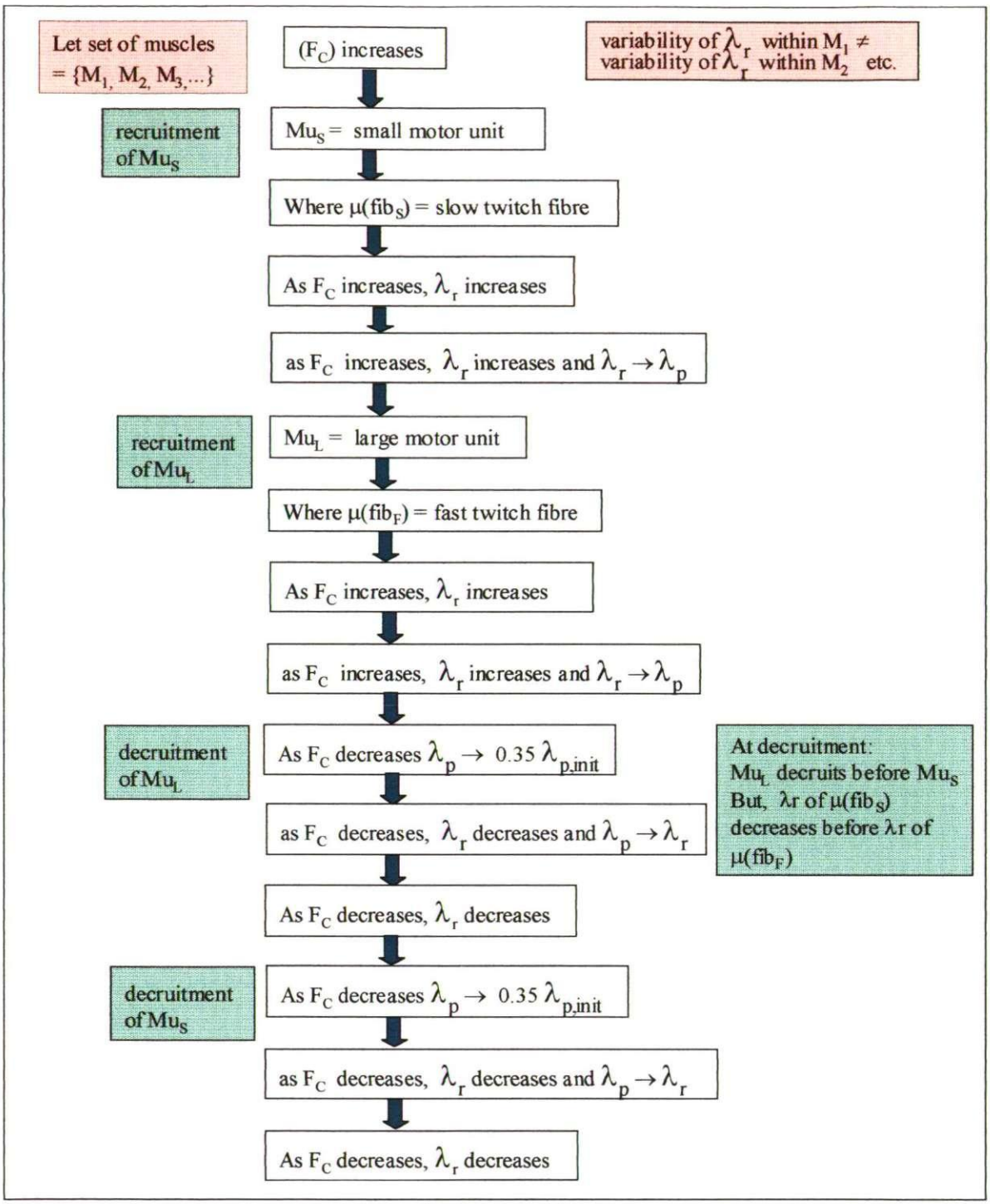


Figure 7.3 above shows the recruitment/decruitment process involving the changing relationships between muscle size, motor unit size, firing rate, and fibre type. The overall variability between and within different muscles allows for differences to *'emerge'* as the surface MES.

7.3.1 Maximum Voluntary Contraction (MVC)

Most research agrees that the firing rate increments, at least up to the level of 50% of MVC **(1)**

where F_C max = Maximum Voluntary Contraction (MVC)

for $F_C < \frac{F_C \text{ max}}{2}$, λ_r increases and $F_C \alpha \lambda_r$

Less agreement occurs as MVC approaches 70-80 %. (this may well be due to the lack of consistency between research groups, with muscle and muscle-region selection). Most research shows a levelling off and other research (a minority) shows an increase in firing rate all the way up to 100% MVC. There is some consensus with the force and firing rates being linearly related **(1)(page 142,151)**

for $F_C < 0.8\ F_C$ max, rate of change of $\lambda_r \rightarrow 0$ and $F_C \propto \lambda_r$

In general, small muscles with fewer motor units (e.g. hand, first dorsal interosseous has 120) recruit all motor units below 50% MVC and from 50 to 100% MVC, rely primarily on firing rate to modulate their force. Rates reach as high as 60 pps. **(1)(page 167)**

For first dorsal interosseous:

When $F_C < \frac{F_C \text{ max}}{2}$, $\lambda_r \rightarrow 60$ pps

By recruiting during the first 50% MVC the 'unit force increment' is one half the increase compared if recruitment extended to 100 % MVC. **(1) (page 166)**

Let δF_C = unit force increment

For $F_C < \frac{F_C \text{ max}}{2}$, $\delta F_C = \delta F_C$ max

i.e. given a total available pool of motor units to recruit, the strategy of recruiting all the motor units by 50% MVC means that each recruited motor unit has only one half of its

share of the F_C demand placed upon it compared to the strategy of continuing recruitment up to 100% MVC **(1)(page 167)**

This gives fine control of force (0.8% increase per unit), as is required of small muscles (e.g. first dorsal interosseous has 120 motor units). For larger muscles with more motor units (e.g. upper arm, biceps brachii has 770 units), overall force is greater and spread over many more units. Unit force increment is small with unit increments of 0.12%. **(1)(page 166)** Large muscles, where recruitment occurs throughout the full force range, rely primarily on recruitment to modulate their force. Thus we have:

for small muscles (M_S): for $F_C < \frac{F_C \max}{2}$, $\delta F_C = .008\, F_C$

for large muscles (M_L): for $F_C < \frac{F_C \max}{2}$, $\delta F_C = .0012\, F_C$

Let $M_{U(full)}$ = full motor unit recruitment

For M_S with Mus_S, full recruitment ($M_{U(full)}$) occurs at $\frac{MVC}{2}$

For M_S , $F_C \ \alpha \ \{ \ M_U(TOT),\ F_C < \frac{MVC}{2}$ and $\lambda_r, F_C > \frac{MVC}{2}$

where: $M_U(TOT)$ = Number of motor units recruited at that moment in time

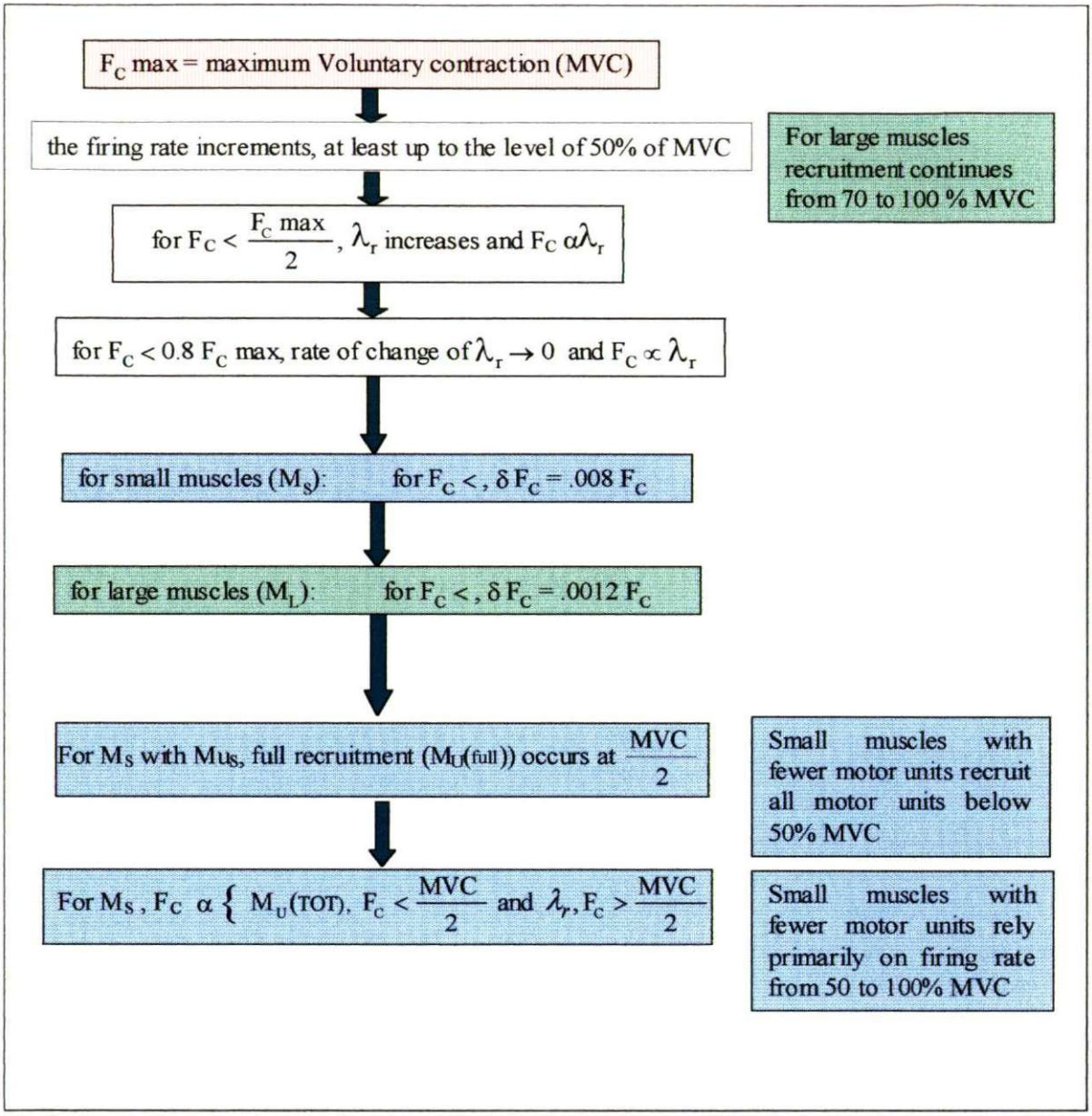


Figure 7.4 above shows the different motor unit recruitment and firing rate strategy between small muscles and large muscles. The additional variable of different ratios of fibre types (slow and fast twitch) associated with small to large motor units within the extremes of muscle size, emphasize the potential for characteristic features to be found associated with muscle actions and the surface detected MES.

7.3.2 Fused-Tetanic Contractions

To produce fused-tetanic contractions requires higher firing rates **(8)(page 286)**.

F_C max = $\sum$ all Mu_S + $\sum$ all Mu_L

where: F_C max = Maximum Voluntary Contraction (MVC)

With agonist/antagonist activity in a muscle action, when the firing rate is increased in one it is decreased in the other. **(2)**

As μ (-) λ_r increases, μ (+) λ_r decreases

$$\mu(-)\lambda_r \propto \frac{1}{\mu(ag)\lambda_r}$$

where μ (-) = antagonist muscle

where μ (+) = agonist muscle

This implies that the nervous system 'sees' (commands) the opposing muscles as one unit with reciprocal levels of excitation and inhibition. **(1)(page 153)**. Although firing rate of motor units increase with force, there is also a slowing of the firing rates of previously recruited motor units **(1)**. De Luca conjectures this is a means by which the nervous system smoothes the force increase, (as larger motor units are brought into play).

7.3.3 Fatigue Effect:

The fatigue effect can be described as follows: During sustained muscular contractions, the observed spectrum has a tendency to decrease independently of the force output of the muscle. A decrease in bandwidth occurs with a frequency shift from higher to lower frequencies (observed near the beginning of a sustained contraction), accompanied by an increase in the amplitude of the lower frequencies (observed near the end of a sustained contraction).

The author proposes the fatigue effect has a simple explanatory basis due to the decreasing contribution of the [fast-firing rates, (fast-fatiguing)] fast-twitch motor units as they fail (fatigue), with no alteration in the contribution from slow-twitch [slow-firing rates of the (slow-fatiguing)] fibres **(7)**. This has been probably understood by those in the field of physiology but not formally presented. Though not included in the previous model description, it is can be assumed that the intermediate type of fibre can be briefly considered as an intermediate phase in the transition of the signal frequency content from high to low.

Fatigue effect of force of contraction = F_{CFE}

At 100% MVC, $F_C \downarrow F_{CFE}$

At 100% MVC, $F_C \alpha [\ \lambda_r \text{ of } \mu(fib_S) + \lambda_r \text{ of } \mu(fib_F).]$

At F_{CFE} , $F_C \alpha [\ (\lambda_r \text{ of } \mu(fib_S) + \lambda_r \text{ of } \mu(fib_F)\ ]$, but $\lambda_r \text{ of } \mu(fib_F) \rightarrow 0$

low frequency BW = $BW_L = \sum\mu(fib_S)$

high frequency BW = $BW_H = \sum\mu(fib_F)$

Total Bandwidth = $BW_T = [\ BW_L + BW_H\ .]$

Total Bandwidth = $BW_T = [\sum\mu(fib_S) + \sum\mu(fib_F).]$

At 100% MVC, Total Bandwidth = $BW_T = [\sum\mu(fib_S) + \sum\mu(fib_F).]$

Before F_{CFE} , $BW_T \alpha \dfrac{\mu(fib_F)}{\mu(fib_S)}$ i.e. BW ≥ 1

At F_{CFE} , Total Bandwidth = $BW_T = [\sum\mu(fib_S) + \sum\mu(fib_F).]$

$$BW \alpha \frac{\mu(fib_F)}{\mu(fib_S)} \qquad \text{i.e. BW.} \leq 1$$

7.4 Factors Contributing to Variations in the Frequency Content of the MES

7.4.1 Temperature of Muscle Fibres: the **conduction velocity** of a muscle fibre is proportionally related to temperature. A muscle tested for spectral content in a cool lab compared to the muscle used for pattern recognition within a covered prosthesis may vary a few percent. **(1)(page 218)**

Let V_C = velocity of conduction (of muscle fibre)

Let T_M = temperature of muscle

$V_C \propto T_M$

7.4.2 Muscle Interactivity

Agonist and Antagonist muscles interact through what can be described as a 'triphasic pattern'. **(1)(page 225-226)**. This triphasic pattern could be modelled as a feedback control loop which responds to the following directives:

1) An initial burst of agonist activity/limb acceleration with concurrent silence of the antagonist muscle, is followed by

2) A reduction of agonist activity with a concurrent burst of antagonist activity resulting in limb deceleration, is followed by

3) Further agonist/antagonist activity as the limb stabilises.

With ballistic movements (of a limb), the antagonist activity appears to be influenced by the subject's movement strategy. For full deceleration (stopping) of the muscle action, the strategy varies from antagonist relaxation (for no time constraints) to antagonist activation (for rapid deceleration). For both power grip and precision grip, almost all the finger and hand muscles of the hand and forearm are brought into play **(1)(page 28).** The extent of this can be seen with the mapping work done by the author.

7.4.3 Muscles At Rest: at complete rest there is no detectable neuromuscular (electrical) activity. When muscles at complete rest are passively stretched, there is still no activity in both flexor and extensor, regardless of speed of movement.

7.4.4 Muscle Stretch Receptors: are used for Proprioception (the sense of joint position and movement). Spinal reflex control of skeletal muscles is mediated through the feedback mechanisms of the muscle-based muscle spindle and tendon-based Golgi tendon (force sensing) organs. **(2)(page 198-203)** The spindles have a very complex activity and involve both motor and sensory activity for their function. The spindle actually use modified small muscle fibres (parallel to and nested amongst the normal muscle fibres) as driven units that activate integral stretch receptors that feedback information about the level of stretch (the engineering equivalent of a strain gauge) in the muscle body. Spindles are most abundant in slow-twitch fibres. Spindles come in two types; one gives feedback on dynamic (rate of change in length) and the other on static (length only) responses. Contraction of the fibre/spindle (decrease in muscle length) decreases the discharge rate (frequency) and relaxation increases the discharge rate. The output of the spindle and Golgi sensors drives (through fibre branching) both the reflex response and the higher levels in the cerebellum and informs the cortex. **(2)** The end result is that the alpha motorneurons operating the opposing muscle sets, are excited and inhibited as appropriate. The type A fibre (which is the same myelinated type used for skeletal muscle fibres) is also used for spindle and Golgi sensing **(8)(page 395).** Type A fibres have diameters between 5 to 20 micrometers and conduction velocities of 12 to 130 metres /second.

De Luca interprets the proportional firing rate increases with increasing force as implying that an increased general excitation to the muscle motoneuron pool increases the firing rates of all the active motor units. **(1)(page 151).** De Luca describes this as the 'common drive' in which the nervous system acts as a modulator of inhibition and excitation upon

the motoneuron pool. The lack of any appreciable time-shift in the correlation function of changes in firing rates indicates that the modulation occurs essentially simultaneously and in similar amounts per motor unit. **(1)**

7.4.5 Training of the Subject:

De Luca considered that training had no effect on the MES generation but other branches of physiology suggest otherwise. The effect of training of the subject is to control the 'interaction' of the muscles rather than the control strategy of individual motor units. Before training, (training on *rhythmic* extension and flexion of the elbow), there is wasteful activity of the antagonist muscles interacting to moderate the agonist activity (co activation). After training there is progressive inhibition of the antagonist activity until, with advanced training, full inhibition is reached. Co-activation activity is observed to reduce as infants mature. The nervous system is subject to feedback to modify the 'reciprocal inhibition' control scheme of muscle activity. Co activation of agonist/antagonist muscles is found in infants, in isometric activities, in requirements for a joint to be stiff, rapid deceleration of muscles controlling a joint, in unskilled movements (prior to training) and in spastic patients.

7.4.6 Conduction Velocity: of both nerve and muscle fibres. If the conduction velocity of a fibre changes the depolarisation event (that produces the wave shape) and the AP takes a different time to traverse a fixed distance along the fibre (and consequently to pass the detection electrodes) the detected AP will have an altered time duration. Any signal that follows the relationship: (velocity = frequency x wavelength) will see a change in frequency such that a drop in (conduction) velocity produces a drop in frequency and a rise in (conduction) velocity produces a rise in frequency (assuming no change in the wavelength). A change in the 'rise time' of the signal will be seen as a change in the frequency. The slower conduction velocities and thus smaller axons were found associated

with the lower threshold motor units (9). De Luca confirmed this behaviour and suggests this relationship indicates a highly ordered process that remains invariant with muscle-force, rate, and training **(1)(page 158)**. There is a difference in the conduction velocity of myelinated and unmyelinated nerve fibres (2). The distance, (known as the length constant), that a signal can be transmitted along an unmyelinated nerve or muscle fibre, is between 1 and 3 mm. before the signal has been attenuated to 37% of its starting value **(2)(page 51).** A myelinated fibre has approx. 100 times less capacitance in the signal path seen by an action potential. This translates as large decrease in the CR time constant of the fibre and consequently as an increase in the conduction velocity of the nerve fibre (2). The myelinated fibre differs by the wrapping of a Schwann cell membrane (insulating myelin) around and along the length of the fibre. This membrane/sheath around the fibre is broken periodically every 1-2 mm. by a 1-micrometre gap. These gaps, called 'Nodes of Ranvier', separate one Schwann cell from the next along the fibre. In myelinated fibres, conduction occurs by 'saltatory conduction' because the impulse 'jumps' from one node of Ranvier to the next node of Ranvier. This jump occurs because the action potential is reproduced/regenerated only at the nodes of Ranvier (where there is no myelin sheath) because the internodal section of the fibre is covered by a wrap of 50 or so layers of Schwann cell membrane that reduces the membrane depolarisation to 1or 2 mv. and thus is insufficient to reach the threshold value for AP propagation **(2)(page 52-53).** The author suggests this process of nodal regeneration creates short periodic (as seen if travelling along the fibre) pulses up to 1 KHz (limited by the refractory period of the AP pulse) and are necessarily a component of the surface MES.

μ_A (fib) = type A nerve fibre (large diameter) have a refractory period of about 0.4 ms and can produce up to 1000 pps (1 kHz)

μ_B (fib) = type B nerve fibre (small diameter) have a refractory period of about 4.0 ms and can produce up to 250 pps (250 Hz).

Nerve impulses normally range from 10 Hz to 1 kHz

High frequency firing rate bursts (60 –120 pps) are encountered in muscles with the fast-twitch, larger motor units.

firing rate recruitment (biceps brachii) at the **lowest force levels** is 7 to 12 pulses per second (pps.) to a maximum of 20 pps.**(6)** Other sources put the maximum at 65 pps to 100 pps for the smaller muscles **(1)(page 140**

7.5 Factors Limiting the Frequency Content of the MES

7.5.1 Synaptic Delay is about 0.5 ms. or 2 kHz **(2, p.62)** and is consequently only significant in assigning the 'origins' of the surface-detected MES above 1 kHz. Synaptic delay could will contribute to detected frequencies greater than 1 kHz. This limitation to frequencies greater than 1 kHz needs to be included in any model of the MES. The inclusion over the full range of frequencies in the MES model by De Luca (Chapter 2) and presentation as a basis for ascribing an inherently stochastic element within the 'firing rate' of the MES model cannot be justified. It has only limited influence in blurring synchronization between motor unit AP's and their subsequent detected temporal overlap.

7.5.2 Refractory Period (*def: the period of time during which an excitable cell cannot generate another action potential*) of nerve fibres and muscle fibres influences the maximum possible frequency of the AP's along their lengths.

Nerve fibres have a refractory period of 0.4 to 4.0 ms. **(8)(page 394).** This yields an upper limit for inclusion in the MES of 250 to 1000 Hz. Nerve fibres however will contribute a frequency component along the fibre (at the nodes of Ranvier) through the tissue to the surface MES. The controlling alpha motor neuron pool in the spinal chord,

Peripheral nervous System (PNS) (with its inhibitory or excitatory action) will determine which motor units will be activated. This implies that, over time, individual training can introduce a level of additional control in the production of the frequency characteristics of the MES.

Skeletal muscle fibres have a refractory period of 5 ms. **(8)(page 286).** This yields a limit of 200 Hz on single AP's but due to the phenomenon of summation activity (resulting in 'fused tetanus') the frequency of fibre response may well be higher. This is as yet unquantified, but could add up to 50% to the 200 Hz limit.

7.5.3 Nodal Regeneration creates short periodic signal pulses up to 1 KHz at gaps called 'Nodes of Ranvier' along the nerve fibre.

7.5.4 Action Potentials always have the same size in a given nerve or muscle fibre **(8)(page 285).** As the nervous system uses frequency as the means of recruiting and controlling the muscles fibres at the neuromuscular junction, it should be expected to find a remnant of that frequency recruitment as an MES signature.

7.5.5 Filtering: (Electrode, Tissue (TFF), CMR)

The surface MES is composed of the fibre AP's interacting with and attenuated by the tissue encountered en route. This is necessarily a 'low-pass' filtering action and is primarily manifested as a loss of higher frequency signals (TFF). There is also some 'low-pass' loss of signal at the skin surface/electrode interface and some preferential amplification due to CMR (see Chapter 2 page 76).

Shape of muscle i.e. long, short, parallel or angled fibres will affect the surface MES if the electrodes are not aligned parallel to the direction of the fibres.

Noise from outside the muscle; e.g. mains noise 50 Hz and harmonics.

Electrode interdetection surface spacing:(Chapter 2 page 78) If notable spectral dips and peaks are seen and the electrode interdetection surface spacing is known, it is possible to

determine the fibre conduction velocity. This assumes that all contributing fibres have the same conduction velocities, and that is not always the case. Zero crossings of MES: are approximately linearly dependent **(10)** upon the force of contraction during relatively low muscle efforts. (Note: this is probably related to the signal transient, as the lowest levels of contractile force are triggered within the time span of the transient, (see University of New Brunswick usage, Chapter 1, page 30).

7.6 Relationship between the Fibre Type Composition of a Muscle and the Value of the Median and Mean Frequencies

De Luca suggests that several different research groups have indicated that there may be a relationship between the fibre type composition of a muscle and the value of the median and mean frequencies. Note: the median frequency is the frequency point where the power spectrum is divided into two regions of *equal power*, the mean frequency is the *average* frequency over the spectrum, and the mode frequency is the frequency of the *most common frequency* value of the spectrum **(1)(page 222)**. The author sees this 'fibre spectral contribution' as a possible extension for further 'mapping' activity.

7.7 In Brief:

The author concludes that the MES therefore must be composed of the superimposition in time of the generated AP's derived from the progressive recruitment of motor units (of a given fibre composition of different frequency types) from both nerve and muscle fibres, and will result in an '**emergence**' of either a unique or a common pattern at the skin surface.

7.8 What is still Conjecture/Unexplained?

The basis of the deterministic element found in the MES is a combination of a fundamental difference in the MES signal generated by different muscles (muscle antagonist/agonist groups) at differing sites, orientations, and depths (TFF). The Tissue Filter Function (TFF) has not been fully investigated, for its utilitarian potential, in the past, and has probably been the assigned recipient for any unexplained anomalies. The TFF failed to account for the overlaying of muscle signals that yield surface spectra that are the converse of what would be expected if the Filter Effect were to be the invoked as the explanation.

This opens up the field to suggestions that the muscles (considered as a larger unit) are contributing either selective frequency generation or selective combination, only detectable (emergent) at a higher, composite level and not apparent at the lower source level (see Lindstrom [11]). Various muscle actions investigated have shown surface MES clustering at low, medium, and high ranges of the measured spectrum. With the peak amplitudes for a variety of selected muscle actions centring at various points over the observed spectrum, yet with similar qualitative and quantitative tissue overlay of the muscle site, there is a need to develop a more detailed explanation for the observed muscle 'signatures'. The research at the University of Plymouth has presented sufficient evidence to further develop the underlying structure of these signatures.

7.8.1 Fibre contributions to the MES

As mentioned in Chapter 2, page 68, the muscles are composed of various combinations of the 3 different types of muscle fibre. Although the skeletal muscles are a mixture of all 3 fibre-types, the fibres of any one motor unit are all of the same type. Their various proportions depend on the usual activity of the muscle. These fibres have differing 'twitch' response rates of contraction velocity [12]. Muscles of the arms also have a proportion of

fast-twitch white fibres with fast contraction velocities. What is not known are the fibre-type proportions in each muscle and the cross-gender and individual variations.

An area for useful research would be to correlate the detected ratios of fibre types in a given muscle with a detected spectral response over a range of contraction forces.

The contraction-velocity is directly a result of the fibre-action-potential as it propagates along the fibre. A fast contraction velocity requires a fast, fibre-action-potential. A fast action potential implies a shorter time for the fibre to depolarise and re-polarise (during which time the sodium and potassium channels are involved in driving the fibre contraction (see Muscle physiology [12]). This shorter time gives a steeper edge to the action potential and thus gives the signal a higher frequency. If only a weak contraction is needed to perform a task, only slow twitch red fibres motor units are activated. If a stronger contraction is required, the motor units of fast-twitch red fibres are brought into activation. If maximum contraction is required, additional motor units of fast-twitch white fibres are brought into play.

7.8.2 Training/Recruitment strategy

The motor unit choice is determined in the brain and spinal chord. The number of different skeletal fibres in the muscle does not change over time (excepting atrophy and disease conditions) but the characteristics of those present can be altered. Endurance exercises (running) cause a gradual transformation of fast-twitch white fibres into fast-twitch red fibres, but with no significant increase in muscle mass. Exercises where short bursts of great strength (weightlifting) are required, produce an increase in the size and strength of the fast-twitch white fibres and an overall increase in muscle mass. This would suggest a difference should be seen between the athletic and non-athletic muscle spectral characteristics (as is the case between the two female volunteers).

Consider the action of the wrist flexion and ring finger flexion as found in our research. It can be seen that the ring finger flexion has a spectral envelope that occupies a lower frequency range than the wrist flexion envelope. The ring finger flexion is a strong candidate for the weak contraction task undertaken by the slow-twitch fibres and the wrist flexion is a candidate for the additional activation of the fast-twitch red fibres.

The author proposes that recruitment strategy gives a physiological basis for some of the frequency characteristics of detected MES in our research. Fibre type is then a level of recruitment strategy (as it has been mentioned that motor units are largely populated by one type of fibre only). Person **[13]** reported that recruitment order has been found to be stable for a given movement task but not stable when the movement task for that muscle was changed. It appears, to the author, that the brain can send an initiating, task-specific, pattern for motor unit recruitment order. The organisation of neurons in the Central Nervous system (CNS) is known to be in definite patterns called 'neuronal pools' (thousands or even millions of neurons per pool) all of which are of different patterns. These patterns are known to control the skeletal muscles.

There are other frequency-determining features, such as muscle size. As muscle size increases there is an associated increased size in the number of motor units. The number of motor fibres innervated by a motoneuron is proportional to its size. Smaller, lower threshold motor units (activated by smaller motorneurons) are recruited first by the smaller nerves **[14]**. Given that the motor unit does not fire at absolutely constant intervals, discharges of the motor unit have been measured (De Luca **[14]**) as the 'average firing rate' (see definitions in appendix). This firing rate has been shown to increase quasi-linearly (with some complex adjustments) over the range of contraction force, with the threshold of recruitment **[15]**.

Muscle size has an effect on the power spectrum. Increasing values of muscle size increase the observed energy in the low frequency region [11]. Small muscles generally have fewer fibres per motor unit and generate higher amounts of high-frequency activity for a given contraction force, than muscles with larger motor units [11].

7.8.3 Gender Differences

Given a similar musculature and fat thickness/density, the MES comparisons between the two tested males gave a broad agreement in principle. The two females chosen probably gave a good span of the female range in general but still show a strong similarity between their general sites and features and those of the males. The female sportsperson was so similar to the male pair that arguments for a physiological difference between males and females regards general structure of muscle layout were without basis. Differences detected seem to be derived from individual muscle developmental skills.

7.8.4 Mapping

In the 'thumb extension' action, there are two widely separated muscles involved" Corresponding sites on all four volunteers (on all four adults) show similar spectral features for the one muscle site but different spectral features for the other site. MES (*see Figures 6.1 and 6.2 and Table 6.1*). This needs to be statistically investigated with a larger database of people and other muscle sites similarly examined for deterministic features.

The author proposes that the localised muscle may be responding to a recruitment strategy that is itself a frequency generated characteristic of the neural pathway or earlier origins in the brain/ central nervous system. The neural signals interaction with differing masses of fast twitch and slow twitch muscle fibre types, at different muscle sites, has been proffered. It would be necessary to carry out simultaneous signal analysis on both the neural pathway (at muscle insertion points) and subsequent muscle firing responses. The neural pathway

detection, by necessity, would be an invasive technique and the muscle response would be a surface detection method

The author considers: because innervation of the muscle body by the nerve occurs at the middle of the fibre, the greatest chance of detecting the *muscle-only* AP would appear to be furthest away from the centre of the muscle. This should manifest as a reduction in spectral frequency as the surface electrodes move further away from the muscle centre. Results of the research at the University of Plymouth show the MES source with a different, "Hot Spot " spectrum (assuming same source tissue-depth) for each of the different muscle actions. The results show a strong support for declaring an at least partly deterministic MES source.

The MES source did not show the same, "Hot Spot " spectrum (assuming same source tissue-depth) for each of the different muscle actions, and consequently, the results do not show a strong support for declaring a non-deterministic, stochastic MES source.

The investigation undertaken **does not support** a wholly non-deterministic conclusion for the MES at the skin surface.

At the skin surface, the MES has ***both*** *a random and a deterministic* content detectable on two counts

1. The MES can be examined as to its original frequency content i.e. bandwidth. The *random* contribution is partly a result of the superimposition of the generated motor unit (muscle and nerve fibre) AP's and partly a result of the inherent imperfection over time in the 'firing rate'. The *deterministic* content is the 'emergent' property of the imperfect 'firing rate' in combination with the varying proportions of motor units and fibre types.
2. The 'Tissue Filter Function' has introduced a means by which the MES and its subsequent overall frequency loss can be measured.

7.9 Applications of Results

7.9.1 Pattern Recognition for Control Purposes

Suitability for Interface with Neural Networks

The use of an Artificial Neural Network program as an appropriate pattern recognition technique for biosignals has attracted considerable interest both past, active, and pending. The author sees the need to monitor, as an original proposition, 3 to 4 distinct very narrow bandwidth regions on each signal channel so that discrimination can occur for the frequency shift. Using frequency analysis, the ability to discriminate between hand actions has been shown. Clearly different and repeatable frequency peaks can be used in conjunction with digital filters to identify the different actions. Thus, it is possible to use one electrode at a single site to detect two (or more) different signals, each signal having differing amplitudes in the frequency "bins". This increases the number of control actions (on/off) available at a single site from 2 to 4.

Using the Medilec equipment test results (solely due to their slightly enhanced bandwidth) an examination of the test results (see chapter 7 page 110) indicated that a minimum set of 2 digital pass band filters with an intermediate sharp cut-off characteristic will distinguish these user actions (i.e. ring finger flexion versus wrist flexion), with pass band frequencies:

one @ 78 Hz and one at either 158 Hz or 222 Hz. respectively.

At a stroke, this doubles the number of control actions over a standard prosthetic hand.

The choice of digital filters comes as a consideration of their much greater flexibility. In order to accommodate a wider range of actions and to include the inputs from 4 rather than just 1 electrode, the following range of filters has been selected. The separation of these filters by a band of 32 or 64 Hz was based upon repeated testing to give adequate filter separation but with a sufficient number of discrimination points across the useable bandwidth. If it is possible to introduce other control sites simultaneously, this will

increase the number of control actions proportionally, i.e. 4 sites, gives 16 control actions. In addition, cross correlation between electrode signals will provide further information, increasing the available control sources.

These filters could operate at the following centre frequencies:

78 Hz, 94 Hz, 110 Hz, 126 Hz, 158 Hz, 222Hz, 270Hz, 318 Hz

The Boolean Notation (Table 7.1) would approximately describe the user action for:-

1.) ring finger flexion

2.) wrist flexion

3.) index finger flexion

4.) wrist extension

5.) middle finger extension

1.)Ring Finger Flexion:

78 Hz • 94 Hz • $\overline{110Hz}$ • $\overline{126Hz}$ • $\overline{158Hz}$ • $\overline{222Hz}$ • $\overline{270Hz}$ • $\overline{318Hz}$

2.)Wrist Flexion

$\overline{78Hz}$ • 94 Hz • 110 Hz • 126 Hz • 158 Hz • 222Hz • 270Hz • 318 Hz

3.)Index Finger Flexion (fast action)

78 Hz • 94 Hz • 110 Hz • 126 Hz • $\overline{158Hz}$ • $\overline{222Hz}$ • $\overline{270Hz}$ • $\overline{318Hz}$

4.)Wrist Extension

78 Hz • 94 Hz • 110 Hz • 126 Hz • 158 Hz • 222Hz • 270Hz • $\overline{318Hz}$

5.)Middle Finger Extension

78 Hz • $\overline{94Hz}$ • $\overline{110Hz}$ • 126 Hz • $\overline{158Hz}$ • $\overline{222Hz}$ • $\overline{270Hz}$ • $\overline{318Hz}$

Table 7.1 above shows the Boolean notation for each frequency 'bin' or filter. A different Boolean description is applicable to each different muscle action. This will give a different control signal from each muscle action for the purposes of prosthesis control.

These 5 actions were recorded at one site by one electrode. The first actions [1.) and 2.)] were clearly distinct and reliable. Actions 3.) 4.) 5.) were sufficiently different to be considered as useable signals. Unlike actions 1.) and 2.), the muscle source for the latter actions were not located close to the electrode site and consequently the signals were of a comparatively reduced, (<50%) amplitude.

The number of frequency bins above is large (eight) and probably only half that number (four) would suffice to be useful for channelling the detected MES to the inputs of a Neural Network/

The task will be to keep all computing time before response, to within the acceptable 300-ms.-delay range (where delay = measurement + processing + action).

It will be necessary to detect the onset of an intended MES and then quickly sample the signal using the exponential averaging process (see appendix) or a modified version. To 'overshoot' and miss the onset or transient of the signal, will record a signal of less-well defined frequency and of lower amplitude. This was a problem noticed when using the HP analyser. The HP did not allow for a user specified sampling frequency nor did it have a reliable (though operational) transient onset detector.

The basis for transient detection will require a continuous sampling process of at least 1 KHz (assuming a 450 Hz maximum bandwidth), with sampled data continuously being updated in a small memory block and retrieved for further processing when an MES (signal strength threshold) is detected. At this stage, the sampled data is passed on for digital filtering followed by presentation to a Neural Network where a decision is made as the probability of an intended user action and consequent execution of that action by the prosthesis.

7.9.2 Gender Differences

Enough differences between males/males/females were shown to conclude that training for a general Neural Network (NN) -to be applied to a class of 'all males' or 'all females'- would not produce an optimal result. For a practical application, a NN training should take place for each user. A general NN for the single electrode/single site can be used to detect the wrist/ring finger actions with good success but reliability decreases rapidly as demands for additional actions are applied. One female had developed or utilised certain muscles that can be used for an action (in preference to others that also could have been used). Consequently when comparing the amplitude peaks between the 2 females there was a significant difference between some actions regarding the site amplitudes observed, rather than the sites as such. This is a further consideration against attempting to develop a general NN program.

The number of detecting electrodes placed on the amputee increases dramatically the number, reliability and repeatability of detectable hand/finger actions.

As a demonstration of both gender similarities and as an indication of a deterministic element to the detected muscle MES, the "thumb extension" MES of all four volunteers was compared (Table 6.1). There are two widely separated muscles involved in the action (*see Figures 6.1 and 6.2*). Corresponding sites (on all four adults) show similar spectral features for the one muscle site but different spectral features for the other site.

7.9.3 Testing Using Standard Neural Nets

The choice of Neural Network Topology /software for the pattern recognition will be a Multi-Layer Perceptron (MLP)

7.9.4 Digital Filter Methods

Advantages

The selected frequency pass bands will be realised using digital methods for 2 reasons:

1). **Weight and space**: The digital filter can be practically created with a steep pass band to stop band transition region, in software, without incurring the physical components of an analogue filter. The analogue filter, at the high orders required for a sharp filter edge (greater than 10th order) would add undesirable penalties of weight and space to the prosthesis.

2). **Flexibility:** It is unlikely that a single set of optimal filter pass bands would exist for any group of amputees; due to individual differences in stump shape, surgical technique involved and residual muscle depth/mass/atrophy. With digital filters, pass bands can be adjusted very quickly and reliably. As phase is not an issue then an IIR filter could be used. With an analogue filter, the adjustments would prove very much more time consuming and less reliable regards the outcome.

Disadvantages

Of course, the penalty cost of a digital filter is in the processing time incurred and, in this respect only, the analogue filter will then be a first choice.

7.9.5 Control Algorithm (see Figure 7.5 block diagram)

When the gross signal breaches a set threshold voltage the sensor or control system triggers a response to open the hand (if it is the extensor muscles activated). Any further variations above that threshold are either ignored or used to activate another function, such as grip force variation (reduction) or grip opening velocity variation. When the gross signal drops below that threshold the actions either (a) lock into the states achieved or (b) return to a previous or resting state.

Activity at the electrode site, above a set threshold, will then produce the desired hand action and variations in levels in excess of that threshold produce velocity or force variations according to the chosen control system. Below-threshold values again produce

lock or 'return-to-state' responses. Therefore, each electrode site can produce more than one on/off function with a single further intensity variation as optional.

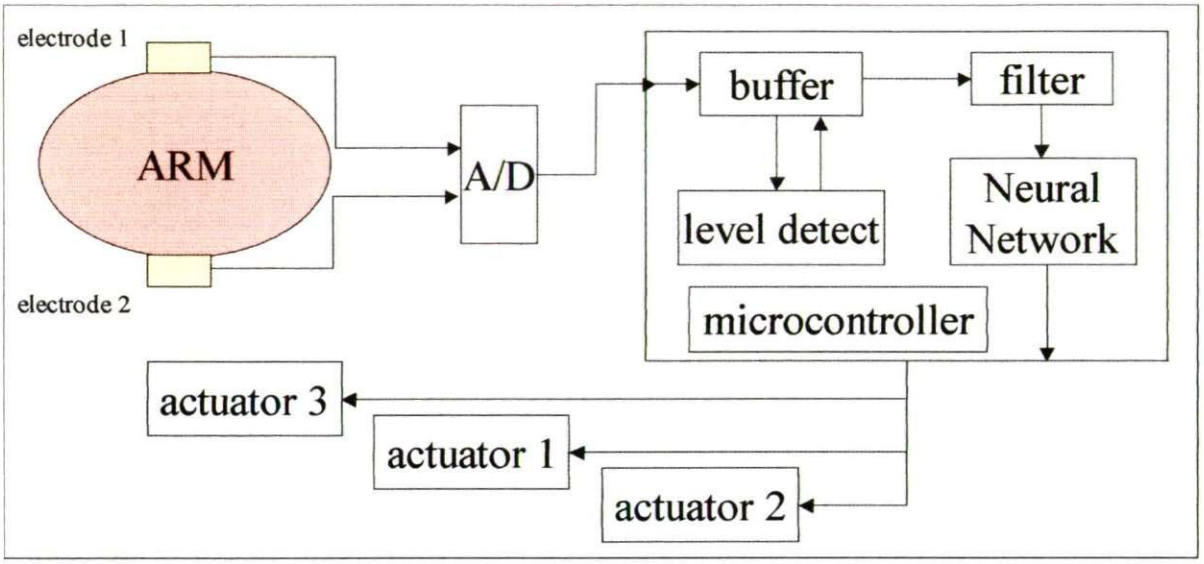


Figure 7.5: Block diagram of a two-channel electrode MES detector with microcontroller and software based filter and neural network. Controller outputs to the finger actuators.

7.9.6 Design of Controller Software

The controller software will need to consider:

- when the signal is valid,
- operate on the signal (averaging),
- filter the signal into 'bins,'
- compare with Neural Network,
- decide what action to take,
- how fast to move ,
- what force limits to apply,
- maintain position or go to next position or to return to rest position

7.10 Further Research Needed

The "Tissue Filter Function"(TFF) makes itself evident in the frequency domain analysis of which, in the past, little effort has been directed. The TFF is like a message from the MES that says; "I am a signal that has come further than the others and as a consequence have lost my high frequency components according to the distance I have travelled (*see Figure 2.18, page 71).* When two or more signal sources of sufficient strength interact at a single electrode site, this TFF shows itself as a frequency shift, between those signals that are observed. Given that: (a) the signal sources of interest are identifiable by sufficiently distinctive features at sites close to their origins), the observed shift at the combined site will occur to all signals as a function of the distance between electrode and muscle signal origin. The proposal is that the cross talk between a multiple set (4) of surface electrodes will detect these frequency-shifted signals throughout the 3 dimensional medium of an amputee upper forearm. Here the use of a "weighting factor" is proposed to represent the individual spatial distances/attenuation of these signals. To develop this requires the simultaneous use of two or more electrodes and appropriate recording equipment.

As mentioned (see Chapter 1 page 28), in Japan in 1991, Ito used a back propagation NN on the frequency domain conversion of the MES detected by a 4-electrode configuration. Ito divided the overall detected frequency bandwidth into 4 frequency band pass regions. Ito took each electrode signal through a single frequency band-pass region (filter) i.e. each electrode looked at only one portion of the MES spectrum. Ito ignored the initial transient and monitored a 2 second portion of the steady state signal for NN training data. High computational costs (2 transputers were used) and long time delays were noted. He used on-line training to try to counter the "fatigue" effects upon the signal. Recognition with the trained NN was notably high (90 %).

The use of the NN as a pattern recognition tool will substantially differ from Ito in a number of ways. Ito used the steady state and the author's use will be in the brief, transient region. Ito used one filter /signal per electrode channel. The author proposes, 3 to 4 distinct very narrow bandwidth regions on each signal channel so that the discrimination can utilise the frequency shift due to the Tissue Filter Function (TFF) and the 'weighting factor'. It is likely that the aforementioned "weighting factors" will be represented in the weighting action nodes in a Neural Network.

Research has determined that a 300 ms delay (where delay = measurement + processing + action) between user muscle action and prosthetic response is acceptable for a practical sampled data system. Delay times in excess of 300 ms. become increasingly less acceptable to the amputee. With only a few averages of the continuously sampled signal a small delay in response to the user action occurs. The research undertaken at the University of Plymouth has shown that only the transient MES is necessary for a control signal derived from a muscle action from the user (amputee). This delay will be well within a 200ms delay period. The task will be to keep all computing time before response, to within the acceptable range.

It will be necessary to detect the onset of an intended MES and then quickly sample the signal using the exponential averaging (see appendices, p.240) process (or a modified version). To miss the onset or transient of the signal, will record a signal of less-well defined frequency and of lower amplitude. This was a problem noticed when using the HP analyser. The HP did not allow for a user specified sampling frequency nor did it have a reliable (though operational) transient onset detector.

The basis for transient detection will require a continuous sampling process of at least 1 KHz (assuming a 450 Hz maximum bandwidth), with sampled data continuously being updated in a small memory block and retrieved for further processing when an MES

(signal strength threshold) is detected. At this stage, the sampled data is passed on for digital filtering followed by presentation to a Neural Network where a decision is made as the probability of an intended user action and consequent execution of that action by the prosthesis.

The use of the Liberty MYO115 research electrode made this whole research program possible. The use of adhesive type electrodes would have been very difficult and much more time consuming and arduous for the volunteers (imagine the effects of slowly moving a pair of electrodes along an arm and replacing them every five uses/ 6 inches of travel after the adhesive weakens). The use of invasive wire or needle electrodes would have been difficult in the extreme. To achieve a full mapping would have required a volunteer willing to be used as a pincushion. The development of an improved Liberty electrode, with a wider bandwidth and low noise, would be an automatic increase in number of the control actions available to any future controller using these research results. The future direction of microelectronics will inevitably reduce the size and weight of the controllers necessary for multiple action prosthetic hands. These controllers, although an important and complex design exercise are well within the scope of basic consumer manufacturing products. The power supply will be minimal to run the controller. The next real power hungry barrier will be the actual working prosthetic arm.

The ultimate solution for a lost limb would be to do as the Salamander and grow a new limb from the remains of the residual limb. This may well become a reality in the not so distant future but we are probably at least one or two decades away from that happening.. Until then, the 'really-improved' prosthesis can be developed based upon the 'mapping' work undertaken in this thesis. This next generation prosthesis will result from the development of a structural prosthesis with the actual surface of the prosthesis/ skin contact area being a thin and flexible, all-encompassing multiple-electrode grid array,

which provides a full mapping of whatever residual arm is presented. The same silicon (or similar) technology that gives us very thin and flexible photovoltaic power supplies or plastic 'smart cards' can be harnessed to create a flexible membrane grid of transistors and electrodes that input to a Programmable Logic Array (PLA) or constantly scanned by a dedicated processor that is also part of the membrane. The use of the single pick up and single site will be superseded by the vastly improved performance and versatility of the grid based multi electrode detector.

7.11 Implications for other Biosignals

Other biological signal sources may well respond favourably to the application of these signal separation techniques. The non-invasive approach of the MYO115 electrode allows the searching out of muscle regions and identification of 'hot spots', overlapping muscles, under and overactive muscles. The mobility of the MYO115 and the frequency dimension introduces an additional means for the diagnosis of muscle related diseases or disorders. Most of the existing equipment, for Myoelectrograph (MEG) and Electroencephalograph (EEG) use, is designed to analyse in the 'time domain'. All low-level skeletal/postural equilibrium muscles are in a near-constant state of use, producing signals that may well be obscuring or interfering with weaker target signals. By evaluating the surface MES in a region surrounding the target area it may be possible to 'weed out' and examine the residual signal for neuropathological and myopathological diagnostic purposes.

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CHAPTER 8: Conclusions

8.1 Summary

As stated in Chapter 1, the objectives of the research are:

- 1)-to investigate the information content of a MES.
- 2)-to study the nature of the Tissue Filter Function (TFF)
- 3)-to map and identify optimum upper limb (forearm) myoelectric sites
- 4)-to analyse the mapped data for frequency content and other unique identifiers
- 5)-to recommend the practical application of MES analysis for control purposes
- 6)-to provide a greater range of user-generated control signals

Progress has been made on objectives:

1)-to investigate the information content of a MES.

In Chapter 7, section 7.1 past research using needle electrodes to detect MUAPT's has been shown to be not appropriate as a means to describe the surface MES. The AP's are not seen at the surface as MUAPT's but as superimposed components of mixed AP's.

We only ever see a small window on the skin surface using surface electrodes. All those action potentials (AP's) have interacted with other AP's locally and en route in a way very different from that seen at any needle electrode site. The AP's are not behaving as obedient members of a stationary MUAP. The AP's strike out on their radiative path and will combine with each other (*not with other needle detected MUAPTS*), interact with the tissue (TFF), and arrive with subtle differences (depending upon the path taken) at each surface point.

An expanded model of the surface MES has been presented that includes updated knowledge of the physiology of muscles.

The MES has been shown to have ***both*** *a random and a deterministic* content. The MES can be examined as to its original frequency content i.e. bandwidth. The *random* contribution is partly a result of the superimposition of the generated motor unit (muscle and nerve fibre) AP's and partly a result of the inherent delays over time in the measurement of the 'firing rate' associated with each motor unit. The *deterministic* content is the 'emergent' property of the varying proportions of motor units and fibre types (unique to each muscle) and their associated 'firing rates'.

2)-to study the nature of the Tissue Filter Function (TFF)

The TFF has been assigned as a major contributor in previous chapters. Chapter 7 has given a value to the range of signals generated at the level of the nerve and muscle fibre (up to 1 kHz) and the TFF has to be credited with responsibility for the attenuation of these frequencies en route to the surface. Without the TFF intervention the MES would be extended from 300 to 1000 Hz. and be composed of significant components of the superimposed muscle-fibre AP's plus the higher control frequencies of the nerve fibres.

3)-to map and identify optimum upper limb (forearm) myoelectric sites

Chapter 6 applied a Standard deviation analysis to the mapped grid pattern for all 20 muscle-actions. This makes it possible to select the optimum site for electrode placement. The analysis in Chapter 7, sections 7.1 to (7.8 inclusive), demonstrates an underlying determinism in MES generation. Along with training, sufficient malleability in the nervous system exists to enhance the selected sites over time.

4)-to analyse the mapped data for frequency content and other unique identifiers

The mapping technique of Chapter 5 contributed the bulk of information and Chapter 6 analysed those results for frequency content and unique identifiers. More analysis of those mapped results (outside of the available research time) would yield more identifiable features for the individual volunteers involved. The model developed in Chapter 7 section 7.2 suggests a possibility of searching the mapped data for fibre type contributions would yield an identifying character for each muscle. The author considers it better to approach the fibre type research with a fresh-targeted approach (including needle type electrodes). It would be necessary to carry out simultaneous signal analysis on both the neural pathway (at muscle insertion points) and subsequent muscle firing responses. The neural pathway detection, by necessity, would be an invasive technique and the muscle response would be a surface detection method. The comparison of surface MES to site-generated signals would allow fibre composition to be estimated with a high degree of certainty.

5)-to recommend the practical application of MES analysis for control purposes

Chapter 4 offered the first definite improvements in control signal detection with the wrist and ring finger actions. This has been extended in Chapter 7, table 7.1, with 3 additional detected muscle actions. The results of mapping in Chapters 5 and 6 offered further features detected and a means of selecting for optimal electrode site location. Chapter 7 outlines how Neural Networks can be utilised to interact with the values of frequency bins (through which the amputee signal is passed).

6)-to provide a greater range of user-generated control signals

Signal spectra can direct the output activity of a multifunctional prosthesis. Signal strength (magnitude) is easily utilizable as an additional control function of either prosthesis finger-

closure speed or applied gripping power. The limitations of current prosthetic arm technology is emphasised. A foundation for further research is discussed.

8.2 Contributions to Knowledge

1): This thesis presents **a coherent set of design criteria** for the construction and control of a myoelectric upper-limb prosthesis. These criteria are drawn from the prosthetic community including:

- **a) user requirements** both structural, functional and aesthetic user requirements with a time limit on system response i.e. < 500 ms. (all too often overlooked by research groups focused on signal analysis). Looking at signals of 2 or 5 or 20 seconds duration is only beneficial if the analysis yields information for control purposes that can equally be extracted in <300 ms.
- **b)** A **novel movement geometry** and set of 20 commands for the arm to follow.
- **c)** In *Chapter 1, Figures 2.6 and 2.7 (pages 59-60)* are **the author's original compilation** of the muscles related to the 20 commands presented in a comprehensible way, for the use of the prosthetic design engineer

2): **Arm Mapping** results have:

- **a)** revealed the overall interaction of individual muscle actions describes the combined effect. This demonstrates a deterministic nature in the observed results. The differences that do exist are largely due to the inclusion of synergistic muscles as they stabilize a joint.
- **b)** established the need for due care and attention with electrode positioning on the arm for optimising any frequency analysis techniques (unlike the more acceptable rough and ready placement with RMS/smoothing time-domain analysis)

- **c)** revealed the misleading conclusions leading to 'MES stochasticity' by past researchers who have assumed a more casual method of electrode placement for signal extraction. This has led to the lack of interest in exploring the 'Tissue Filter Function' (TFF) and the positioning of the sites of nerve to muscle fibre 'innervation zones'. The use of these latter two factors is important in understanding the 'MES hot spots' shown on the mapping results.
- **d)** given options and a direction to signal acquisition methods with:
  - a single-site/single electrode approach will require the frequency analysis breakdown of the site generated MES into multiple control signals
  - additional electrode sites will further expand the range and reliability of control signals. This is exemplified in **the suggested novel use** of 3 to 4 control-site, surface electrodes with each control site signal fed into its own narrow-band filter fed into a common Neural Network and decoded for control signals. The control sites would be placed using the, grid-based, best-site Standard Deviation assessment method.
  - the authors suggested use of **grid-based, novel multiple electrode arrays** and assure a reliable, full range of control signals available for the following two approaches
    i. an RMS signal value assessed over the full grid including the antagonist/synergistic muscle inputs. These grid values will feed into a Neural Network.
    ii. a frequency analysis signal value assessed over the full grid including the antagonistic/synergistic muscle inputs. These grid values will feed into a Neural Network.

- **e)** The use of a brief user-generated signal that can be referred to as the 'signal-transient' has shown the user MES command signal can be generated within the time constraints for user acceptance. This research confirms the University of New Brunswick findings of useful signal information found in the 'signal transient' and extends the utility of those findings. The signal transient is further examined in the' Improved model of the MES' by the author.

3.): Improved MES Recruitment Model and surface detected MES model: an updated model of the surface MES is developed from anatomical, physiological and neuro/muscular research sources. The model is presented on a flowchart of recruitment/decruitment activity. This model draws heavily on the involvement of muscle fibre types in recruitment. The model draws upon all contributions of past MES research, observed phenomena, and recent physiological and anatomical advances. The model details have been scattered throughout the various fields but not previously presented in a unified form. This involvement of fibre-types is in full agreement with all past research material and gives a solid basis for the assertion of deterministic behaviour in surface detected MES, as it is accepted knowledge of the varying fibre-type composition of athletes muscles according to their performance demands.

e.g. long distance= endurance =slow fibres dominate

short dash (burst activity) = fast fatigue = fast fibres dominate

Because of the previous disorder even recent researchers have spoken tentatively and with qualifications of their conclusions, citing seemingly unresolved past models.

4): Reinterpretation of the applicability of the J. Bamajian/ C. De Luca MUAPT model of the surface detected MES:

The MUAPT model has been assumed and accepted (by default) by researchers as a model for the surface MES. The author has shown this to be over simplified and misleading. The MUAPT is only a local phenomenon defined by the detecting needle electrode while the surface detected MES is time slice of individual fibre AP's (not MUAPTS). The artificial nature of the MUAPT is defined by those AP's that have a common (+/- 10% to 25%) firing rate as detected at that (needle) point. The decrement function (losses) of the AP is such that the signal loses 75 % of its peak-to-peak value if the signal is moved by 100 micrometers. (De Luca page 40 'Muscles Alive'). As the motor unit can extend over regions of diameter from 5 mm. to 20 mm. and up to 30 different motor units may exist within that smaller region the MUAPT can truly be seen of limited use (except to investigate myopathies). There are many papers written describing how to decompose the needle signal into its MUAP entities usually gleaned from, at best, 10 to 20 members per MUAP. As the surface MES is up to 500 Hz and the needle electrodes see up to 2 KHz, then a lot of summation is going on unseen/unknown. The Bamajian/ De Luca MUAPT model of the surface MES has led to many researchers trying to shoehorn their results to fit the MUAPT model with consequent lost momentum in their research endeavours.

5): Inclusion of Nerve Impulse contribution to the MES: The contribution of the nerve impulse signal has not been included in the MES in the past despite its similar magnitude and proximity to the muscle fibre signal. It has been the focus of past researchers, on extracting a group of MUAP's (using needle electrodes), to exclude as noise these higher frequency (up to 1kHz) signals or include their superimposition without

knowing their origin. The nerve fibres produce AP's of similar magnitude at the demyelinated ' 'Nodes of Ranvier' along the nerve fibre.

6): the author suggests the outcome of the spectral research/grid mapping lends support to the suitability of the MES to interface with a Neural Network for control purposes.

8.3 Research Links

The research at the University of Plymouth was illuminated by the old computer adage "Rubbish in, Rubbish out". It will be of no value to have designed an all singing and dancing prosthesis that can move in mimicry of the human hand and not be able to drive it effectively due to a shortage of MES derived control signals. That barrier is now lifted considerably and the opportunity exists now to achieve that mimicry. The last remaining barrier then will be to reduce the operating weight of such a complex articulating hand. Existing complex hands are driven by individual motor/gearbox mechanisms. Each finger requires a minimum of one motor/gearbox drive per finger. These drives are power hungry and far and above the most power hungry element in any prosthesis. Although the development of improved battery supplies will lengthen time between battery changes for the prosthesis user, the weight issue may well be a limiting factor in the take-up and take-off of the improved controller. What is needed is a radically different form of drive actuator that operates more closely in action to the human muscle /tendon drive system. What is needed is an artificial muscle that can be coerced to lengthen and shorten in response to an applied electrical control signal. Research has been going on in this field for many years and the advances have been slow, but may soon be able to offer prosthetics that final piece of the' bionic' jigsaw.

LIST OF ABBREVIATIONS AND DEFINITIONS

AGONIST MUSCLE: the prime mover muscle that initiates a desired contraction

ANTAGONIST MUSCLE: a muscle that actively provides a **negative** contribution to a net torque around a joint (e.g. an extensor may varyingly relax to assist the net torque (around a joint) action of an excited flexor)
AEROBIC CAPACITY: Fibre capacity to do work in short bursts using oxygen as a fuel.

ANAEROBIC CAPACITY: Fibre capacity to do work in short bursts in the absence of oxygen as a fuel.
AVERAGE FIRING RATE: Represents the reciprocal value of the average IPI

BIPOLAR ELECTRODE: One that consists of two detection surfaces.

COSMESIS: cosmetic appearance of prosthesis. Usually desired as most closely approximating a natural limb

DECOMPOSITION: The analytic process whereby individual MUAP's are extracted from the electromyographic signal. This usually undertaken by invasive techniques close to the site of the motor units.

(EMG) ELECTROMYOGRAPHIC SIGNAL: The name given to the total signal detected by an electrode. It is the algebraic summation of all MUAPT's from all active motor units within the pick-up area of the electrode.

INSTANTANEOUS FIRING RATE: Represents the reciprocal value of the IPI

(IPI) INTERPULSE INTERVAL: The time between adjacent discharges of a motor unit. It is a semi random quantity.

ISOMETRIC CONTRACTION: A muscle contraction during which the length of the contracting muscle remains constant or there is a minimal shortening. Tension on the muscle increases, pulling on another structure, but there is no movement of that structure produced.

ISOTONIC (ANISOMETRIC) CONTRACTION: A muscle contraction in which tension remains constant but the muscle shortens and pulls on another structure to produce movement

MYOELECTRIC: from the Latin Myo; as in muscle. The electrical potential, as detected on the skin surface, generated by underlying muscle activity

(MES) MYOELECTRIC SIGNAL: An alternative nomenclature for the electromyographic signal (EMG).

(MAP): (MUSCLE-FIBRE ACTION POTENTIAL OR MOTOR ACTION POTENTIAL
The name given to the detected waveform resulting from the depolarisation wave as it propagates in both directions along each muscle fibre from its motor end plate.

(MU) MOTOR UNIT: The term used to describe the single smallest controllable muscular unit. The motor unit consists of a single alpha-motor neuron, its neuromuscular junction and the muscle fibres it innervates (as few as 3, as many as 2000).

(MUAP) MOTOR UNIT ACTION POTENTIAL: The name given to the detected waveform consisting of the spatiotemporal summation of individual muscle fibre action potentials originating from muscle fibres in the vicinity of a given electrode or electrode pair.

(MUAPT) MOTOR UNIT ACTION POTENTIAL TRAIN: The name given to a repetitive sequence of MUAP's from a given motor unit.

PHASE: In electromyography, phase refers to the net excursion of the ***amplitude*** of a signal in either the ***positive or negative*** direction. This differs from the electronics definition where phase refers to the ***time*** difference between two waveforms of the same frequency.

SHAPE: The characteristics of a signal that remains unaltered with linear scaling in either the amplitude or time domains. An example of such characteristics is the phases of an action potential.
SYNERGIST MUSCLE: a muscle that actively provides an **additive** contribution (to the agonist muscle) to a particular contraction function (net torque around a joint)

TWITCH RESPONSE (CONTRACTION): is the rapid jerky response of the muscle fibre to a single stimulus

TISSUE FILTER FUNCTION (TFF): The capacitive reactance (Xc) of the tissues (skin, fat, tendons, vascular pathways, etc.) and its attenuating effect on the higher frequencies of the MES. The attenuating effect is that of a 'low-pass filter', with lower frequencies passed and higher frequencies attenuated.

UNIPOLAR ELECTRODE: electrode set up that consists of only one detection surface.

WAVEFORM: The term that describes all aspects of the excursion of the potential, voltage, or current associated with a signal as a function of time. It incorporates all the notions of shape, amplitude, and time duration.

Anatomical Position and Anatomical Names

When in the anatomical position, the subject stands erect *facing the observer*, the upper extremities are placed at the sides, and the *palms* of the hand are turned forward.

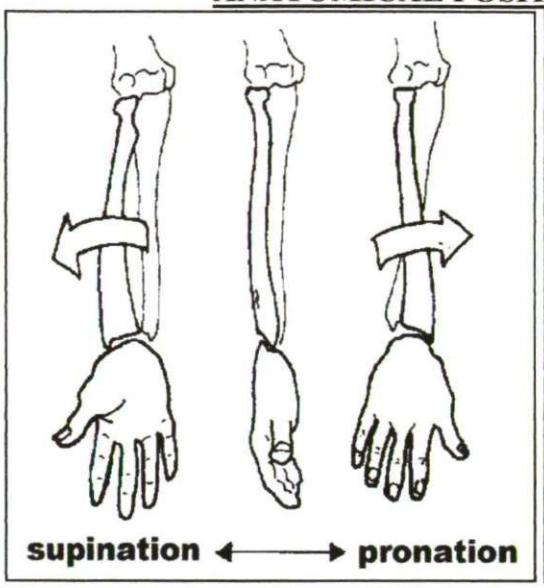
Directional Terms

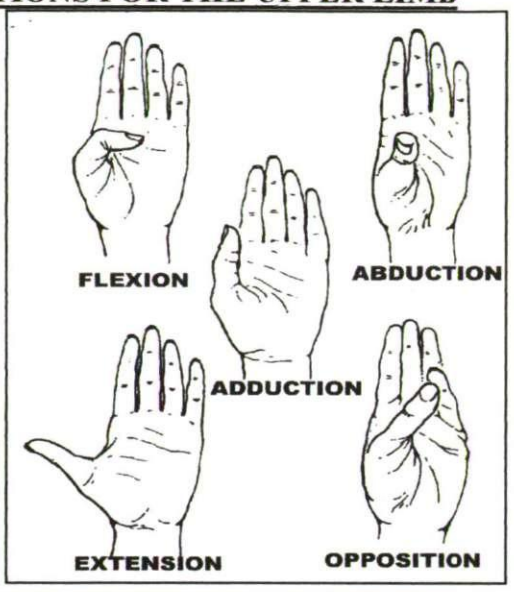
Adduction: movement of a bone toward the midline
Abduction: movement of a bone away from the midline
Distal: farther from the attachment of an extremity to the trunk or a structure;
farther from the point of origin
Proximal: nearer to the attachment of an *extremity*, to the trunk or a structure;
nearer to the point of origin
Superficial: toward or on the surface of the body
Superficialis: closer to surface
Deep: away from the surface of the body
Profundus: deep
Pronation: a movement of the flexed forearm
in which the palm of the hand is turned down (posteriorly) (inferior)
Supination: a movement of the flexed forearm
in which the palm of the hand is turned up (anteriorly) (superior)
Flexion: an decrease in the angle between the the anterior surfaces of articulating bones
Extension: an increase in the angle between the the anterior surfaces of articulating bones
Hyperextension: continuation of extension beyond the anatomical position
(see definition above of 'anatomical position')
Note; although the term 'hyperextension' should be technically used for accuracy in describing the flexion actions involved in this research, it is often in practise abbreviated to simply 'extension' and is widespread in use on the area of prosthetics.
Posterior (dorsal) view: nearer to or at the back of the body, e.g. back of hand
Anterior (ventral) view: nearer to or at the front of the body, front (palm) of hand
Lateral View: further from the midline of the body
Medial View: nearer to the midline of the body
Tendon: a cord of connective tissue that attaches the muscle to bone
Muscle Names:

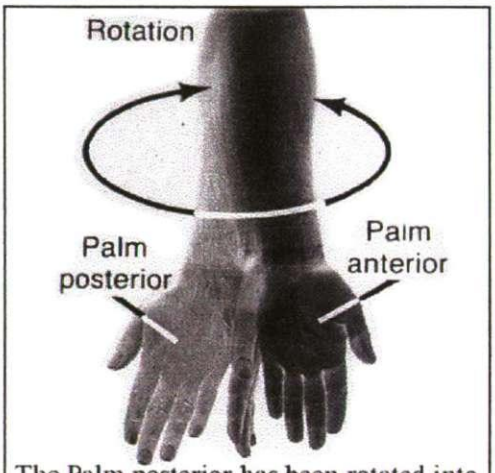
'maximus' : means largest 'Minimus'; means smallest
'Longus': means long 'brevis': means short
'Biceps' means two origins 'Triceps' means three origins Quadriceps means four

ulnarus: of the ulna
radialis: of the radius
palma: of the palm
carpus: of the wrist
indicis: of the index
digit: of the finger
pollicis: of the thumb

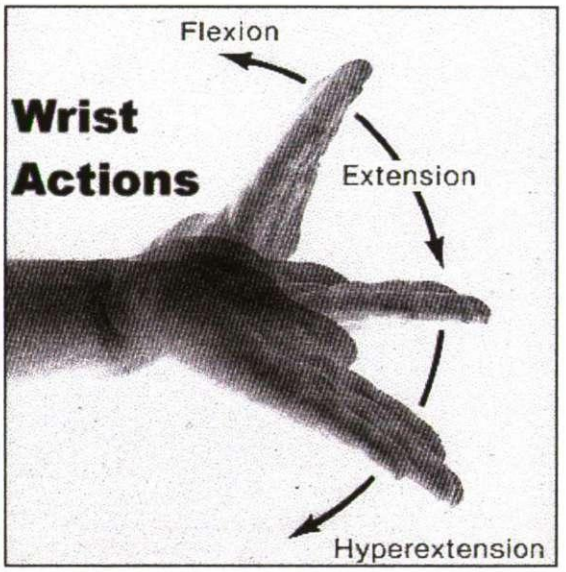
ANATOMICAL POSITIONS FOR THE UPPER LIMB

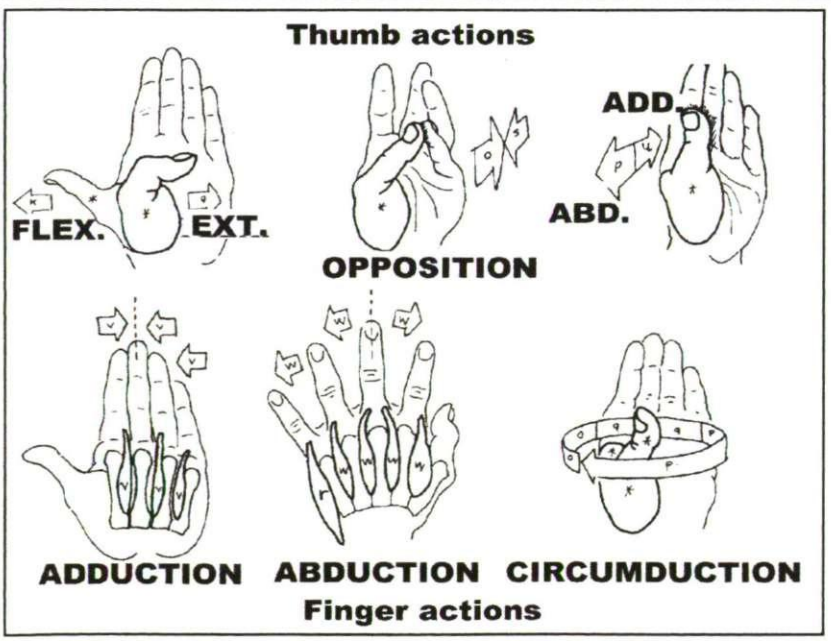




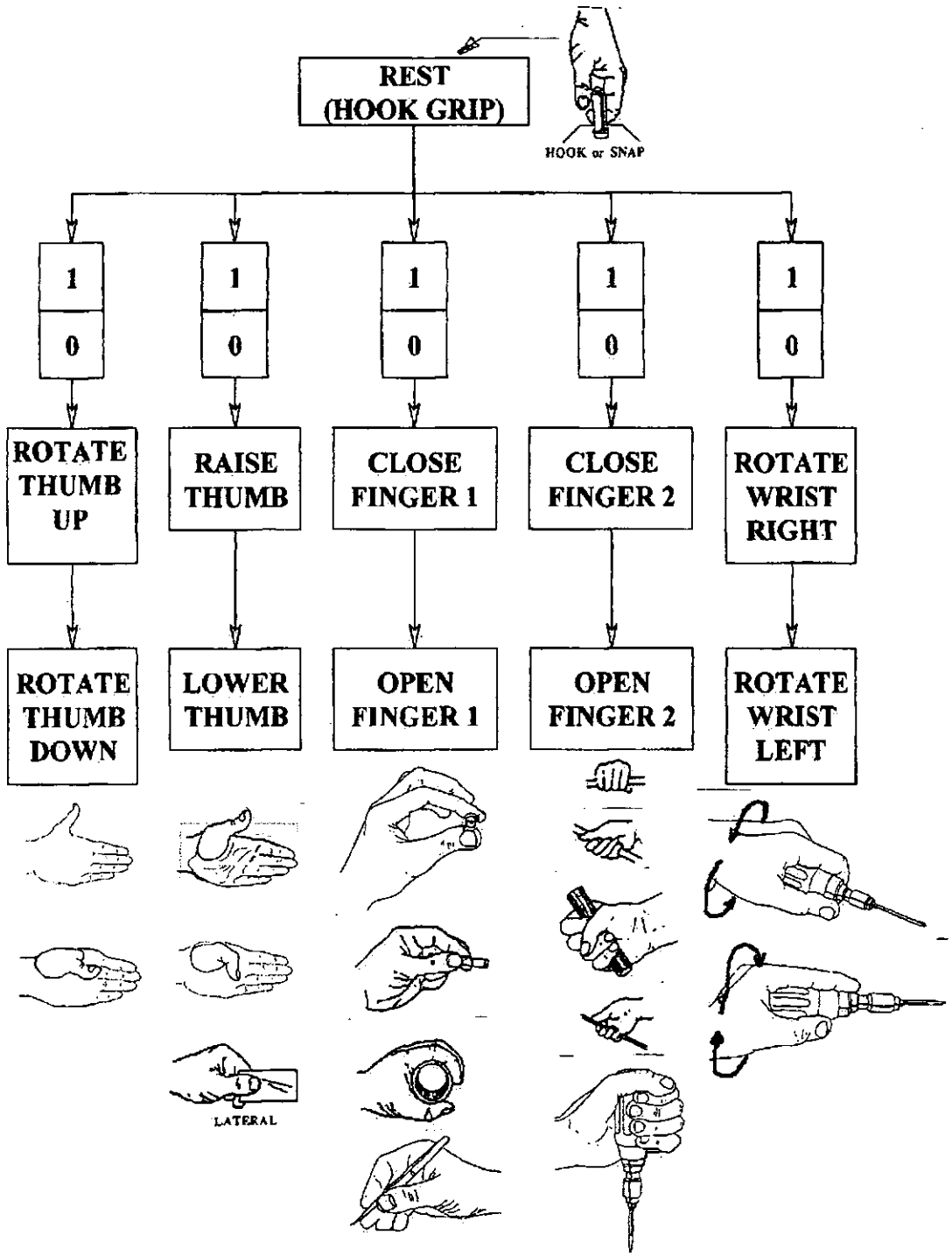


The Palm posterior has been rotated into the supination position. The Palm anterior rotated into the pronation position.

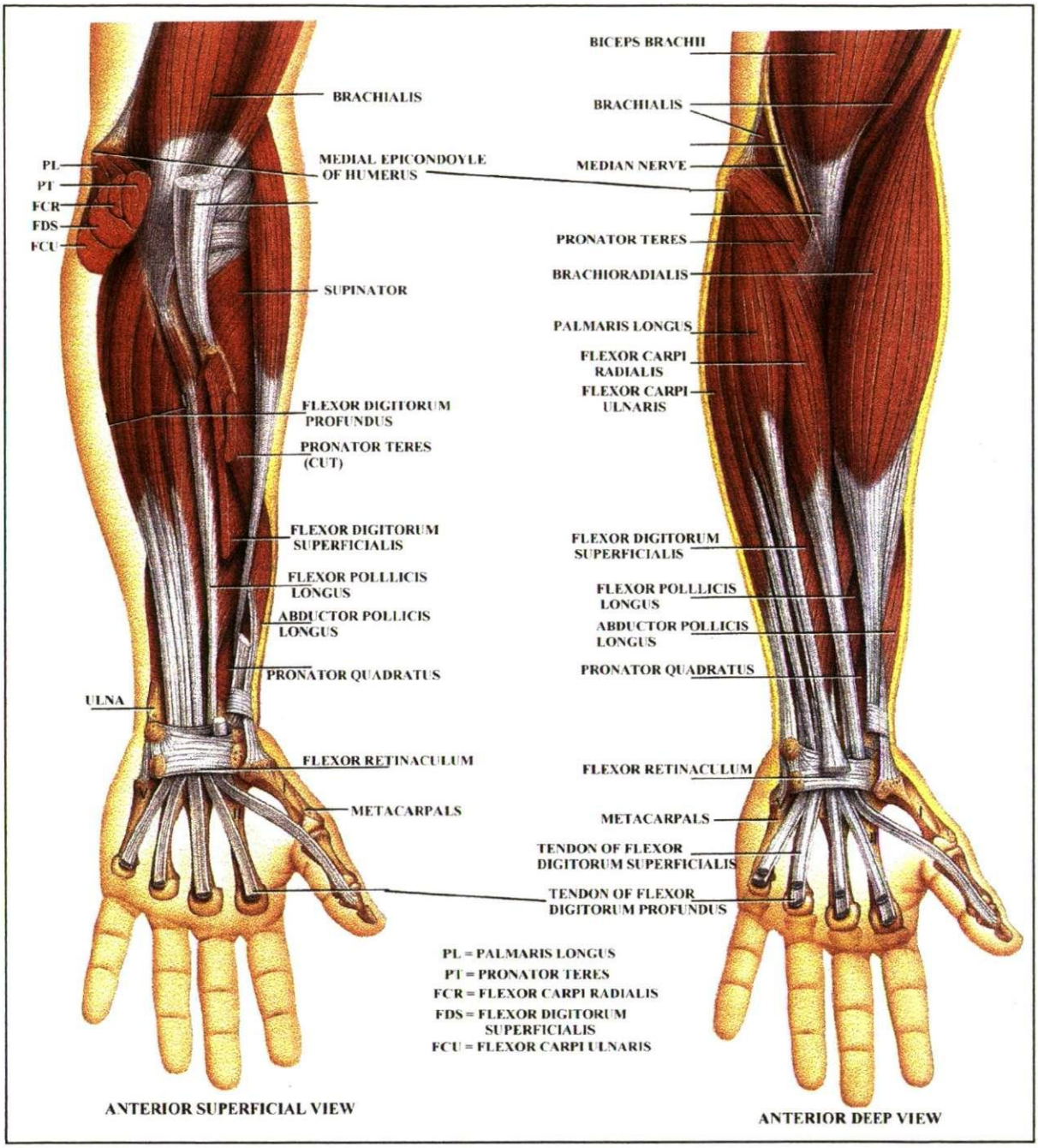




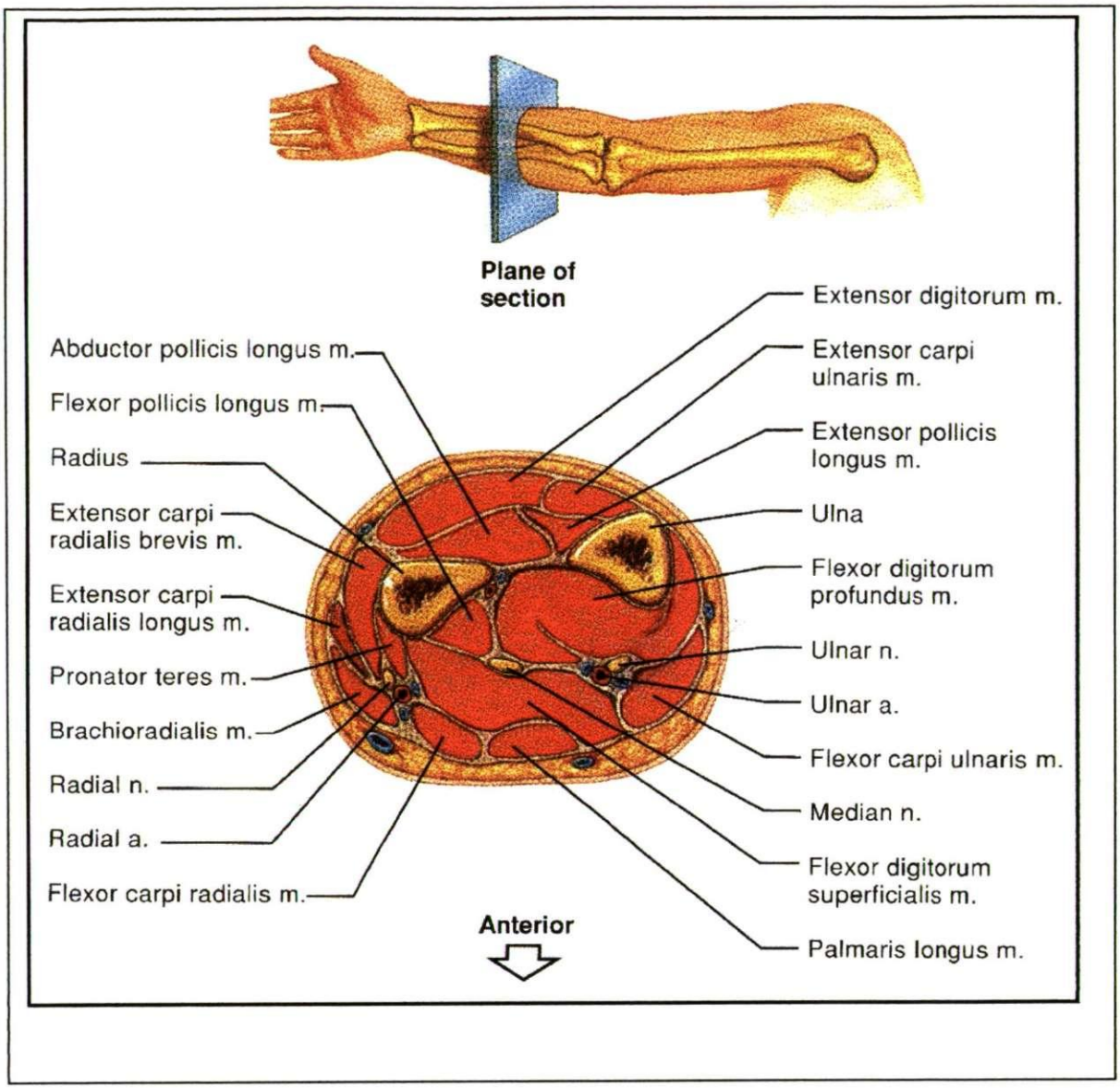
GRASP PATTERNS



Conversion of thumb and finger positions into variable grasp patterns represented by a coded 5 digit state



Anterior view of the muscles of the forearm used in wrist, hand and digit action.
View (a). shows the deeper muscles, while
View (b) shows the overlying superficial muscles.
Adapted from 'Principles of Anatomy and Physiology' by Tortora and Grabowski, Wiley and Sons 9th Edition, 2000. ISBN o-471-36692-7



Cross-section of the mid forearm showing the overlapping of the muscles within the muscle compartments.
Adapted from 'Hole's Human anatomy and Physiology', McGraw Hill 1999 page 316, ISBN 0-697-34193-3.

AVERAGING WITH THE HP3566A/3567A

PEAK HOLD AVERAGING : With peak hold the analyzer takes data until it reaches the specified number of averages. The analyzer compares each frequency line in the measured frequency span with the corresponding frequency line from the previous data. Only the largest value for each frequency is saved.
PEAK CONTINUOUS: Same as peak hold averaging except that the analyzer takes data continuously (until told to stop).
STABLE AVERAGING: weights old and new data records equally to yield the arithmetic mean for the number of averages selected The measurement stops after the selected number of averages has been calculated. This is the most common averaging type.
EXPONENTIAL AVERAGING: Unlike stable averaging, exponential averaging weights new data more than old data.This is useful for tracking data that changes over time. The number of averages you select determines the weighting of old versus new data, not the total number of averages calculated. Measurement is continuous until paused or aborted.
The analyzer sets the number of averages chosen to the nearest power of 2 that is a closest value (to the chosen number of averages).
To calculate the exponential average the analyser uses the following formula:-

$$\frac{1}{N} \times New + \frac{N-1}{N} \times Old$$

where: N is a weighting factor (number of averages).
When starting an exponential average, the analyzer sets N equal to 1 for the first analysis, and so on until N equals the number of averages you specified.
Example: If number of averages selected = 32, the exp. average would be:-

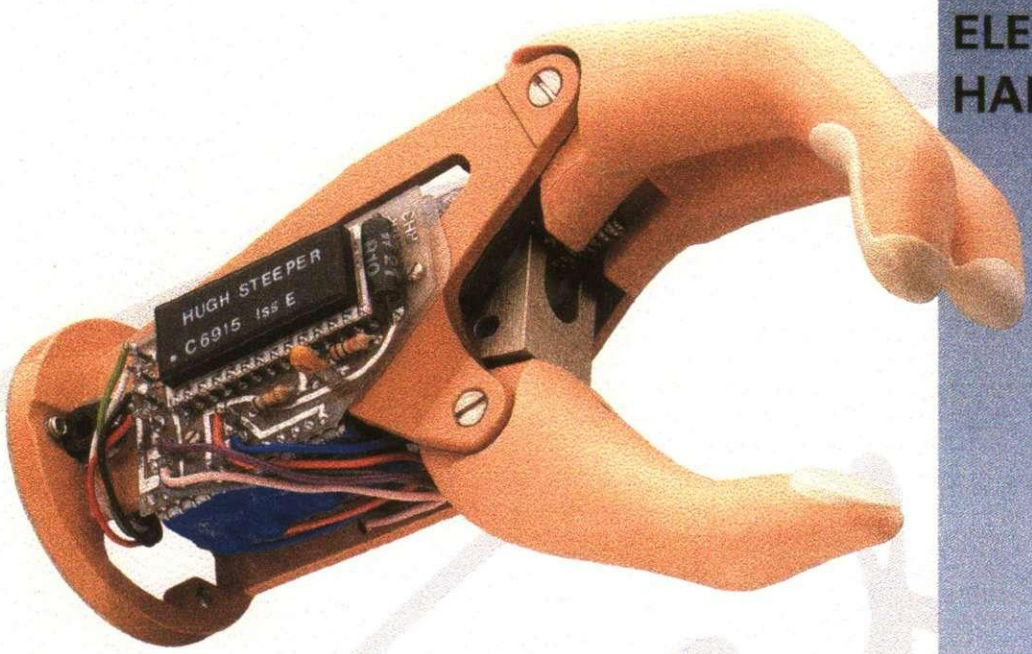
$$\frac{1}{32} \times New + \frac{31}{32} \times Old$$

Thus as N increases the influence of the Newest data sample value decreases and the influence of the older sample dominates the results (increases).
If number of averages selected = 4,the exp. average would be:-

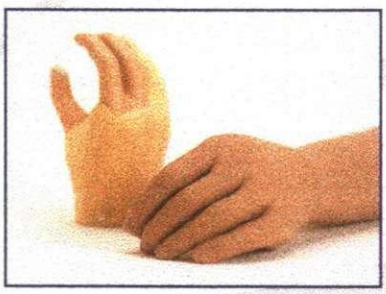
$$\frac{1}{4} \times New + \frac{3}{4} \times Old$$

Thus as N is decreased, the newest (most recent) data sample dominates the results.

THE STEEPER MYO ELECTRIC HAND



The Steeper Myo hand offers the user ultimate electric control in a lightweight hand. Weighing from just 231g, the hand provides a fast and compliant grip combined with reliable electronics housed within a foam cosmesis.



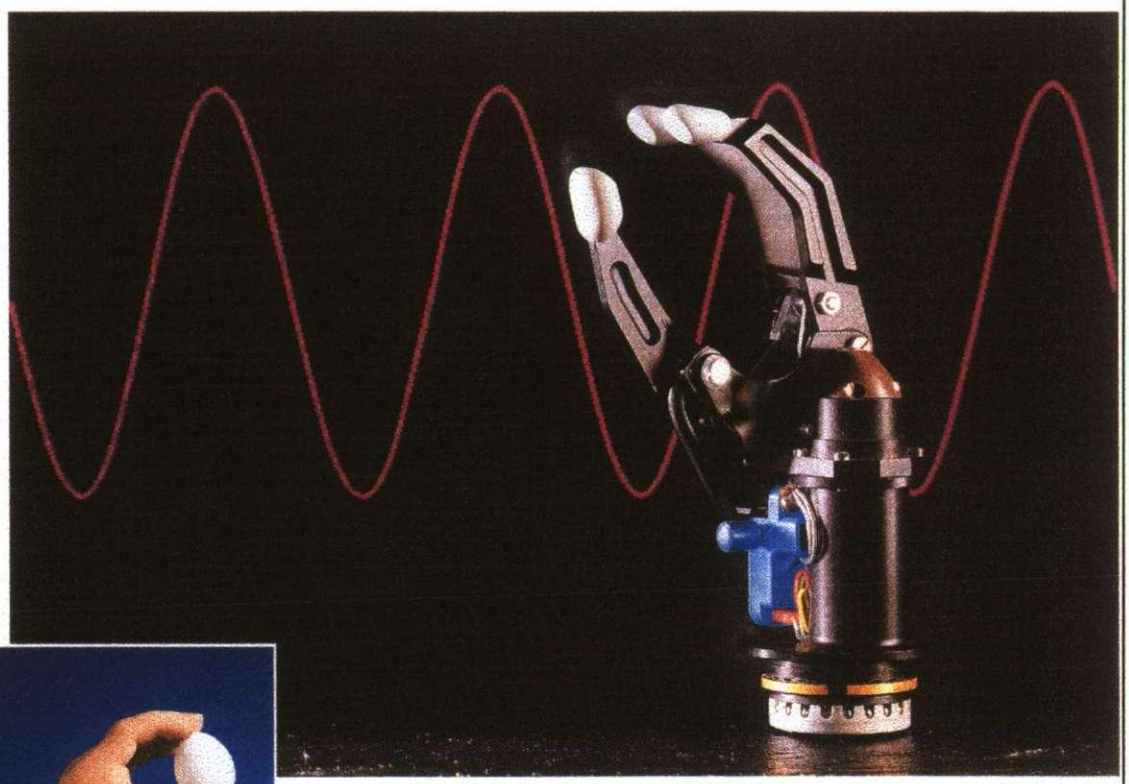
A choice of Proportional or Threshold control can be supplied to cater to the needs of most users. Available in a range of 5 sizes, the hands may be fitted with either PVC or silicone cosmetic gloves to complete the cosmesis.

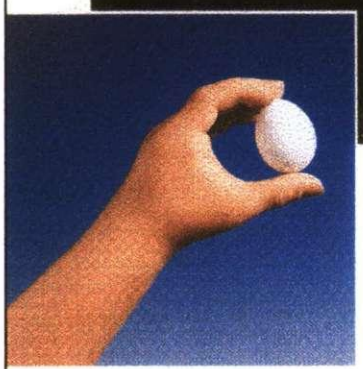
The Steeper Group of Companies

The **Steeper** model: The above year 2000 prosthetic hand is representative of the standard technology that has hardly changed since the 'Vaduz Hand' of the 1960's

The new Otto Bock System Electric Hand.

With proportional Dynamic Mode Control.





*The System Electric Hand **with yellow anodized finish** will be available from September 1994.*

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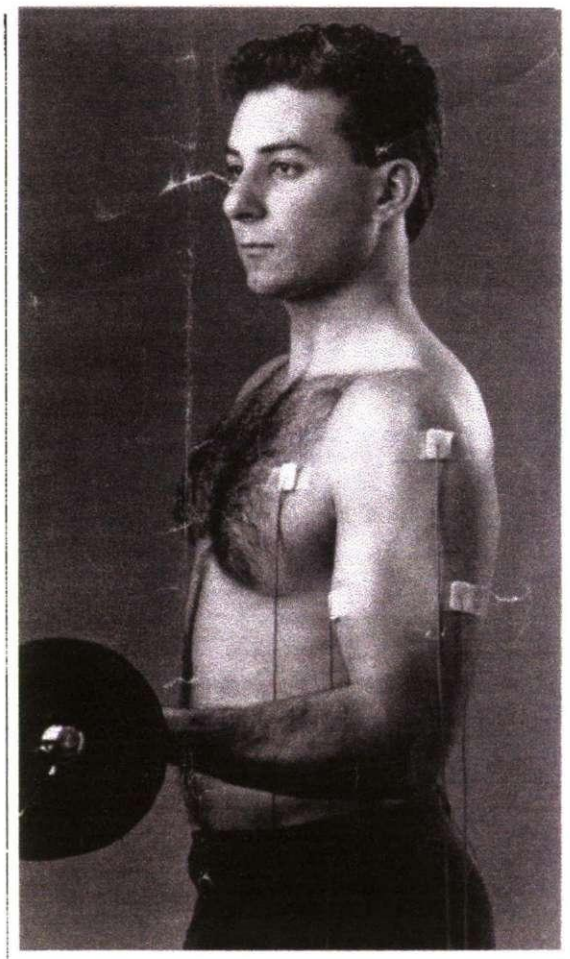
Product Bulletin

EMG Research Electrodes



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The MYO115 uses a bipolar, differential amplifier to provide myoelectric signals in the same form as they appear on the skin. The common-mode rejection ratio (CMRR) is greater than 90dB, and the input impedance exceeds $10^{14}\Omega$. Power consumption averages only 6mW, and the electrode is protected from electrostatic discharge (ESD) up to 2,000V. We will customize the MYO115's gain settings to your specifications at no extra charge. If you're not sure what the optimal gain setting is, we can offer technical assistance in determining the proper level. In addition, our staff can assist you in selecting the appropriate circuitry or power supply for your intended use.

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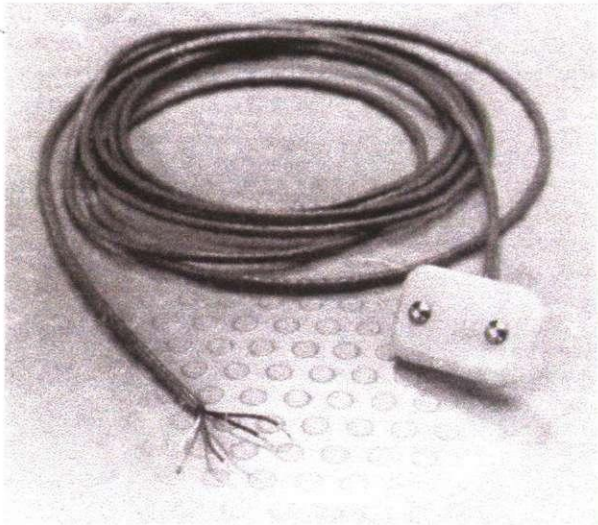

MYO 115 – EMG Research Electrode
White Wire: Signal Output
Green Wire: Ground or Common
Black Wire: Supply (–)
Red Wire: Supply (+)

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Supply Rejection	>70dB
Power Consumption	6mW (avg.)
Input Protection	ESD ≤2,000V
Input Impedance	$>10^{14}\Omega$
Input CMRR	>90dB
Input Range	0.5 to 1,500 µV
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13	KYBERD, P. J. CHAPPELL, P.H. NIGHTINGALE, J.M.	"Sensory Control Of A Multifunction Hand Prosthesis." Biosensors 3, 347-357, 1987-1988.
14	KYBERD, P.J. CHAPPELL, P.H..	"Characterization Of An Optical And Acoustic Touch And Slip Sensor For Autonomous Manipulation." Meas. Sci. Technol. Vol. 969-975, 17-23, 1992.
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16	NIGHTINGALE, J.M.	"Microprocessor control of an Artificial Arm." Jnl. of Microcomp. Apps. 8, 167-173, 1985.
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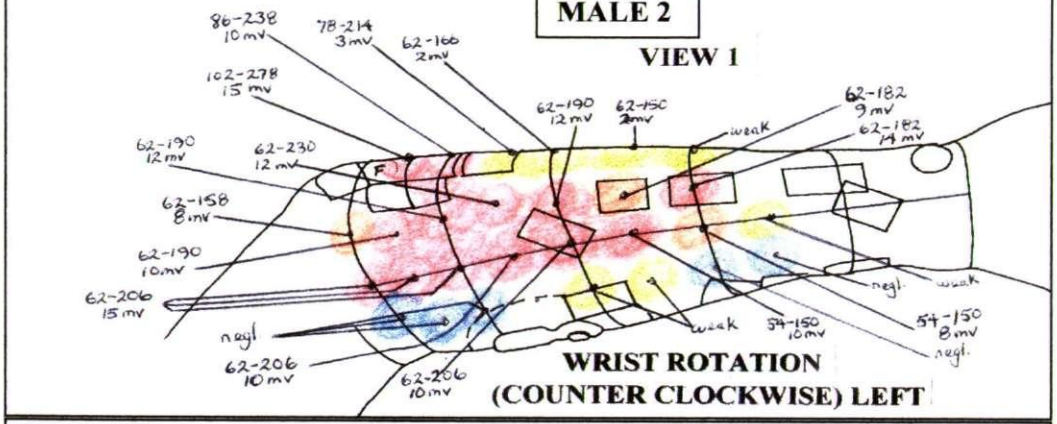
SUPERIOR VIEW OF PRONATED FOREARM

MALE 2

VIEW 1

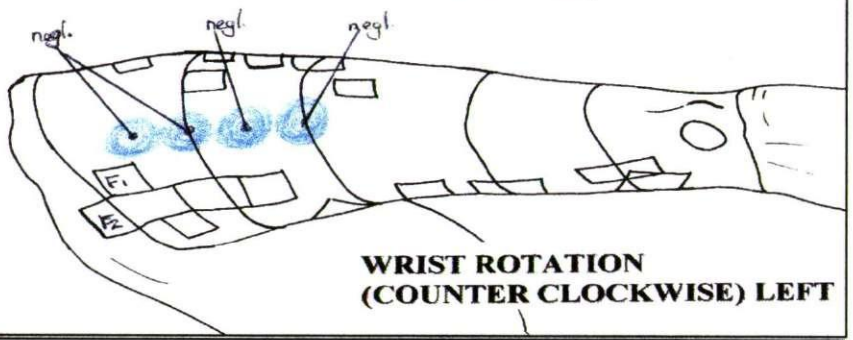


WRIST ROTATION
(COUNTER CLOCKWISE) LEFT

1

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 2 VIEW 4



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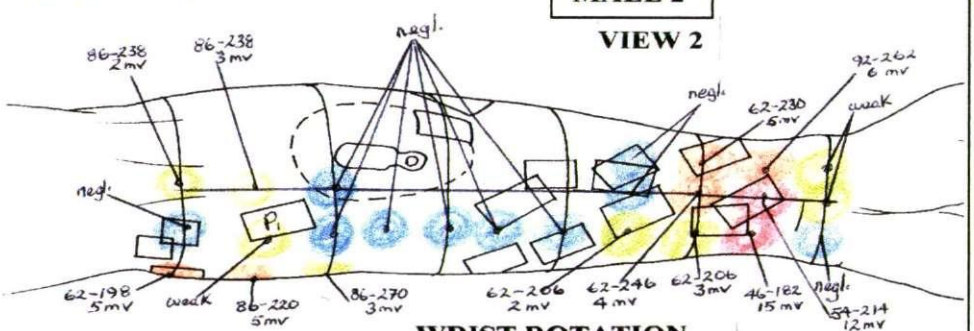
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 2

VIEW 2



WRIST ROTATION
(CLOCKWISE) RIGHT

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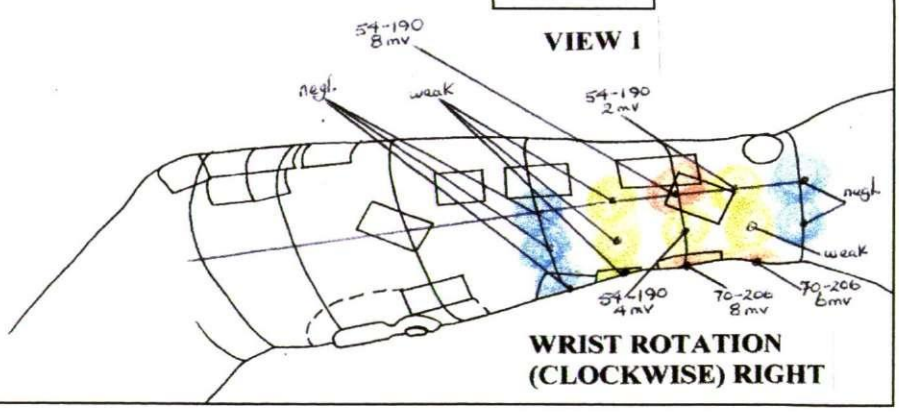
SUPERIOR VIEW OF PRONATED FOREARM

MALE 2

VIEW 1



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(CLOCKWISE) RIGHT

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SUPERIOR VIEW OF PRONATED FOREARM

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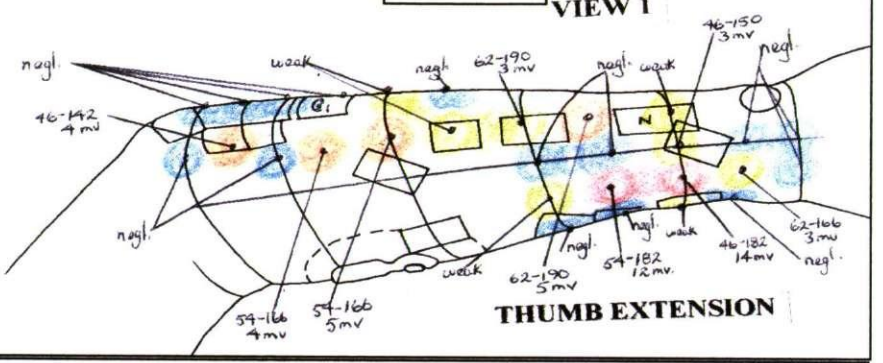

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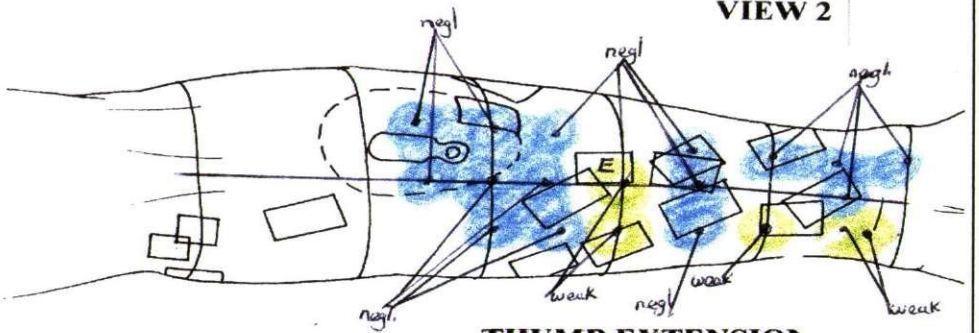
SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

MALE 2 **VIEW 2**



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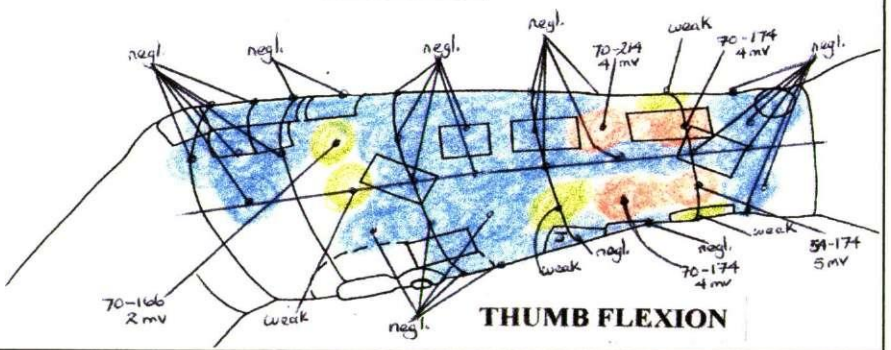
SUPERIOR VIEW OF PRONATED FOREARM

MALE 2 **VIEW 1**



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SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

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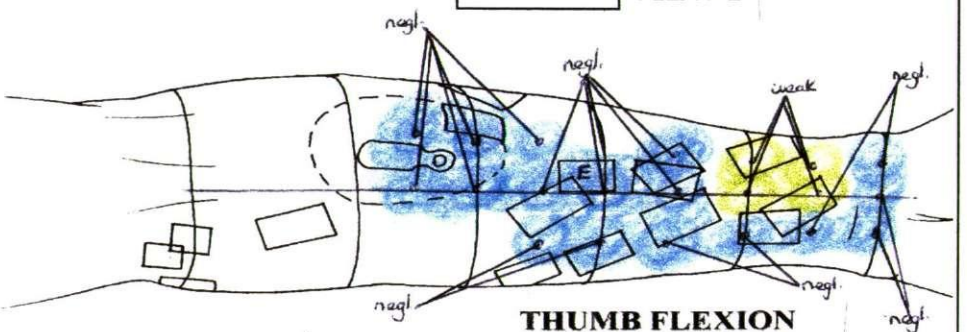

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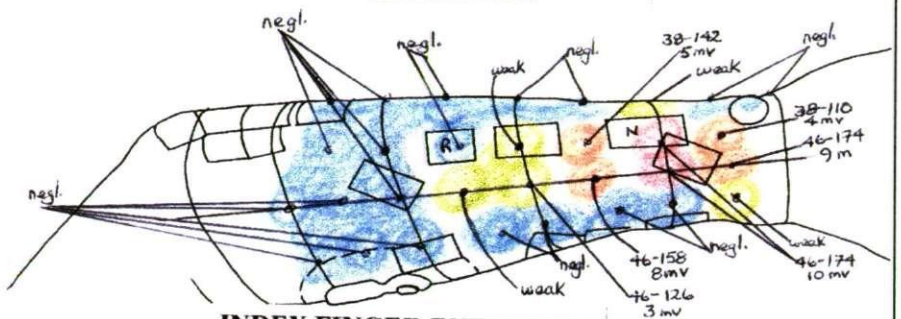
SUPERIOR VIEW OF PRONATED FOREARM

MALE 2 VIEW 1



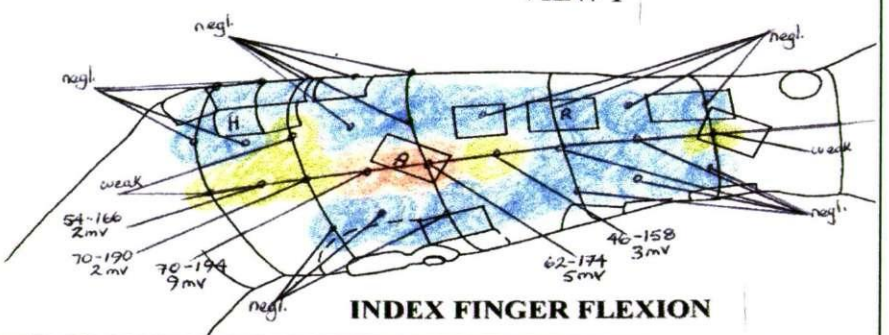
INDEX FINGER EXTENSION

9

SUPERIOR VIEW OF PRONATED FOREARM

MALE 2

VIEW 1



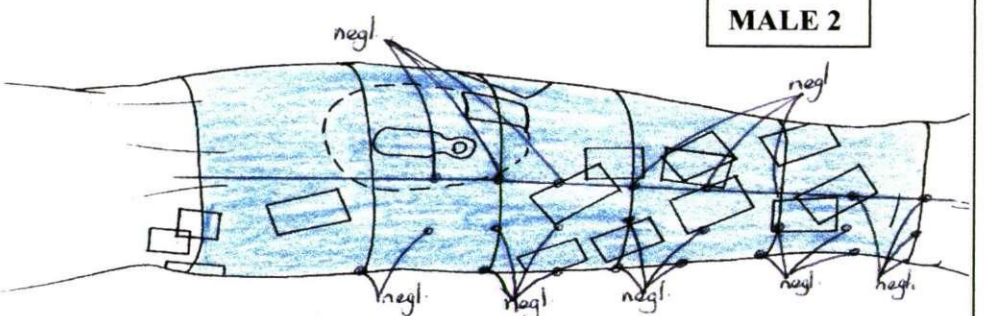
INDEX FINGER FLEXION

10

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

VIEW 2

MALE 2



INDEX FINGER FLEXION

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SUPERIOR VIEW OF PRONATED FOREARM

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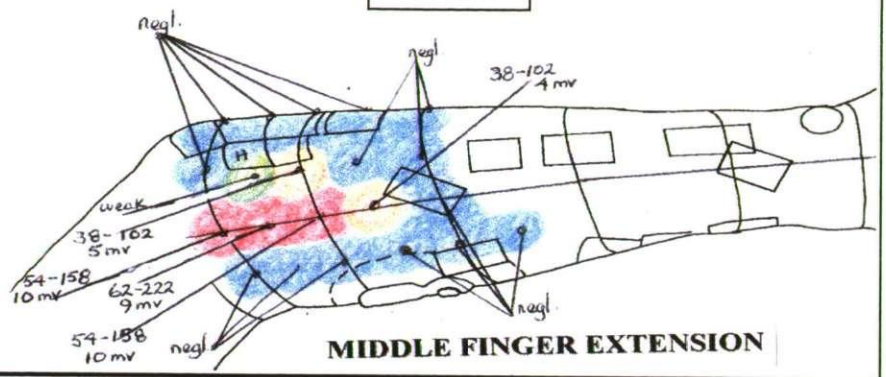
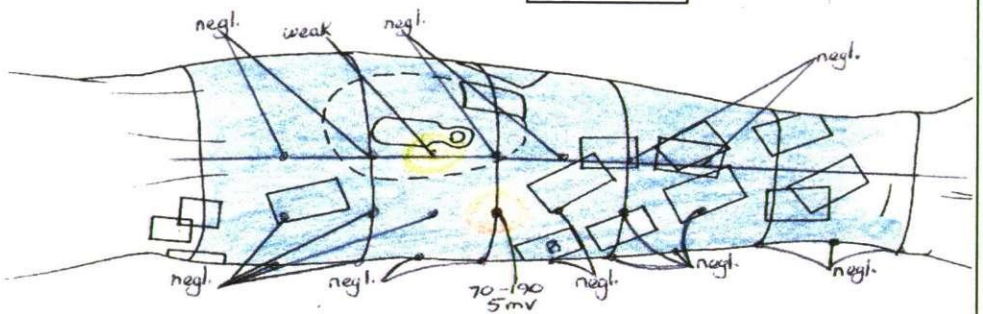


MIDDLE FINGER EXTENSION

13

SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

MALE 2 VIEW 2



MIDDLE FINGER EXTENSION

14

SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

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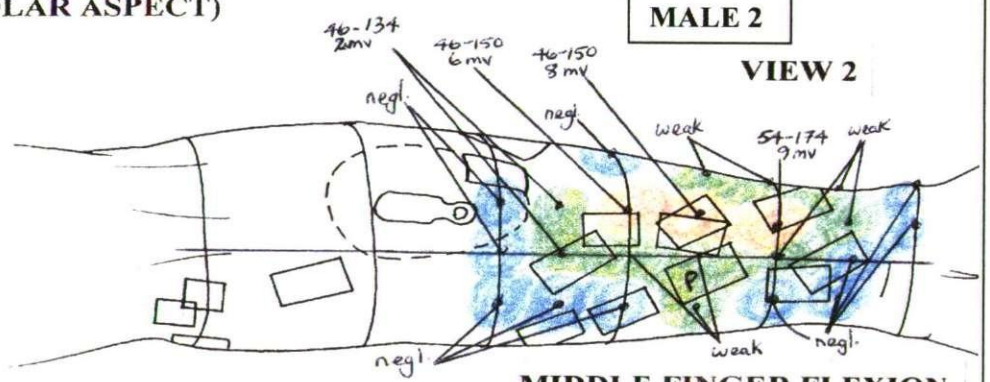

MIDDLE FINGER FLEXION

16

SUPERIOR VIEW OF PRONATED FOREARM

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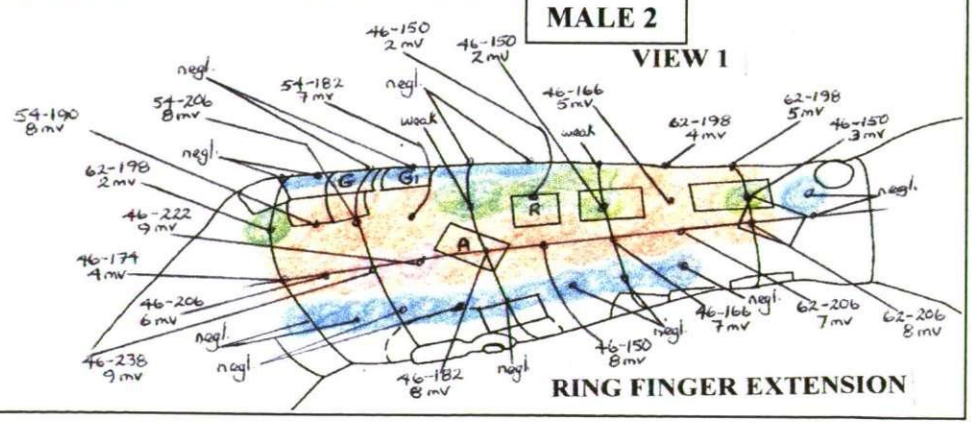
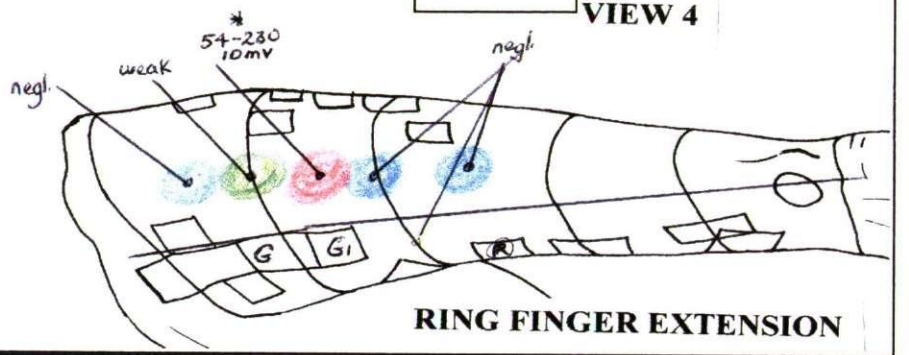


RING FINGER EXTENSION

17

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 2 **VIEW 4**



RING FINGER EXTENSION

18

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

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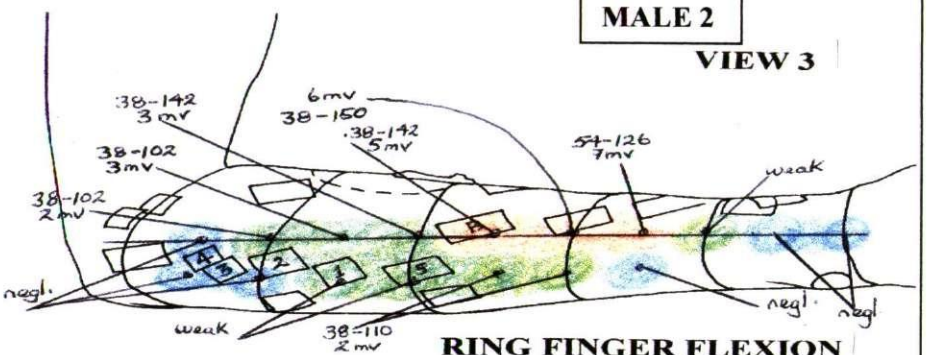

RING FINGER FLEXION

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SUPERIOR VIEW OF PRONATED FOREARM

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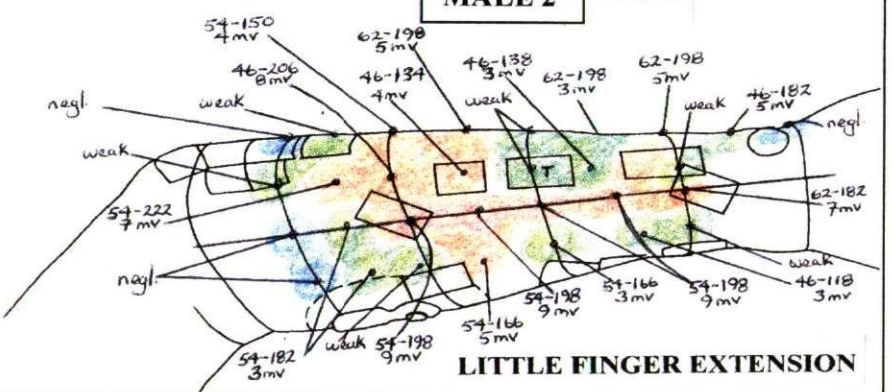
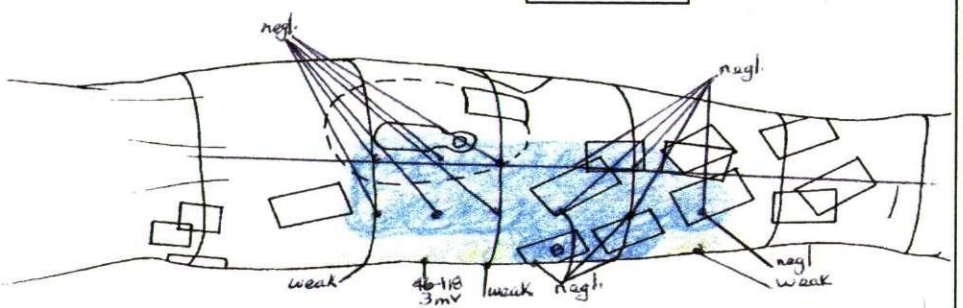


LITTLE FINGER EXTENSION

20

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 2 **VIEW 2**



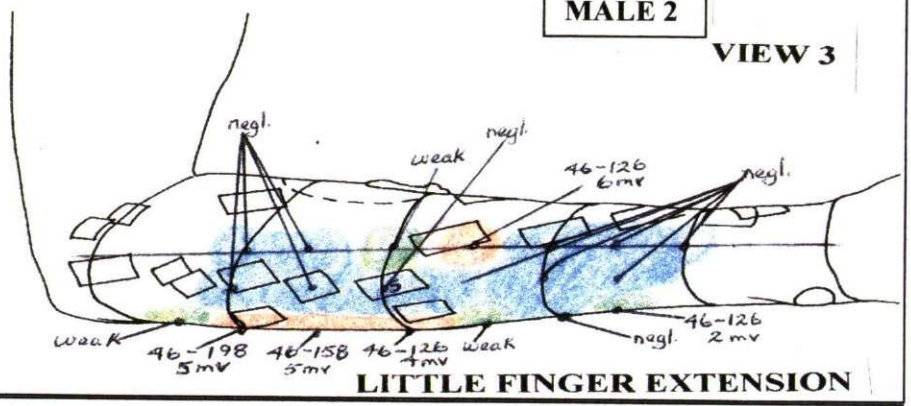
LITTLE FINGER EXTENSION

21

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 2 **VIEW 3**

22

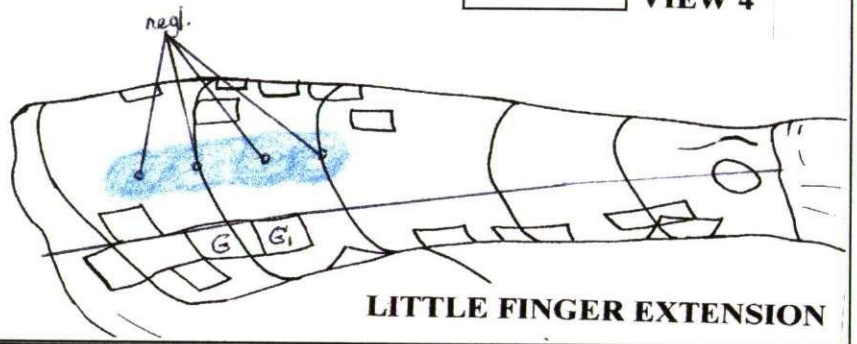


LITTLE FINGER EXTENSION

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 2 **VIEW 4**

23

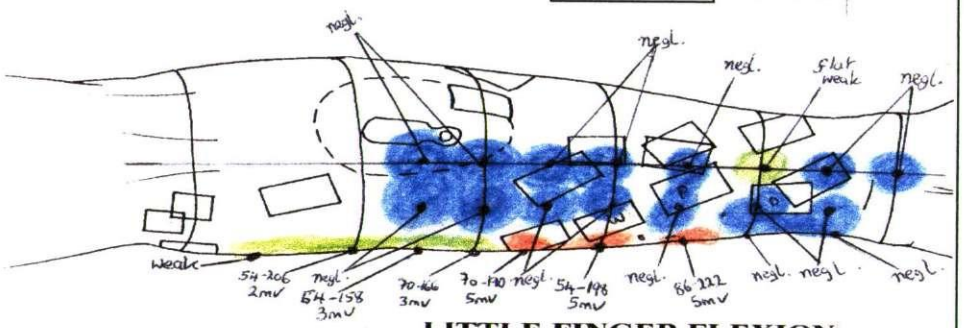


LITTLE FINGER EXTENSION

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 2 **VIEW 2**

24

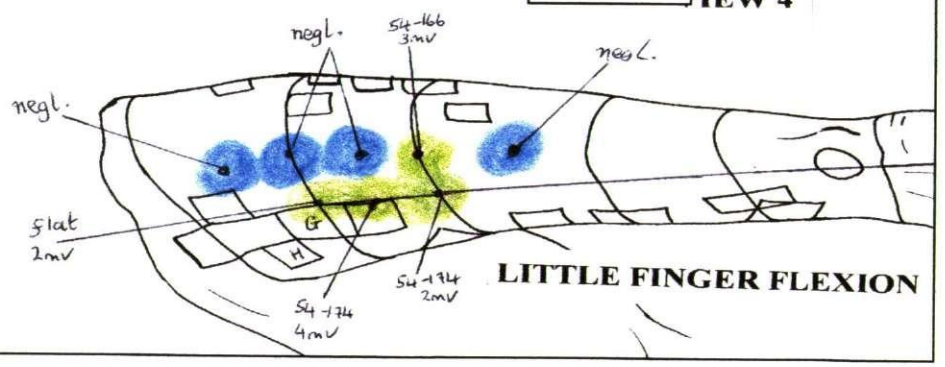


LITTLE FINGER FLEXION

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 2 **IEW 4**

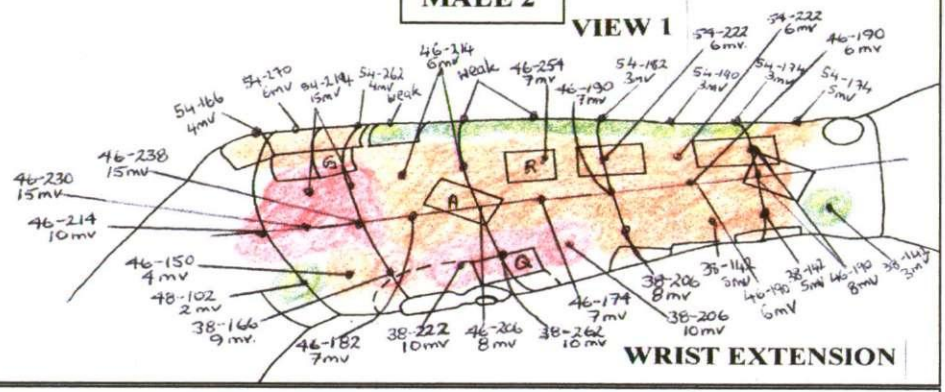
25



LITTLE FINGER FLEXION

SUPERIOR VIEW OF PRONATED FOREARM

MALE 2 **VIEW 1**



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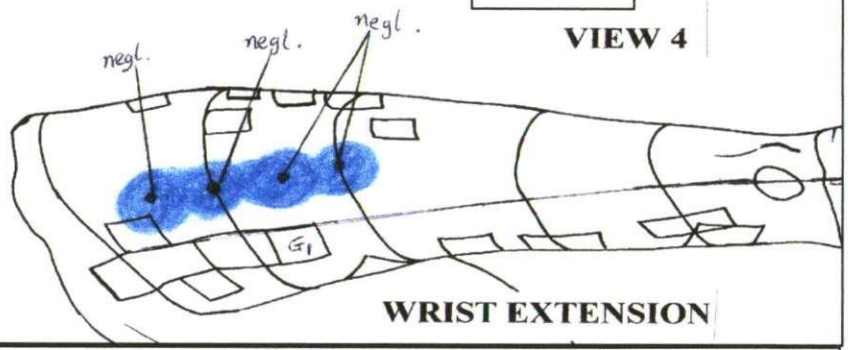
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 2 **VIEW 4**



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SUPERIOR VIEW OF PRONATED FOREARM

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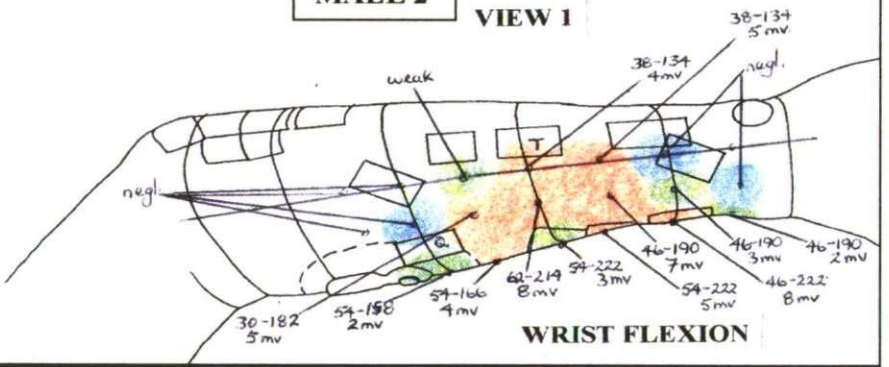
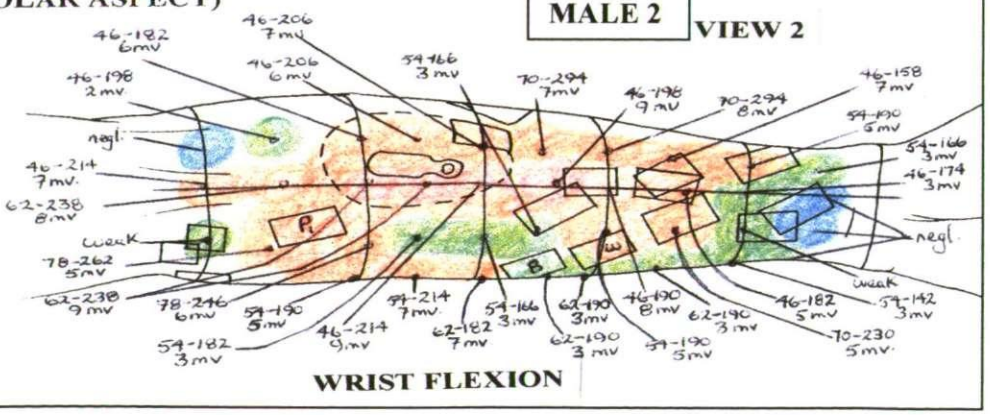


28

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 2 **VIEW 2**



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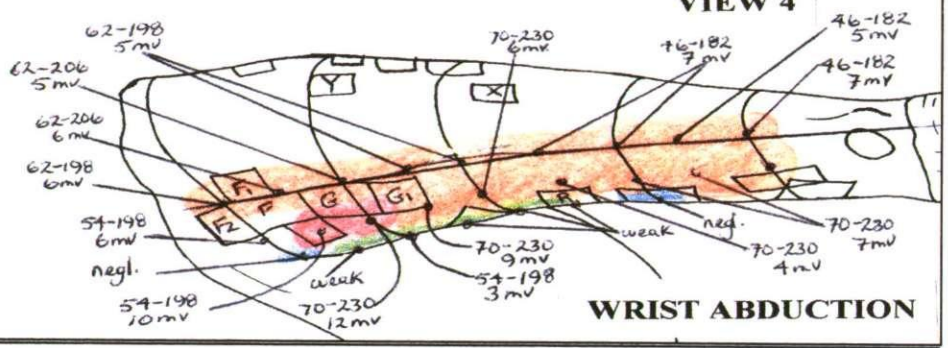
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 2

VIEW 4

31



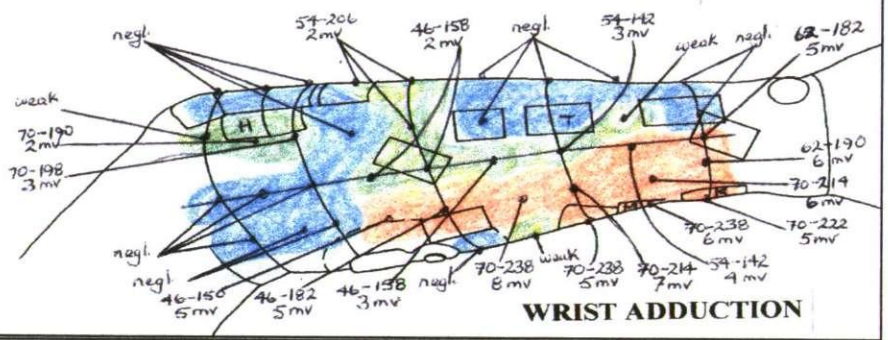
WRIST ABDUCTION

SUPERIOR VIEW OF PRONATED FOREARM

MALE 2

VIEW 1

32



WRIST ADDUCTION

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 2

VIEW 2

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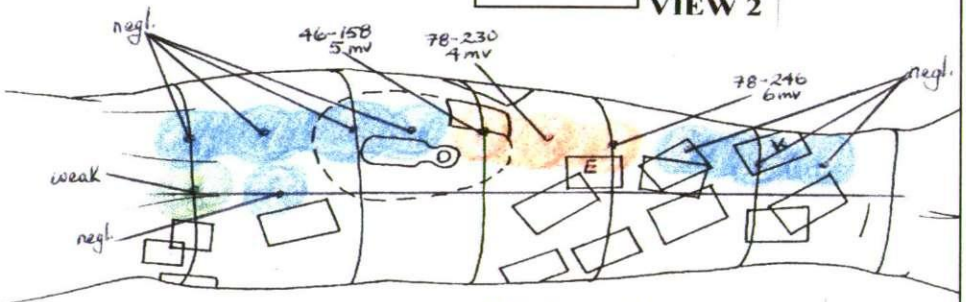

WRIST ADDUCTION

SUPERIOR VIEW OF PRONATED FOREARM

MALE 2

VIEW 1

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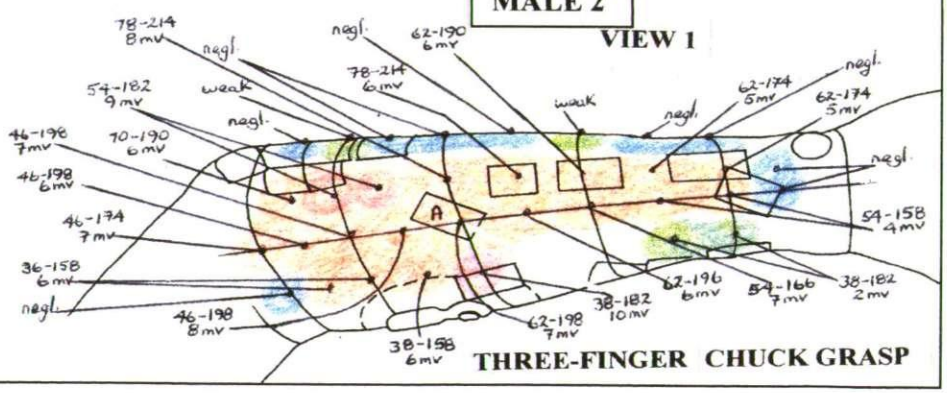
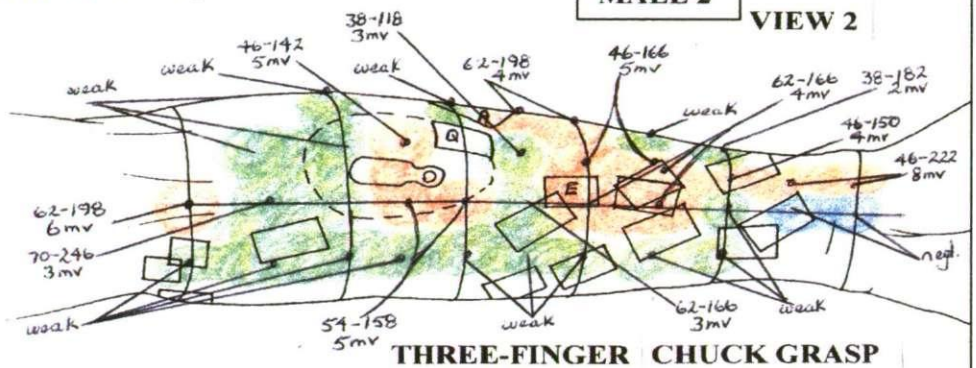


THREE-FINGER CHUCK GRASP

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 2

VIEW 2



THREE-FINGER CHUCK GRASP

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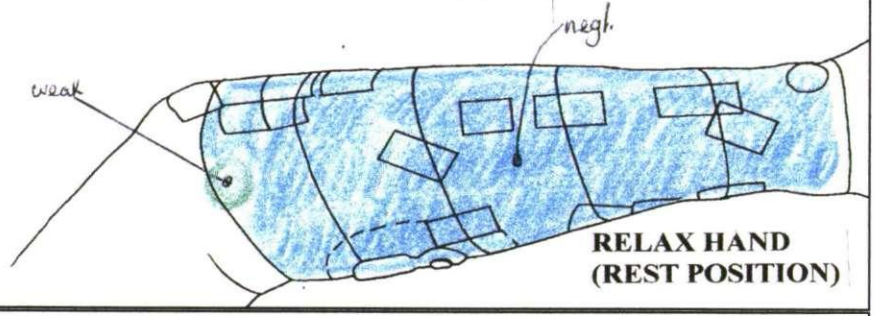
SUPERIOR VIEW OF PRONATED FOREARM

MALE 2

VIEW 1



RELAX HAND
(REST POSITION)

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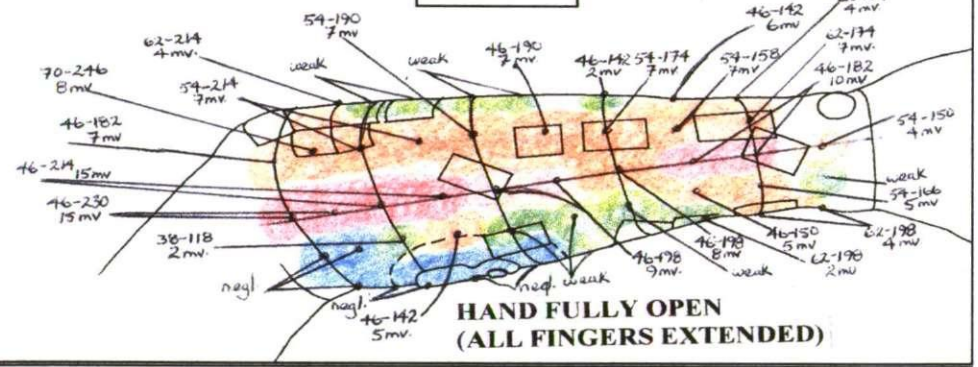
SUPERIOR VIEW OF PRONATED FOREARM

MALE 2 VIEW 1



HAND FULLY OPEN
(ALL FINGERS EXTENDED)

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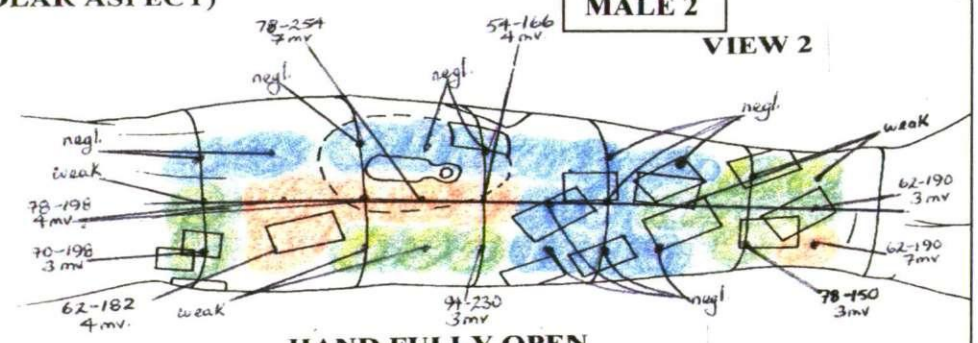
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 2

VIEW 2



HAND FULLY OPEN
(ALL FINGERS EXTENDED)

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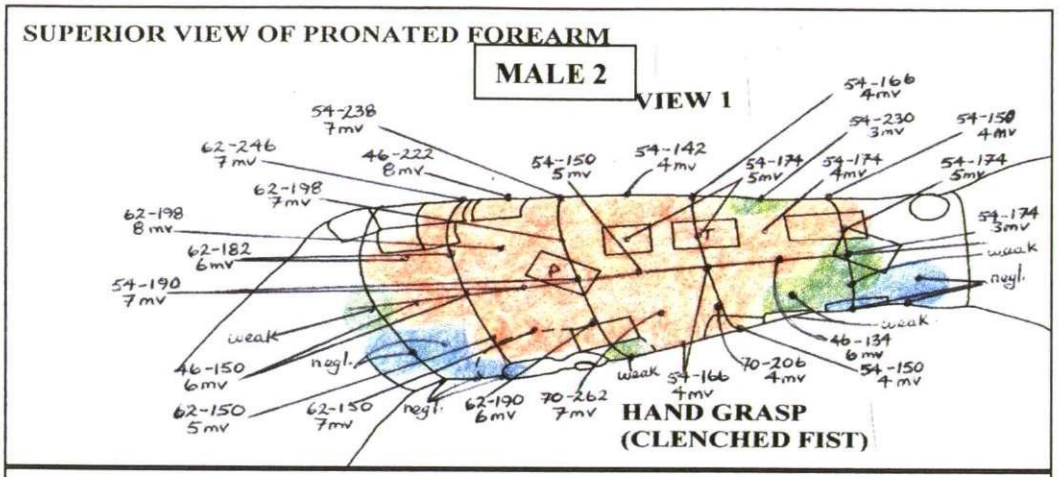
SUPERIOR VIEW OF PRONATED FOREARM
MALE 2
VIEW 1
54-238 7mv
62-246 7mv
46-222 8mv
62-198 7mv
62-198 8mv
62-182 6mv
54-190 7mv
54-150 5mv
54-142 4mv
54-166 4mv
54-230 3mv
54-150 4mv
54-174 5mv
54-174 4mv
54-174 5mv
54-174 3mv
weak
negl.
weak
46-134 6mv
54-150 4mv
70-206 4mv
54-166 4mv
weak
46-150 6mv
62-150 5mv
62-150 7mv
negl.
62-190 6mv
70-262 7mv
HAND GRASP
(CLENCHED FIST)

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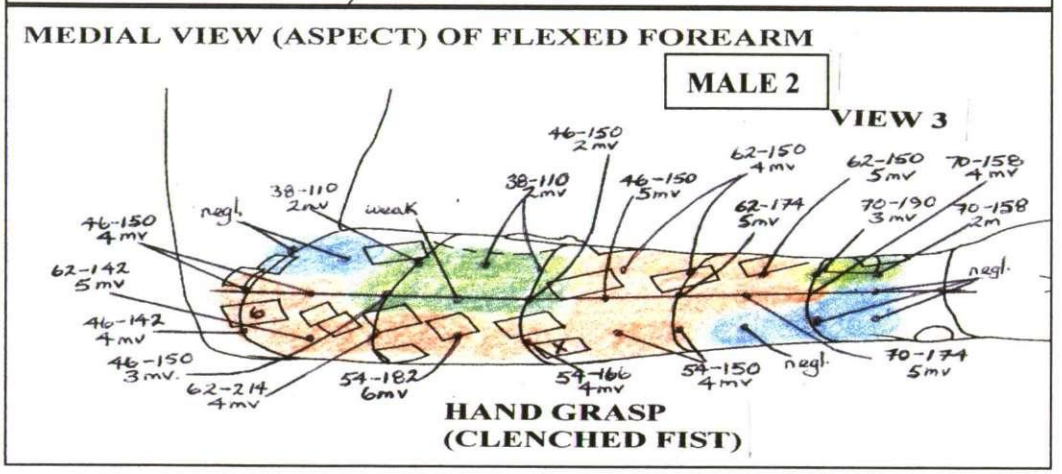
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM
MALE 2
VIEW 3
46-150 2mv
38-110 2mv
46-150 5mv
62-150 4mv
62-150 5mv
70-158 4mv
38-110 2mv
negl.
weak
62-174 5mv
70-190 3mv
70-158 2m
46-150 4mv
62-142 5mv
negl.
46-142 4mv
46-150 3mv.
62-214 4mv
54-182 6mv
54-166 4mv
54-150 4mv
negl.
70-174 5mv
HAND GRASP
(CLENCHED FIST)

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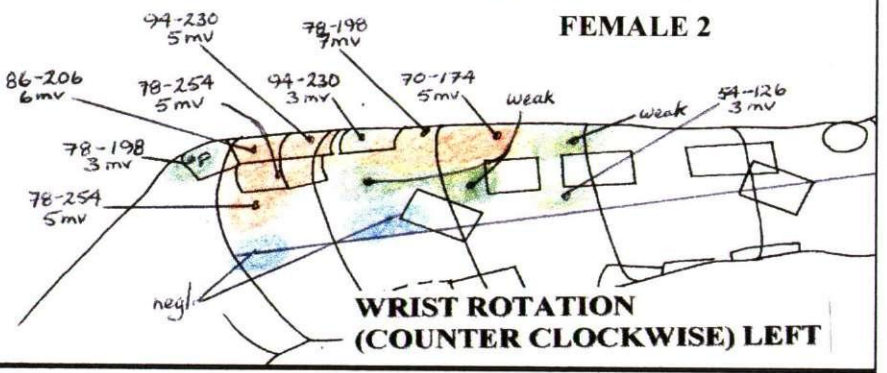
SUPERIOR VIEW OF PRONATED FOREARM

VIEW 1

FEMALE 2

1



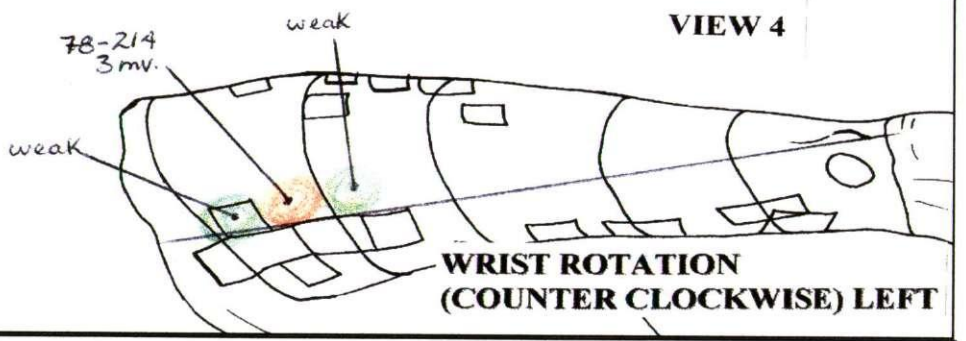
WRIST ROTATION
(COUNTER CLOCKWISE) LEFT

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

FEMALE 2

VIEW 4

2



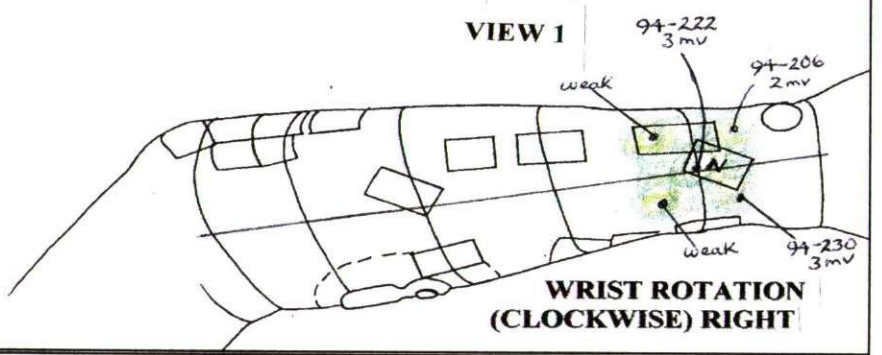
WRIST ROTATION
(COUNTER CLOCKWISE) LEFT

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1

3



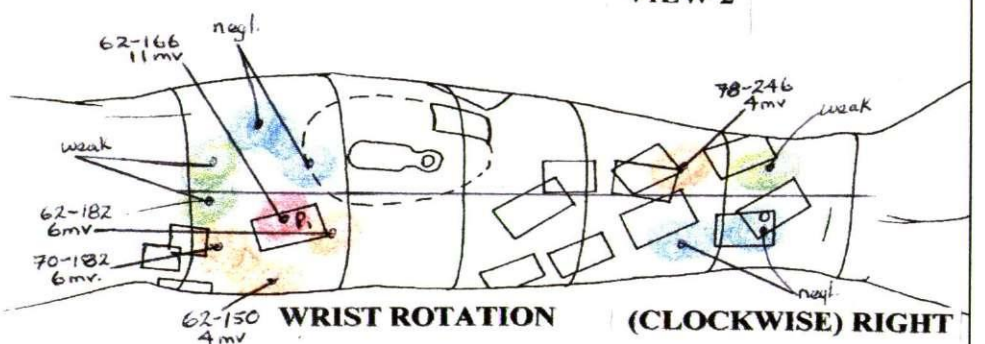
WRIST ROTATION
(CLOCKWISE) RIGHT

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 2

VIEW 2

4

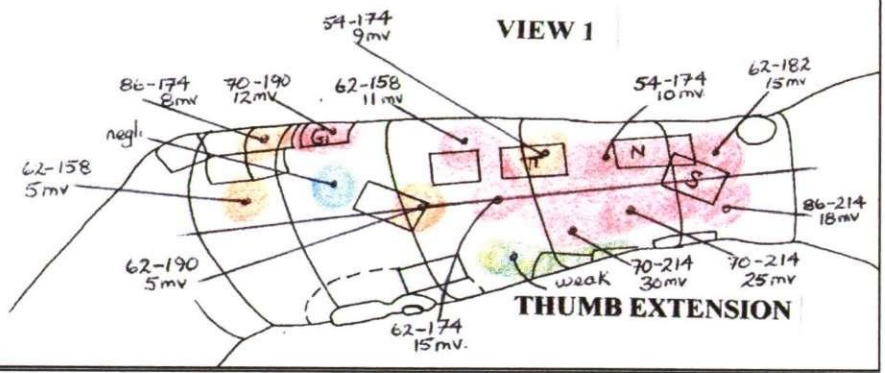


WRIST ROTATION (CLOCKWISE) RIGHT

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



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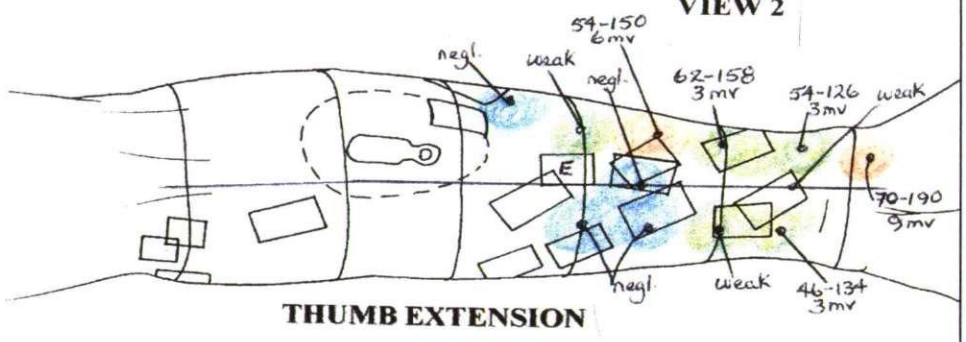
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 2

VIEW 2



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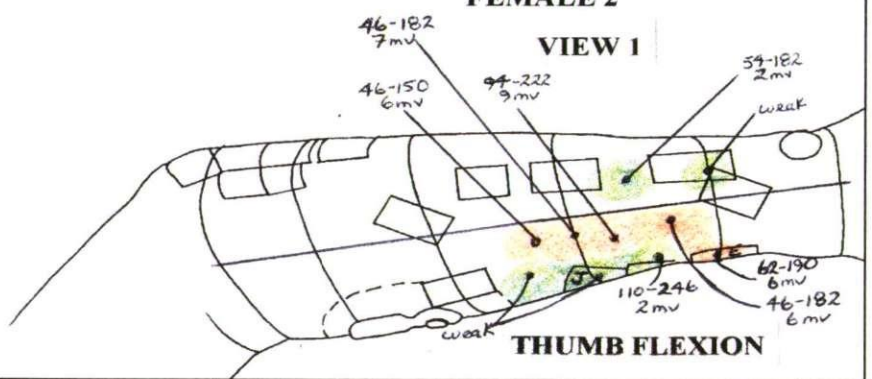
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



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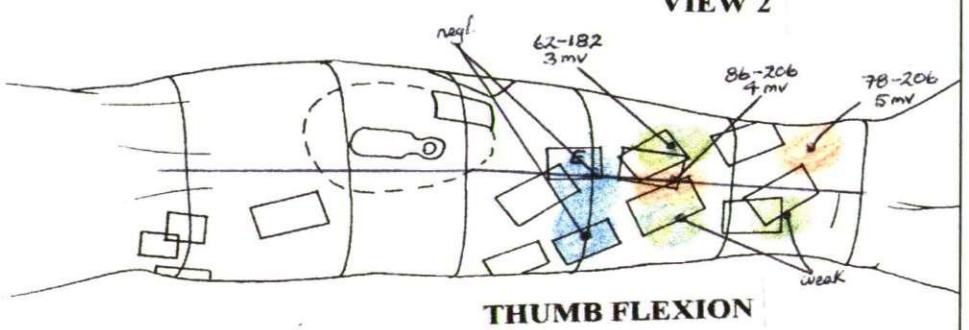
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 2

VIEW 2



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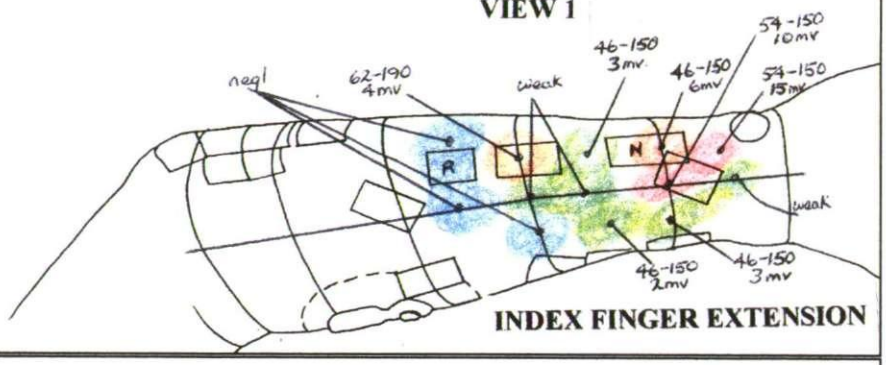
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



INDEX FINGER EXTENSION

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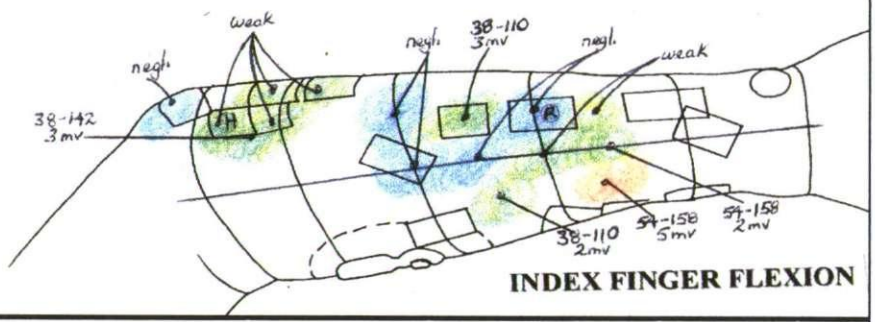
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



INDEX FINGER FLEXION

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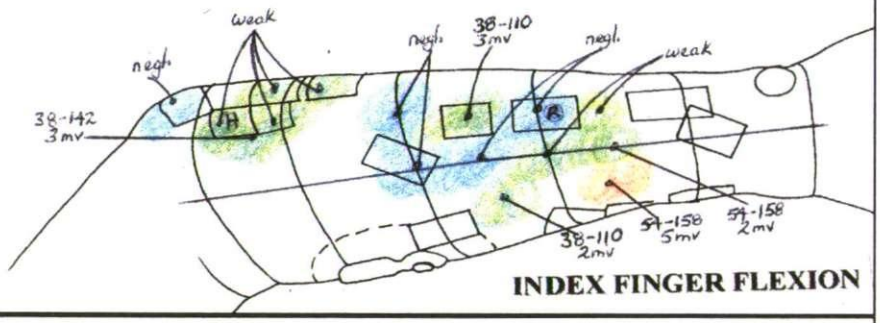
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



INDEX FINGER FLEXION

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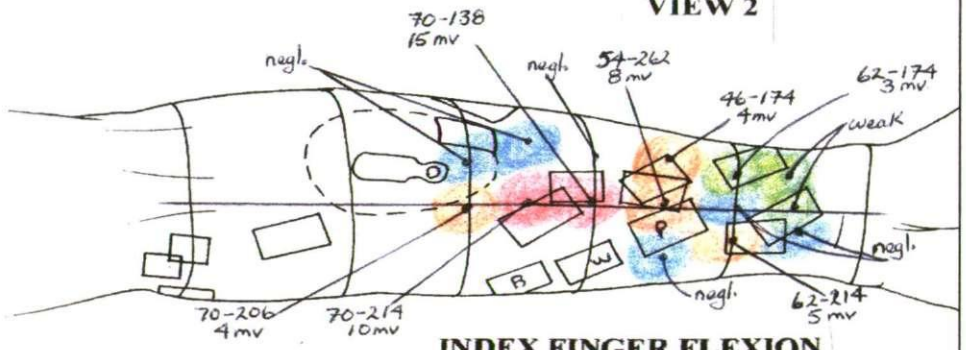
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 2

VIEW 2



INDEX FINGER FLEXION

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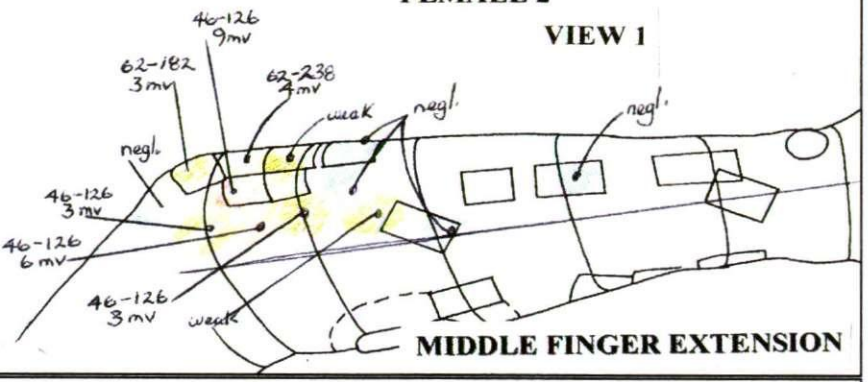
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



MIDDLE FINGER EXTENSION

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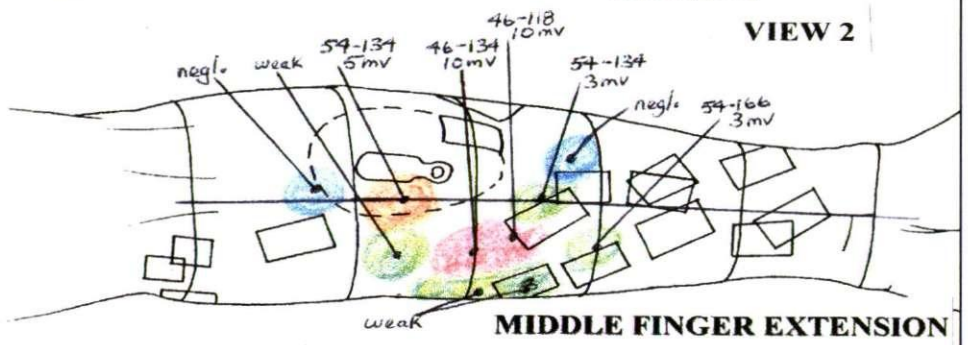
SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

FEMALE 2

VIEW 2



MIDDLE FINGER EXTENSION

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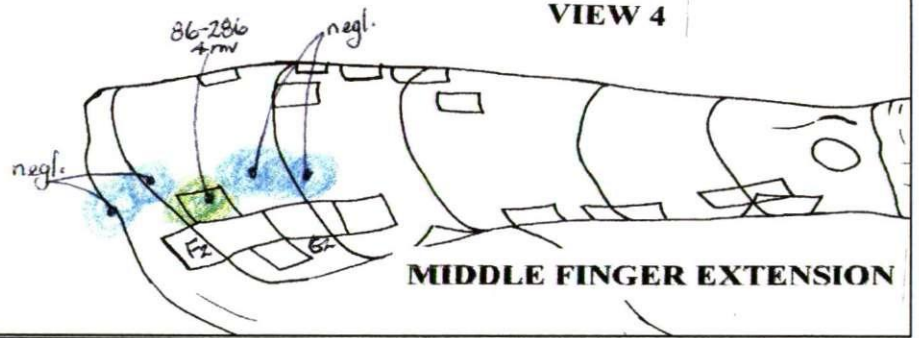
LATERAL ASPECT OF PRONATED FOREARM ELBOW FLEXED @ 90 DEG.

FEMALE 2

VIEW 4



MIDDLE FINGER EXTENSION

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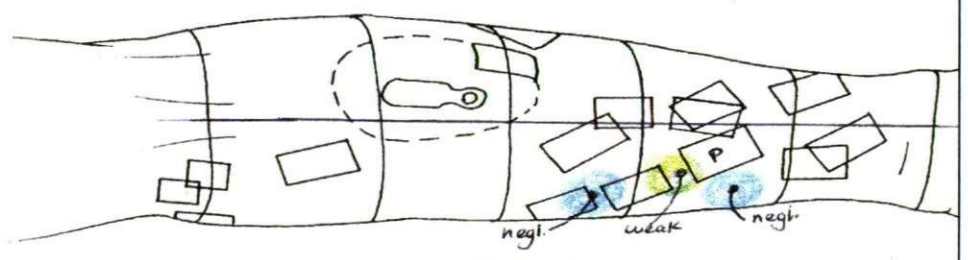
SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

FEMALE 2

VIEW 2



MIDDLE FINGER FLEXION

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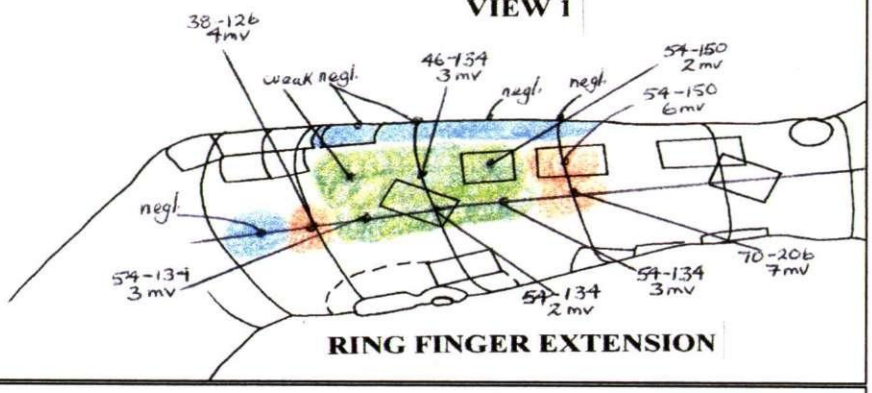
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



RING FINGER EXTENSION

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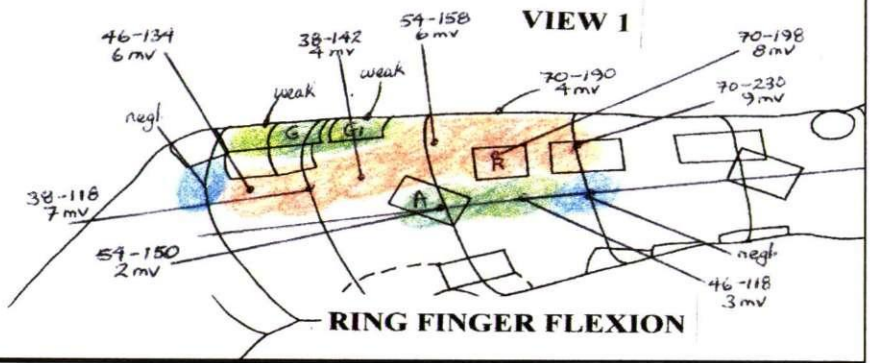
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



RING FINGER FLEXION

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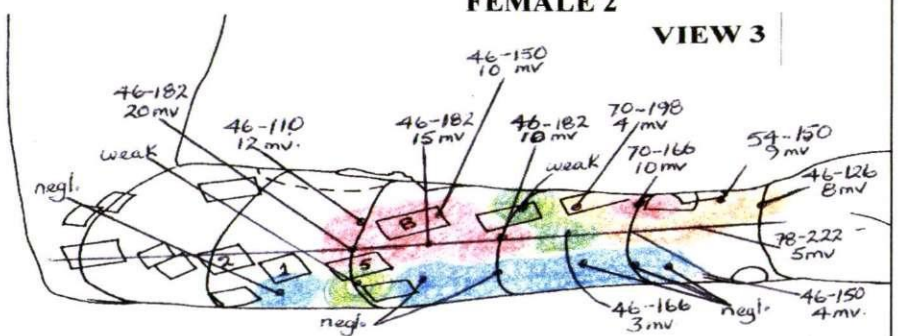
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

FEMALE 2

VIEW 3



RING FINGER FLEXION

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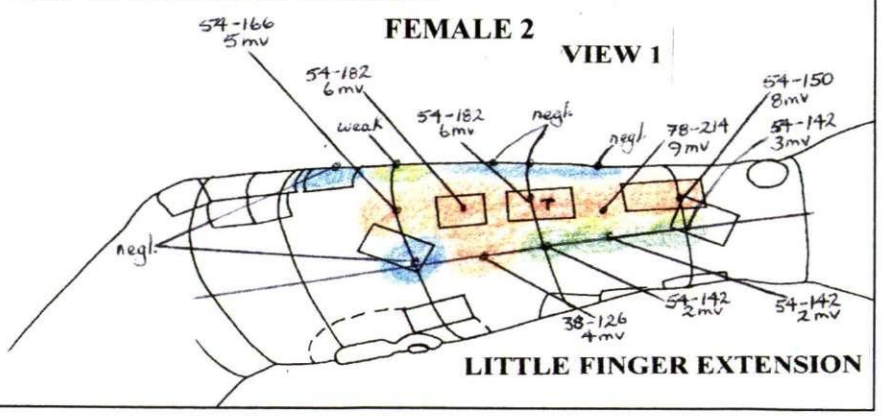
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



LITTLE FINGER EXTENSION

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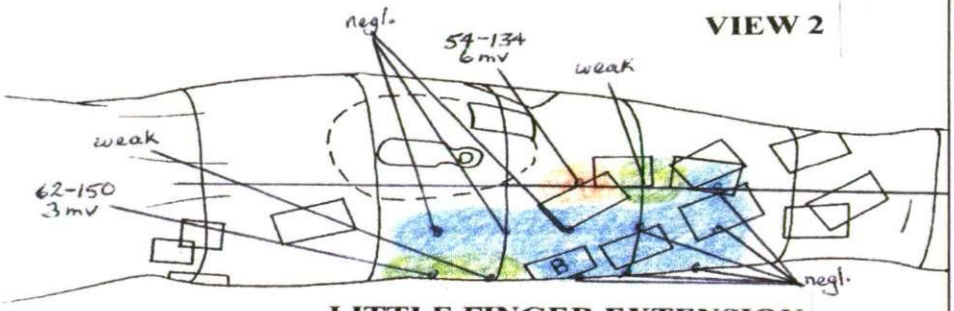
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 2

VIEW 2



LITTLE FINGER EXTENSION

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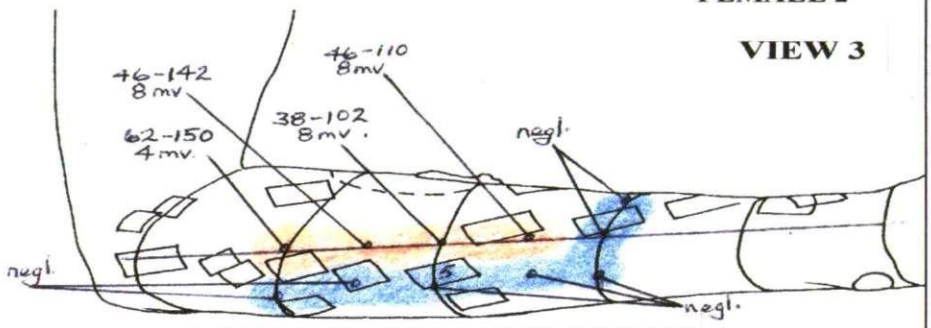
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

FEMALE 2

VIEW 3



LITTLE FINGER EXTENSION

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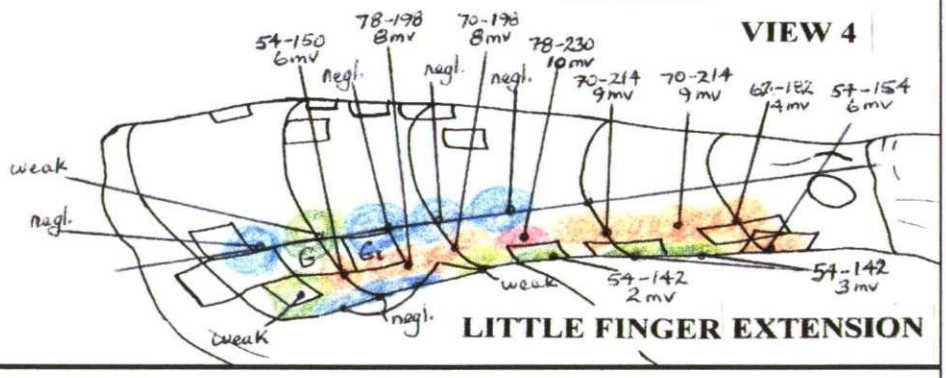
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

FEMALE 2

VIEW 4



LITTLE FINGER EXTENSION

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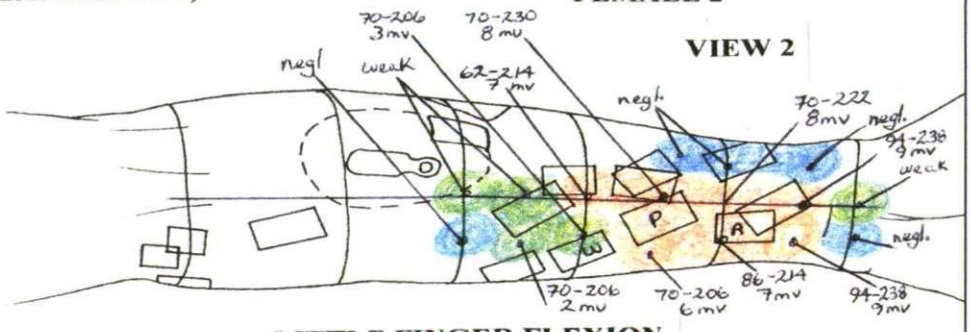
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 2

VIEW 2



LITTLE FINGER FLEXION

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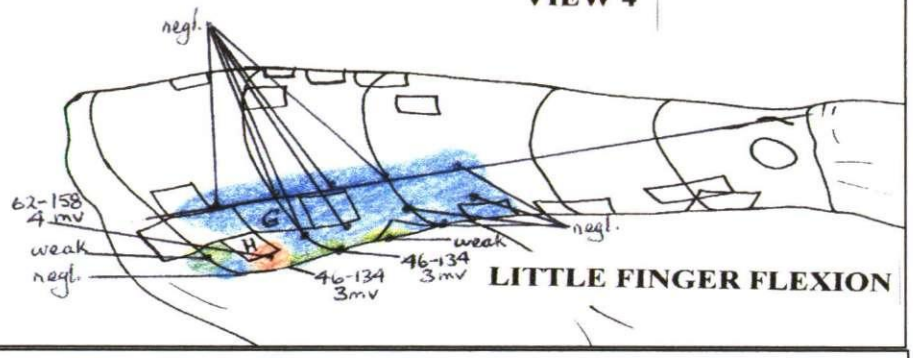
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

FEMALE 2

VIEW 4



LITTLE FINGER FLEXION

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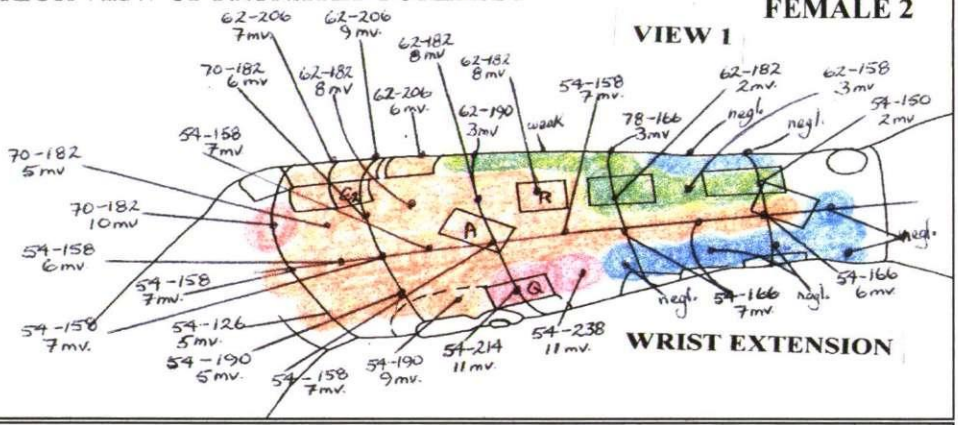
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



WRIST EXTENSION

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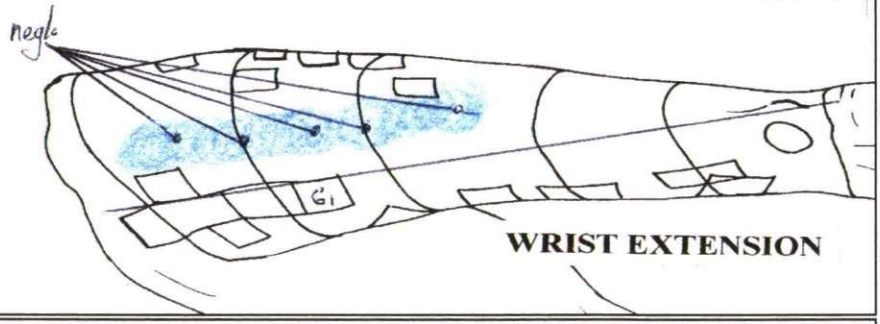
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

FEMALE 2

VIEW 4



WRIST EXTENSION

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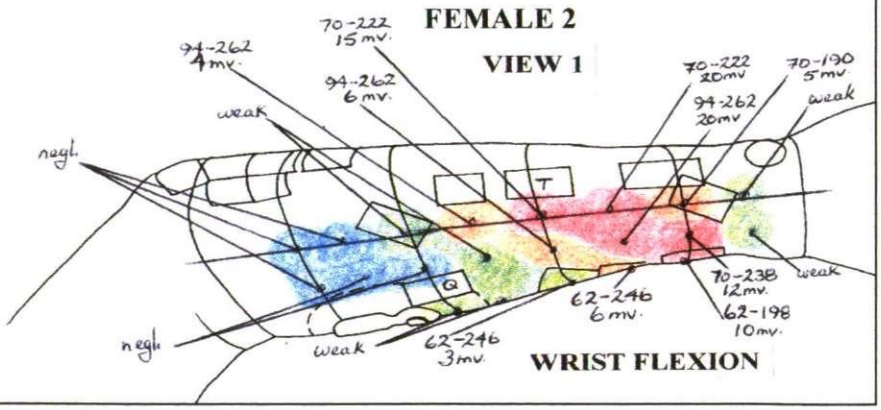
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



WRIST FLEXION

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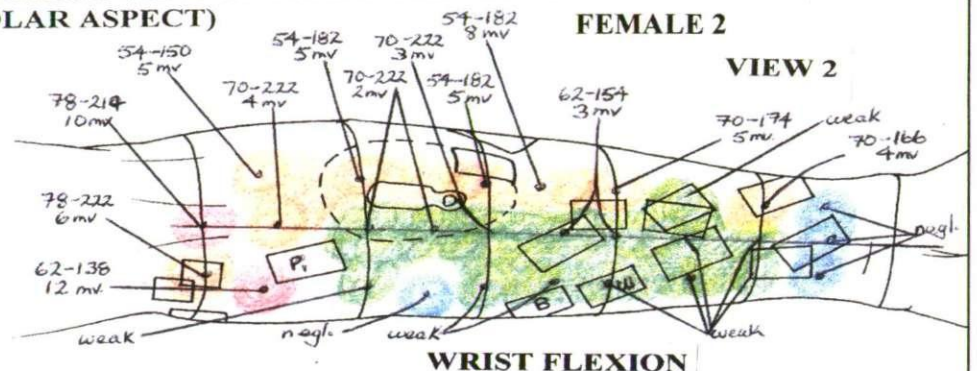
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT) **FEMALE 2** **VIEW 2**



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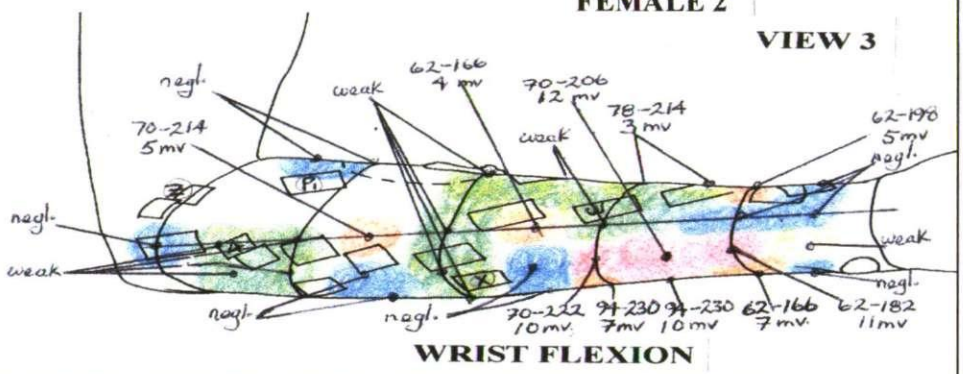
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM
FEMALE 2 **VIEW 3**



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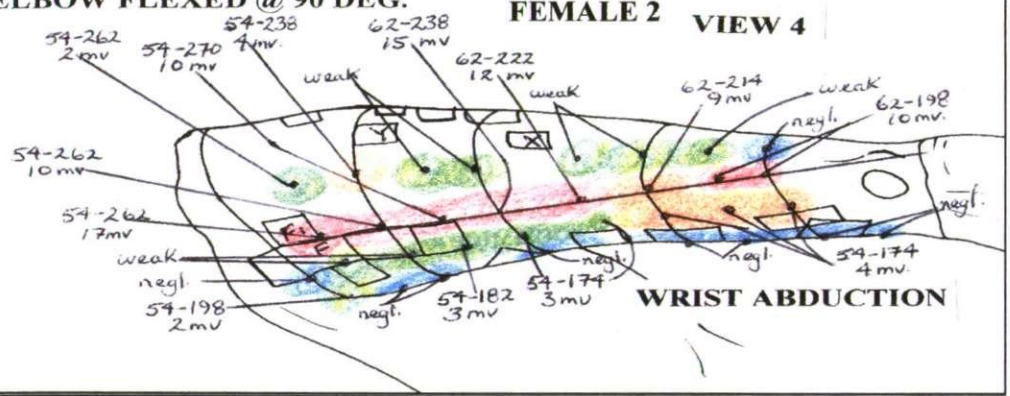
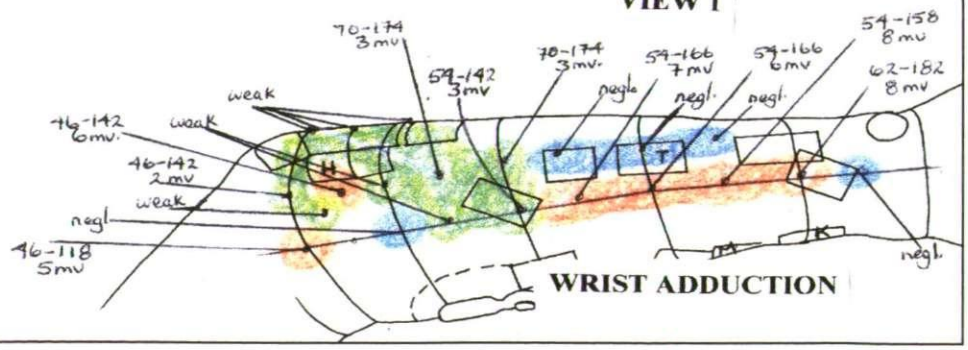
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG. **FEMALE 2** **VIEW 4**



31

SUPERIOR VIEW OF PRONATED FOREARM
FEMALE 2 **VIEW 1**

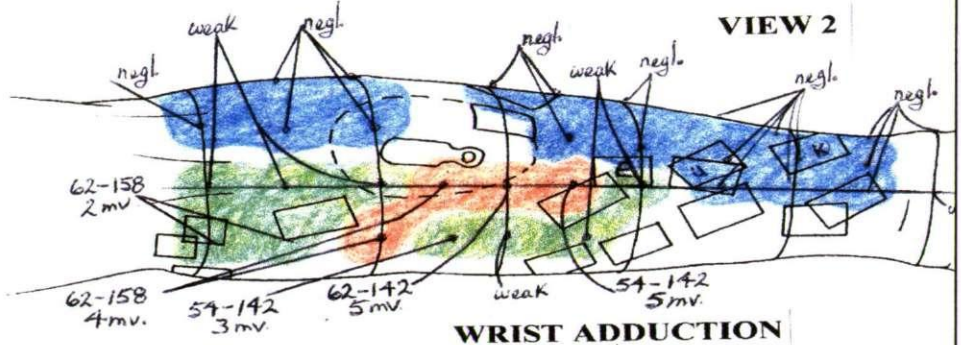


32

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 2

VIEW 2



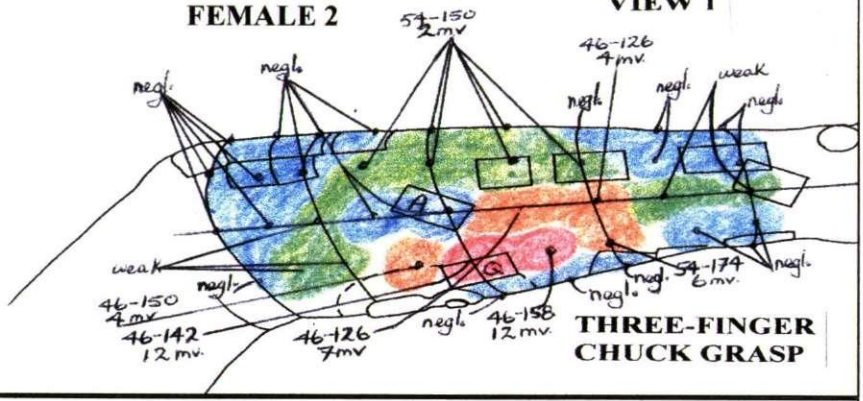
WRIST ADDUCTION

33

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

VIEW 1



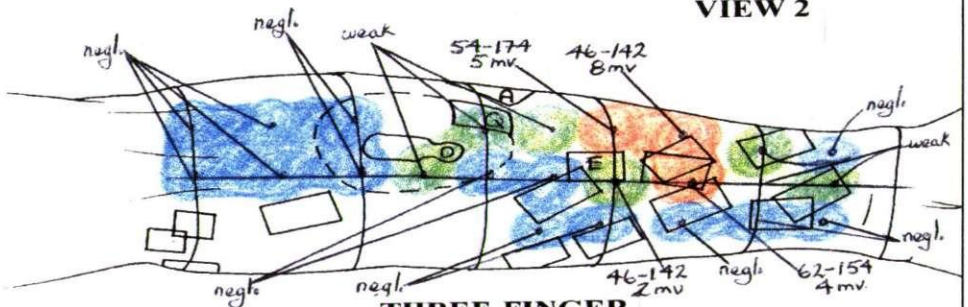
THREE-FINGER CHUCK GRASP

34

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 2

VIEW 2



THREE-FINGER CHUCK GRASP

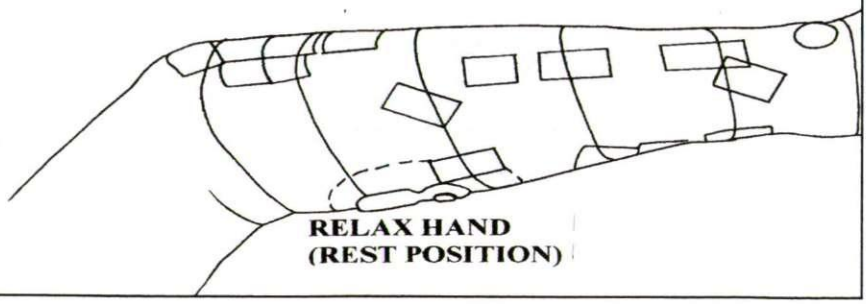
35

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 2

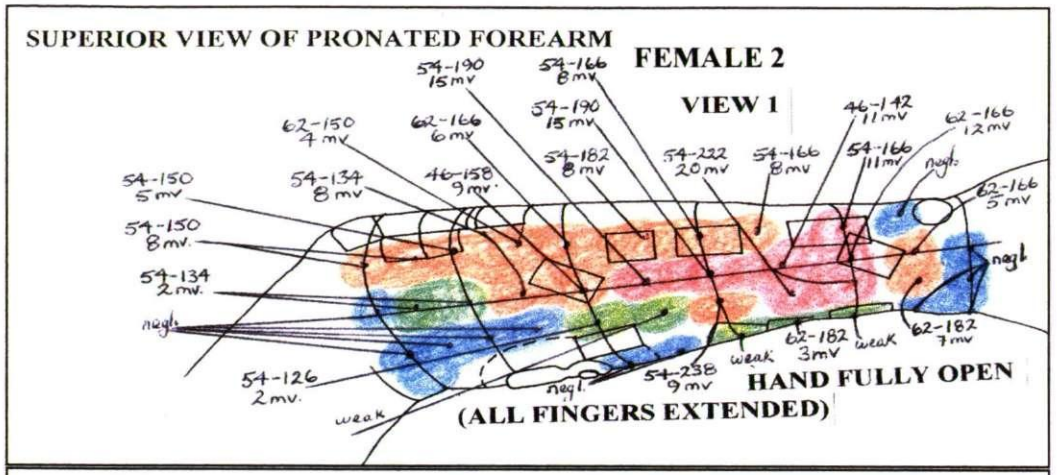
no action detected anywhere!

VIEW 1

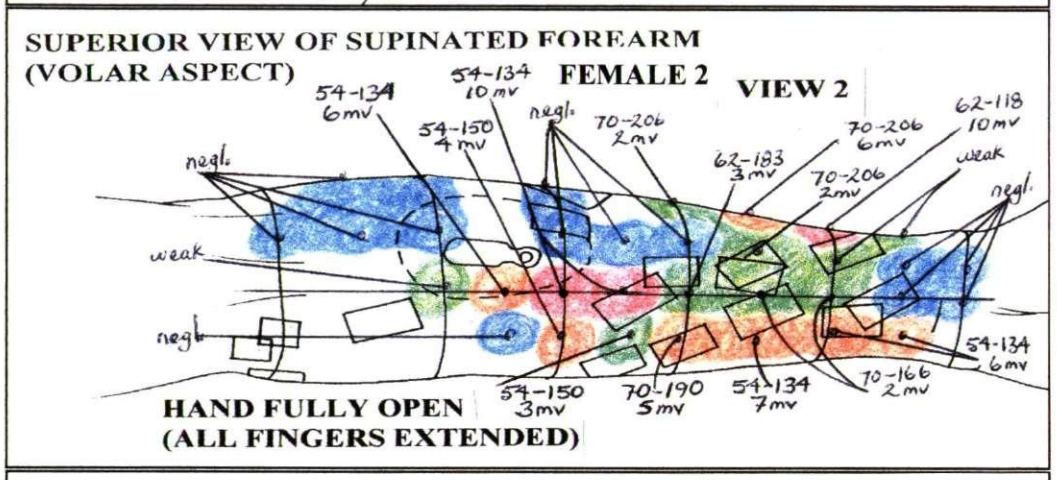


RELAX HAND
(REST POSITION)

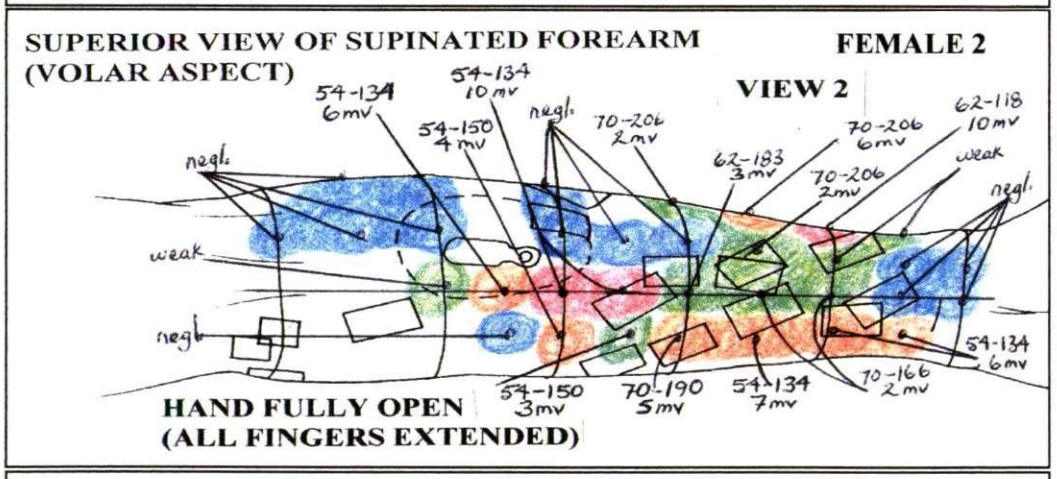
36


SUPERIOR VIEW OF PRONATED FOREARM
FEMALE 2
VIEW 1
54-190 15mv
54-166 8mv
62-150 4mv
62-166 6mv
54-190 15mv
46-142 11mv
62-166 12mv
54-150 5mv
54-134 8mv
46-158 9mv
54-182 8mv
54-222 20mv
54-166 8mv
54-166 11mv
negl.
62-166 5mv
54-150 8mv.
54-134 2mv.
negl.
negl.
62-182 3mv
62-182 7mv
weak
weak
54-126 2mv.
weak
negl.
54-238 9mv
HAND FULLY OPEN
(ALL FINGERS EXTENDED)

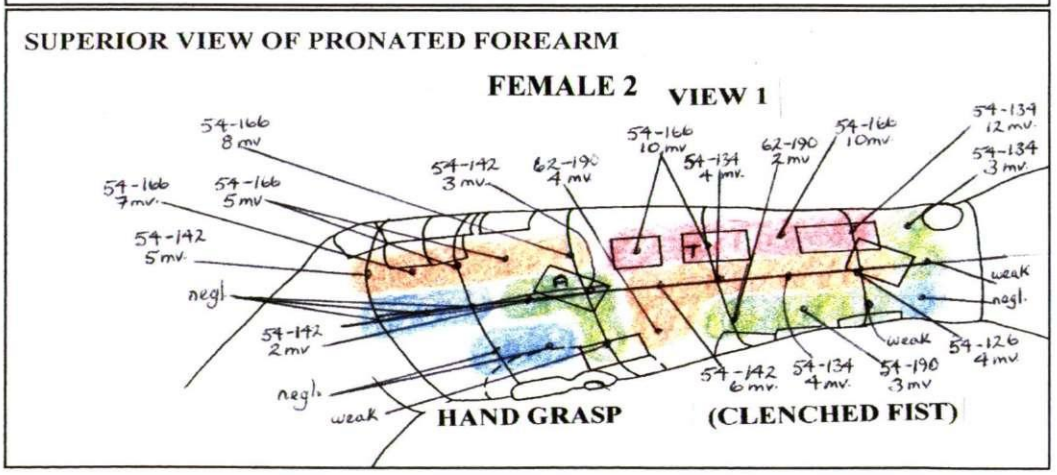
37


SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)
FEMALE 2
VIEW 2
54-134 6mv
54-134 10mv
54-150 4mv
negl.
70-206 2mv
62-183 3mv
70-206 6mv
62-118 10mv
70-206 2mv
weak
negl.
negl.
weak
negl.
54-134 6mv
54-150 3mv
70-190 5mv
54-134 7mv
70-166 2mv
HAND FULLY OPEN
(ALL FINGERS EXTENDED)

38

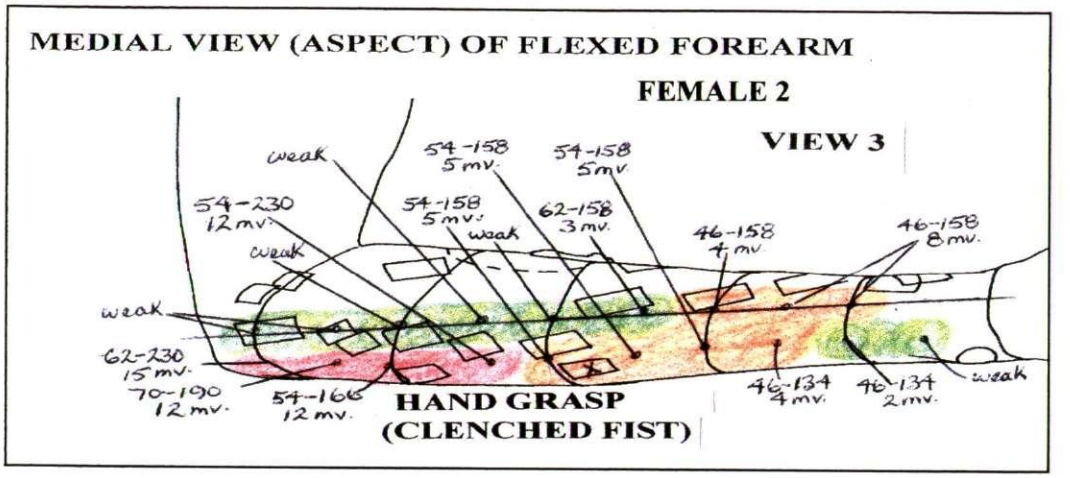

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)
FEMALE 2
VIEW 2
54-134 6mv
54-134 10mv
54-150 4mv
negl.
70-206 2mv
62-183 3mv
70-206 6mv
62-118 10mv
70-206 2mv
weak
negl.
negl.
weak
negl.
54-134 6mv
54-150 3mv
70-190 5mv
54-134 7mv
70-166 2mv
HAND FULLY OPEN
(ALL FINGERS EXTENDED)

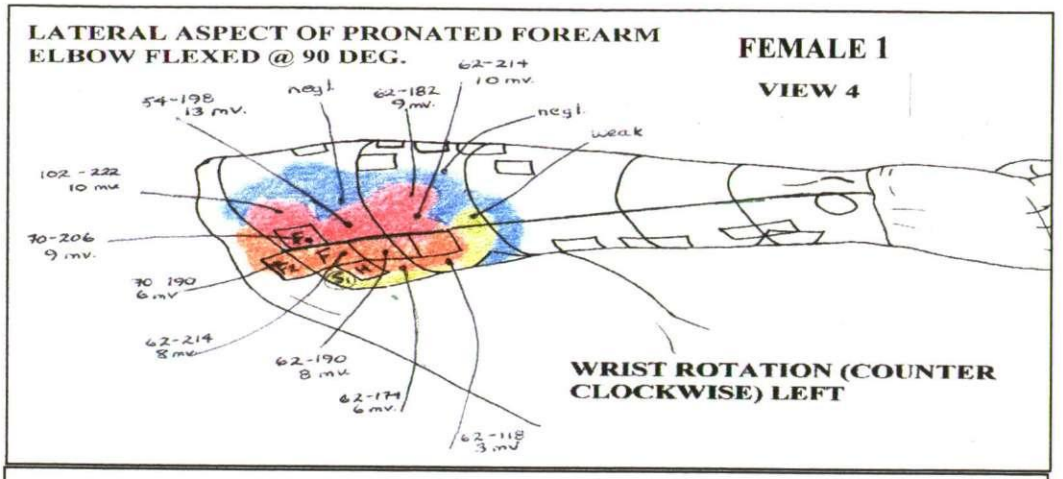
39


SUPERIOR VIEW OF PRONATED FOREARM
FEMALE 2
VIEW 1
54-166 8mv
54-166 7mv.
54-166 5mv
54-142 3mv.
62-190 4mv
54-166 10mv
54-134 4mv.
62-190 2mv
54-166 10mv
54-134 12mv.
54-134 3mv.
54-142 5mv.
negl.
weak
negl.
54-142 2mv
negl.
weak
54-142 6mv.
54-134 4mv.
54-190 3mv
weak
54-126 4mv
HAND GRASP
(CLENCHED FIST)

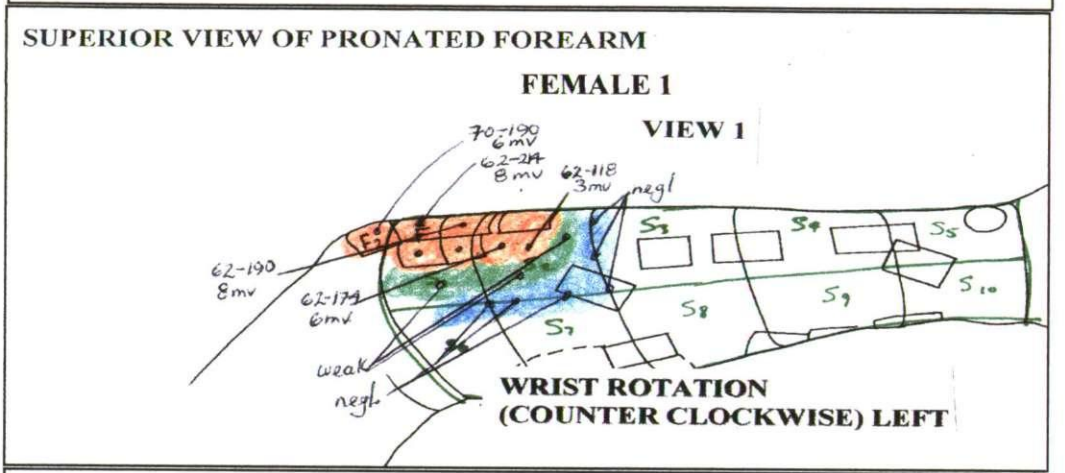
40

41

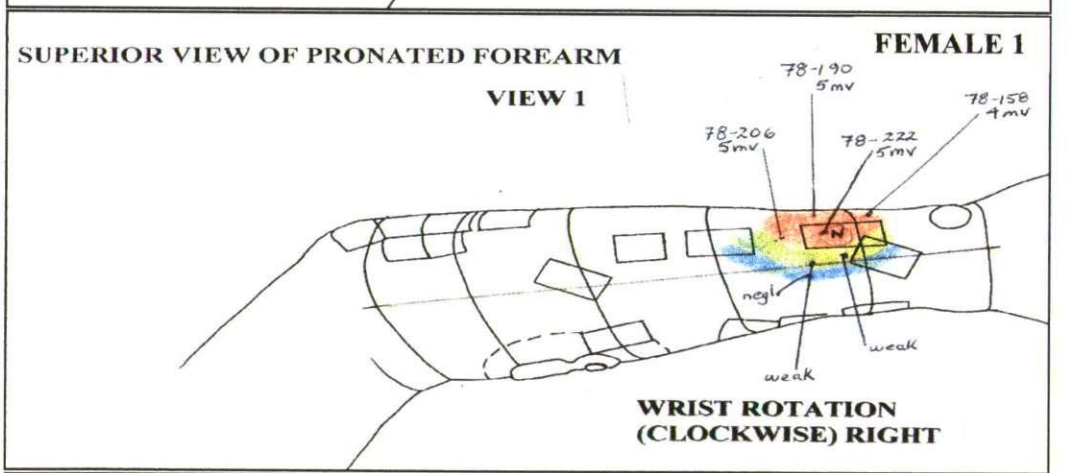

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM
FEMALE 2
VIEW 3
weak
54-158 5mv.
54-158 5mv.
54-230 12mv.
54-158 5mv.
weak
62-158 3mv.
46-158 4mv.
46-158 8mv.
weak
weak
62-230 15mv.
70-190 12mv.
54-166 12mv.
46-134 4mv.
46-134 2mv.
weak
HAND GRASP
(CLENCHED FIST)


LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.
FEMALE 1
VIEW 4
54-198 13 mV.
negl.
62-182 9 mV.
62-214 10 mv.
negl.
weak
102-222 10 mv.
70-206 9 mv.
70 190 6 mV
62-214 8 mv.
62-190 8 mv.
62-179 6 mv.
62-118 3 mV
WRIST ROTATION (COUNTER CLOCKWISE) LEFT

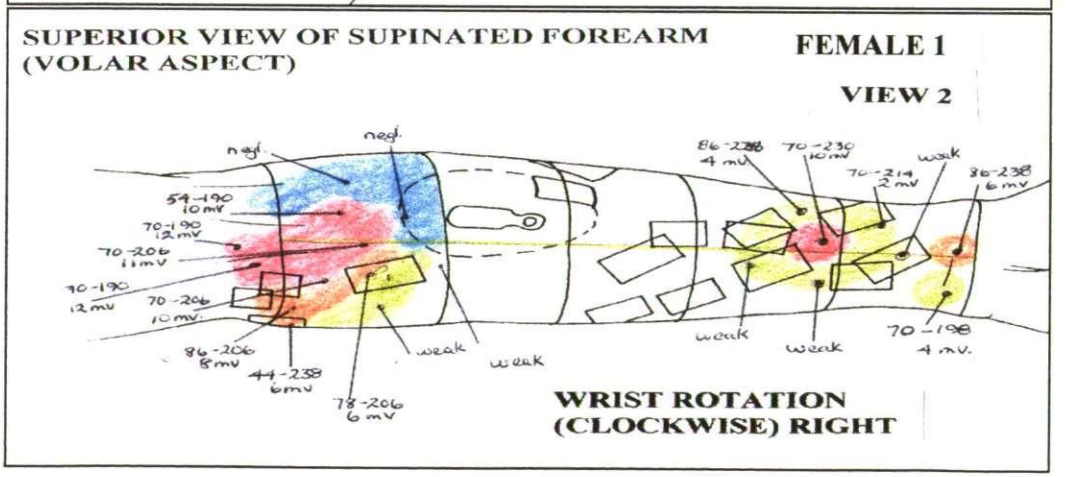
1


SUPERIOR VIEW OF PRONATED FOREARM
FEMALE 1
VIEW 1
70-190 6 mV
62-214 8 mv
62-118 3mv
negl
62-190 8mv
62-179 6mv
weak
negl.
WRIST ROTATION (COUNTER CLOCKWISE) LEFT

2


SUPERIOR VIEW OF PRONATED FOREARM
VIEW 1
FEMALE 1
78-190 5mv
78-158 4mv
78-206 5mv
78-222 5mv
negl.
weak
weak
WRIST ROTATION (CLOCKWISE) RIGHT

3


SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)
FEMALE 1
VIEW 2
negl.
negl.
54-190 10 mV
70-190 12 mV
70-206 11 mV
70-190 12 mv
70-206 10 mv.
86-206 8 mV
44-238 6 mV
78-206 6 mV
weak
weak
86-238 4 mV
70-230 10 mV
70-214 2 mV
weak
86-238 6 mV
weak
weak
70-198 4 mv.
WRIST ROTATION (CLOCKWISE) RIGHT

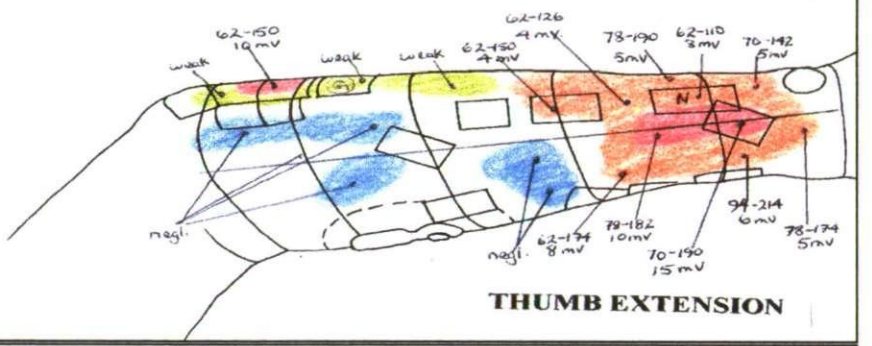
4

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1

5



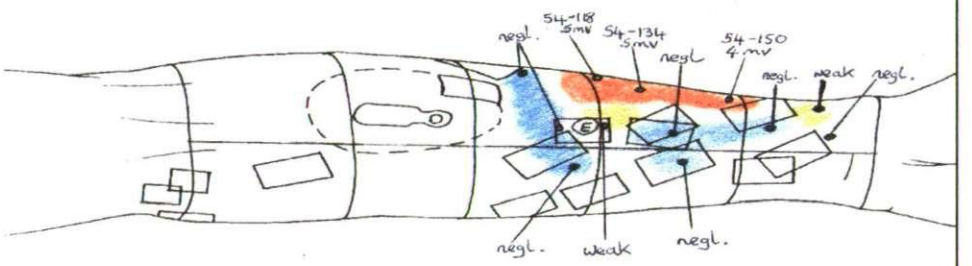
THUMB EXTENSION

SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

FEMALE 1

VIEW 2

6



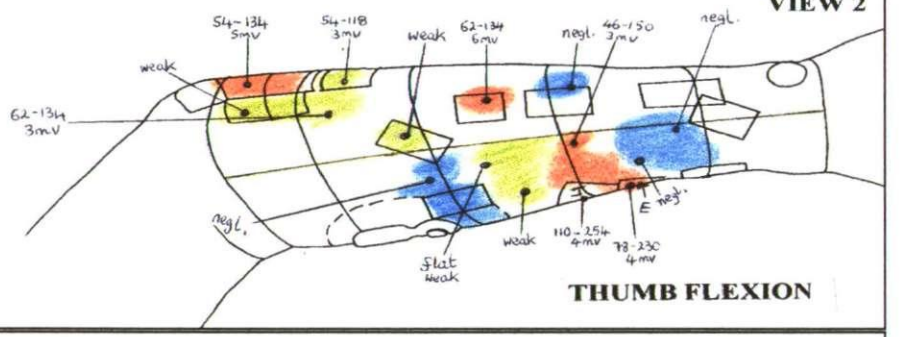
THUMB FLEXION

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 2

7



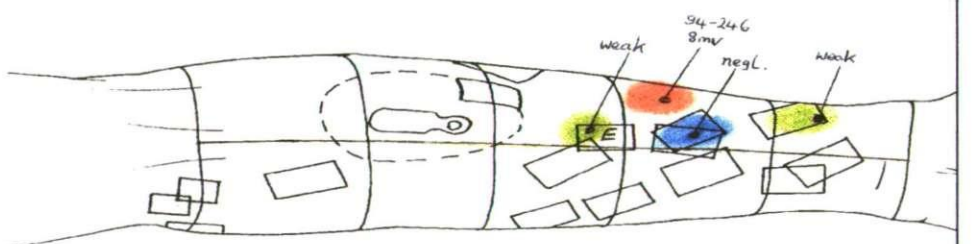
THUMB FLEXION

SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

FEMALE 1

VIEW 2

8

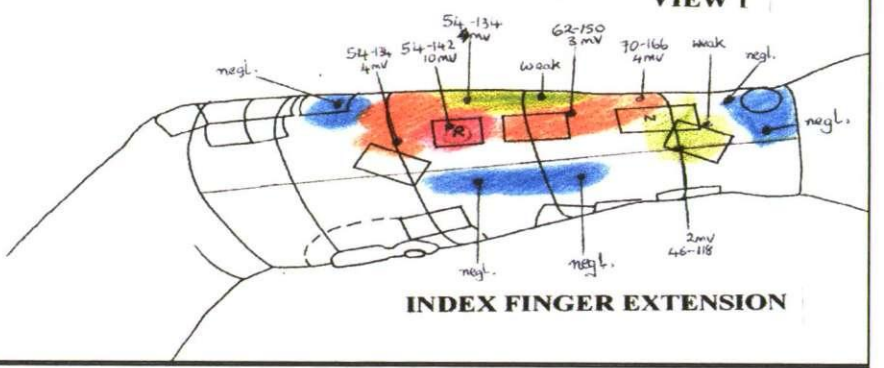


THUMB FLEXION

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1



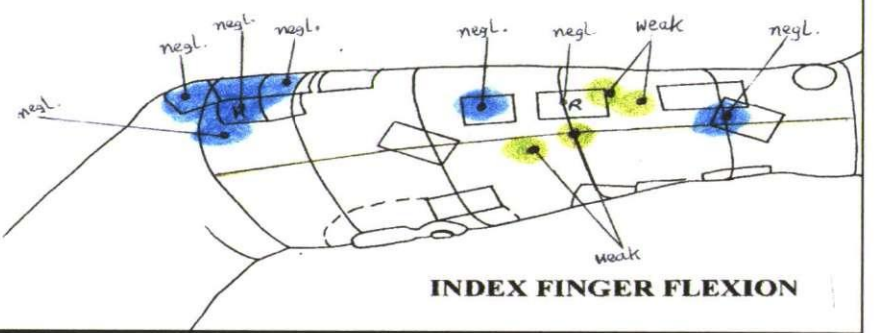
INDEX FINGER EXTENSION

9

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1



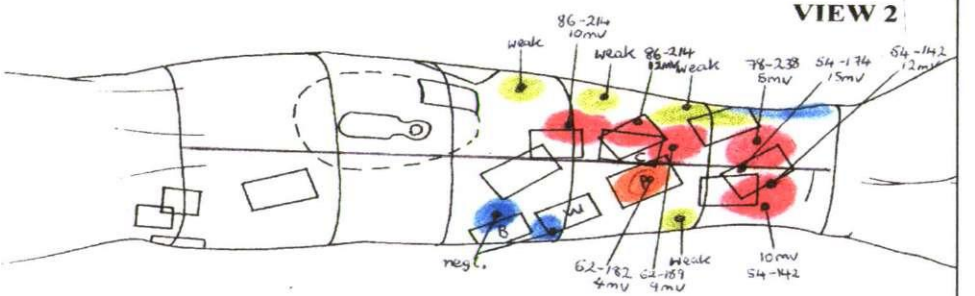
INDEX FINGER FLEXION

10

SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

FEMALE 1

VIEW 2



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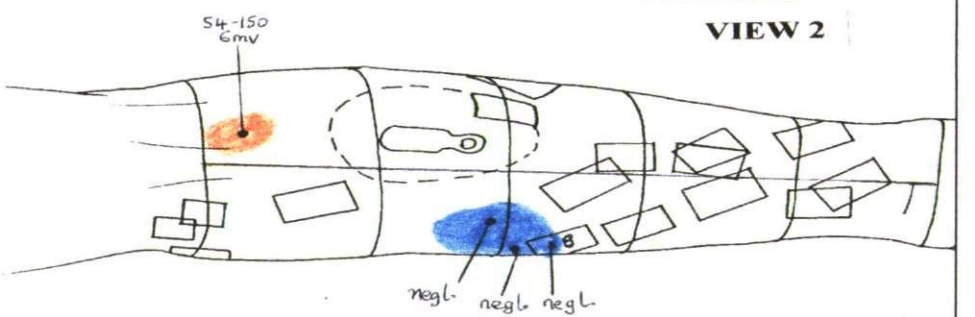
SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

FEMALE 1

VIEW 2



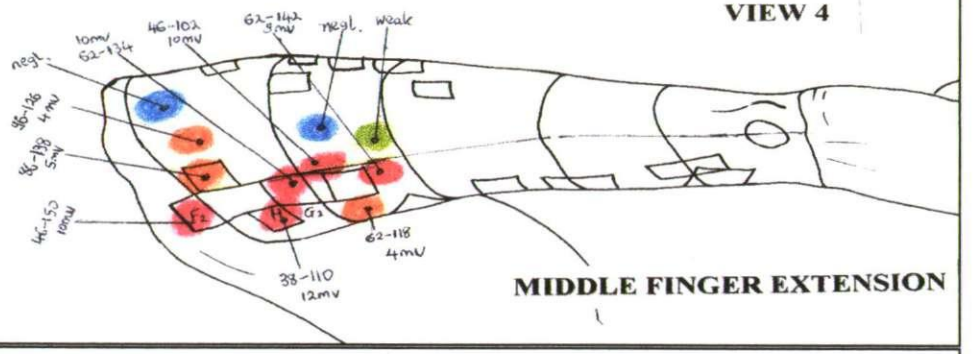
MIDDLE FINGER EXTENSION

14

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

FEMALE 1

VIEW 4



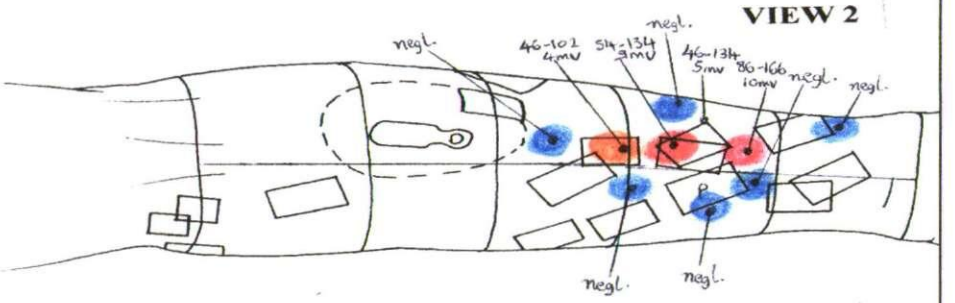
MIDDLE FINGER EXTENSION

15

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 1

VIEW 2



MIDDLE FINGER FLEXION

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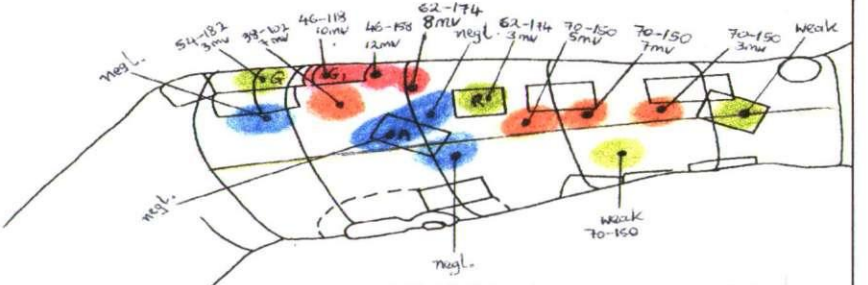
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1



RING FINGER EXTENSION

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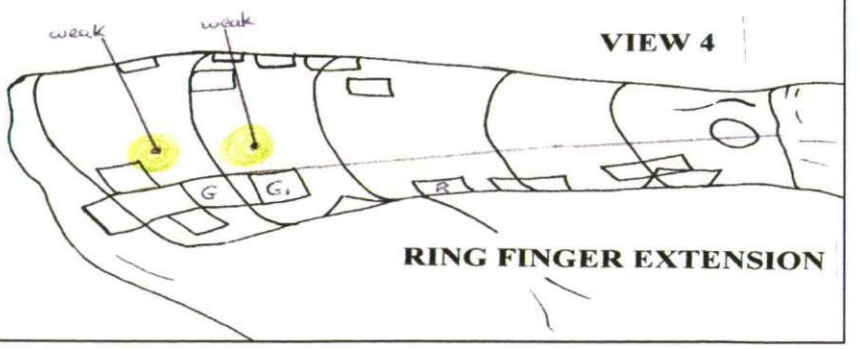
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

FEMALE 1

VIEW 4



RING FINGER EXTENSION

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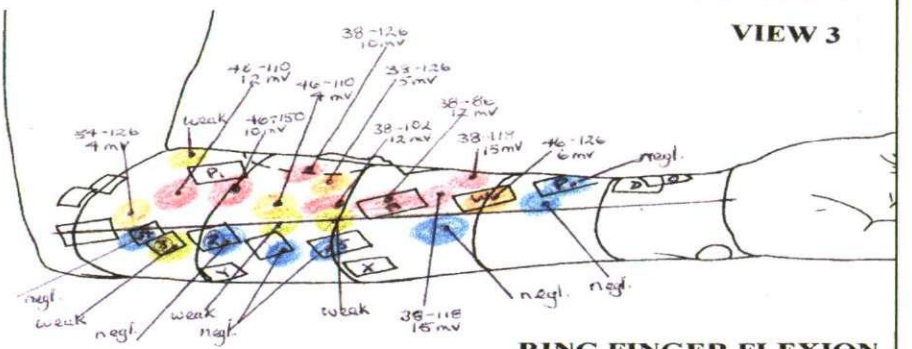
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

FEMALE 1

VIEW 3



RING FINGER FLEXION

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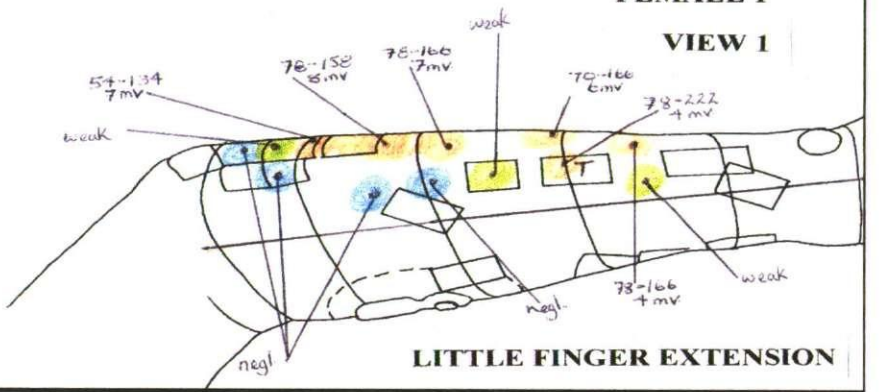
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1



LITTLE FINGER EXTENSION

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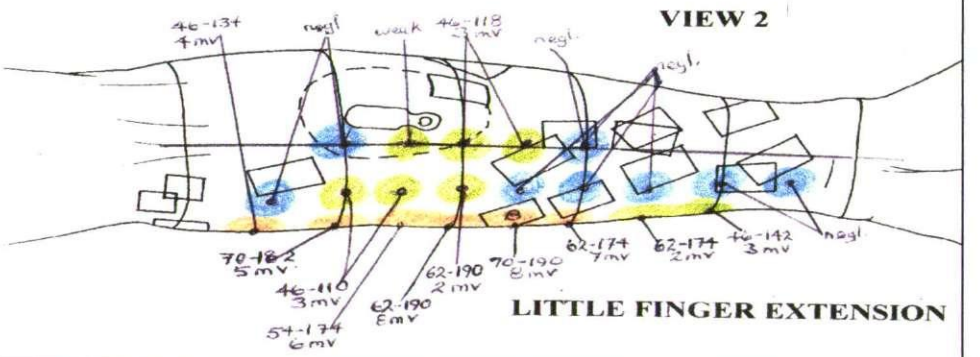
SUPERIOR VIEW OF SUPINATED FOREARM (VOLAR ASPECT)

FEMALE 1

VIEW 2



LITTLE FINGER EXTENSION

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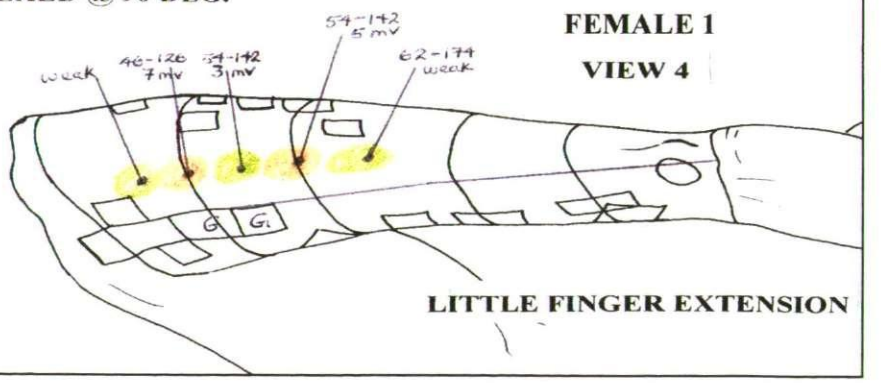
LATERAL ASPECT OF PRONATED FOREARM ELBOW FLEXED @ 90 DEG.

FEMALE 1

VIEW 4



LITTLE FINGER EXTENSION

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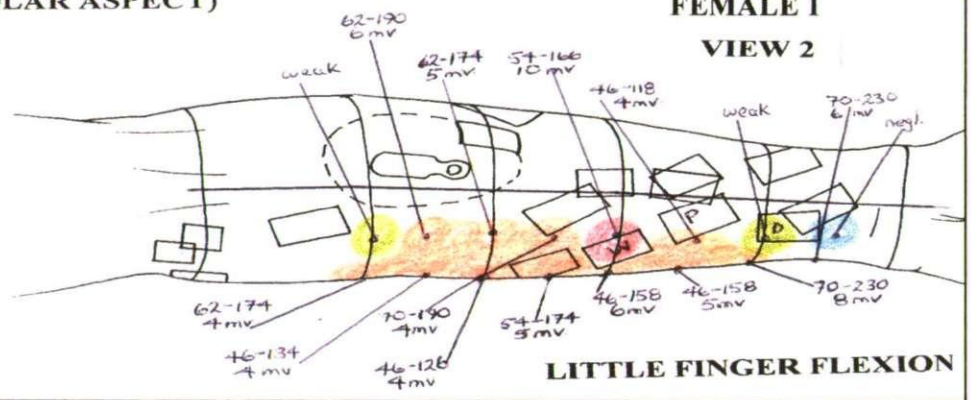
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 1

VIEW 2



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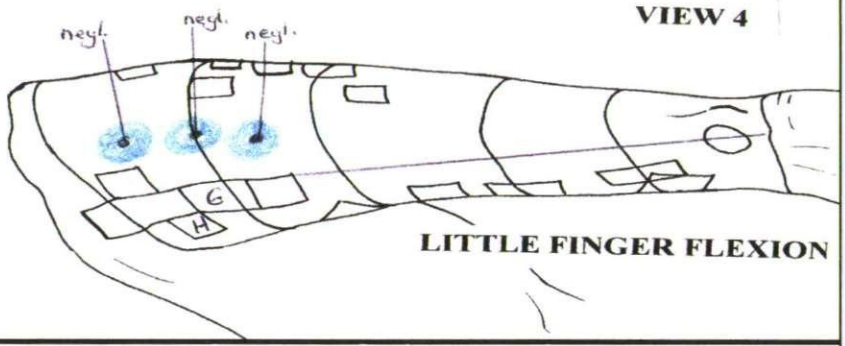
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

FEMALE 1

VIEW 4



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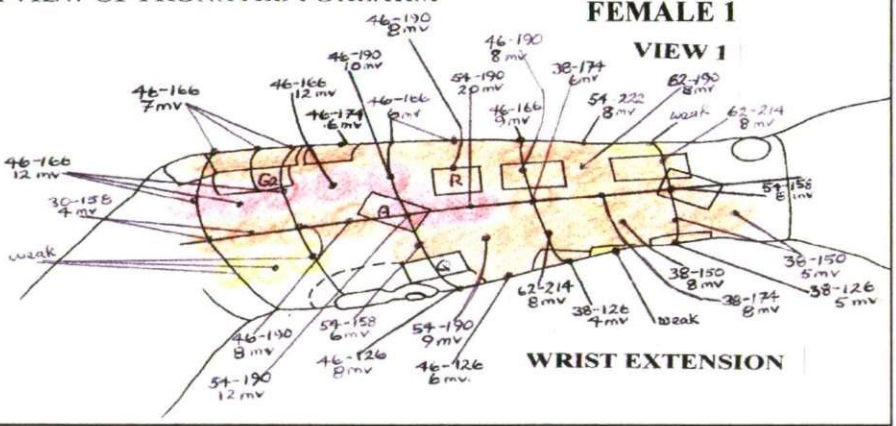
SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1



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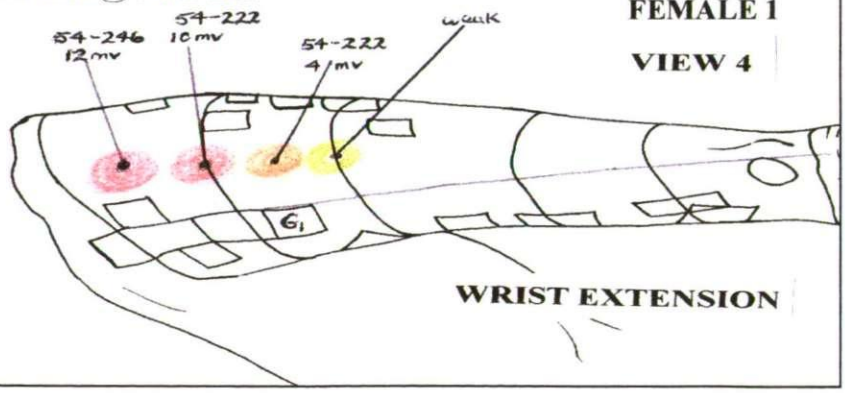
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

FEMALE 1

VIEW 4



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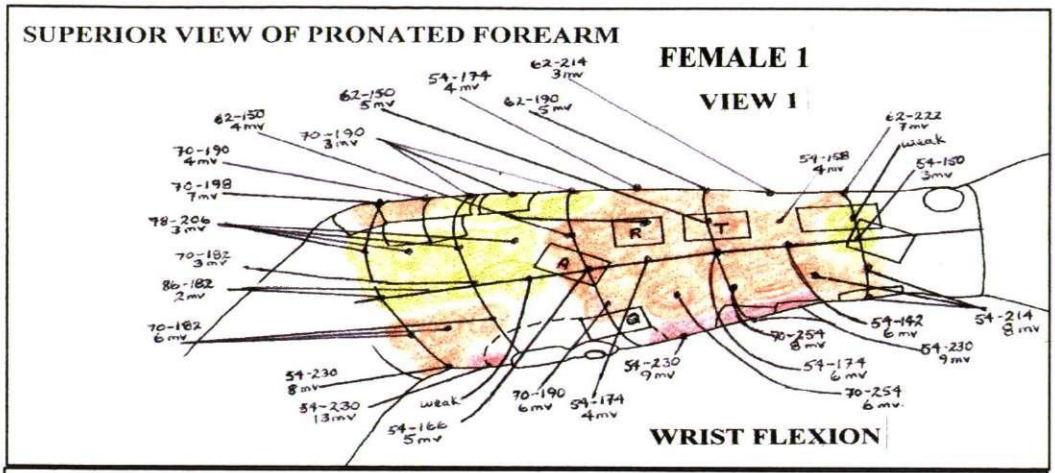
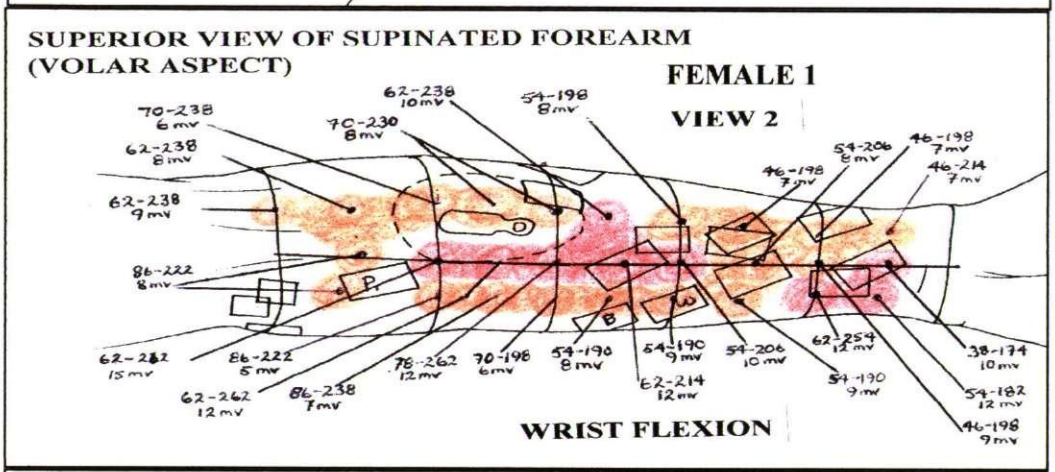
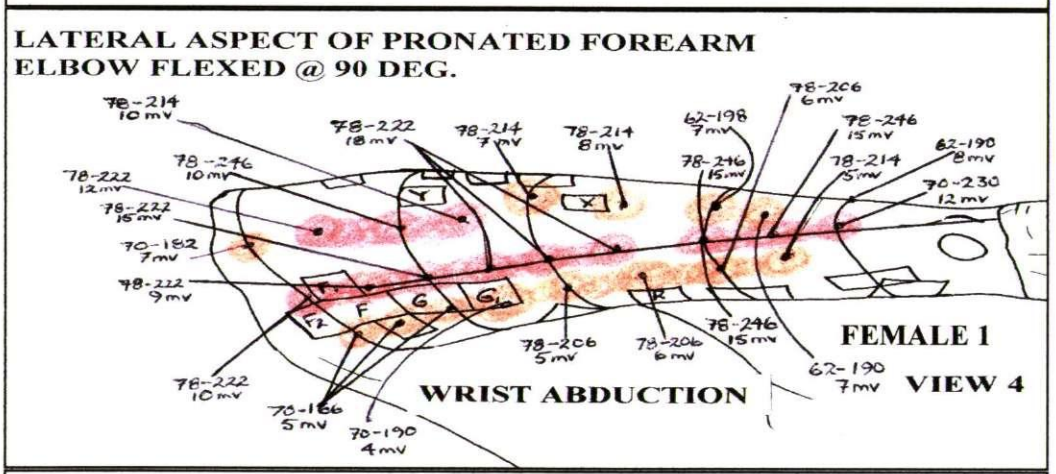

SUPERIOR VIEW OF PRONATED FOREARM
FEMALE 1
VIEW 1
WRIST FLEXION

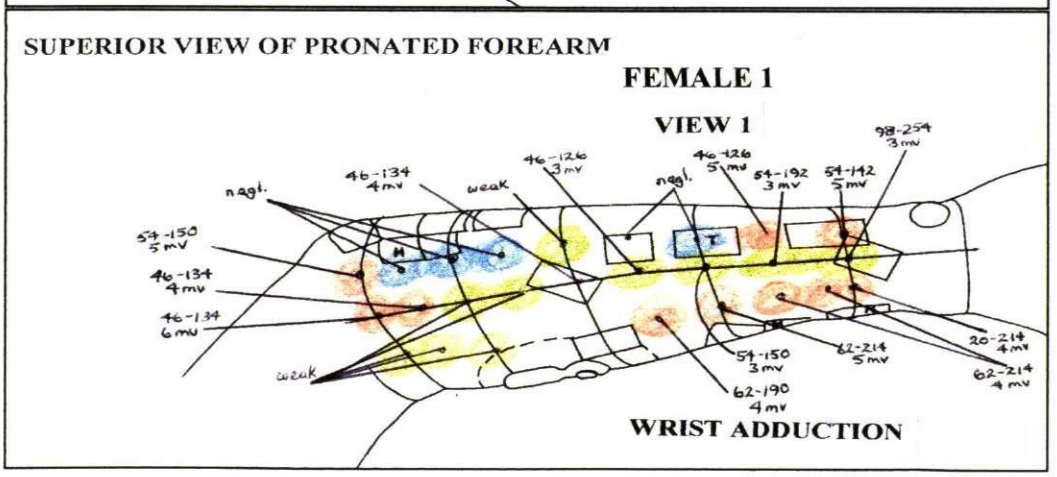
28


SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)
FEMALE 1
VIEW 2
WRIST FLEXION

29


LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.
FEMALE 1
VIEW 4
WRIST ABDUCTION

31

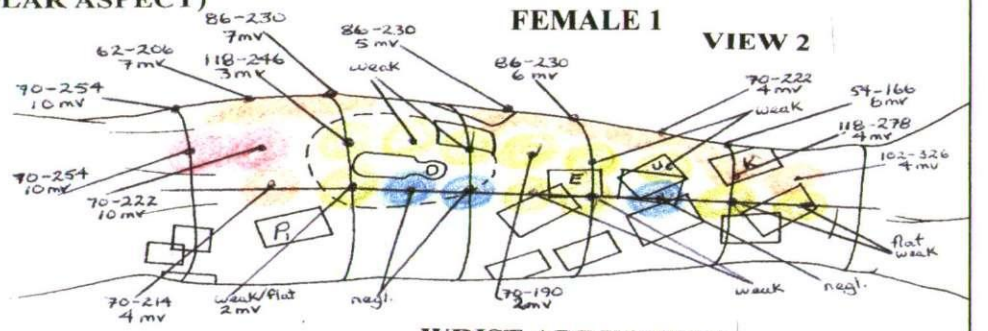

SUPERIOR VIEW OF PRONATED FOREARM
FEMALE 1
VIEW 1
WRIST ADDUCTION

32

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 1

VIEW 2



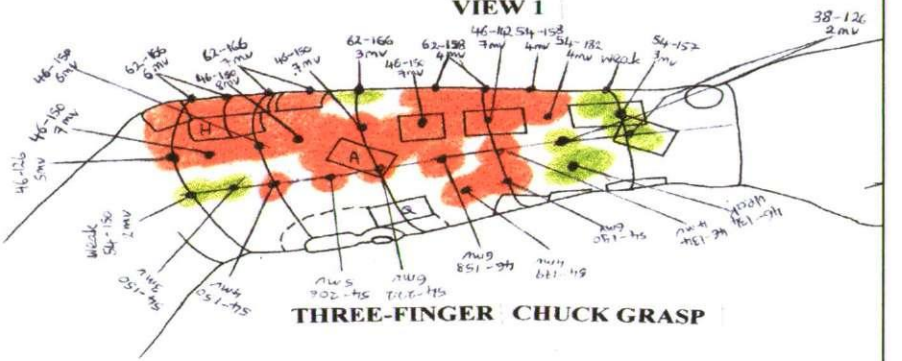
WRIST ADDUCTION

33

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1



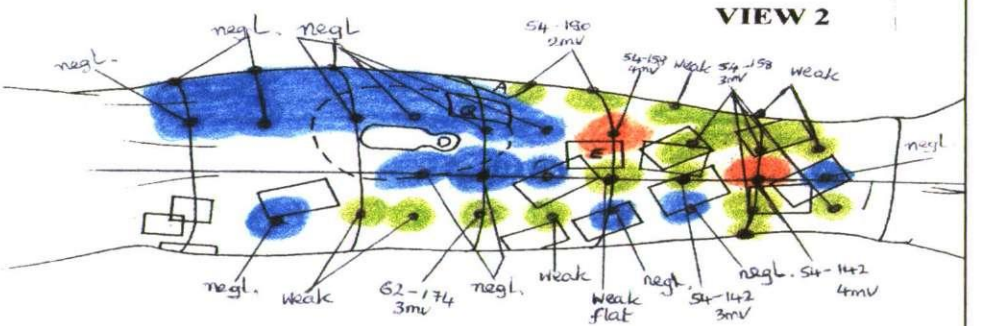
THREE-FINGER CHUCK GRASP

34

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 1

VIEW 2



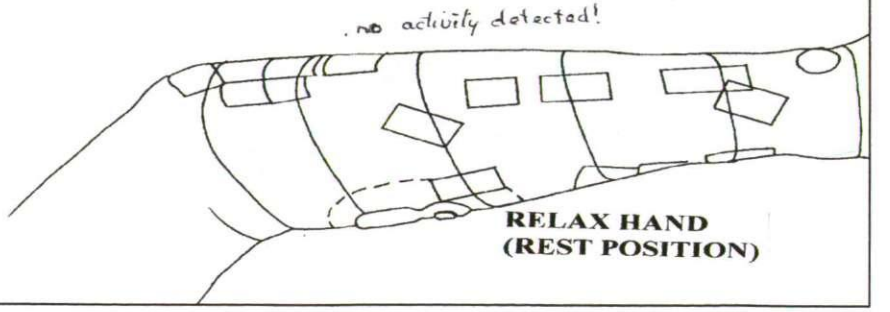
THREE-FINGER CHUCK GRASP

35

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1



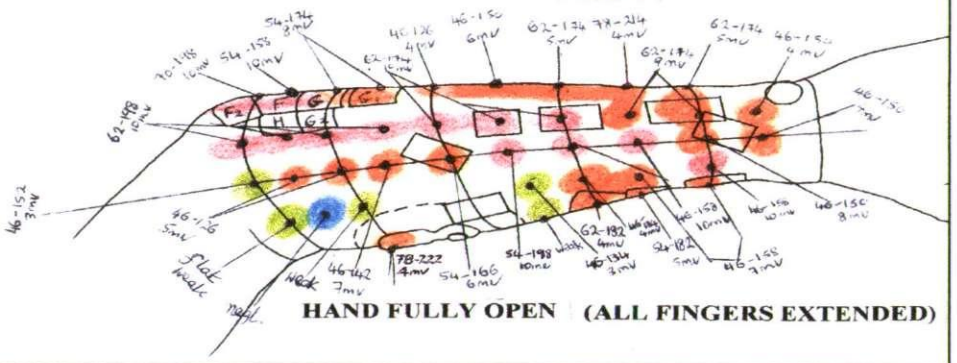
RELAX HAND
(REST POSITION)

36

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1



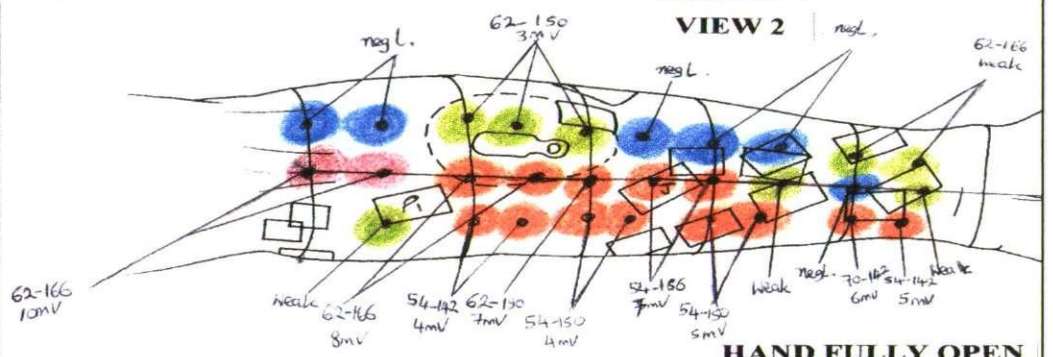
HAND FULLY OPEN (ALL FINGERS EXTENDED)

37

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 1

VIEW 2



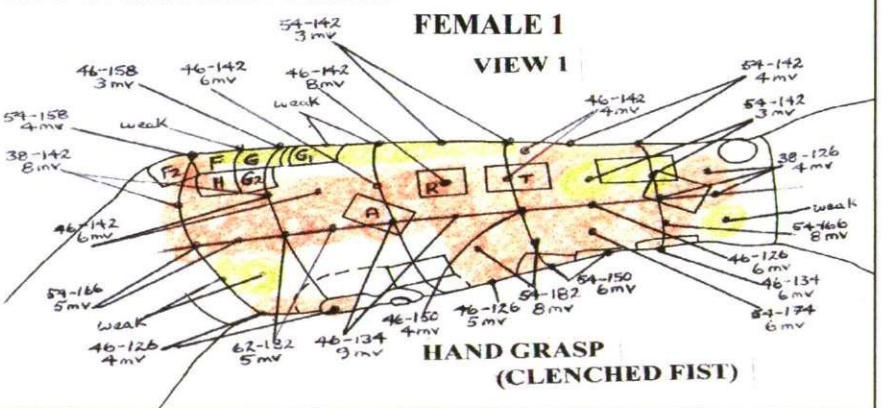
HAND FULLY OPEN

38

SUPERIOR VIEW OF PRONATED FOREARM

FEMALE 1

VIEW 1



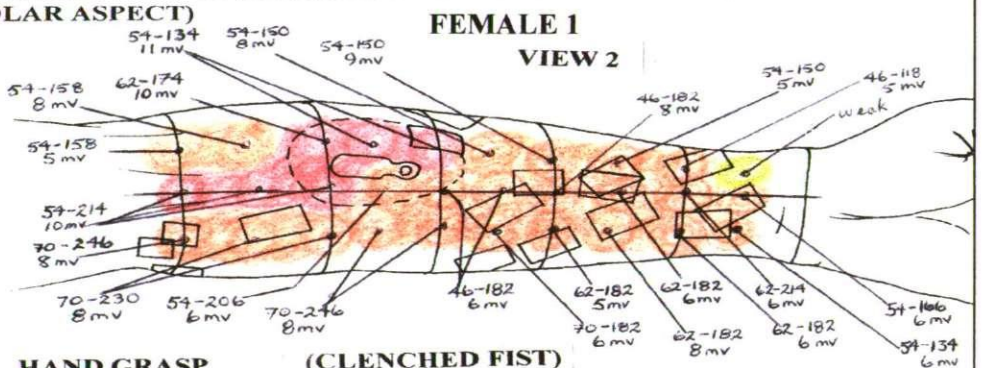
HAND GRASP
(CLENCHED FIST)

40

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

FEMALE 1

VIEW 2



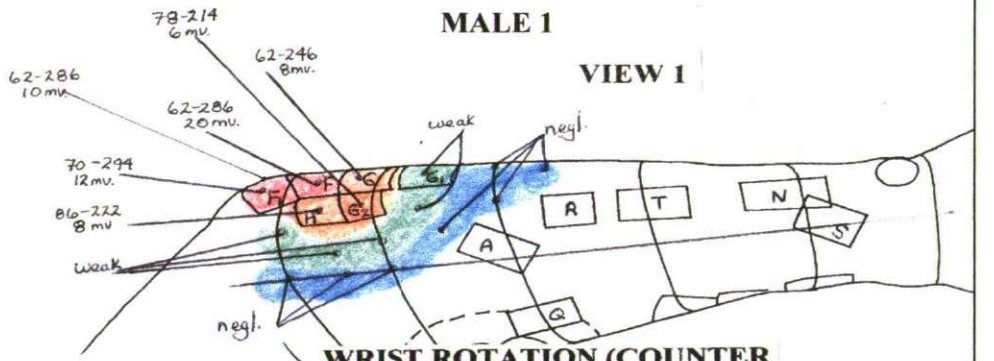
HAND GRASP (CLENCHED FIST)

41

SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



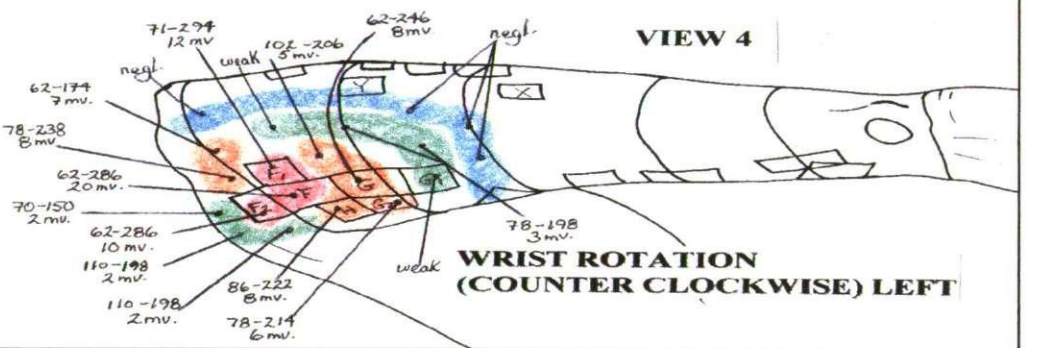
WRIST ROTATION (COUNTER CLOCKWISE) LEFT

1

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4



WRIST ROTATION (COUNTER CLOCKWISE) LEFT

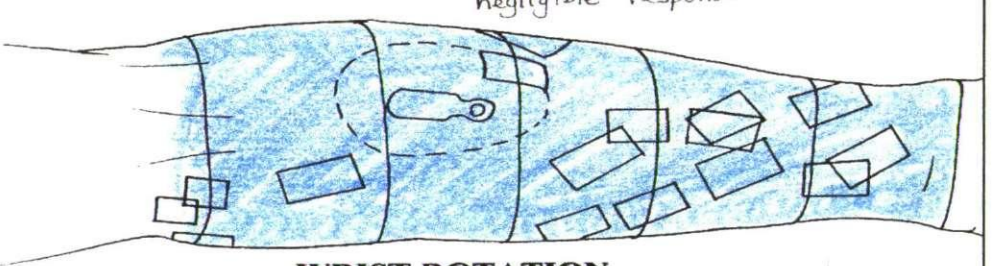
2

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2

negligible response!



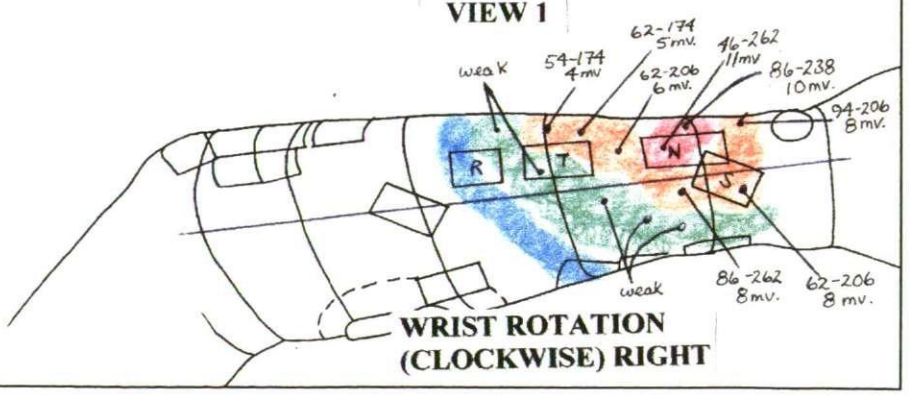
WRIST ROTATION (COUNTER CLOCKWISE) LEFT

4

SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



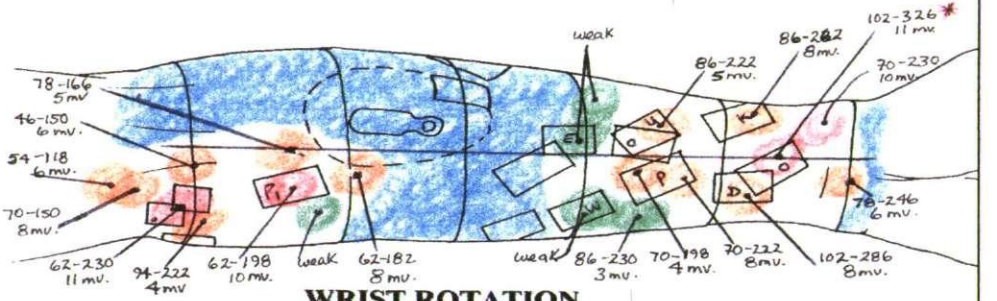
WRIST ROTATION (CLOCKWISE) RIGHT

5

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



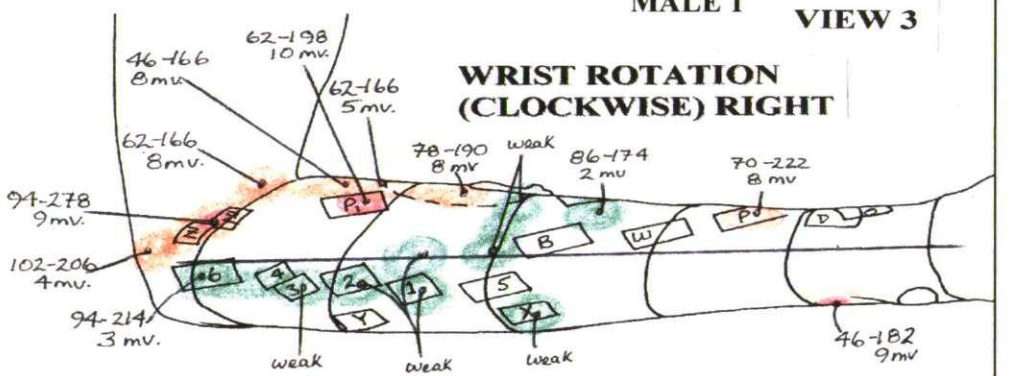
WRIST ROTATION
(CLOCKWISE) RIGHT

6

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3



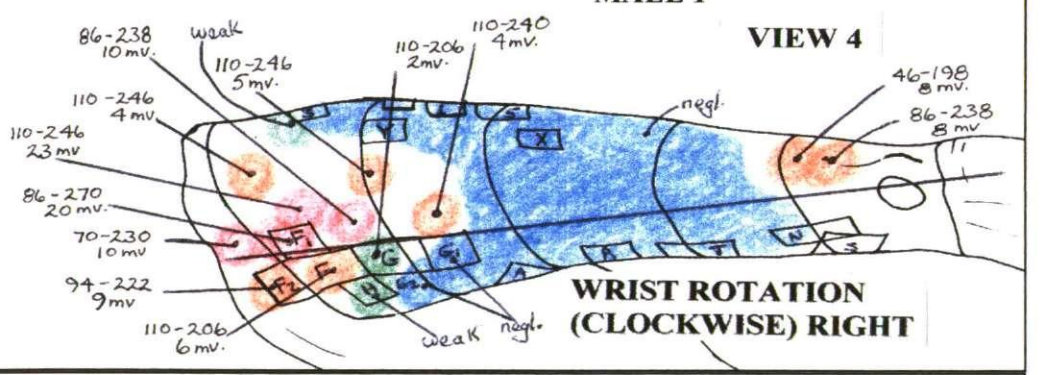
WRIST ROTATION
(CLOCKWISE) RIGHT

7

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4



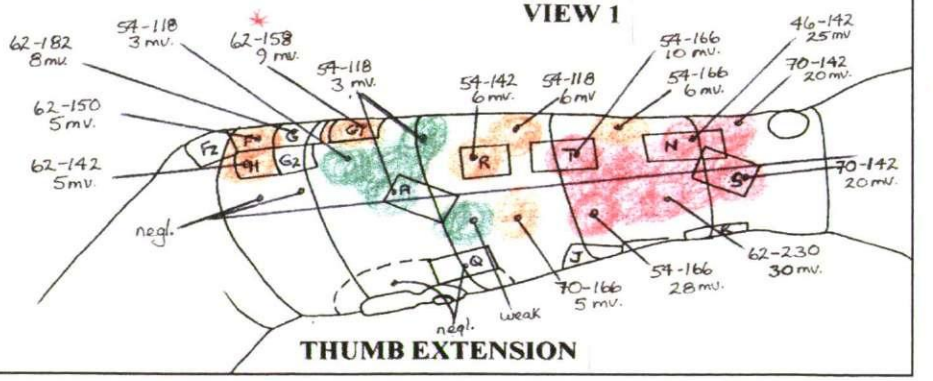
WRIST ROTATION
(CLOCKWISE) RIGHT

8

SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



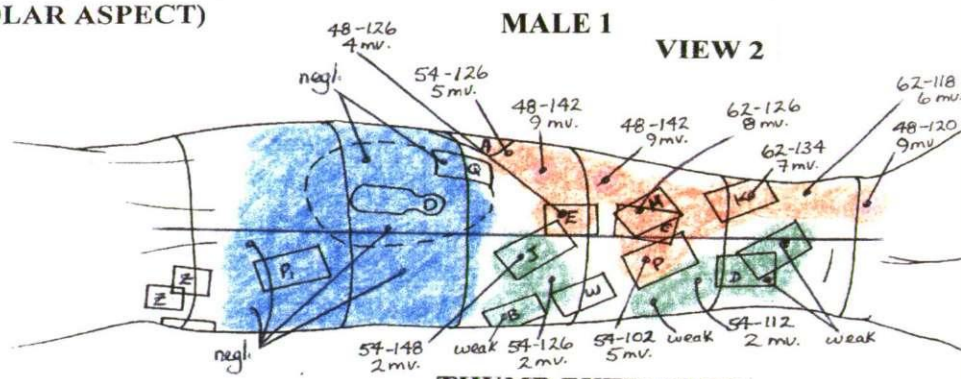
THUMB EXTENSION

9

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



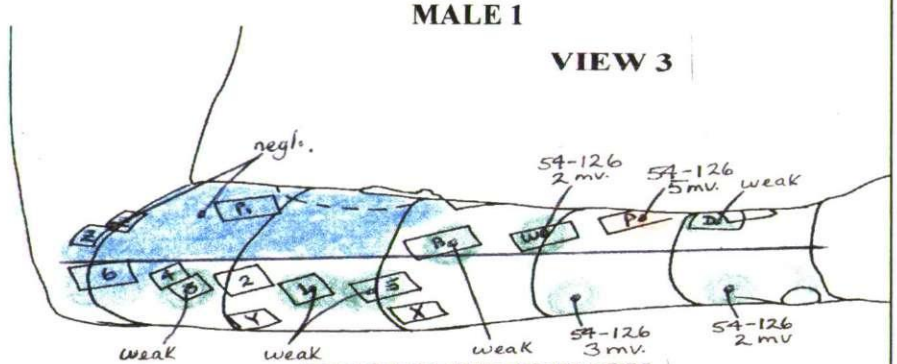
THUMB EXTENSION

10

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3



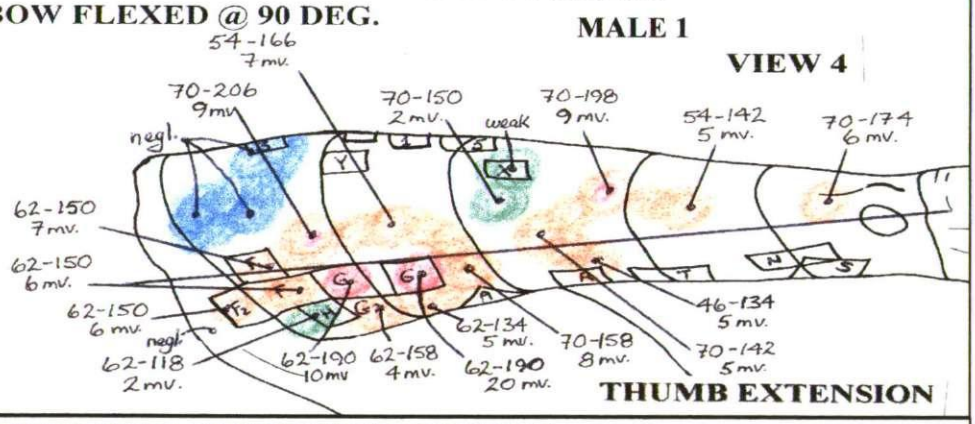
THUMB EXTENSION

11

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4



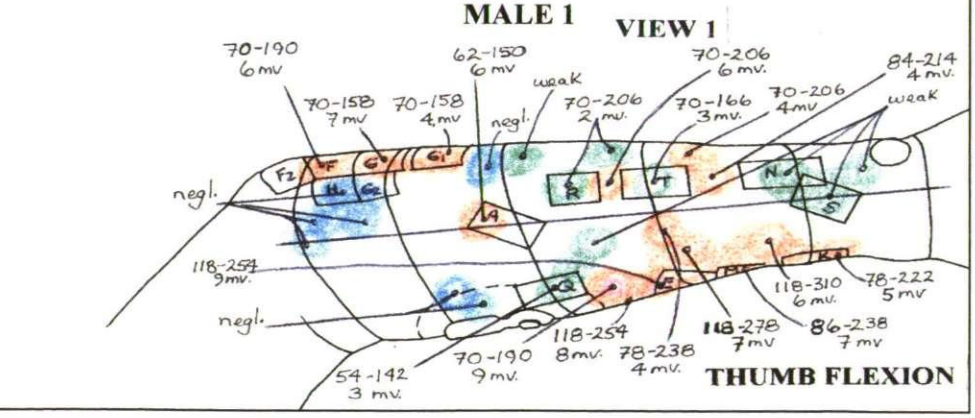
THUMB EXTENSION

12

SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



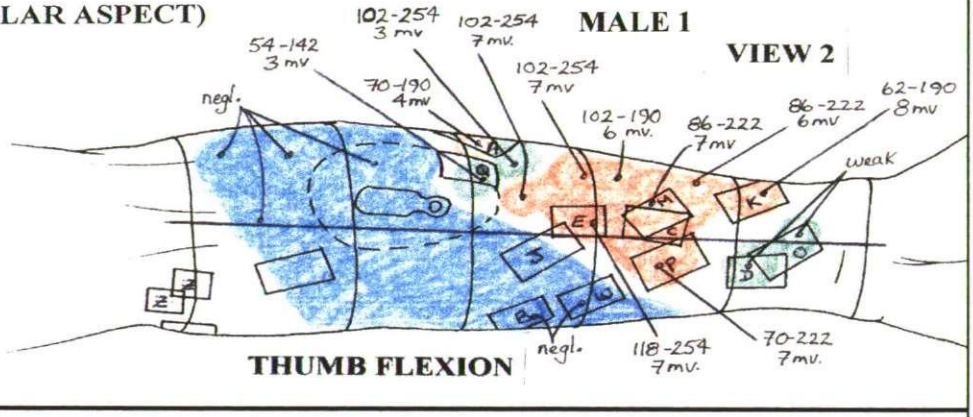
THUMB FLEXION

13

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



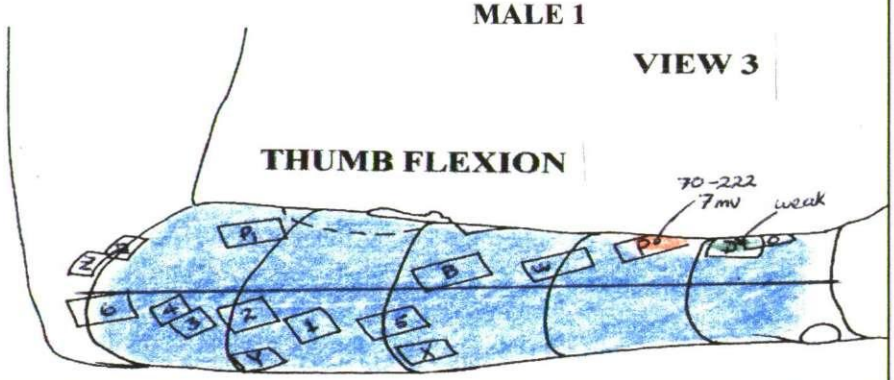
THUMB FLEXION

14

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3



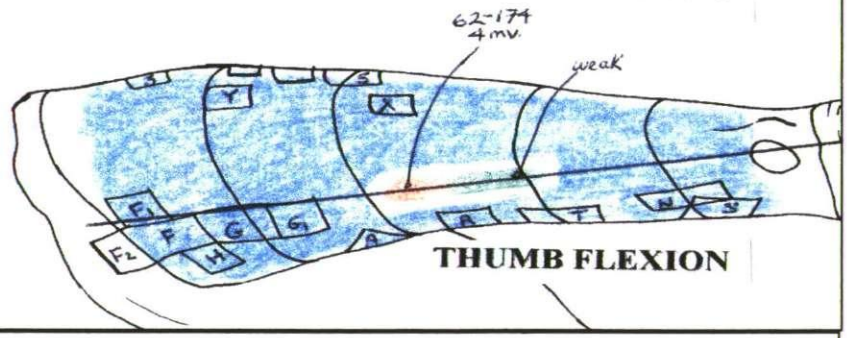
THUMB FLEXION

15

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4



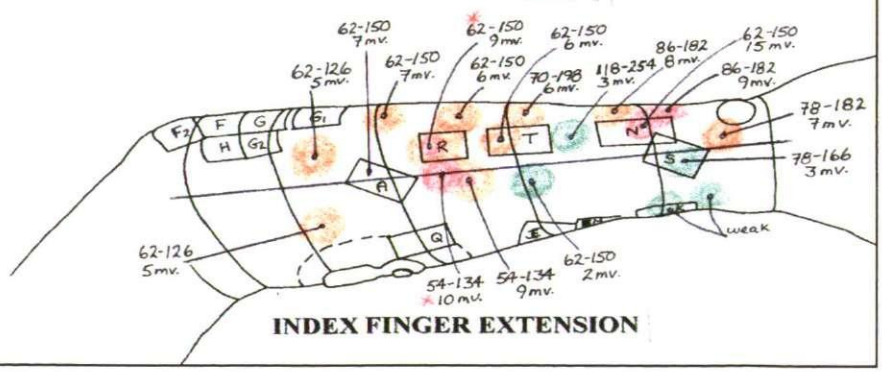
THUMB FLEXION

16

SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



INDEX FINGER EXTENSION

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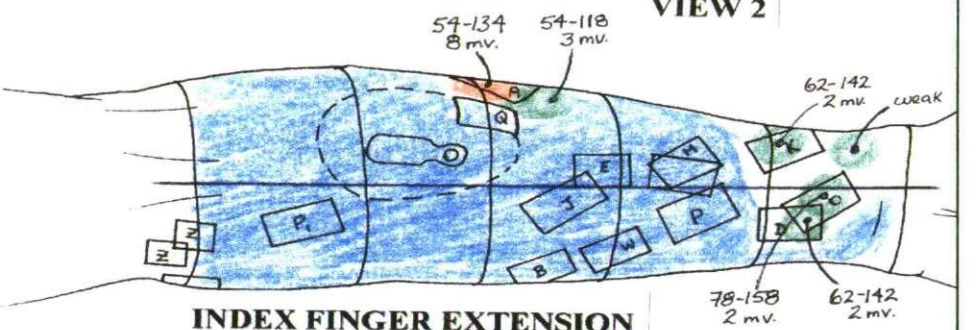
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



INDEX FINGER EXTENSION

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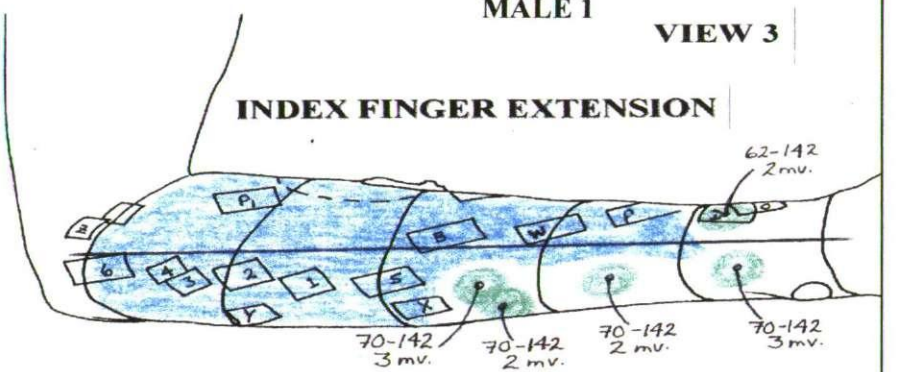
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3

INDEX FINGER EXTENSION



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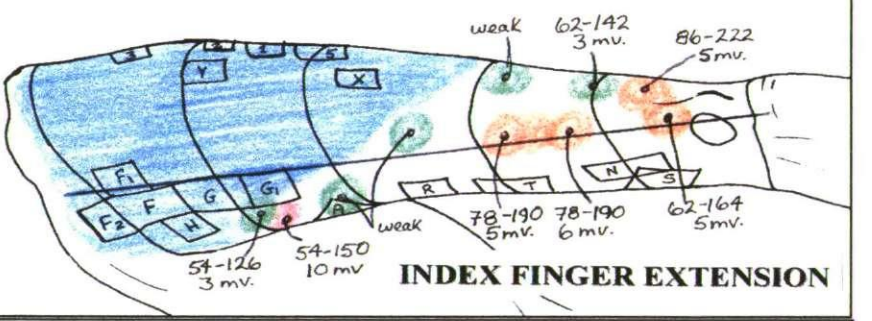
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4



INDEX FINGER EXTENSION

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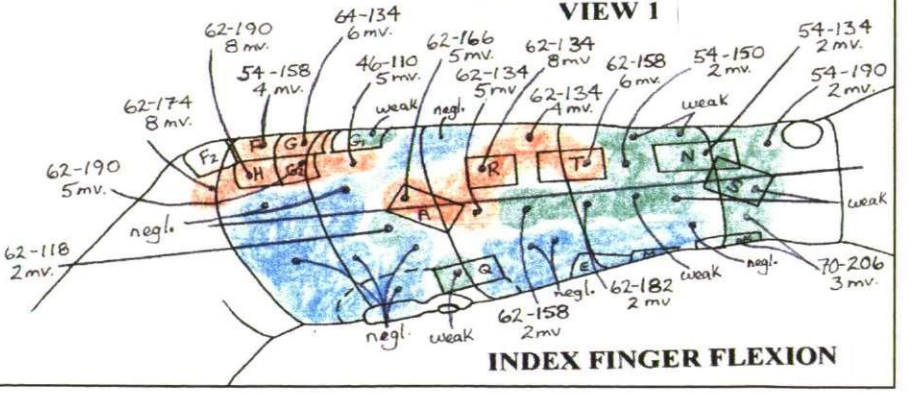
SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



INDEX FINGER FLEXION

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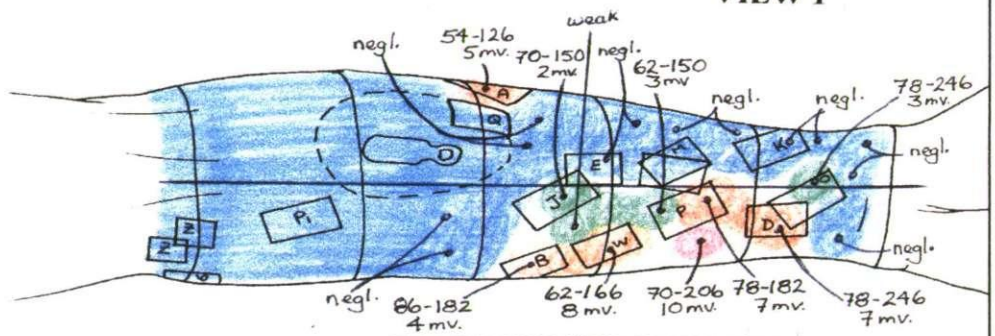
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1 **VIEW 1**

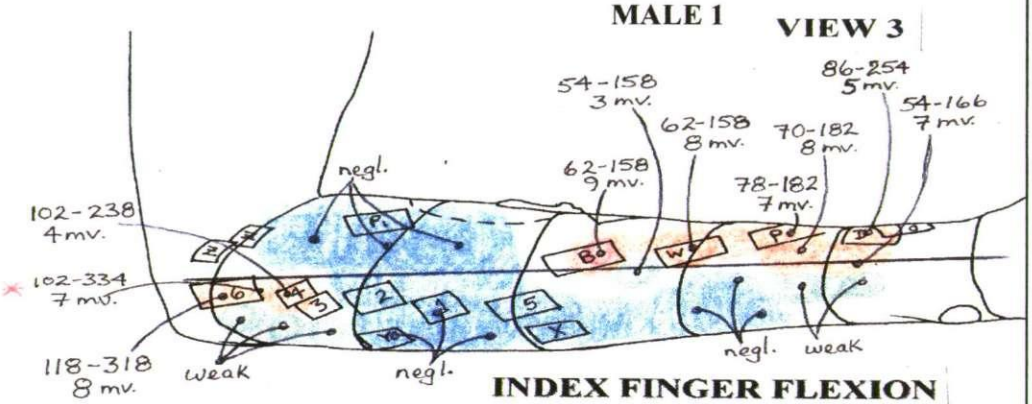


INDEX FINGER FLEXION

22

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1 **VIEW 3**



INDEX FINGER FLEXION

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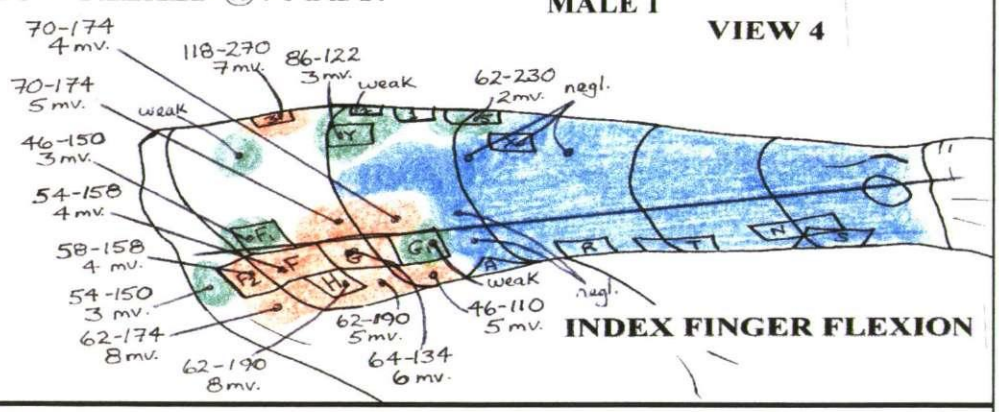
LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1 **VIEW 4**



INDEX FINGER FLEXION

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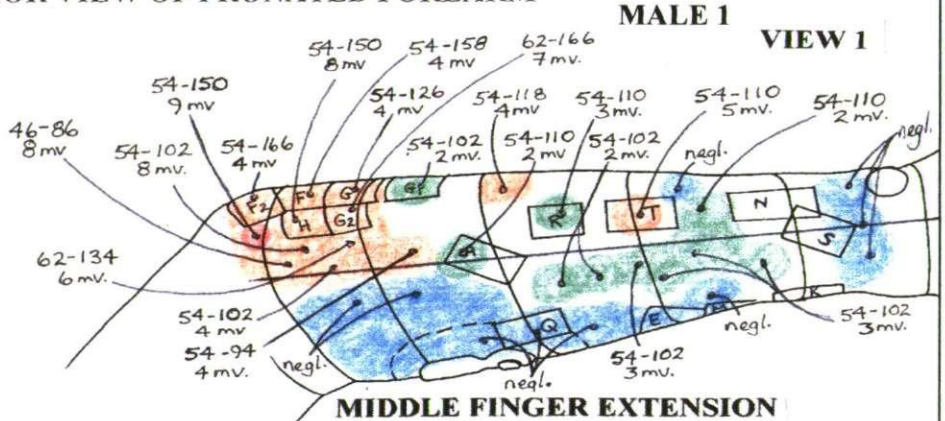
SUPERIOR VIEW OF PRONATED FOREARM

MALE 1 **VIEW 1**



MIDDLE FINGER EXTENSION

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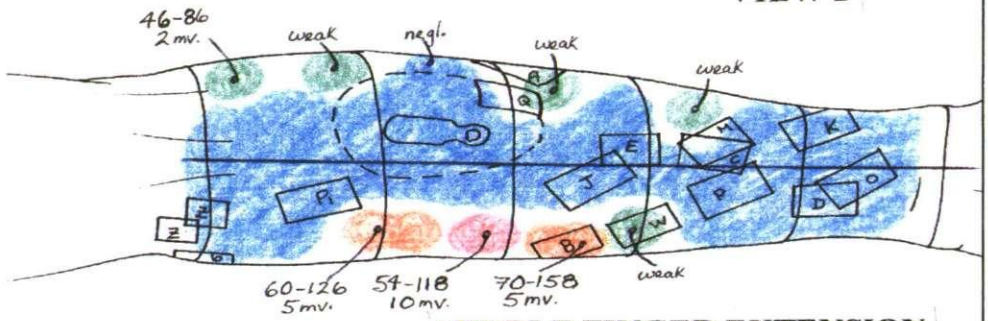
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT) **MALE 1**

VIEW 2



MIDDLE FINGER EXTENSION

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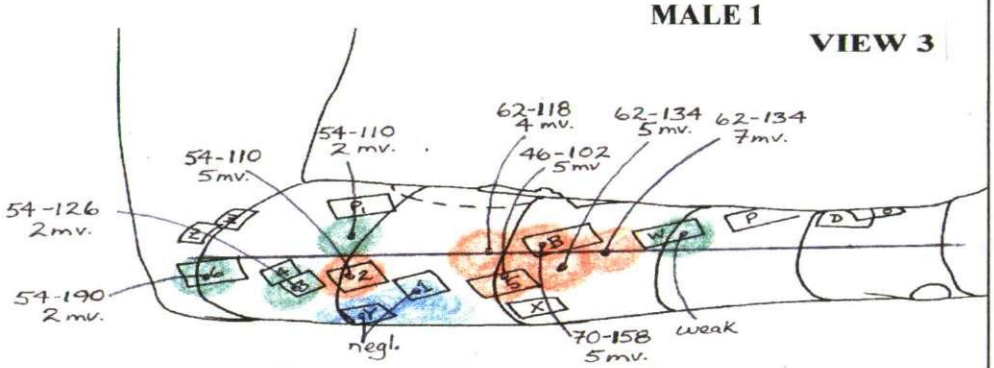
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3

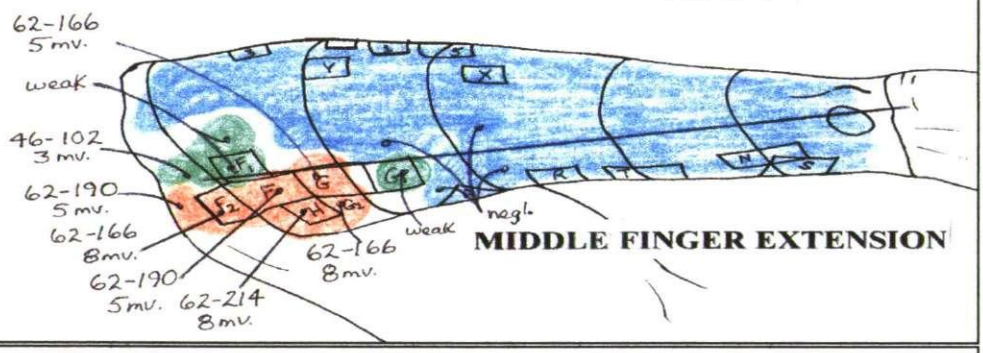


MIDDLE FINGER EXTENSION

27

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG. **MALE 1**

VIEW 4



MIDDLE FINGER EXTENSION

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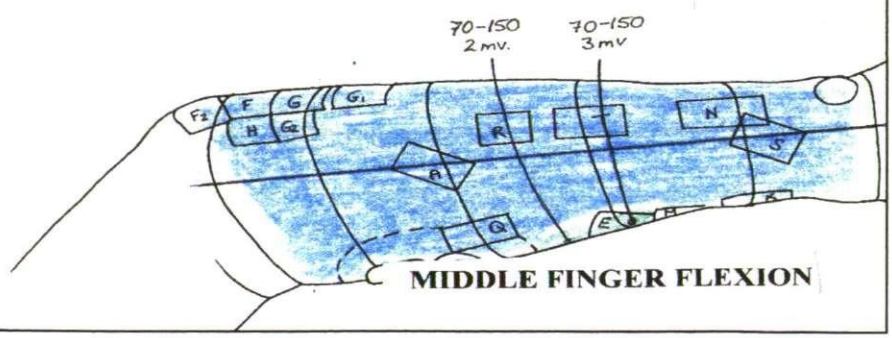
SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



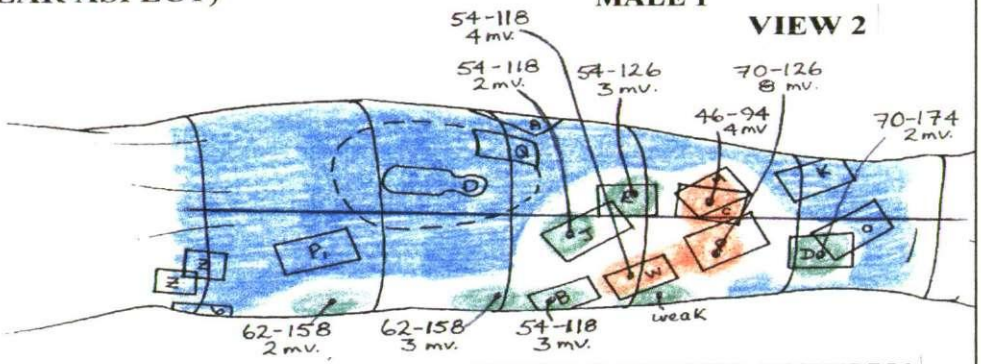
MIDDLE FINGER FLEXION

29

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



MIDDLE FINGER FLEXION

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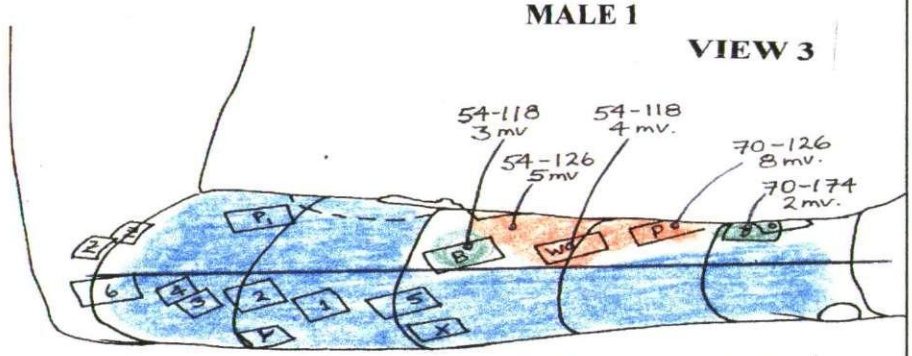
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3



MIDDLE FINGER FLEXION

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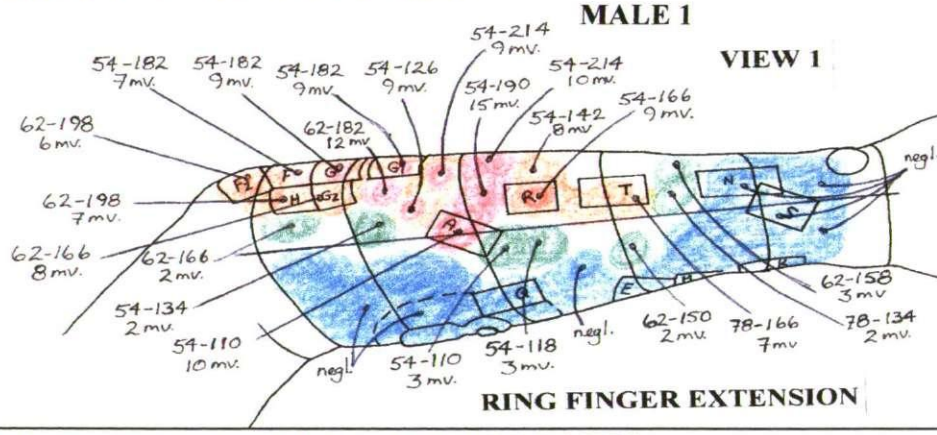
SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



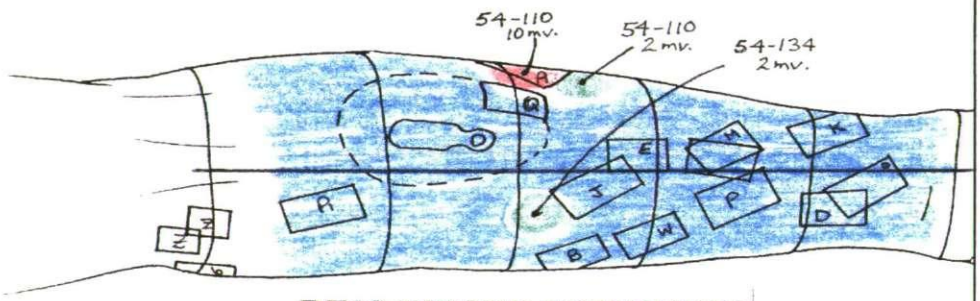
RING FINGER EXTENSION

33

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



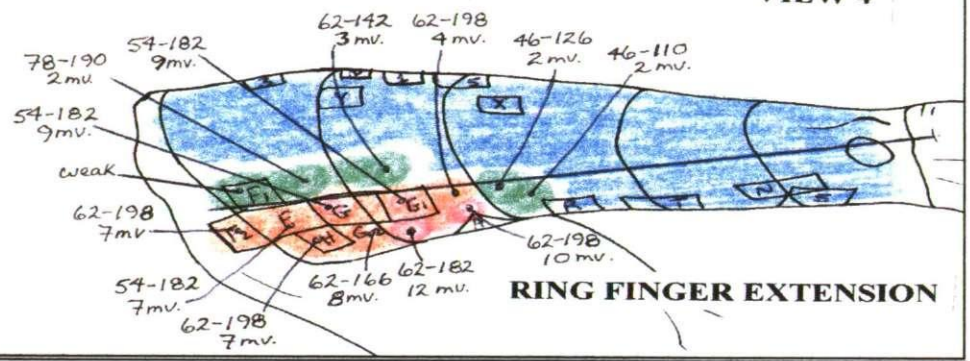
RING FINGER EXTENSION

34

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4

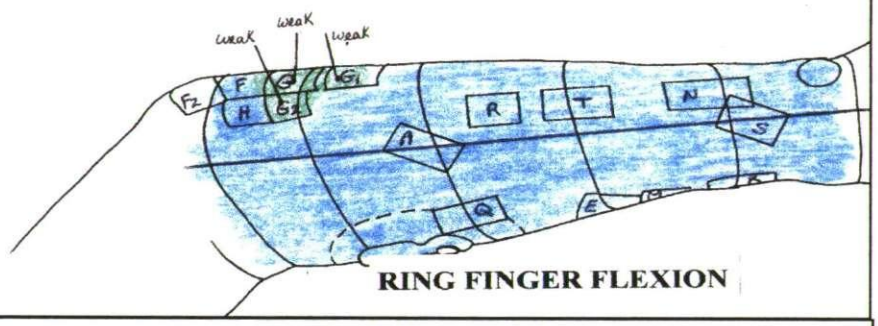


36

SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1

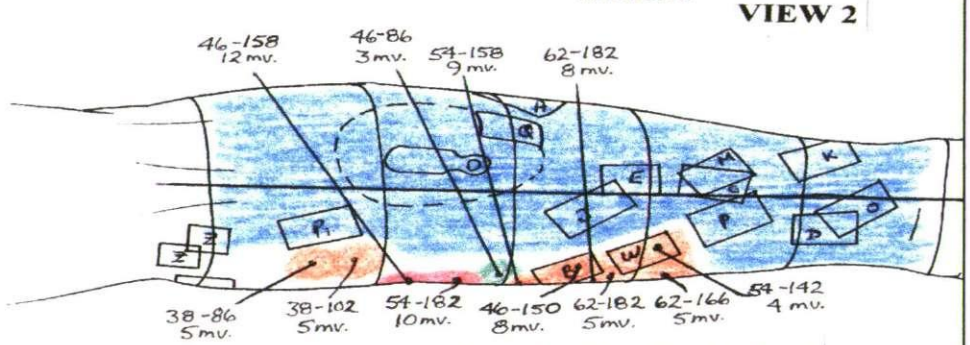


37

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2

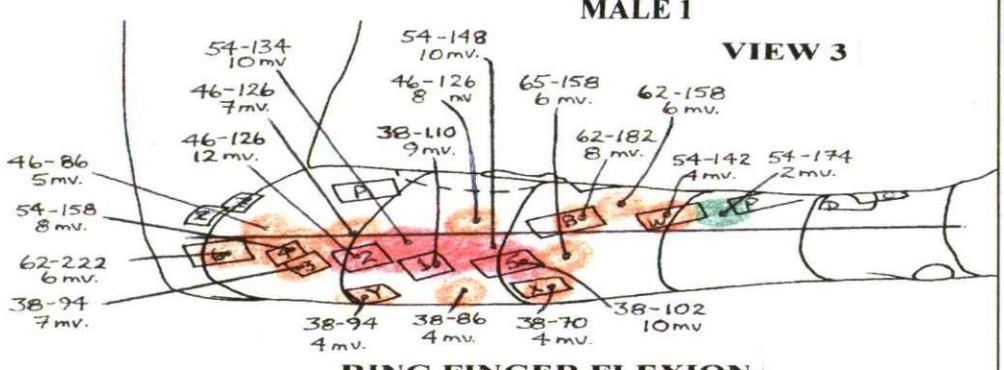


38

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3

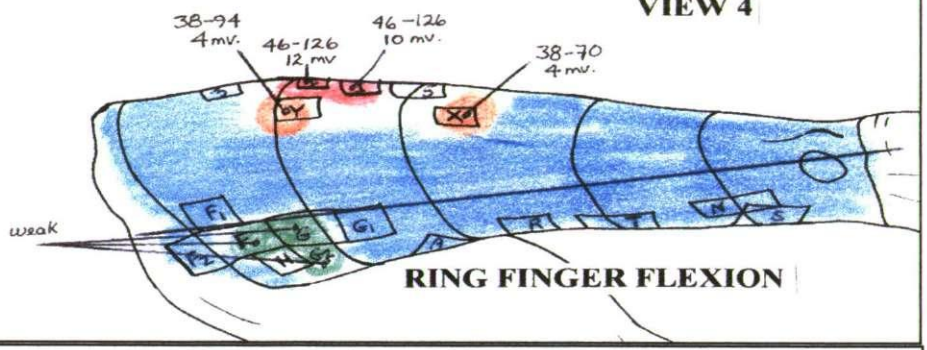


39

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4

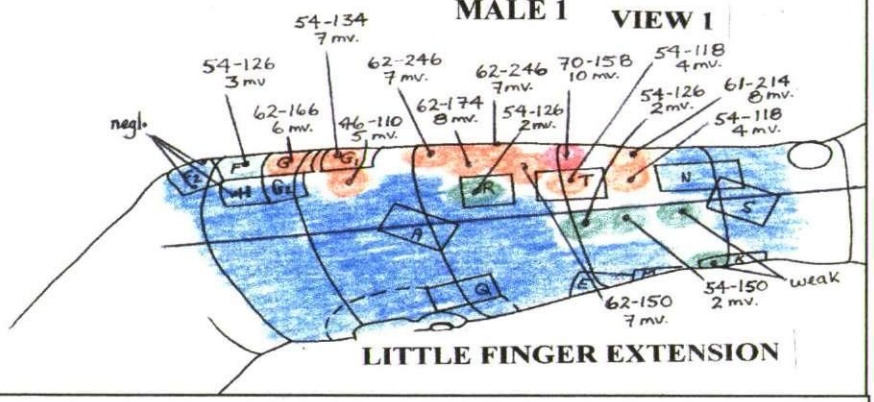


RING FINGER FLEXION

40

SUPERIOR VIEW OF PRONATED FOREARM

MALE 1 **VIEW 1**



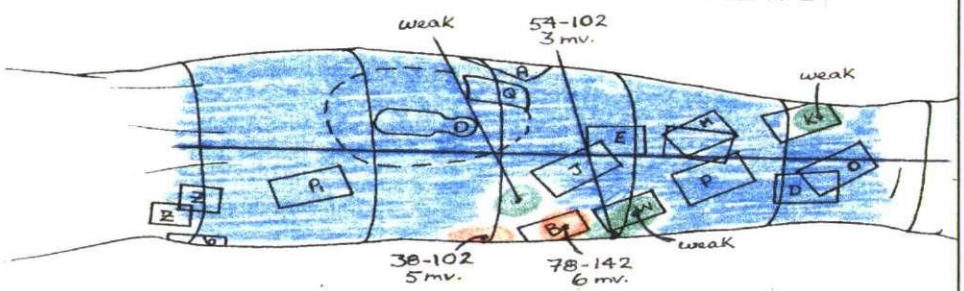
LITTLE FINGER EXTENSION

41

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



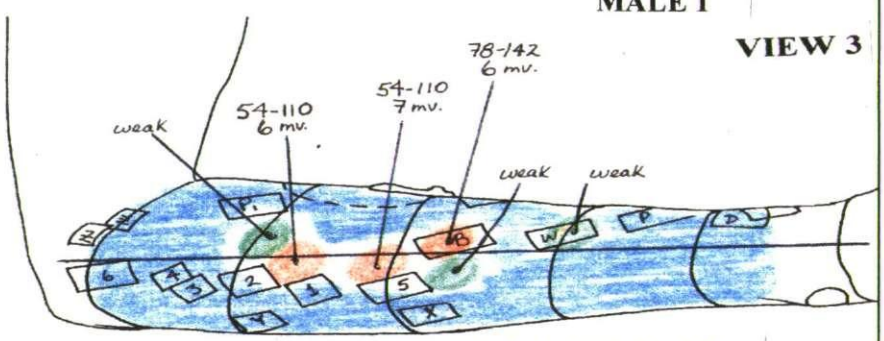
LITTLE FINGER EXTENSION

42

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3



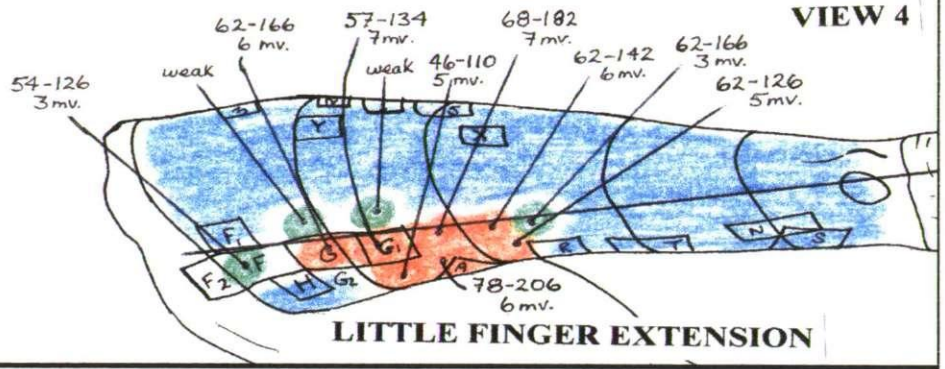
LITTLE FINGER EXTENSION

43

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4



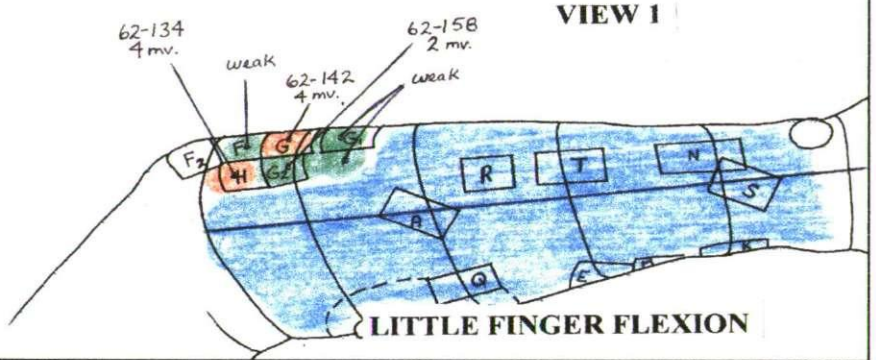
LITTLE FINGER EXTENSION

44

SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



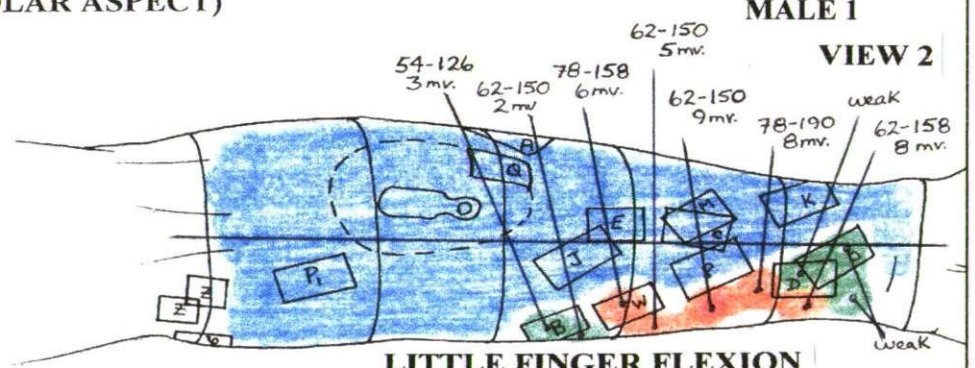
LITTLE FINGER FLEXION

45

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



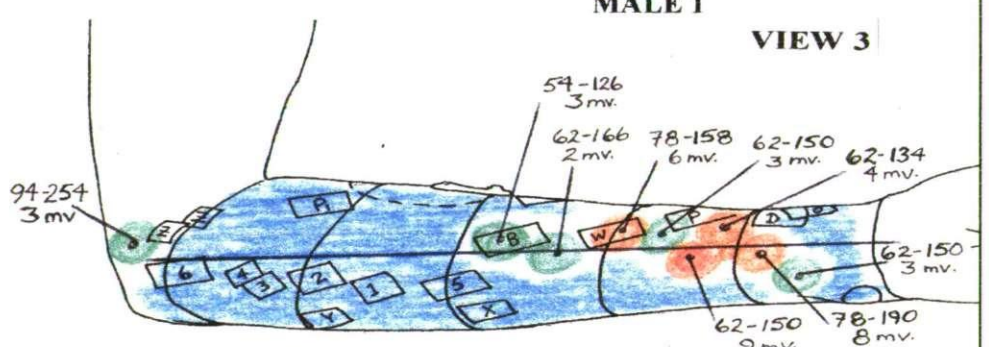
LITTLE FINGER FLEXION

46

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3



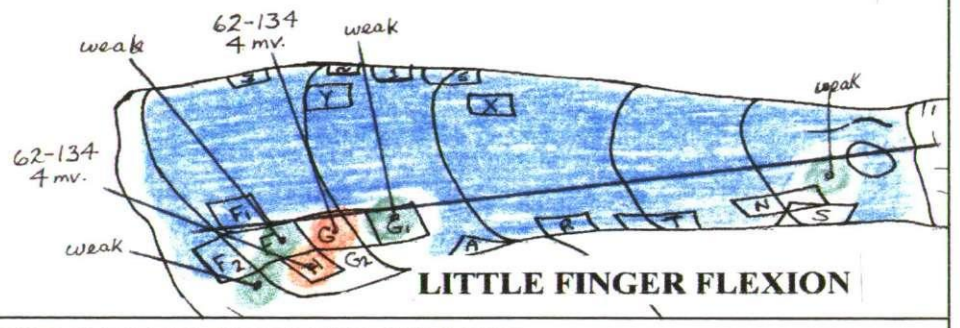
LITTLE FINGER FLEXION

47

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4

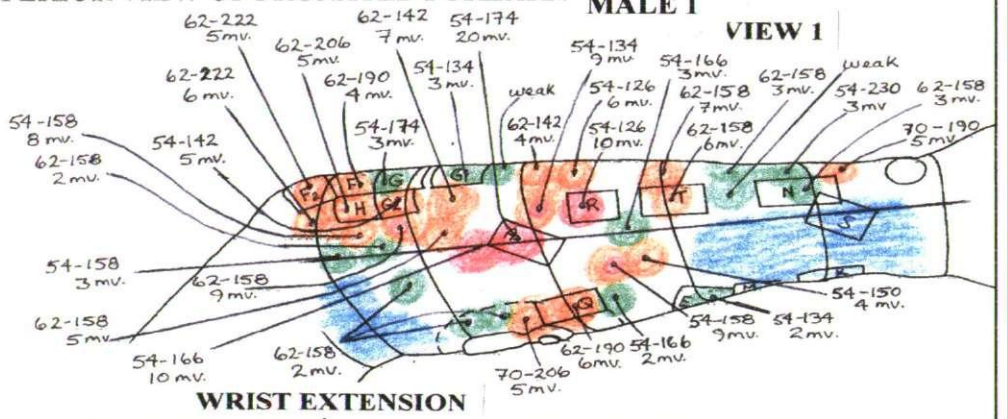


48

SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1

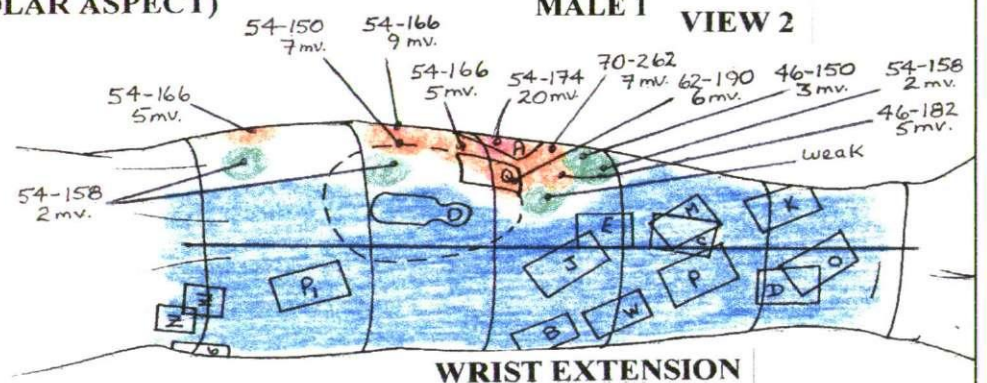


49

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2

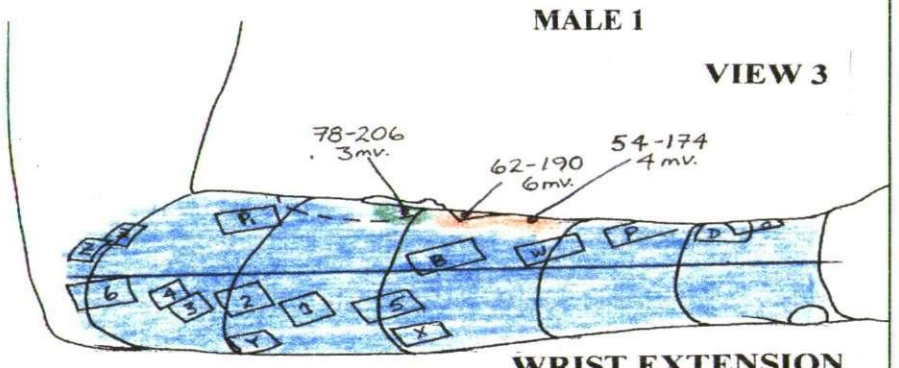


50

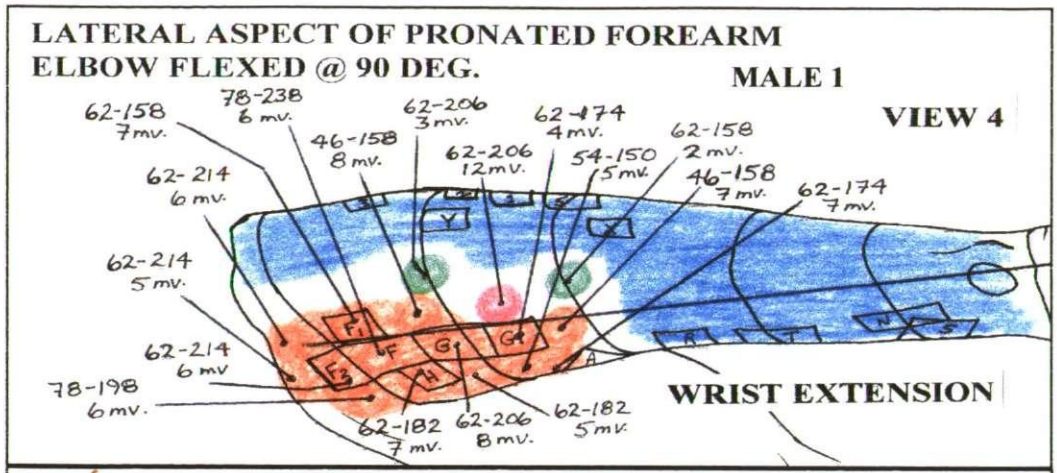
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

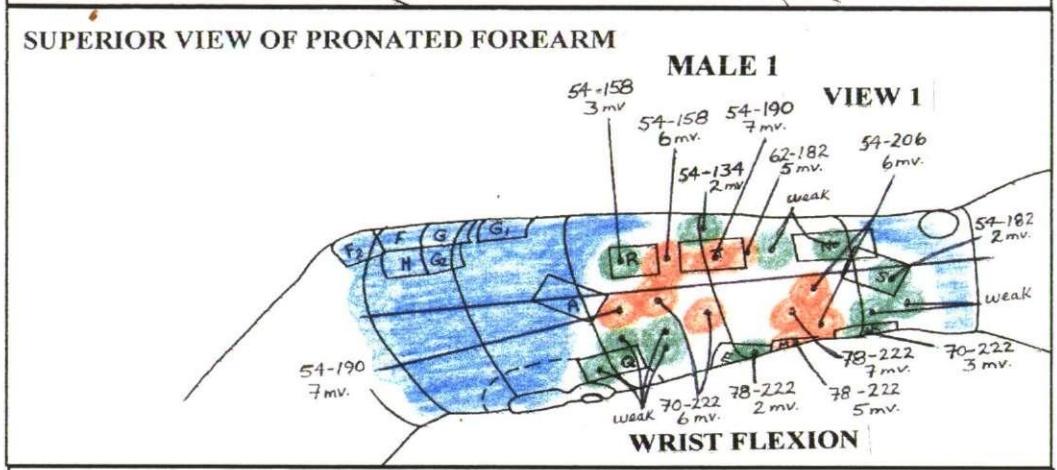
VIEW 3



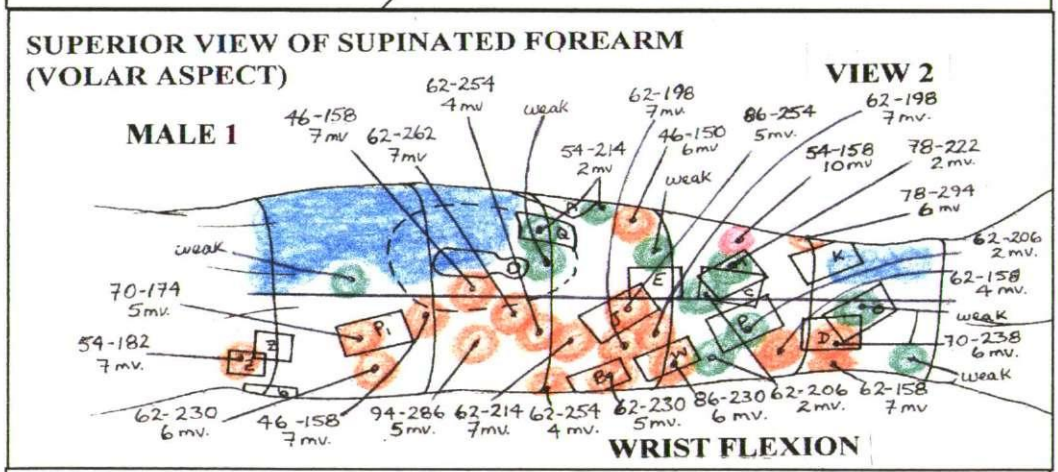
51


LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.
MALE 1
VIEW 4
WRIST EXTENSION

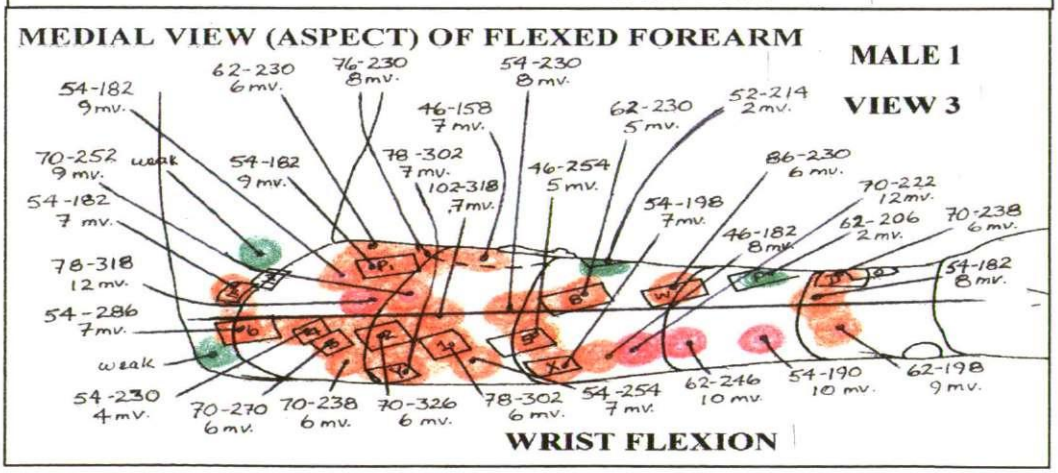
52


SUPERIOR VIEW OF PRONATED FOREARM
MALE 1
VIEW 1
WRIST FLEXION

53


SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)
MALE 1
VIEW 2
WRIST FLEXION

54

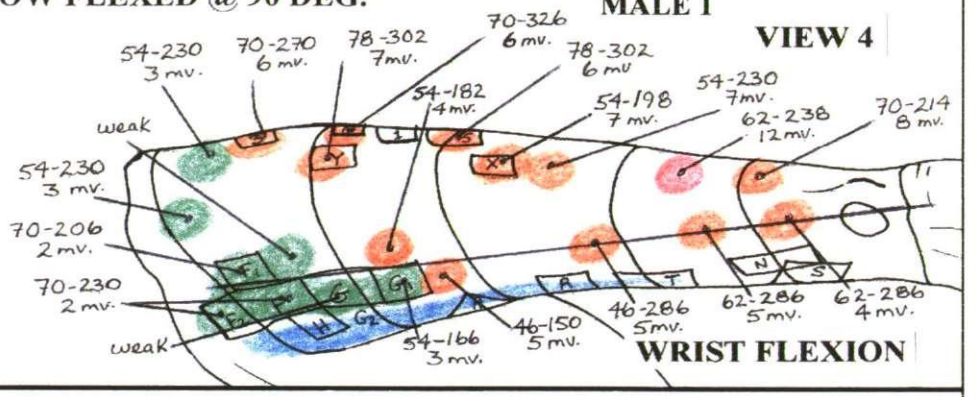

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM
MALE 1
VIEW 3
WRIST FLEXION

55

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4



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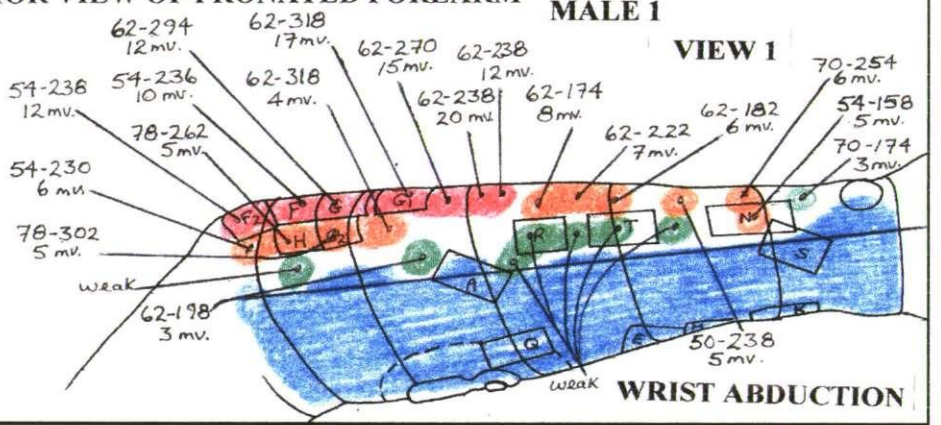
SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



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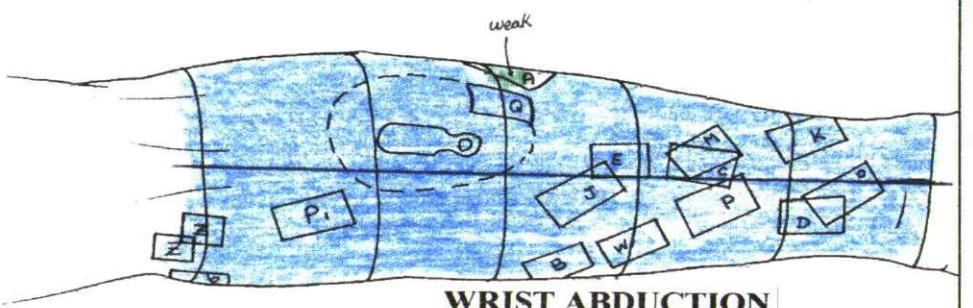
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



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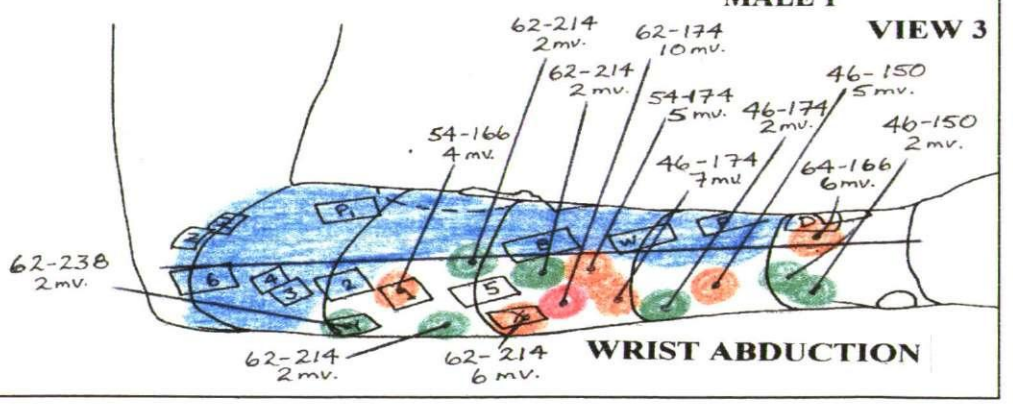
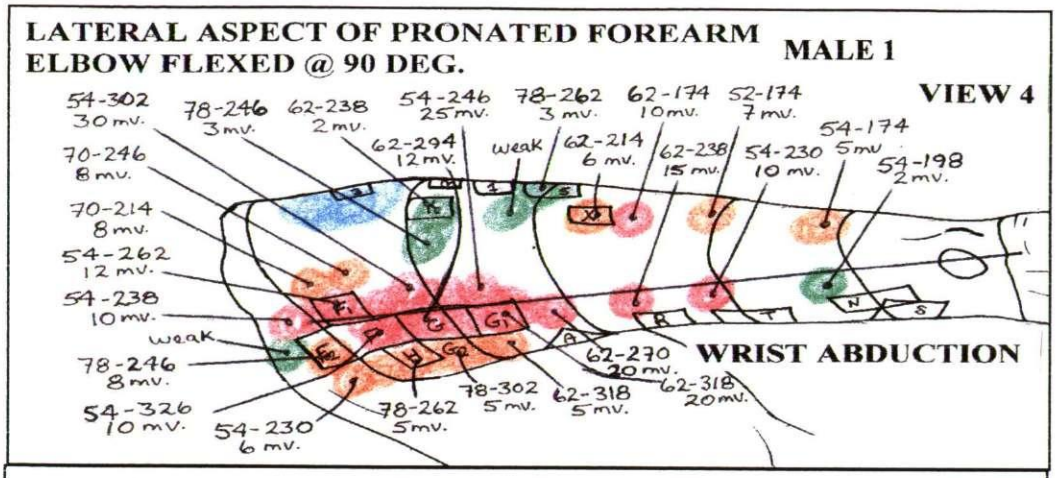
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

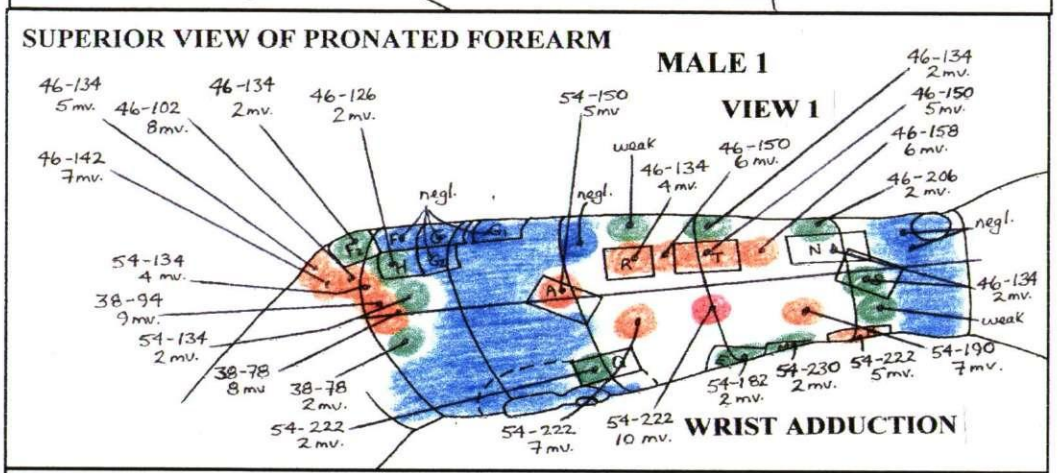
VIEW 3



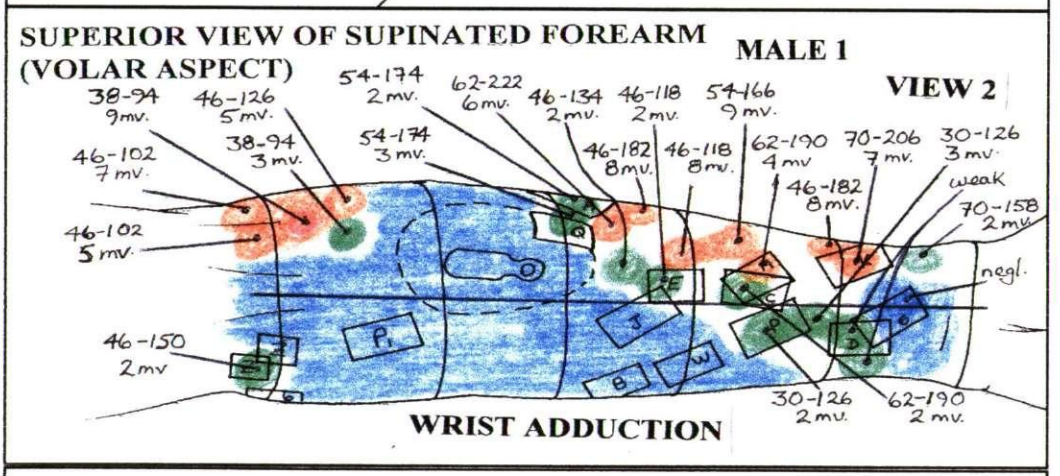
59


LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.
MALE 1
VIEW 4
54-302 30 mv.
78-246 3mv.
62-238 2 mv.
54-246 25mv.
78-262 3 mv.
62-174 10mv.
52-174 7 mv.
54-174 5mv
54-198 2mv.
54-230 10 mv.
62-238 15 mv.
62-214 6 mv.
weak
62-294 12mv.
70-246 8 mv.
70-214 8 mv.
54-262 12 mv.
54-238 10 mv.
weak
78-246 8 mv.
54-326 10 mv.
54-230 6 mv.
78-262 5mv.
78-302 5 mv.
62-318 5 mv.
62-270 20 mv.
62-318 20 mv.
WRIST ABDUCTION

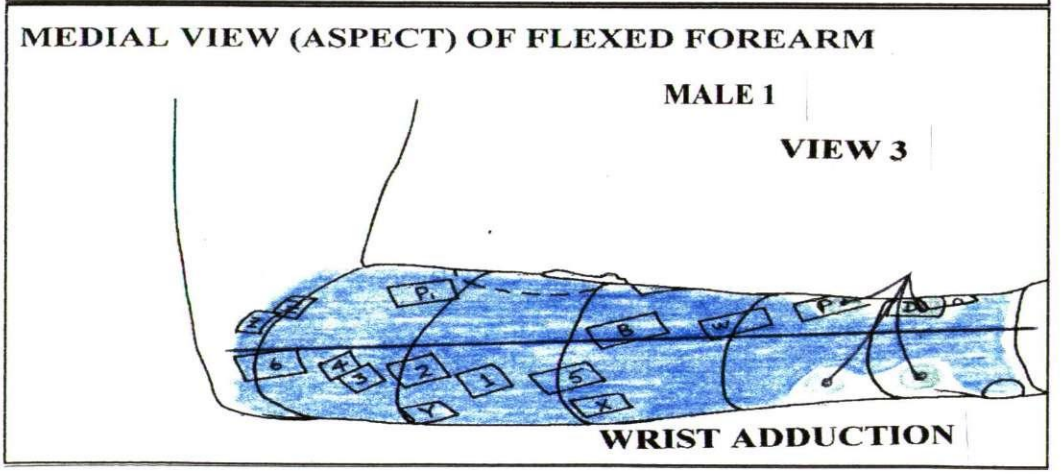
60


SUPERIOR VIEW OF PRONATED FOREARM
MALE 1
VIEW 1
46-134 5mv.
46-102 8mv.
46-134 2mv.
46-126 2mv.
46-142 7mv.
54-150 5mv
weak
46-134 4mv.
46-150 6 mv.
46-134 2mv.
46-150 5mv.
46-158 6 mv.
46-206 2 mv.
negl.
54-134 4 mv.
38-94 9mv.
54-134 2 mv.
38-78 8 mv
38-78 2mv.
54-222 2 mv.
54-222 7 mv.
54-222 10 mv.
54-182 2 mv.
54-230 2 mv.
54-222 5mv.
54-190 7 mv.
46-134 2mv.
weak
WRIST ADDUCTION

61


SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)
MALE 1
VIEW 2
38-94 9mv.
46-126 5mv.
54-174 2mv.
62-222 6mv.
46-134 2mv.
46-118 2mv.
54-166 9 mv.
38-94 3mv.
54-174 3 mv.
46-182 8mv.
46-118 8mv.
62-190 4 mv
70-206 7 mv.
30-126 3 mv
46-182 8mv.
weak
70-158 2mv
46-102 7 mv.
46-102 5 mv.
46-150 2mv
negl.
30-126 2mv.
62-190 2 mv.
WRIST ADDUCTION

62

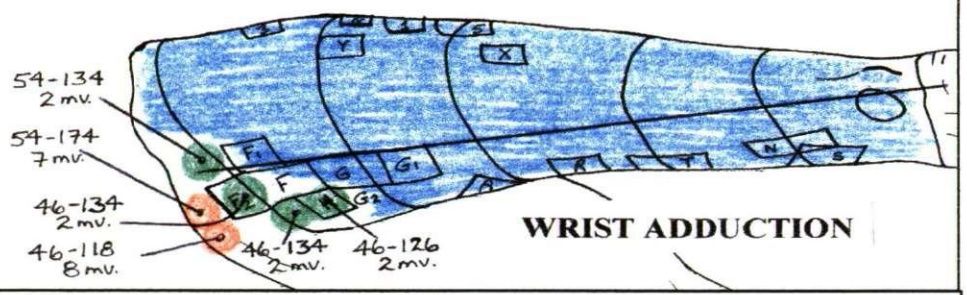

MEDIAL VIEW (ASPECT) OF FLEXED FOREARM
MALE 1
VIEW 3
WRIST ADDUCTION

63

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4



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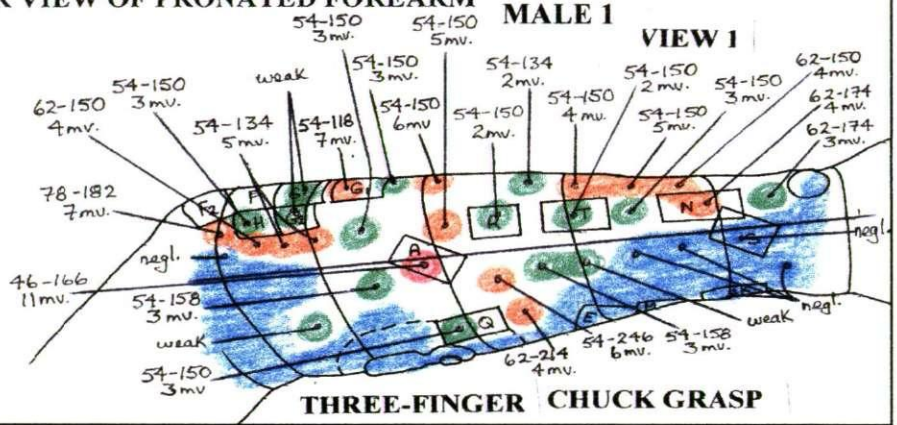
SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1

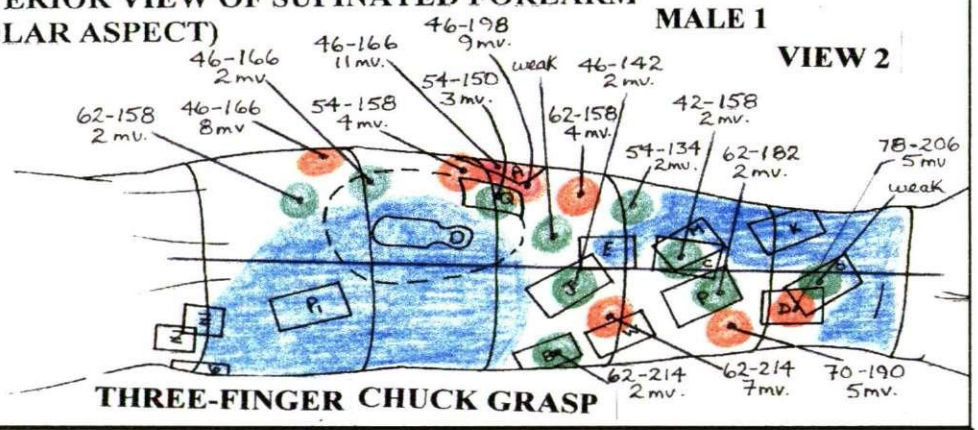


65

SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



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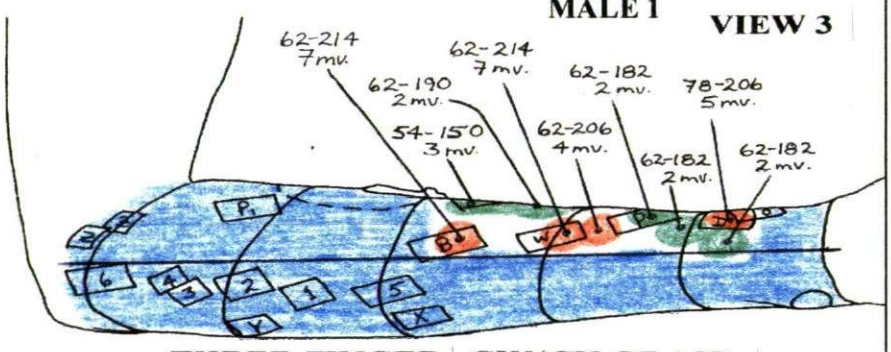
MEDIAL VIEW (ASPECT) OF FLEXED FOREARM

MALE 1

VIEW 3

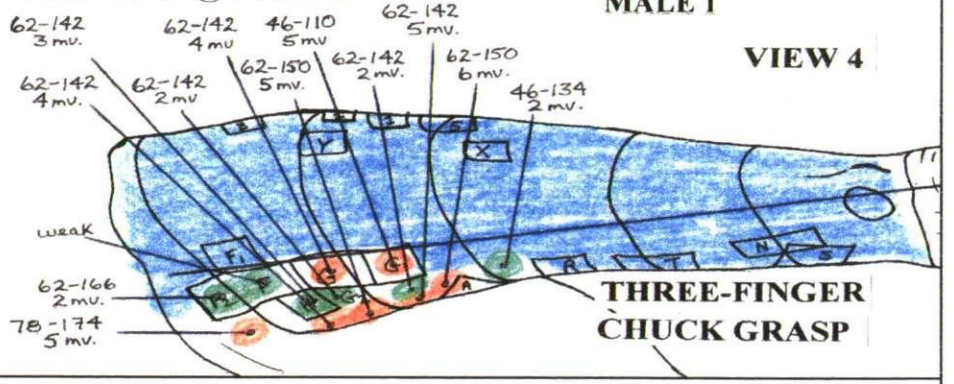


67

LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.

MALE 1

VIEW 4



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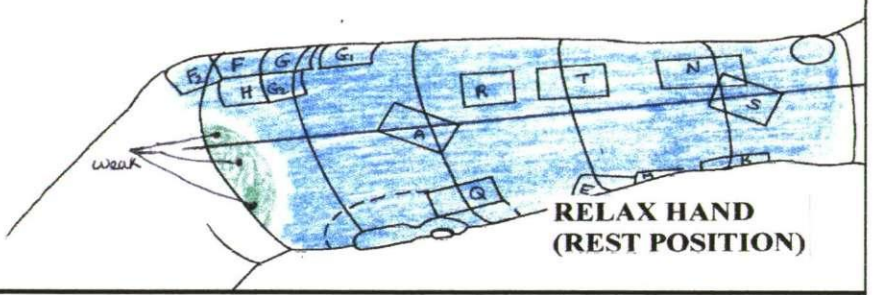
SUPERIOR VIEW OF PRONATED FOREARM

MALE 1

VIEW 1



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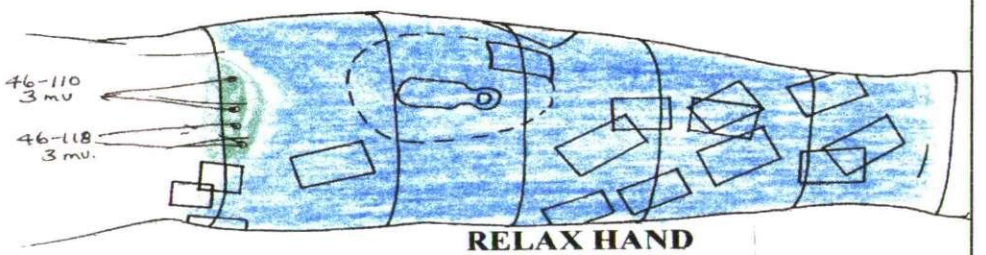
SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)

MALE 1

VIEW 2



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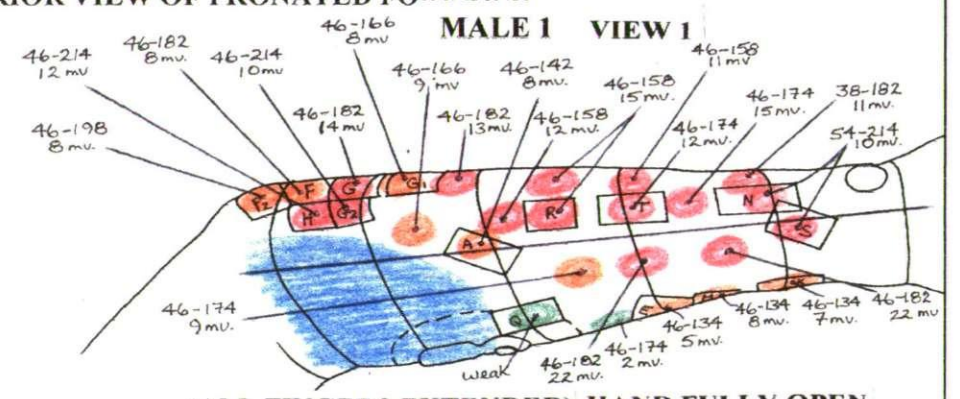
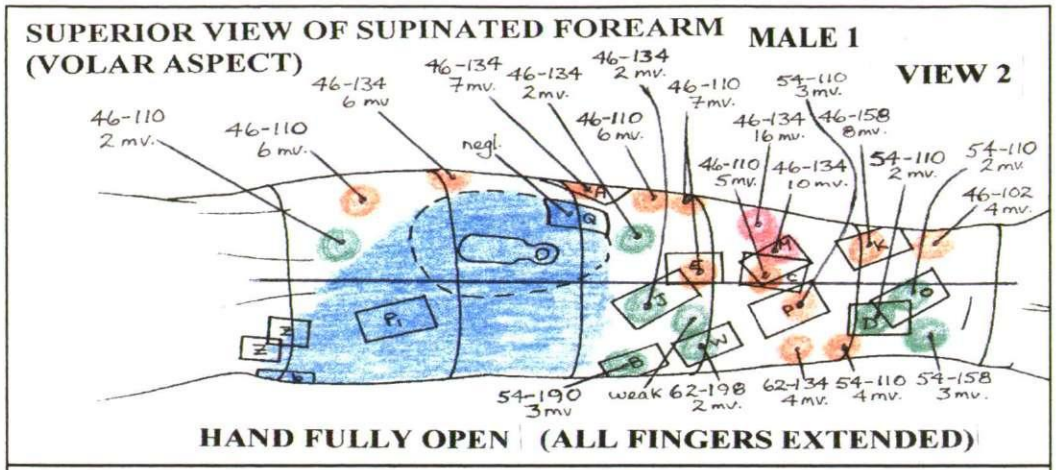
SUPERIOR VIEW OF PRONATED FOREARM

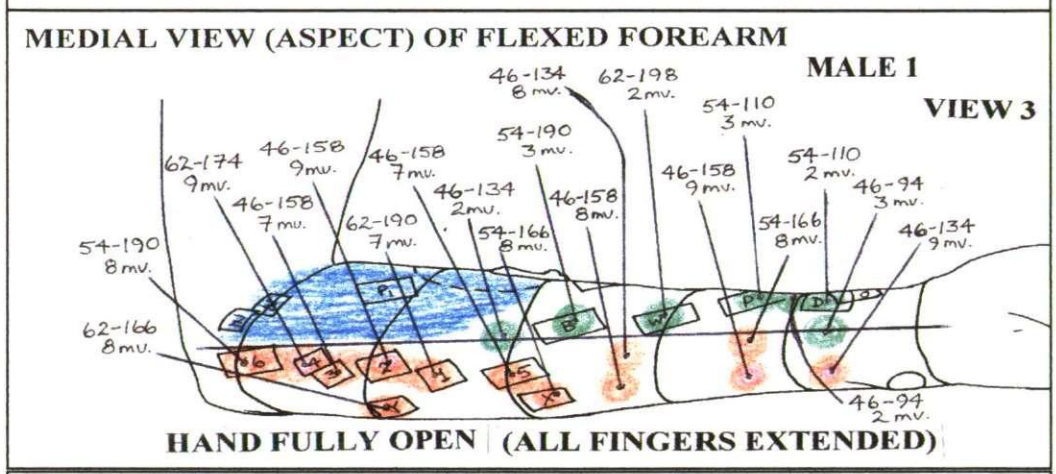
MALE 1 **VIEW 1**



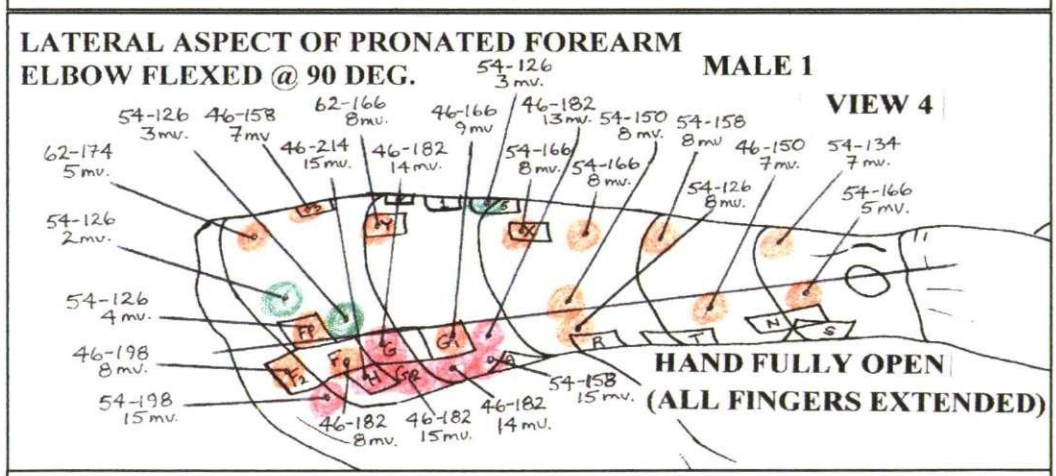
73


SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)
MALE 1
VIEW 2
HAND FULLY OPEN (ALL FINGERS EXTENDED)

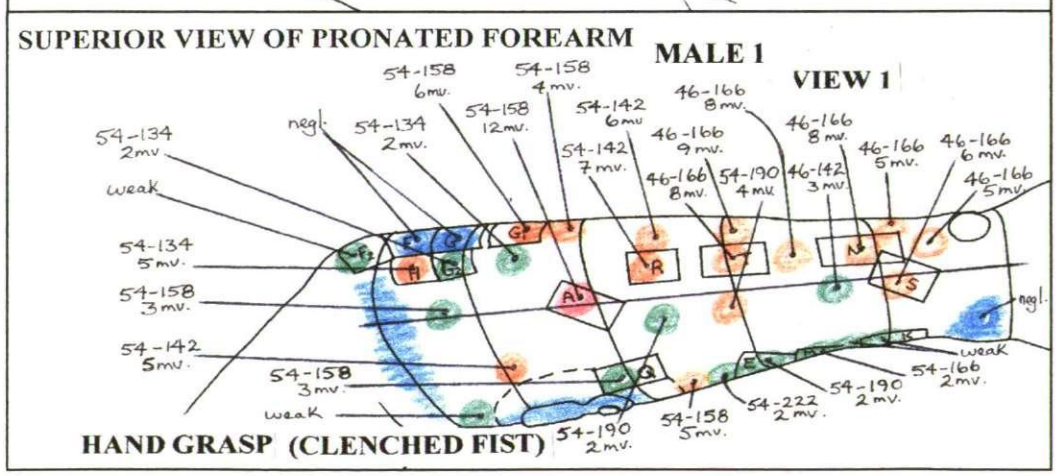
74


MEDIAL VIEW (ASPECT) OF FLEXED FOREARM
MALE 1
VIEW 3
HAND FULLY OPEN (ALL FINGERS EXTENDED)

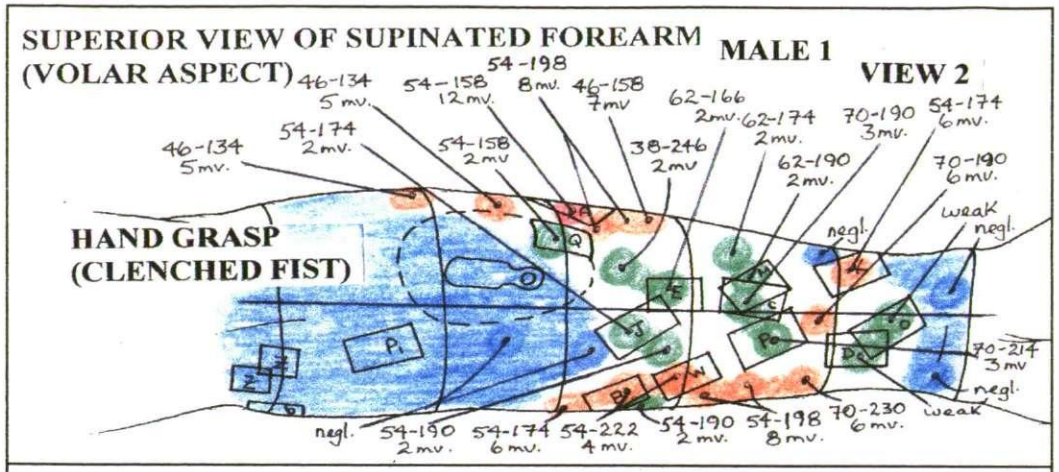
75


LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.
MALE 1
VIEW 4
HAND FULLY OPEN
(ALL FINGERS EXTENDED)

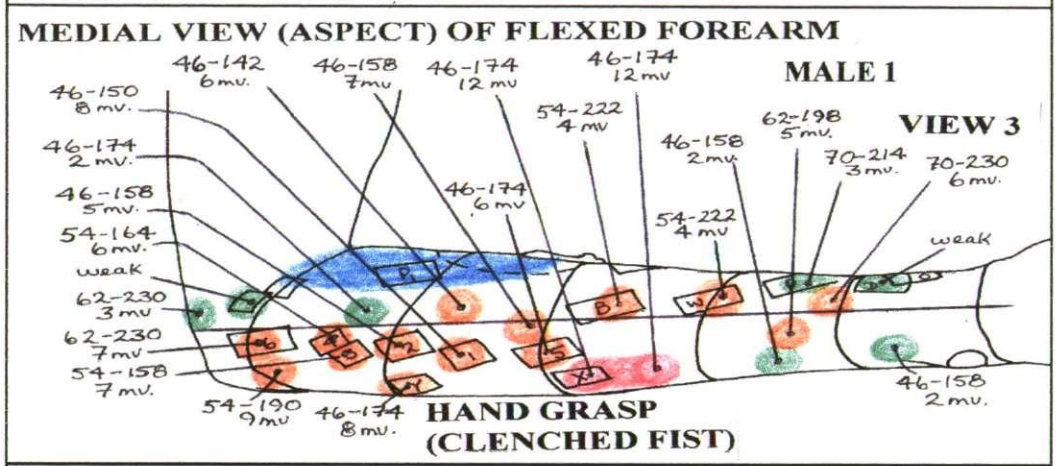
76


SUPERIOR VIEW OF PRONATED FOREARM
MALE 1
VIEW 1
HAND GRASP (CLENCHED FIST)

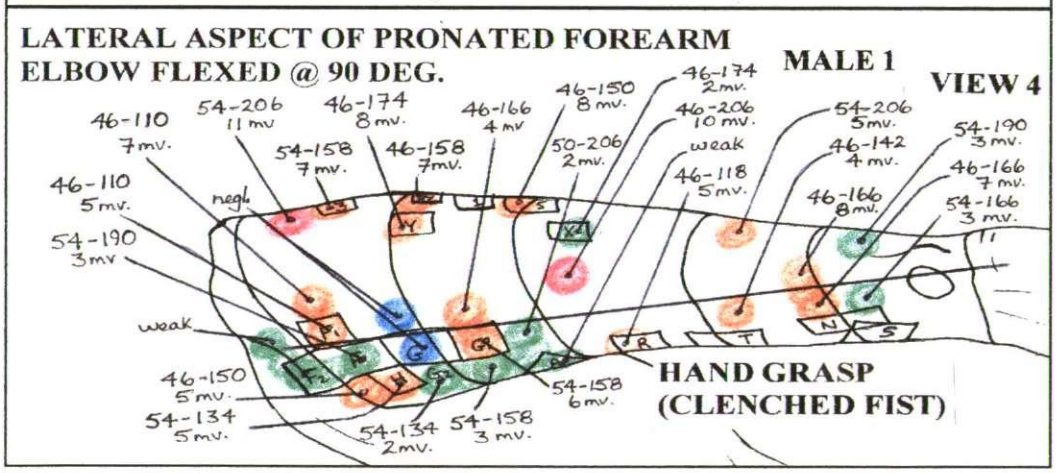
77


SUPERIOR VIEW OF SUPINATED FOREARM
(VOLAR ASPECT)
MALE 1
VIEW 2
HAND GRASP
(CLENCHED FIST)

78


MEDIAL VIEW (ASPECT) OF FLEXED FOREARM
MALE 1
VIEW 3
HAND GRASP
(CLENCHED FIST)

79


LATERAL ASPECT OF PRONATED FOREARM
ELBOW FLEXED @ 90 DEG.
MALE 1
VIEW 4
HAND GRASP
(CLENCHED FIST)

80