Understanding Gesture Expressivity through Muscle Sensing

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Expressivity is a visceral capacity of the human body. To understand what makes a gesture expressive, we need to consider not only its spatial placement and orientation, but also its dynamics and the mechanisms enacting them. We start by defining gesture and gesture expressivity, and then present fundamental aspects of muscle activity and ways to capture information through electromyography (EMG) and mechanomyography (MMG). We present pilot studies that inspect the ability of users to control spatial and temporal variations of 2D shapes and that use muscle sensing to assess expressive information in gesture execution beyond space and time. This leads us to the design of a study that explores the notion of gesture power in terms of control and sensing. Results give insights to interaction designers to go beyond simplistic gestural interaction, towards the design of interactions that draw upon nuances of expressive gesture.

Categories and Subject Descriptors: [**Human-centered computing**]: Gestural input

General Terms: Human Factors

Additional Key Words and Phrases: gesture, expressivity, muscle sensing, electromyogram, mechanomyogram, feature extraction, experimental study

1. INTRODUCTION

Body movements are a powerful medium for non-verbal interaction, particularly through gesture. Gestures are increasingly exploited in human-machine interaction for workplace, leisure, and creative interfaces. While human-human interaction involves rich and complex gesticulation, gestures as they are captured for human-computer interaction on consumer devices such as touch screens, depth camera video controllers, and smartphone rotation sensors, remain relatively simplistic, consisting mostly of simple postures, 2D shapes and movement primitives. Similarly, while human interaction relies on gestural nuance, gestures in human-computer interaction often discard or avoid nuance through techniques of invariance for the sake of inter-trial consistency and inter-user generalisability. We present an approach that conceives of variation in gesture as a way of understating expression and expressivity, and describe techniques using physiological interfaces to explore the use of gesture variation in human-computer interaction. In this way, we present techniques to extend simple gesture interaction towards more expressive, continuous interaction.

Human limb gesture is nuanced in a number of different ways. One can change how fast one performs a gesture, how much space the gesture takes or how tense the body is while executing the gesture. These variations combine and contribute to convey the expressive content of a gesture. There exists a significant challenge to capture gestural nuance through sensors and interactive systems. While position-based representation of motion has been used in most prior work, one promising approach is

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to capture dynamic gesture through physiological signals that are rich in information on qualitative aspects of a gesture. Movement qualities as a new paradigm for interaction has been of interest to recent works in the HCI community [Fdili Alaoui et al. 2012; Fdili Alaoui 2012; Mentis and Johansson 2013], however these qualities have not yet been broached through physiological sensing. Physiological sensors, ranging from brain-computer interfaces, to biometric readers, to muscle sensors, have become increasingly accessible with low cost electronics creating the potential for broad, consumer applications [Fairclough 2009; Silva et al. 2014]. Muscle biosensing has certain advantages to non-physiological motion sensing such as fiducial based motion capture or accelerometer sensing. Rather than report on the resulting physical output of a gesture, physiological sensing of muscle activity reports on the intention and activation of the body to create a gesture.

Muscle sensing has been used in a range of application areas, such as biomedical engineering, human-computer interaction and computer music. In the field of biomedical engineering, muscle activation and articulation have been exploited to control prosthetic limb systems [Saridis and Gootee 1982; Silva et al. 2005; Castellini and van der Smagt 2009; Farina et al. 2014]. Because muscle sensing provides insights not only on volitional control but also on sensorimotor control strategies, it has been applied to the monitoring of muscle fatigue [Barry et al. 1992; Tarata 2003], the evaluation of muscle functions and responses to stimuli [Beck et al. 2004; Kuriki and Azevedo 2012] and neurophysiological assessment [Orizio et al. 1992; Orizio et al. 1997].

In the field of Human-Computer Interaction (HCI), the use of muscle-based interfaces has been motivated by the need to interact with a non-physical interface [Putnam and Knapp 1993], a strategy which has been shown to be relevant in the case of users with disabilities [Barreto et al. 2000], or in the context of pervasive computing where wearable devices are too small to embed physical interfaces, such as joysticks or keyboards [Wheeler and Jorgensen 2003]. Other interesting use cases include enabling interaction without any visible or audible user actions [Costanza et al. 2005; Costanza et al. 2007; Schultz and Wand 2010], or while the hands are busy in other tasks, allowing forms of always-available interaction [Saponas et al. 2009; Saponas et al. 2010].

Finally, muscle interfaces have been used in the field of computer music to allow for the control of sound synthesis directly from muscle tension [Tanaka and Knapp 2002], and to sonify the subtle variations in the articulation of a performer's body kinetic energy [Donnarumma 2012].

In this paper we present ways in which gesture expressivity is suitable for the design of gesture-based interaction. Looking at gesture expressivity as deliberate variation of gesture, our goal is to understand if such approach is possible as a motor task. In particular, the emphasis will be put on dynamic aspects of a gesture detected by muscle sensing. This insight is fundamental to interaction designers in imagining scenarios to make expressive use of limb gesture.

The article is structured as follows. First we give working definitions of gesture and expressivity in gesture performance, introducing *dimensions of expressivity* to represent gesture variations. We then present different muscle activation mechanisms to arrive a bimodal approach using electromyogram (EMG) and mechanomyogram (MMG) signals, and focus on the gestural dimension, *power*, in the activation of forearm muscles. We then present a series of studies that explore: 1) the use of gesture temporal and spatial variations for control; 2) the use of muscle sensing as an interface for musical interaction. This leads to an experiment in which we explore the deliberate control of power variations of gesture. We analyse the results and discuss their implications for interaction design.

2. GESTURE EXPRESSIVITY

In this section, we establish working definitions of gesture and the notion of gesture expressivity. We present a number of dimensions including temporal, geometrical and dynamical variations in gesture execution. Among these dimensions, we focus on a dynamic dimension, called power, that involves variation of the intensity of gesture.

2.1. Gesture: a working definition

Gesture is an intricate notion used across many different research fields. In social psychology, [Efron 1941] in his seminal work relates gesture style to a cultural basis. Gesture in HCI can refer to something as simple as a shape drawn on a tactile surface, while gesture as used in character animation of embodied conversational agents (ECA) might refer to body movement accompanying speech and utterances. In music composition, a musical gesture can refer to the melodic progression in a score while in musical performance it can designate deliberate and non-deliberate movements of an instrumentalist [Jensenius 2014]. Finally, Mulder differentiates posture and gesture [Mulder 1996], where posture is seen as static, while gesture is dynamic.

One generic definition of gesture in the HCI context comes from Kurtenbach and Hulteen [Kurtenbach and Hulteen 1990], who define a gesture as "a movement of the body that contains information" [Kurtenbach and Hulteen 1990]. In psychological study of non-verbal communication, Kendon writes "Gesture [...] is a label for actions that have the features of manifest deliberate expressiveness" [Kendon 2004]. (It should be noted that here Kendon does not intend deliberateness as in the control of the expression, but rather as in the voluntary act of expressing a meaning.)

From those different definitions, we extract a series of keywords which characterise our understanding of gesture: *movement*, *dynamic*, *information*, *deliberate expressivity*. A recomposed definition of gesture is as follows:

A gesture is a dynamic movement of the body (or part of the body) that contains information in the sense of deliberate expression.

We can unwrap this definition as follows. Deliberateness in the movement differentiates gesture from simple movement by inducing an intentional will of expressing thought, feeling or meaning. Interestingly, deliberate expressivity refers to the capacity of varying the gesture execution intentionally. We now define gesture expressivity and its constitutive components.

2.2. Gesture expressivity

Expressivity is a notion used to describe the articulation of information in genetics and computer science. In genetics it refers to the variations in the observable characteristics and traits among individuals with the same genotype [Miko 2008]. In computer science, expressivity (or expressive power) has been used in programming language theory and refers to a measure of the range of ideas expressible in a given programming language [Felleisen 1991]. Thus, expressivity involves the idea of potential variation instantiated by the consistent constitutive structure.

In HCI related fields, examining and designing medium for allowing expressivity is part of the core research in Music Technology, and more precisely in the NIME community, where NIME stands for New Interfaces for Musical Expression[1]. See for example the works by Jordà [Jordà 2005] and Dobrian et al. [Dobrian and Koppelman 2006]. Expression in interactive music is understood to be musical expression, connecting it to the art of all musical performance. In instrumental performance, for example, of classical music, musical expression is related directly to variation as re-interpretation

[1] http://www.nime.org

of an existing piece. One pianist may interpret an established repertoire composition differently than another pianist: we can think of this as inter-user variation [Palmer 1997]. Or, a single performer may interpret the same composition differently in different performances: this may depend on their emotional or psychological state at the moment of a concert, the feedback the performer gets back from the audience, or through changes of context such as the size of the performance venue. In order to accommodate these contextual changes, an instrumentalist may vary the dynamics (soft and loud moments) or tempo (speed) of the music, and performs different gesture to execute these musical changes. A fast passage may work better in a smaller, intimate recital hall, where the reverberant nature of a large concert hall may require more emphatic playing, with broader gestures to communicate musical phrasing to an audience further away from the stage. In this way, musical performance serves as a useful example of understanding expressive gestural interaction not just as an intuitive and emotional, but as volitional, contextual input to interactive systems that may facilitate human-human communication.

Another active field in the investigation of gesture expressivity concerns embodied conversational agents (ECA). Gesture expressivity is seen as *how* a gesture is performed [Pelachaud 2009], in other words the potential variations in its execution. Variation in gesture performance can exist across different users, or within a single user in multiple iterations recreating the same gesture primitive. The artefact of variability can occur due to a lack of skill to perform it or due to noise in the motor system. This differs from variation as the deliberate intention to nuance gesture execution in order to modulate its meaning. Hence we propose the term gesture expressivity as deliberate and meaningful variation in the execution of a gesture.

2.3. Dimensions of expressivity

Expressivity varies across different users of an interactive system, or within a single user in multiple iterations of the same gesture primitive. The dimensions across which expressivity varies have been initially studied in fields such as experimental psychology, and then applied in computer graphics animation, computer-mediated communication and the performing arts.

Wallbott [Wallbott 1998] proposes that expressiveness can be characterised by movement qualities: *movement activity, expansiveness, movement dynamic*. These movement qualities can be the source of expressiveness, in "the type of emotion encoded, the specific ability of the encoder, and specific, discriminative movement indicators for certain emotions versus indicators of the general intensity of the emotional experience" (p.892, §2). These ideas have been applied in design, digital media performance, and the generation of expressive animated characters using ECA [Cassell 2000].

Camurri et al. have used overall activation (quantity of motion) to define interaction between a performer and digital media [Camurri et al. 2004]. Laban Movement Analysis (LMA) [Laban 1963], originally used as a method for observing, describing, notating, and interpreting human movement to enhance communication and expression in everyday and workaday life, it has also been applied to understand movement qualities in terms of physical effort. Chi et al. use LMA to derive dimensions of expressiveness to be applied in the synthesis of expressive movements for animated characters [Chi et al. 2000].

Discussing the generation of expressive ECAs, Pelachaud maintains that, when analysing expressiveness, it is important to consider that "behaviours encode content information (the 'What' is being communicated) and expressive information (the 'How' it is being communicated)" [Pelachaud 2009]. Thus, in order to characterise movement expressiveness, Pelachaud developed a model for the generation of ECA based on six dimensions.

— *Spatial extent*: quantity of space occupied by the arm;
— *Temporal extent*: movement velocity;
— *Fluidity*: continuity in successive movements (jerky vs smooth movements);
— *Power*: dynamism (weak vs strong);
— *Overall activation*: quantity of movement on a channel;
— *Repetition*: repetition of the stroke of a movement.

Among these dimensions, gesture power offers a novel way to consider expressive interaction going beyond geometrical and temporal descriptions of gesture, following recent studies on movement qualities in interaction [Fdili Alaoui et al. 2012]. According to Pelachaud, power is related to "the degree of acceleration of body parts and corresponds to the dimension movement dynamics/energy/power defined by Wallbott" ([Pelachaud 2009], pp. 4). The hypothesis underpinning the research presented here is that gesture intensity, or power, is an expressive dimension that is suitable for tracking through physiological sensing, in particular, muscle sensing. The study described in this paper looks at users' ability to vary different aspects of gesture power captured by muscle sensors. The emphasis is not on the dynamic aspects of the final limb movement but on the dynamic muscular aspects of user intention that result in gesture that can be expressively modulated through variation of exertion, tension, and force

3. DESCRIBING GESTURE THROUGH MUSCLE SENSING

Human limb gesture is initiated by the activation of muscle groups to generate limb movement. Sensing muscle activity allows us to detect the intention of the subject to create a gesture, and glean its dynamic, varying characteristics. In this section we describe the physiological mechanisms involved in muscle activation and the related biosignals, the EMG and the MMG. The characteristics of both biosignals are illustrated in table I. This section draws on biomedical literature [Kaniusas 2012] with the aim to help the reader better understand the further choices in sensors and data analysis.

Voluntary muscle control is part of the somatic nervous system (SNS), part of the peripheral nervous system. The SNS operates through two different kinds of nerves, the *afferent* nerves, which handle the transport of signals from sensory receptors to the central nervous system (CNS) and *efferent* nerves. which transport signals from the CNS to the muscles. It is through the efferent nerves that muscle activation takes place (Figure 1).

At the onset of stimulus integration, the SNS sends an electrical voltage, an *action potential*, to the motor neurons. When the action potential reaches the end plate of a neuron it is passed to the muscles by the neuromuscular synapse. The neuromuscular synapse is a junction that innervates the skeletal muscle cells and is able to send the electrical potential throughout the muscle to reach all muscle fibers. A network of neuromuscular synapse and muscle fibres is known as a *motor unit* (MU). At this point, the motor unit action potential (MUAP) causes an all-or-none contraction of the muscle fibres. A gradation in muscle contraction is achieved by a changing number of MUAPs firing and differing, stochastic, frequencies.

By positioning surface electrodes on the skin above a muscle group, it is possible to register the MUAP as an electrical voltage. The resulting signal is known as electromyogram or EMG. This is the algebraic sum of all the motor unit action potentials (MUAPs) at a specific point in time. It is a stochastic signal because any number of MUAP pulses is triggered asynchronously.

Muscle contraction is the product of a bio-electrical effect, but also results in a biomechanical effect. When the muscle cells contract, they produce a mechanical vibration, known as muscle twitch, which lasts about 10-100ms. The mechanical vibration

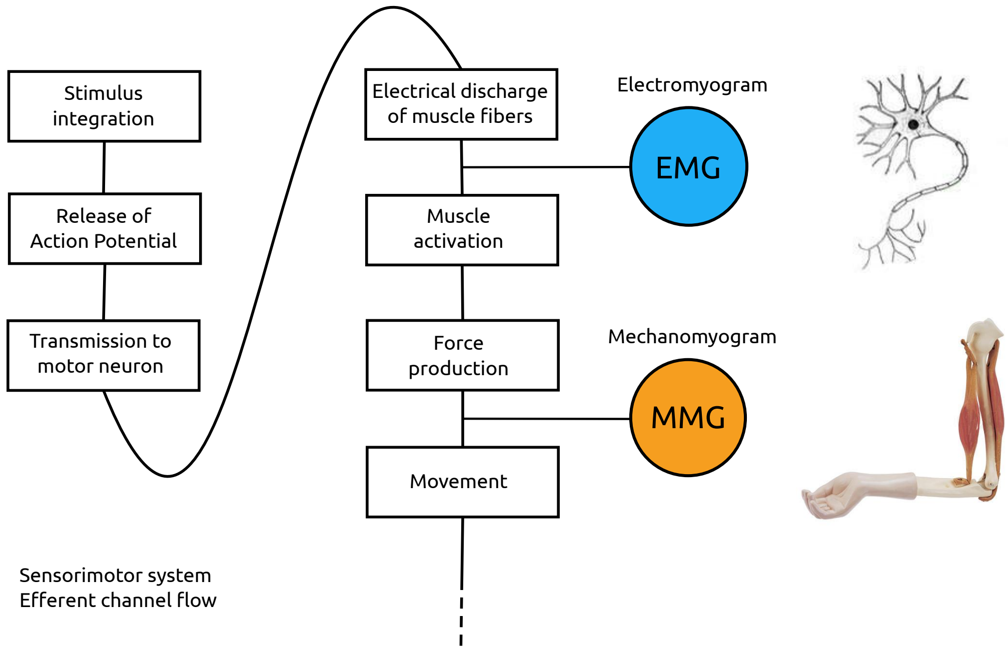

Fig. 1. The SNS. Detail of the efferent nerve information flow illustrating the muscle activation process. The blue and orange circles indicate respectively the EMG and MMG signals. The location of the circles illustrates the different stages of the activation process at which the signals are captured (assuming non-invasive recording methods using on-the-person stationary or ambulatory sensors [Silva et al. 2013]).

Table I. EMG and MMG description

	EMG	**MMG**
Type	electrical	mechanical
Origin	neurons firing	muscle tissue vibration
Description of	muscle activation	muscle contraction force
Freq. range	0-500 Hz	0-45 Hz
Sensor	wet/dry electrodes	wideband microphones
Skin contact	yes	no
Sensitivity area	local	broad (due to propagation)

of the muscle cells causes a subsequent mechanical contraction of the whole muscle which, by means of its oscillation, can be picked up as an acoustic signal. Using a microphone on the skin above a muscle group it is possible to record a mechanical signal produced by the perturbation of the limb surface. This signal is knowns as mechanomyogram, or MMG. Table I reports a summarized description of both sensing modalities.

While the EMG carries information on the neural trigger that activates muscle contraction, that is, it informs us of the deliberate intention of performing a gesture, the MMG bears information on the mechanical contraction of the muscle tissues, giving access to the physical effort that shapes the gesture. In this way, the two signals provide complementary information on muscle activity [Tarata 2009], potentially providing important information on the expressive articulation of a gesture.

4. CONTROL AND SENSING IN GESTURE EXPRESSIVITY: PILOT STUDIES

In this section we report two pilot studies that dealt with the control and sensing of gesture expressivity. The first study presents the control of variations applied to surface gestures. The second looks at gesture expressivity using muscle sensing.

4.1. Pilot 1: Control of Gesture Spatial and Temporal Extent

First, we conducted a pilot experiment to study gesture variation as an expressive vector for interaction independent of physiological sensing. We looked at the execution of 2-dimensional finger gestures on a tactile interface to study whether they can be consciously controlled by users, and to validate our adaptation based machine learning algorithm as a means to track gesture variation [Caramiaux et al. 2013].

The study was divided into two parts. Part 1 aimed to understand whether users can control certain temporal and spatial gestural characteristics and if that control depends on the vocabulary of gesture primitives. Variation of gesture characteristics includes changes in speed (slower and faster) and in size or orientation (geometric changes in space). The gesture vocabulary was comprised of twelve 2D shapes based on Wobbrock's work on tactile interaction [Wobbrock et al. 2009]. In Part 2, we used a machine learning technique based on particle filtering previously used in musical control [Caramiaux et al. 2014] to simultaneously recognise and measure gesture variation in time and space. Gesture variation as tracked by the machine learning algorithm was exploited directly in an end-user graphics effects programme, validating the potential of expressive input to an interactive software system. Meanwhile, results from Part 1 on the control of the gesture temporal and spatial variations provide important insight on users' ability to control gesture that can be applied to physiological interfaces:

(1) Multiple gesture characteristics can be varied independently in slower gestures (change in size and speed);
(2) This is independent of the gesture considered;
(3) When performing the gesture faster, there is a cognitive shift in motor planning from non-ballistic to ballistic motion.

These findings provide insights useful to interaction designers wishing to create continuous interaction scenarios based on variation of gesture characteristics. However, the 2-dimensional gestures, while varying in time and space, offered an over-simplified model for expressivity based on gesture variation. First, the gesture vocabulary, based on shapes, constrained interaction potential. Second, the touch-screen interaction limited variation to size, speed, and rotation, and did not allow dimensions of expressivity such as power (as defined by Pelachaud in [Pelachaud 2009]).

Let us illustrate this statement by an example. A gesture such as clenching a fist can be articulated with greatly different power while looking apparently static. The deliberate variations of a gesture like this, invoking changes in speed or intensity are likely characterised by physiological mechanisms that are would not be picked up by position or motion sensing.

4.2. Pilot 2: Sensing expressive gestures

We next conducted a study looking at dimensions of gesture expressivity using muscle sensing. In Part 1, we introduced MMG sensing alongside spatial motion capture and inertial accelerometer sensing in a multimodal configuration. In Part 2 of this second study, we used EMG and MMG in a bi-modal configuration to look at the ways in which complementarities of these signals could be exploited in end-user interaction scenarios.

4.2.1. Part 1. In the first part, we aimed at examining the complementary information about gesture expressivity where the gesture was captured through different sensing modalities. To do so we defined a set of gestures, drawing upon movements of a performer in a piece of contemporary music. Each gesture was captured by MMG muscle sensors (placed on the forearms), accelerometers (also placed on the forearms) and full-body motion capture [Donnarumma et al. 2013a]. By looking at both physiological and spatial data recorded from the gestures executed with high and low force, we found that:

(1) Physiological and spatial modalities complemented one another;
(2) The physiological modality only could sense the preparatory activity taking place before the actual gesture;
(3) Variation of gesture characteristics (such as power and speed) were detected by modulation of signal in different modalities.

These findings showed that the ability of users to independently vary different dimensions of expressivity in the simple gestures from Study 1 also applied to free space gestures and a range of more sophisticated sensing modalities including muscle sensing.

4.2.2. Part 2. In Part 2, we introduced EMG sensing in combination with MMG and used them together as bi-modal input to an interactive sonification system [Donnarumma et al. 2013b]. We looked at the ability of non-experts to activate and articulate MMG and EMG separately using a given gesture vocabulary. The gesture vocabulary was designed by drawing upon complementarity of MMG and EMG described in the biomedical literature [Jobe et al. 1983; Madeleine et al. 2001; Day 2002; Silva et al. 2004]. We sonified in real time the MMG and EMG signals as a form of feedback to the user, enabling them to understand when each signal was produced. Offline data analysis of the recorded EMG and MMG signals enabled us to understand the physical dynamics behind the users' control of different aspects of their muscle activity. The results showed that:

(1) Following a short training session, non-expert users were able to deliberately vary the degree of activation of EMG and MMG signals independently;
(2) User-specific variations on the gesture articulation yielded different activity at the physiological level.

5. STUDY ON THE CONTROL AND SENSING OF GESTURE POWER

We built upon the insight gained from the two pilot studies to design an experiment looking at the elements underlying variations of gesture power and its characterization in bi-modal EMG/MMG signal data. The methodology consists of asking participants to perform several trials of a gesture, taken from a predefined vocabulary, and variations of this gesture in power, size and speed. As such we aim to understand variations in power as a motor task. A set of signal features are computed to elucidate the effect of variations and gestures on the potential control of power. The quantitative analysis is complemented by a questionnaire collecting subjective measures of users' notion of power.

5.1. Gesture Vocabulary

The gesture vocabulary comprises 6 gestures involving two types of interactions (surface and free-space) and an increasing level of complexity. Figure 2 illustrates the vocabulary considered.

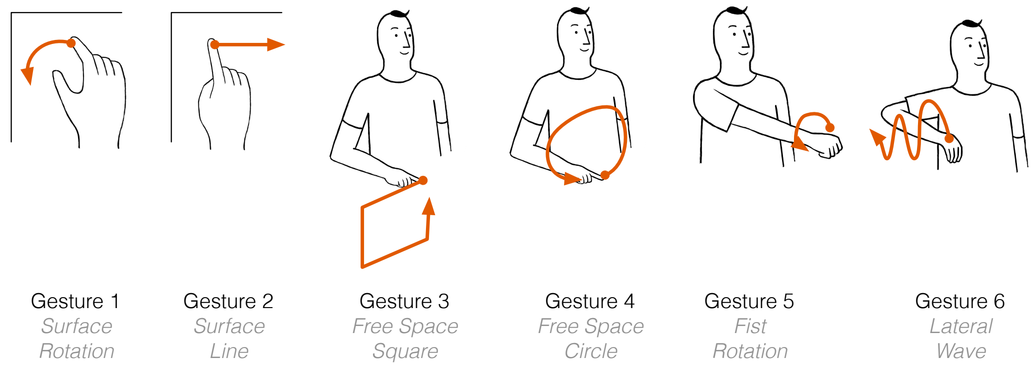

Fig. 2. Gesture vocabulary considered in the Study.

— Gesture 1 (*Surface Rotation*): Two fingers on a flat surface, 180 degrees rotation, counter clockwise (clockwise for left-handed). Example: rotate an image on a touchscreen.
— Gesture 2 (*Surface Line*): One finger on a flat surface, move along an horizontal, straight line from point A to point B, outward. Example: drag a picture on a touchscreen.
— Gesture 3 (*Free Space Square*): Raise arm perpendicular to the body and draw a square with the index finger, start from the up/left corner, move right, clockwise (counter clockwise for left-handed). Example: Next track.
— Gesture 4 (*Free Space Circle*): Rise the arm perpendicular to the body and draw a circle with the index finger, start from the bottom/center point, move counter clockwise (clockwise for left-handed). Example: Fast forward shuffle.
— Gesture 5 (*Fist Rotation*): Rise the arm straight perpendicular to the body, close the fist, move the fist in a circle for 3 times, start left, move counter-clockwise, (clockwise for left-handed). Example: Play higher notes.
— Gesture 6 (*Lateral Wave*): Rise the elbow at the shoulder level, bend the forearm at $90°$, move wrist and forearm downward and upward 3 times while opening the arm outwards. Example: Play louder.

5.2. Gesture Variations

Using the above gesture vocabulary we defined a set of variations to be applied to each gesture. We sought to design tasks whereby participants would be invoked to vary the intensity, or power, of each gesture on its own or in combination with related dimensions of expressivity such as gesture size. In doing so, we wanted to inspect the relationship, in spatial and temporal extent, between power and other dimensions of expressivity (as defined in Section 2.3). We thus devised a set of 7 variations using combinations of dimensions as follows:

— Variation 1: Bigger
— Variation 2: Faster
— Variation 3: More Powerful
— Variation 4: Bigger and Faster
— Variation 5: Bigger and More Powerful
— Variation 6: Faster and More Powerful
— Variation 7: Bigger, Faster and More Powerful

We chose to constrain the variation in one direction (i.e. increasing speed, power, or size) in order to avoid variability due to the participant's choice of variation direction.

5.3. Procedure

The experiment was conducted according to the following procedure. The experimenter positions the EMG and MMG sensors on the participant's dominant arm. They are positioned at the lower interior part of the forearm, at the midpoint of the muscle, illustrated in Figure 3.

Fig. 3. Experimental setup. Left: EMG, MMG sensors placed on the forearm. Middle: EMG, MMG sensors placed on the forearm (close view). Right: Both EMG (left) MMG (right) sensors.

At this point the experimenter introduces the study protocol. A gesture from the vocabulary is chosen randomly. The experimenter gives a visual example of the gesture, and describes the typical scenario in which the gesture might be performed. The participant is given the chance to rehearse the gesture until they feel ready.

The participant performs the gesture and records data by pressing a start button with their free arm. 3 trials of the gesture are recorded. Following the 3 trials, the participant is asked to perform variations on that gesture (*bigger*, *faster*, *more power* and the combinations described in Section 5.2). The order of variations prompted is randomly selected by the software. Three trials are recorded for each variation.

The experimenter then asks the participant how easy was to perform the variation on size, speed and power. The participant replies with a rate in the 1-5 range, where 5 is 'very easy'. In addition, the participant is asked to briefly explain the answer. The procedure is then repeated for each gesture in the vocabulary.

At the end of the session each participant was asked to fill out a questionnaire which included demographic data, along with questions regarding their use of gestural interface in their everyday routine and their knowledge level on the topic. Further questions addressed their experience during the execution of the gestures, and the possible real-world applications they could imagine of the gesture variations we proposed.

We recruited 12 participants (8 female, 4 male), ranging in age between 21 and 43 with a mean age of 29.9 (std=6.5). Each subject took an individual 45-minute session and were recompensed by a nominal fee for their participation. For each participant we collected 3 trials for each original gesture (i.e. without variations), which leads to 12 x 3 x 6 = 216 trials. And then 3 trials for each gesture performed considering each variation, which leads to 12 x 3 x 6 x 7 = 1512 trials.

5.4. Acquisition

Gesture data was recorded by means of a bi-modal sensing system with two input channels, one EMG input and one MMG input. We describe first the acquisition system for the EMG and then for the MMG. Given the HCI target application scenarios, we chose not to use high-end medical equipment, but sought to create a robust configuration of off the shelf components. Criteria included a practical enough number of sensing channels, convenient and non-invasive sensor placement on the user, and modest size and cost to be able to imagine potential incorporation of such sensors into future consumer interactive products.

After initial trials using different wet gel and dry electrodes, and prompted by the fact that gel and dry electrodes have been shown to perform similarly [Silva et al. 2013], we used the Infusion Systems BioFlex with active dry electrode sensors[2] to capture the EMG signal. The BioFlex offers a) on-board hardware calibration system to increase trial-to-trial reliability, b) low baseline noise of the sensor circuit and cable transmission. The EMG signal was transmitted from the BioFlex as an electrical voltage. The signal is acquired through an Olimex board[3], a shield for the Arduino[4] circuit board, at a sampling rate of 100Hz. The Bioflex and Olimex both provide analogue pre-amplification and signal conditioning. The signal is initially amplified and filtered with a one-pole high-pass filter with frequency cutoff (*fc*) at 0.16Hz, then amplified again and passed through a 3rd order Besselworth filter with *fc* at 40Hz.

We used the Xth Sense system to capture the MMG signal. The Xth Sense is comprised of an armband embedded with a wideband electret condenser microphone. This is encased within a silicon mold so not to get in contact with the skin. The silicon mold isolates the microphone from external noise and electrical interferences and amplifies the skin vibration before it reaches the microphone. The design is inspired by the work of Silva and Chau in the design of control systems for prosthetics [Silva and Chau 2003]. The MMG signal was transmitted from the Xth Sense as an analog sound signal through an audio cable. The signal was then acquired through an external sound card which digitised it at a sampling rate of 44100Hz, and sent it to the recording software. The signal was not amplified. A high-pass filter (HPF) with a *fc* of 1Hz was used with both signals in order to bypass artifacts created by the movement of the whole arm [Day 2002].

5.5. Feature extraction

We selected a set of features to be extracted and analyzed from both the EMG and MMG signals. In the prosthesis control literature the predominant signal feature is its amplitude. Here we propose to compute additional features, namely frequency-domain features. The features are computed according to the workflow illustrated in Figure 4. In the following, the features that will be used are: signal amplitudes, signal temporal zero-crossings; and spectral centroids.

Signal amplitudes (time-domain feature). One of the most important features to be computed on both muscle biosignals is the amplitude of the signal along time. Amplitude computed on the EMG and MMG signals has been shown to be related to the force exerted while executing the gesture (see for instance [Perry-Rana et al. 2002]).

Amplitude estimation of the EMG signal has received a great attention and has led to several studies in biomedical or bioengineering literature [Hofmann 2014]. As suggested by the author, we chose to use a Bayesian filter based on the previous work by Sanger [Sanger 2007]. For amplitude estimation of the MMG signal, we used a common estimator used in audio analysis: the root mean square (RMS) estimator.

Zero-crossings (time-domain feature). The number of zero-crossings in the signal is linked to the frequency of the signal. For low-frequency components, where the Fourier

[2]http://infusionsystems.com/catalog/product_info.php/products_id/199
[3]https://www.olimex.com/Products/Duino/Shields/SHIELD-EKG-EMG/
[4]http://arduino.cc

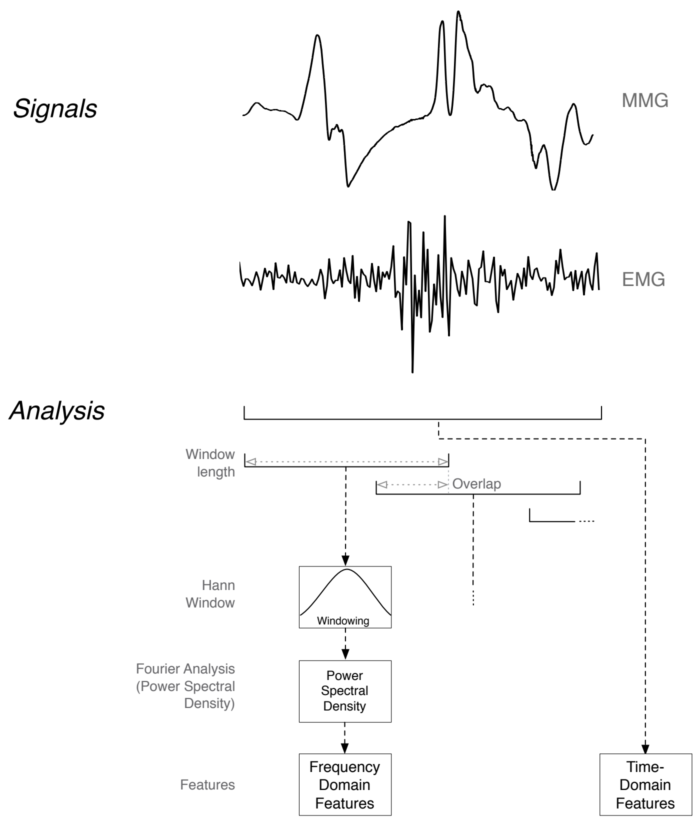

Fig. 4. The feature extraction dataflow.

transform might lack resolution, this feature can be more informative. On the other hand, the feature can be used to discriminate signal from noise [Peeters 2004].

Spectral centroid. The spectral centroid is the mean frequency value in a signal chunk. For both signals we use the same method. The signal is windowed by a Hann window of $\log 2(F_s)$ samples, where F_s is the sampling rate. In other words, the window has a temporal length of about 1sec. The overlap is 1% of the size of the window size, i.e. about 10msec. We use a Fourier analysis with the same number of bins than the number of samples in the windowed signal. The centroid is computed then on the spectrum.

6. RESULTS

In this section, report on results from the study. We first report on subjective measures assessing the subjects' understanding of the dimension 'power' and the perceived difficulty of the tasks proposed. Then we look at the data to understand how participants actually vary what they think of as power through objective measures on the signals' features. Finally we use these measures to investigate relationships between power and the other two dimensions, size and speed.

6.1. Perceived difficulty and understanding of the tasks

Participants were asked to rate between 1 and 5 the difficulty in performing variations in each dimension for each gesture (where 1 is very difficult and 5 very easy). Results are reported in Figure 5. We analyze the difference between the mean scores across variations on gestures by using a Student's T-Test between pairs of mean scores (α set to 0.05).

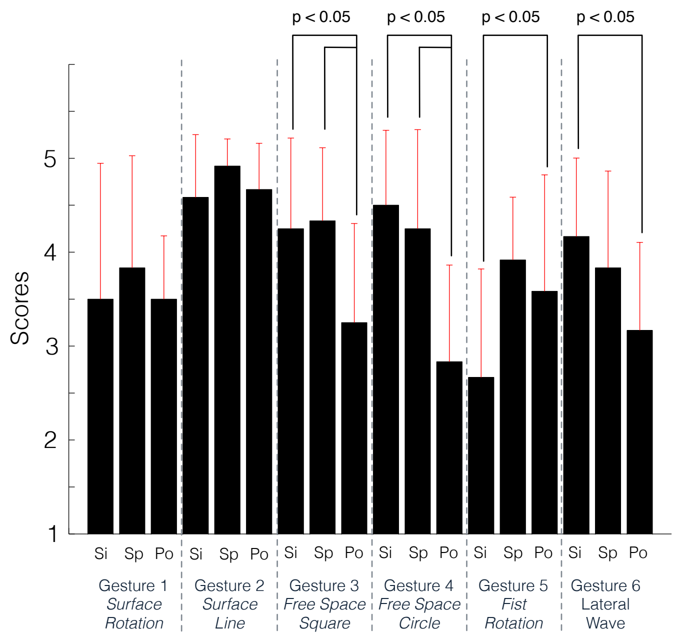

Fig. 5. Subjective ratings of the participants on the easiness of performing variations on each gesture. Scores are given between 1 and 5 where 5 is very easy and 1 very difficult. Si (resp. Sp, Po) denotes the variation in Size (resp. Speed, Power)

The test reveals that variations along each dimension have the same difficulty for gestures 1 and 2. The task of varying a dimension is globally easy for gesture 1 (mean score of 3.6, std=1.1) and very easy for gesture 2 (mean score of 4.7, std=0.5). The test shows that it is more difficult to perform gestures 3, 4 and 6 with more power than performing it bigger (or even faster for gestures 3 and 4). Participants explained their ratings related to the task of varying Power, by mentioning aspects related to:

— the **feedback**, by mentioning the absence of haptic feedback ("*there were no resistance*", Participant 11);
— the **gesture** itself ("*gesture [is] not fluid*", Participant 10), while size and speed are easier since there is "*less limit in space*" (Participant 9), "*a bit easier because of the breakpoints*" (Participant 8);
— the **variation**, by observing that they had to be more focused on other variations, like the size in order to respect the task of performing the given gesture ("*I had to keep control to make the shape*", Participant 6).

Participants found it more difficult to perform gesture 5 bigger than faster. Here the difficulty of applying a change in size is related to the gesture itself and its inherent biomechanical constraints (“*too limited [in space]*”, Participant 7; “*a more constraint movement, awkward*”, Participant 3; “*limit in the movement itself*”, Participant 10) that impacts the relation with the gesture reference (“*default gesture was already at the max*”, Participant 12).

The difficulty of the task seems to be related to the perceived notion of power. This brings us to analyze how participants understood this expressive dimension. Participants were asked to describe the power dimension of a physical gesture using their own words. From the questionnaire, we extract the words used by the participants to describe the characteristics of *Power*. We report the analysis in Table II.

Table II. Subjective descriptions of “power” as extracted from the questionnaires

Description	# Participants	Quote example
Pressure	6	“*In the case of the tactile surface [I changed] pressure*” (P1)
Tension	4	“*Power [...] seemed to be tension in the arm or wrist*” (P3)
Intensity	2	“*[...] a combination of intensity and intentionality*” (P10)
Speed	2	“*wasn’t always sure what doing the gesture with more power meant, or if it just sped it up.*” (P09)
Effort	2	“*increased effort*” (P11)
Energy	1	“*I was using more energy to do the same movement*” (P5)
More Stress	1	“*more stress in muscles*” (P2)
Forceful	1	“*More forceful*” (P4)

The analysis shows that participants used descriptions that can be gathered into three main categories:

(1) Power intended as **pressure** or physical force exerted against a surface
(2) Power as physical **tension** or strain exerted in the absence of an object to manipulate
(3) Power as energy of the physical gesture, intended as **kinetic energy** resulting from motion.

In the following sections, we will first inspect how these interpretations of power (pressure, tension, and kinetic energy) are illustrated through physiological features computed from the EMG and MMG signals. Second we will analyze how the extracted factors (feedback, gesture and variation) affected the variations of power by the participants.

6.2. Objective measure of power as tension, pressure and kinetic energy

We first inspect how the muscle signal amplitudes are linked to the variations of power in gesture execution, considering every gesture from the vocabulary. We compare the averaged amplitudes of both signals computed for each gesture under two conditions: Baseline (gesture performed with no variation) and “More Power”. Figure 6 illustrates the results by reporting both modalities (EMG on the left, MMG on the right) and the averaged amplitudes across participants and trials for both conditions “baseline” (black bars in the figure) and “more power” (orange bars).

A repeated-measure analysis of variance (ANOVA) is performed to investigate the effect of both factors GESTURE (the 6 gestures of the vocabulary) and VARIATION (2 variations here, baseline and more power) on the signals’ amplitudes. There is a significant effect of GESTURE on the EMG amplitudes $F(5, 132) = 11.7, p = 0.0$ (partial η^2 is 0.30) and on the MMG amplitudes $F(5, 132) = 10.3, p = 0.0$ (partial η^2 is 0.28). Moreover, there is a significant effect of VARIATION on EMG amplitudes, $F(1, 132) = 24.3, p = 0.0$ (partial η^2 is 0.16), and MMG amplitudes, $F(1, 132) = 14.7, p = 0.0$ (partial η^2 is 0.10).

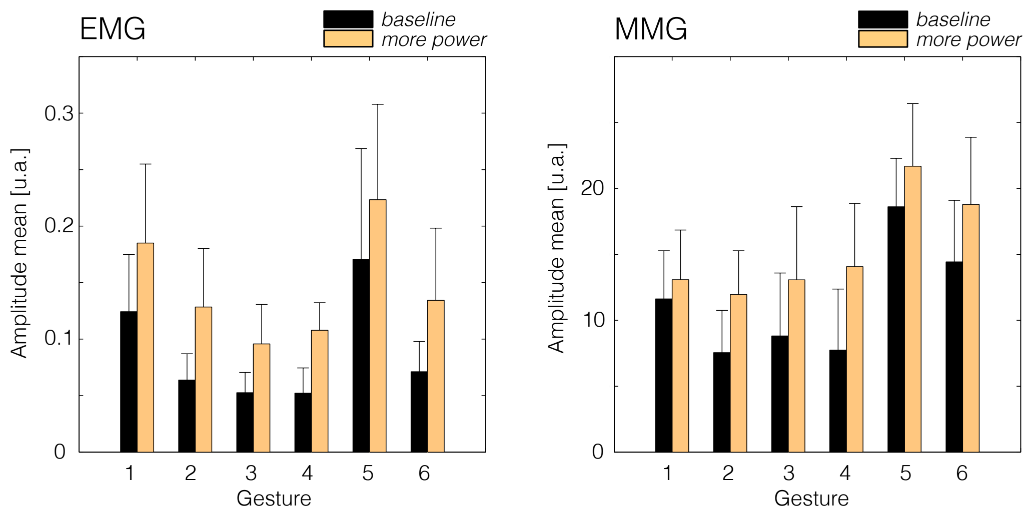

Fig. 6. Power estimations for both EMG (left) and MMG (right) averaged across participants and trials. Black bars show the mean amplitudes when no variation is applied (baseline), orange bars report mean amplitudes when more power is exerted.

There is no interaction between the factors GESTURE and VARIATION in both cases of EMG and MMG amplitudes.

A post-hoc analysis using a Tukey's HSD (Honestly Significant Difference) performed for each gesture reveals that the EMG amplitudes significantly increase with the condition "more power" compared to the baseline ($p < 0.05$) except for gesture 5. Similarly, MMG amplitudes significantly increase (except for the gesture 1 and 5) if more power applied ($p < 0.05$).

Based on these results, performing gestures with more power leads to more muscle tension as shown in both EMG and MMG amplitude estimations. Gesture 5 (Fist Rotation) is a particular case since the gesture itself, without variation, already requires tension in the forearm's muscles. MMG amplitudes, however, do not show significant change in amplitude for the gesture 1 (surface rotation). For this gesture, participants considered power to be pressure exerted on this surface (see Section 6.1). Therefore, the EMG amplitude feature is a good candidate to capture pressure and force exerted on a surface.

Although average amplitudes of EMG and MMG both increase when applying more power, the amplitude increase is not of the same nature across the two modalities. Figure 7 illustrates that with an example.

On the left, two EMG signals are reported: the dashed black line is the signal for gesture 3 (free space square) when no variation is applied and the dashed yellow line is the EMG signal for the same gesture performed with more power. The solid lines are the amplitudes computed from the signals. On the right, two MMG signals are also reported with their computed amplitudes for the same gesture. One can observe that EMG amplitude increases globally while the MMG amplitude has more transients. This illustrates that the EMG is a stochastic signal revealing the number of motor units solicited while MMG refers to the resulting dynamics of muscles. This confirms that EMG amplitude is more suitable to capture pressure than MMG amplitude.

In order to analyze the change in dynamics, related to the kinetic energy in the movement (changes in acceleration), we compute the number of zero crossings on the

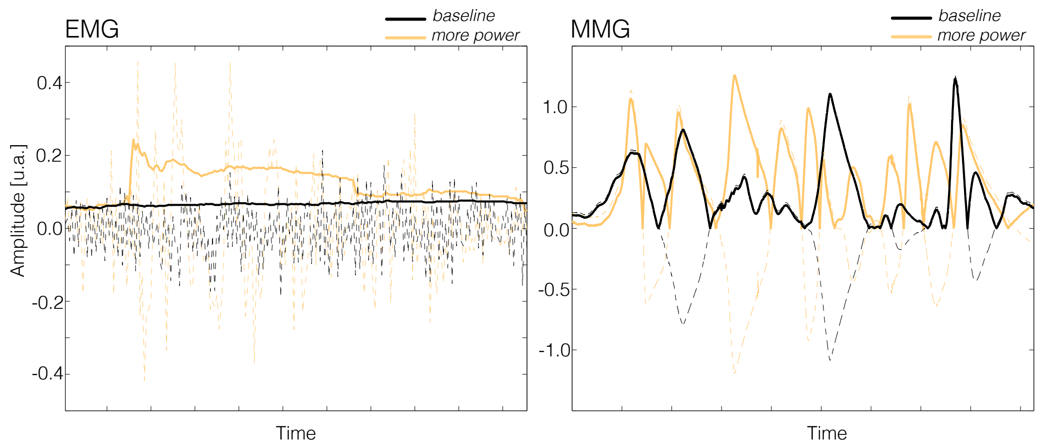

Fig. 7. Examples of EMG signals (left, dashed lines) and MMG signals (right, dashed lines) for gesture 3 (performed by participant 5) are reported for two conditions: baseline (black) and more power (yellow). On top of the signals are reported the amplitude estimations.

signals and inspect how this feature is affected by variations in power. Figure 8 reports the results. A repeated-measure analysis of variance (ANOVA) is performed to investigate the effect of the two factors GESTURE (the 6 gestures of the vocabulary) and VARIATION (baseline and more power) on the signals' numbers of zero crossings. The analysis reveals that there is a significant effect of GESTURE on the EMG zero crossings $F(5, 132) = 37.7, p = 0.002$, but no effect of VARIATION $F(1, 132) = 22.7, p = 0.13$. Regarding MMG, the analyze shows that , there is a significant effect of VARIATION on MMG zero crossings, $F(1, 132) = 4.6, p = 0.02$, but no effect of GESTURE, $F(5, 132) = 1.1, p = 0.34$.

A post-hoc analysis on the MMG zero crossings is then performed to examine the individual differences for each gesture between the two conditions 'baseline' and 'more power'. The analysis reveals that the number of zero crossings significantly increase for gestures 3, 5 and 6 ($p < 0.05$).

Note that a similar analysis performed on the centroid frequency leads to an identical result for the MMG. However for the EMG, the centroid frequency significantly decreases when applying more power (see Figure 9).

Higher frequency in the MMG signal (more rapid oscillations) relate to higher power in the execution of the gesture. Let us inspect the time-frequency representation of the same gesture taken as example in Figure 7. Figure 10 reports the spectrogram of the signal with the centroid curve on top of it (white curve). The figure reports the specific case of gesture 3 performed by participant 5 with no variation (on the left) and with more power (on the right). We observe that on the right side, higher frequencies have more energy when the power is applied. However the peak (in white) of energy is almost the same in both cases.

6.3. Power dependency on gesture, and other dimensions of expressivity

In the previous section, we showed that the EMG amplitude feature significantly increases when participants varied the power of a gesture. This means that the haptic feedback does not affect the change in power measured as the variation of EMG amplitude (i.e. related to the tension exerted in the arm). However the haptic feedback affects the spectral density in the MMG signal, as shown in Figure 9.

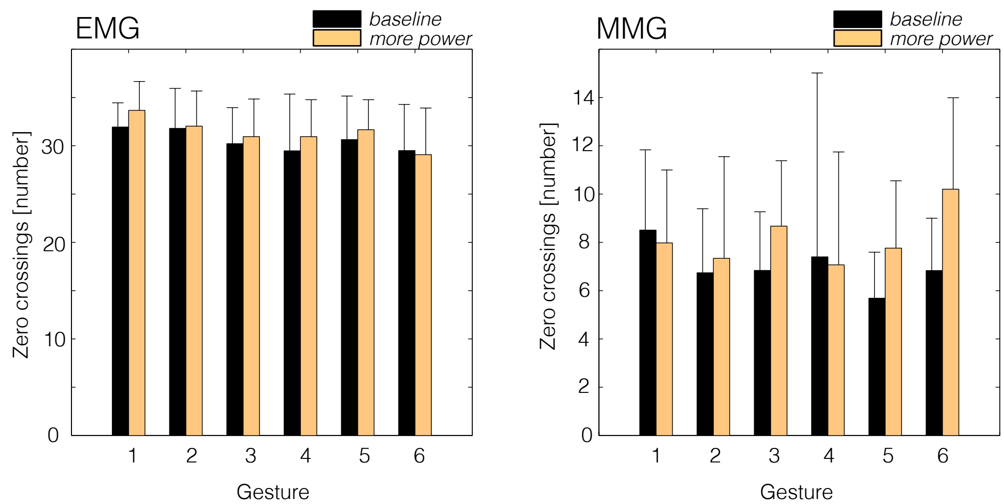

Fig. 8. Zero crossings for both EMG (left) and MMG (right) averaged across participants and trials. Black bars show the mean number of zero crossings when no variation is applied (baseline), orange bars report mean number of zero crossings when more power is exerted.

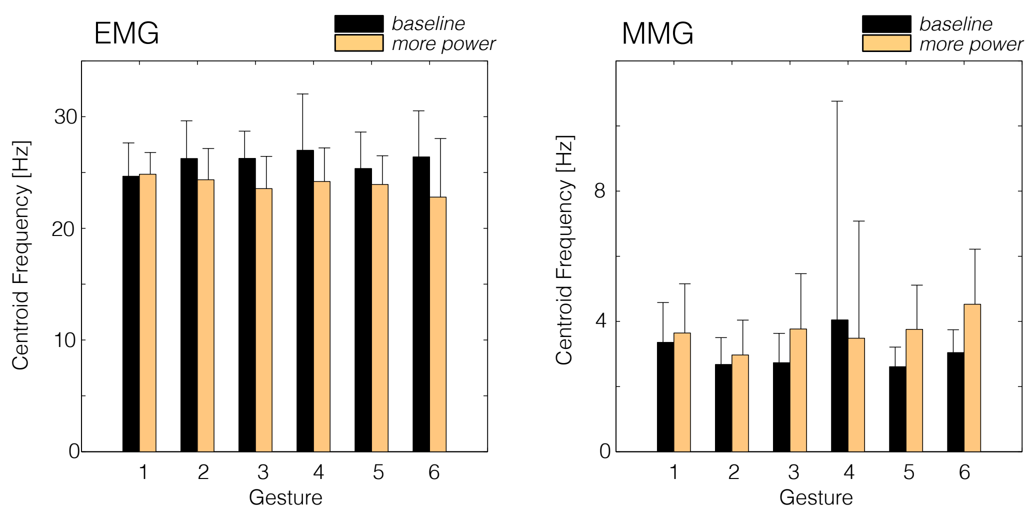

Fig. 9. Centroids for both EMG (left) and MMG (right) averaged across participants and trials. Black bars show the mean centroid frequency when no variation is applied (baseline), orange bars report mean centroid frequency when more power is exerted.

Figure 6 illustrates that the increase in amplitude depends on the gesture performed. In order to examine how each gesture affects the change in amplitude, we computed the percentage of amplitude increase between “no variation” and “more power”. Figure 11 reports the results. We compute a pairwise Student’s T-Test with $\alpha = 0.05$ across gestures to compare amplitude increases. The test reveals that gesture 1 (surface rotation) has a significantly lower increase in either EMG or MMG amplitude

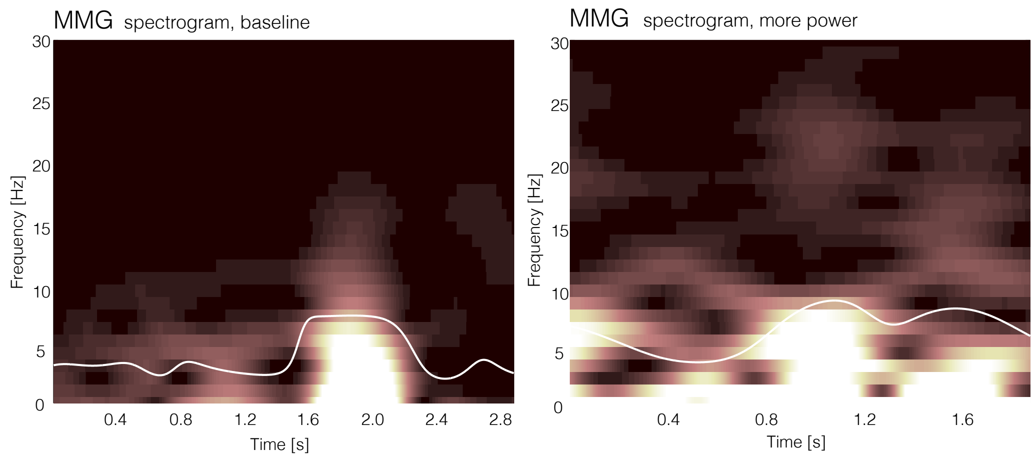

Fig. 10. Spectrogram of the MMG signals for an example trial of gesture 3 in the case of no variation (left) and more power (right). The white curve plotted on top of it illustrates the temporal evolution of the centroid.

compared to the other gestures ($p < 0.05$). Similarly, gesture 5 (fist rotation) shows a significantly lower increase in either EMG or MMG amplitude than gestures $2, 3, 4$ and 6. In other words, the increase of tension when performing gestures 1 and 5 is more limited than for the other gestures.

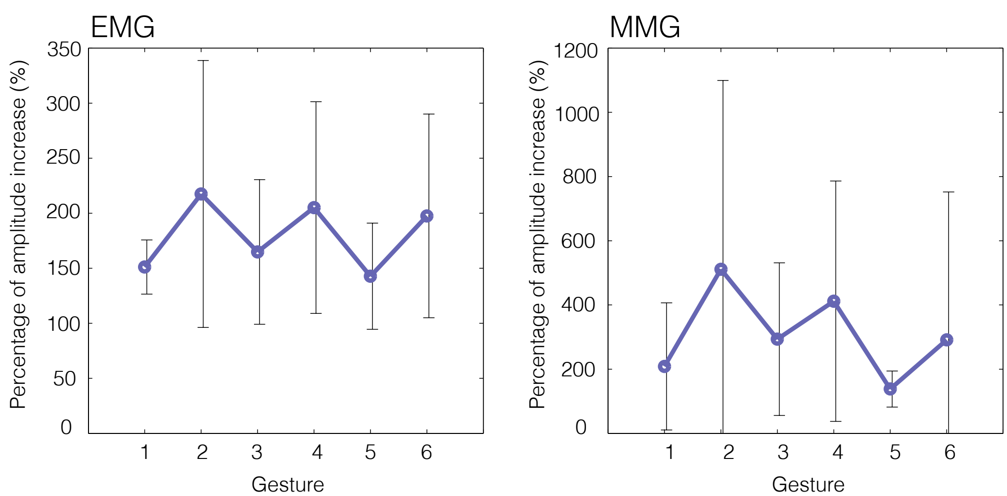

Fig. 11. Percentage of amplitude increase between the condition “more power” and the baseline. On the left are reported the percentages related to EMG, on the right those related to MMG.

Furthermore we examine the link between power and the other dimensions: speed and size. First we inspect if the global speed of the gestures (given by their relative duration) changes if one is performing the gesture with more power. Figure 12 reports the results. We compute a Student’s T-test (with $\alpha = 0.05$) pairwise on the relative durations across variations (baseline, bigger, faster and more power) for each gesture.

Firstly, the test applied between the baseline and the condition "bigger" does not reveal any significant difference for every gesture. In other words, participants maintain the global duration of a gesture equals to the original duration of baseline performance even when varying gesture size. This means by consequence that they also perform the gesture quicker. Secondly, the duration of gestures performed under the task "faster" are significantly shorter than the gesture durations under the conditions baseline, bigger, or more power ($p < 0.05$) for every gesture. Finally, the test shows that gesture lengths decrease when performing gestures with more power compared to the baseline ($p < 0.05$). In other words, when asked to perform a gesture with more power, participants also performed it faster.

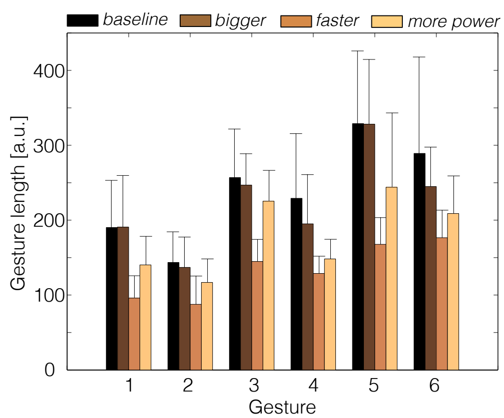

Fig. 12. Lengths of the gestures performed, averaged across participants and trials. Black bars show the mean length when no variation is applied (baseline), orange bars report mean length when more power is exerted.

Finally, we inspect how variations in size affects variations in power in terms of EMG and MMG amplitudes. Figure 13 reports the results. We perform a statistical T-Test between condition for each gesture in order to inspect their relative differences. The analysis reveals that both EMG and MMG amplitudes significantly increase between bigger and more power ($p < 0.05$), but not between more power and the combination bigger and more power. Also the EMG and MMG averaged amplitudes do not increase between the baseline and bigger. In other words, participants are able to modulate the size of the gesture while keeping muscle tension at the same level as in the baseline.

7. DISCUSSION

The studies presented in the paper are a first attempt to understand if an approach considering gesture expressivity for HCI is possible as a motor task. This insight is critical to interaction designers in imagining scenarios that make expressive use of limb movement. A first pilot study reports on the ability for participants to control variations in size and speed separately, and independently on the gesture performed. A second pilot study reports on the importance of considering muscle sensing in the capture of expressive movement in order to go beyond spatial and temporal variations. This led us to the design of the study presented in Section 5 where the notion of gesture power is explored in terms of control and sensing. In the results we explore the role of the haptic feedback on user understanding and control of gesture power variation; the role of the gesture executed; and the inter-dimensional dependencies of expressivity.

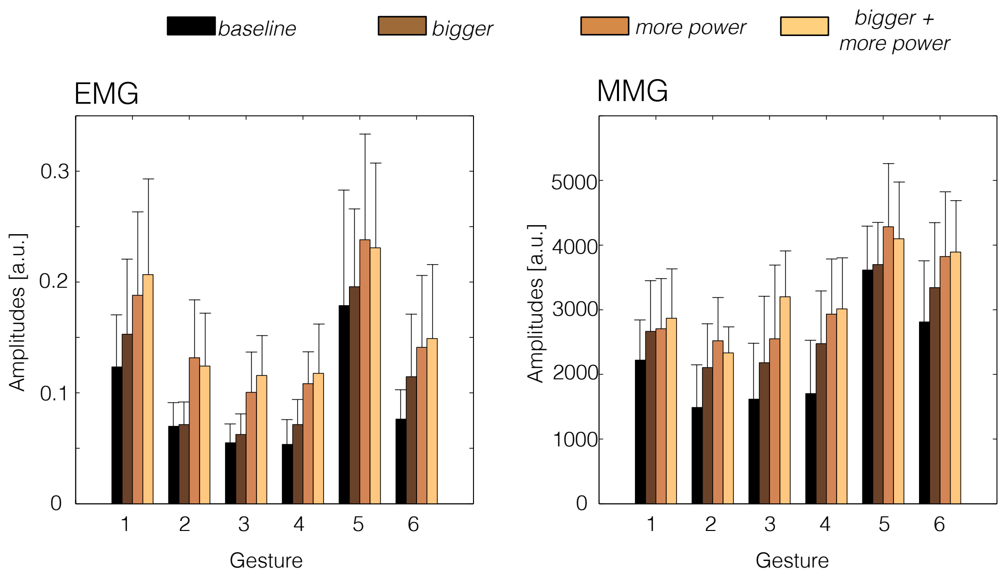

Fig. 13. Amplitudes for both EMG (left) and MMG (right) averaged across participants and trials. Four conditions are considered: baseline, bigger, more power and bigger+more power.

Here we discuss these aspects, report challenges for interaction design involving the proposed approach and give some possible applications in HCI.

7.1. Haptic feedback

The user's ability to understand the task of varying gesture power is linked to the presence of a haptic feedback. As we would expect, power variations carry with it more subjective ambiguity than size and speed.

When a gesture involved haptic feedback, like the resistance of a boundary object, participants associated gesture power to the notion of *Force* (understood as *Pressure*). When the gesture lacked haptic feedback, as in free space movement, participants associated power to the notion of *Tension* or *Intensity*. These three terms, *Force*, *Tension* and *Intensity* refer to three facets of the notion of power. We can think of them operating as "sub-dimensions" of the power dimension.

Tension, measured as EMG amplitude, was shown to be modulated independently to the presence of a haptic feedback. In other words, the variation in power in terms of tension is equally possible for a surface gesture as for a free space gesture. The motor capacity for varying tension is therefore de-correlated from the user's understanding of the variation of power.

On the other hand, the presence of haptic feedback affects the dynamics of the forearm muscles, as we have shown by inspecting spectral information in the MMG. The number of zero crossings inform on the activity of the muscle during gesture execution. We showed that the activity increases for free space movements, and mainly for those that involve wrist rotations or dynamic changes in the gesture execution itself (such as square corners). Therefore, moving in free space induces articulations between the forearm and the hand, dynamically activating the forearm muscles, while performing gestures on a surface mainly solicit movement of the whole arm to exercise pressure (better captured via EMG as discussed above).

7.2. Gesture design

Another factor is the role of the gesture executed. While the pilot study with 2D shape gestures indicate that the ability of users to execute variations are independent of the gesture performed, the results of the main study presented in Section 6 indicate that the gesture performed has an influence on the way users perform variations in the various dimensions. The gesture vocabulary has been designed to encompass gestures with various biomechanical characteristics like wrist torsion or arm articulation. Biomechanics have a direct influence on the power as captured by muscle sensors. From the study we retain that:

— Gestures involving limb torsion are more limited in the range of muscle tension that can be applied. The natural gesture (with no variation) already induces tension in the muscle. The range of potential variations is by consequence limited compared to other gestures.
— Gestures in free space involve higher activity of the muscle, captured in the frequency domain of the MMG signal. Articulations of the forearm lead to higher partials in the frequency response of the muscle. The same is observed for gesture including abrupt changes in their shape (e.g. square).

Hence, gestures can be designed to take into account biomechanics and highlight user modulation of power. For instance, a surface gesture allowing modulation of the pressure over the widest range, or a free space movement with punctuating changes may become part of the gesture typology that interaction designers might incorporate into future interactive products that track user gesture by way of muscle sensing.

7.3. Dependency inter-dimensions of expressivity

While expressive gesture presupposes spontaneity and personal difference, exploiting expressive variation in HCI applications requires reproducibility and the ability of users to intuitively control the expressive dimension in gesture. Note that deliberateness refers to the capacity in motor control to perform a given task. We did not evaluate deliberateness in a task-driven study where error rate and time completion would allow assessment of accuracy.

In the first pilot study, we showed that varying size and speed is natural and can be executed deliberately in 2D gestures. Both can be controlled separately if the gesture is performed slower, otherwise both are intrinsically coupled. $2/3$ Power Law states a strong correlation between instantaneous speed and curvature [Viviani and Flash 1995]. This means that the speed cannot possibly be constant over the pattern (even if the user perceives it as constant), with each gesture having a specific time/speed profile. The law of isochrony further establishes that the average speed of point-to-point movement tends to increases with the distance between the starting and ending point. In other words, we tend to keep constant the time required to perform a gesture if performed bigger. We show that the law also applies to free space gestures. For larger gestures, the total length remains constant, meaning that the average gesture speed increases.

This establishes that speed is not a parameter we are used to controlling or varying in everyday motor task. On the contrary, size is a parameter we often modulate. Note that these facts only hold for ballistic gestures, performed sufficiently fast without feedback. When performed sufficiently slowly, the gestures can be controlled through a sensorimotor loop using, for example, visual feedback. In such a case, the human motion law we mentioned above does not hold.

Power is an expressive dimension that takes advantage of the richness of information in physiological signals, and can be modulated by varying the tension in the muscle. We demonstrated capturing such modulation through EMG amplitude analysis. Varying tension, however, seems to have an incident on the speed of execution of a gesture. Power and speed seem to be intricately linked, but it is not clear what the mechanisms are that link speed and power, like in the previously mentioned laws of motion. On the other hand, size and power are separable in the sense that they can be modulated independently.

7.4. Applications

Our findings provide insights for interaction designers wishing to enhance the expressivity of interaction using muscle sensing. Here we present some possible applications that could make use of the approach proposed.

The first application, Expressive Texting, has been imagined by Participant 12. In the scenario, a user types a text on her mobile phone while commuting on public transport at rush hour. High stress going to work makes her typing more vigorous and she is eager to transmit her mood to the recipient. The messaging application understands the level of stress by analyzing the gesture power picked up by wireless muscle sensors and render the content of the text message in bold upper case or larger font sizes. This scenario is simple, and is useful to clearly illustrate the type of application that can be envisioned leveraging on our approach.

Another set of applications that could be imagined involves adaptive interfaces that respond to the rigidity of user gesture depending on their level of expertise. If the the user's gestures show high tension due to inexperience, the system could simplify its interface relative to a user who is more fluid and relaxed in their interaction. Or if the user's gesture shows high force, the system could visually emphasize a specific part of the interface.

There are further potential applications in games. User engagement with a game is critical to the interactivity with the system and has been measured by brain computer interfaces (BCI). Typically, a user has a limited set of controls to help navigating complex virtual environments. An understanding of physiological aspects of the user's gesture could help gain insight on the user's level of engagement. Some games have recently implemented very basic physiological sensing[5], but the use of different expressivity dimensions, as proposed in this work, could provide more subtle interaction, or even be used to alter the narrative of the video game in real time. High tension in the user's gesture could prompt the game to render a more quiet environments to encourage the user to rest, and high force could make the user's virtual character stronger during fights, with high intensity prompting the soundtrack tempo to increase.

A final set of potential applications relates to the performing arts and digital media art. In this context, the ability to provoke different and unexpected responses in the audience is critical to the success of an artwork [Ouzounian et al. 2012]. A set of tools helping artists to leverage subtle variations of audience reaction while experiencing an artwork could advance new prospects for live digital music, interactive dance, virtual reality, media theatre and interactive installations.

8. CONCLUSION AND FUTURE WORKS

In this paper we explored how limb gesture variation captured by physiological sensors can be suitable for the design of expressive interactions. Results from the first pilot study illustrate that users are able to reliably perform simple variations in size and speed of 2D shape gestures, and do so independently of the gesture performed. The second pilot study introduced muscle sensing in a multimodal context alongside

[5]See review of physiological sensing-based games at http://www.physiologicalcomputing.net/?tag=biofeedback-games

standard physical sensors, and looked at two complementary modes of muscle sensing, the EMG and MMG in a bi-modal configuration. This study showed that muscle sensing gives an indication of the user intent in the execution of a gesture and that given auditory feedback, users are able to reliably perform gestures that highlight differences in complementary modes of the EMG and MMG. This points out that muscle sensing is suitable for detecting expressive input, and that physiological sensing can be exploited by users in a voluntary manner in human-computer interaction settings. We implemented techniques from the biomedical literature on consumer grade muscle sensing hardware. These physiological phenomena needed to be detected in real work setting with higher noise, lower sampling rate, and perturbation, similar to those in which we might imagine future interactive products to be used. The rapid democratisation of sophisticated physiological hardware in the e-health space means that the signal quality, number of input channels, and sampling frequencies, will only improve, making techniques like those presented in this paper increasingly robust in everyday settings.

The main study describes an experiment that focuses on expressive dimensions of gesture from a user oriented, qualitative and quantitative perspective. A questionnaire following task-based trials gauging the participants' perceived difficulty in performing gesture variations as well as their subjective understanding of the gesture dimension, 'power'. For the user, power is an ambiguous, subjective dimension that can be understood differently according to the presence or absence of haptic feedback and can be assimilated to tension or kinematic energy. According to the participants, 'power' is also depends on the gesture performed and other dimensions to be manipulated (e.g. speed).

A quantitative analysis of EMG and MMG data provides signal features, amplitude and zero-crossings, that are useful in measuring objectively the insights from the questionnaire. The analysis first shows that participants were able to modulate muscle tension in gestures and this modulation can be captured through physiological sensing. Exertion by pressure is better explained via EMG signal amplitude while dynamic variation of intensity is better captured through MMG, in the frequency domain. The ability to control variations in power, then, depends on the gesture performed. Finally, we showed that power and speed are dependent.

The proposed approach, using gesture variation as a medium of expressive human-machine interaction, leads to several potential applications for expressive interaction scenarios, addressing diverse fields like personal devices, adaptive systems, video games and the performing arts. We believe that this work has a relevant impact for the HCI community and we see current challenges that will drive our future work in the field.

A first challenge is to build on the results from these studies to create interaction scenarios involving dynamic gesture variations. Such scenarios would allow for evaluate the approach from a task-oriented perspective and assessing aspects such as usability. As the task would require the deliberate activation of muscles, the effect of fatigue and stress would also need to be measured in order to shed light on usability issues for HCI.

The second challenge is the computational modeling of muscle-based variation and their real time tracking. We have developed previously a machine learning based method that is able to recognize a gesture as soon as it starts and to adapt to spatial and temporal variations. The system has been assessed on gesture databases from the state of the art and successfully deployed in gesture-based sonic interaction [Caramiaux et al. 2014]. The study presented in this paper gives insights on the challenges in adapting such a system to track power variations captured by bimodal muscle sensing. This machine learning technique would classify different muscle gestures and perform adaptation that would take into account variations in gestural power. A future work is then a system that considers bi-modal muscle input and tracks variations in power, as an improvement over current position based systems.

Finally, the investigation of gesture expressivity through muscle sensing would allow us to explore higher-level notions such as effort that has been widely used in creative practice such as dance but also in medical fields such as stroke rehabilitation. We believe that the conceptual and methodological approaches presented offer insight for further research in using physiological interfaces to go beyond movement-based HCI.

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APPENDIX

A.1. Additional material of the prior work

In the appendix we report the table of gesture used in our first pilot study.

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METAPHORICAL GESTURE	ARMS PHYSICAL GESTURE
Shaking bells	Right arm lifted up. Wrist bent forward. Multiple contractions of the right hand fingers
Scattering sound grains 1	Right forearm lifted up. Distal phalanges bent forward. Fast multi-directional wrist contractions
Stretch the sound 1	Right arm lifted up and extended frontally towards the right. Palm completely open. Closing rapidly the fist, while rotating and contracting the forearm towards the left.
Stretch the sound 2	Right arm lifted up, extended backwards behind the shoulder, and towards the right. Palm close. Fast wrist rotation, and faster flexion of the distal phalanges.
Dropping something small	Right arm lifted up. Wrist bent forward. Single, neat contractions of the right wrist, and fast flexion of the ring finger.
Rotating bells	Right arm extended backwards behind the shoulder, and towards the right. Palm half close. Very slow wrist rotation.
Grasping the void	Both arms lifted up. Elbows at the shoulder level. Forearms bent perpendicularly to the arm. Fast arms closing, and wrist upward/downward contraction.
Shaping a wave	Left forearm lifted up. Palm half open. Upward wrist contraction, and movement of the forearm from right to left
Throwing a sound wave	Left forearm completely bent upward. Wrist bent forward. Palm half closed. Extension of the forearm, upward wrist contraction, and full opening of the palm.
Holding a growing force	Left arm lifted up. Wrist bent forward. Multiple contractions of the left hand fingers and wrist, and full tension exerted in the whole arm.
Scattering sound grains 2	Left arm resting along the body. Sudden, strong, upwards wrist contractions, and fingers flexion. Lifting left shoulder upwards.
Rotating a wheel	Left arm perpendicular to the body. Forearm slightly bent to the right. Palm half open. Sudden upward wrist contraction, and fast rotation of the forearm from right to left

Fig. 14. Table describing the gesture vocabulary used in our pilot study [Donnarumma et al. 2013a]. The gestures are derived from an existing performance piece of contemporary interactive music.