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How Electromyography Readings from the Human Forearm are Made Cryptic, Trivial, or Non-Trivial Information for Use in Synthetic Systems

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Abstract. The success of reading potentials generating from human muscle activities is evident that proves that the human body's neural system is naturally electronics. Now, modern engineering is accepting it as one field of engineering science. Due to this, the concept of a cyborg is beginning to realize as products such as exoskeletons and neuroprostheses. The object of this work, however, is to view from a different perspective as to how this is beneficial to the functions beyond the mentality of today's applications. We hypothesized that the recorded potentials from muscle activities may be regarded similar as to the signals that jump between synapses in the biological neurons. We suggest that these signals, instead of mere electrical in nature, their waveforms might include emotion characteristics from uniquely combined muscle activities and feeling. The system codes the signals where the newly created information may be made cryptic, trivial, or nontrivial depending on how they are going to be utilized in the synthetic systems. So that the artificial system could sense, for instance, the emotion of the human host.

Keywords: Electromyography, neurons, forearm, muscle

1. Introduction

Present human-machine interfaces have not been successful. It is because the human body has a limit in electric power generation. Traditional electronics circuit designs have not effectively consider the specifications of signals, a surface electro-myoelectric. During the past decade the electromyography (EMG) signal has gained much attention [1]. The main drawback of a surface electromyography (sEMG) is there exists a variation of signal reading among people, that is, an sEMG is uniquely individual. The reasons are the skin conditions, muscle fatigue, and the locations of electrode placement [2], [3]. As a result, the EMG-based control systems are not cross user applicable, and even a single user requires a considerable calibration and training [4].

The outcomes and applications of human-machine interfaces, nevertheless, are limited to custom-designed subsystems, such as neuroprostheses. A somatosensory prosthesis may implement intracortical microstimulation to obtain refined sensations. Intracortical microstimulation provides comprehensive feedback as compared to vibrotactile motors and sensory substitution devices [5]. Nevertheless, people who apply prosthesis commonly claimed they felt a lack of feedback from the replacement limbs that requires considerable effort and concentration for them to execute a routine task. It is the absence of a direct neural interface that provides a comprehensive sensory feedback. In fact, the success stories of their implementations may be found everywhere in the world that needs little elaboration in this paper.

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We hypothesize that the signals that emanate from the skin as a result of muscle stimulations, as they are being recorded, may have additional information—the human emotion. Therefore, the primary object of this work is to view the phenomena in a different perspective as to how this is beneficial to the functions beyond the mentality of today's applications. The scope of the investigation covers the upper limb, specifically the muscles within the forearm.

2. Background

2.1. Anatomy of the Human Forearm

Fig. 1 shows the different views of the human arm anatomy that clearly explains the complexity of the muscles "woven" architecture. In the figure, one can identify the bones of the upper limb, notably the ulna and the radius of the forearm, and the digits of the hand. The origin, insertion, or action of muscles that realize the wrist, hand, and finger movements give the names for the muscles. The muscles of the forearm fall under the groups of the anterior compartment and the posterior compartment. These groups are identified based on their location and function.

For the anterior compartment group, the flexor muscles originate from the insert on the carpals, metacarpals, and phalanges. On the contrary, the extensor muscles originate from the insert on the carpals, metacarpals, and phalanges for the posterior compartment group. In addition, the muscles may be identified as superficial or deep within each compartment. Flexor carpi radialis, palmaris longus, and flexor carpi ulnaris are superficial muscles in the anterior compartment. The flexor digitorum superficialis is a thick muscle to flexor carpi radialis, palmaris longus, and flexor carpi ulnaris [6].

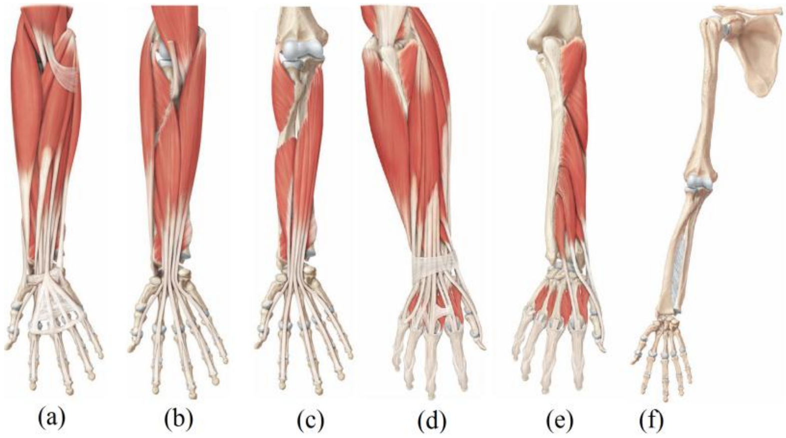

Fig. 1: The anatomy of human upper limb (f) with the forearm muscles (a), (b), (c), (d), and (e). These muscles actuate the fundamental movements such gliding at synovial joints, and flexion, extension and hyperextension at the wrist joint (Source: [6]).

2.2. Modeling for Seeking Signals

Underneath some layers of the human skin, there are networks of nerves that conduct myoelectric of the different multitude of analog waveforms. Some of the signals may be used to carry information of pain to the brain while others give the information for the muscles to contract upon the brain's decision to respond to the sensation of pain.

While the muscles are contracting, the potentials may be recorded using a particular transducer where its electrodes are sensitive to the surface electromyography (sEMG) of the skin. We used our developed sensor to perform sEMG.

Fig. 2 explains the reference position to place the electrodes. It shows a grid system that suggests where to place the electrodes nearby the chosen muscle [3]. The black-cabled electrode functions well if placed on a bony area. Therefore, (e, A) is the best estimation. Table 1 lists the proposed positions of the electrodes based on the forearm anatomy [7].

Let G be a grid system with a horizontal axis is represented by a triangle scale notation for a through e. The vertical axis takes a polygon-shaped notation for A through E. The sub-equation of (1) defines where $g(\rho,\sigma)$ is sub-function in the grid system where ρ and σ represent a vertex and an edge, respectively.

Let Ξ denotes the abscissa and let Ψ represents the ordinate. Sub-equation (1) defines the elements of the axes. We may place the electrodes at a particular point. There exist a number of possible point combinations where Table lists them.

Table 1: Active locations for the electrodes

№	Muscle	Estimated grid position
1	Brachioradialis	(a, A)
2	Flexor carpum radialis	(b, C)
3	Flexor carpum ulnaris	(c,E)
4	Smaller forearm extensors	inv(a,C) [a]

[a]At the back of the arm where the "inv" is a short form for "inverse"

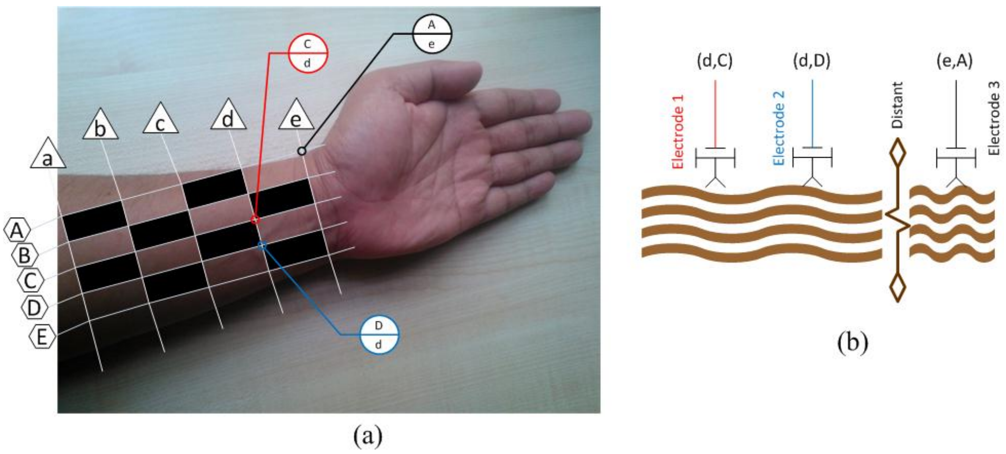

Fig. 2: (a) A grid that depicts the probable location to place the electrodes. For example, there is a vertical axis ⟨a⟩ and a horizontal axis [A]. (b) The suggested position to place the electrodes.

Let Block A represents an interface and Block B a processor (see Fig. 3). Block A accepts raw signals and amplifies them. Block B receives the amplified unprocessed signals and processes them. We identify the processed signals as cryptic or non-trivial information. The developed system has a set of three wires that is color-coded. They link the skin surface to the circuitry in Block A. Fig. 2, for instance, suggests (d,C), (d,D), and (e,A) as the points to place the electrodes. Now; let P represents the electrodes. A set of wires has at most three pieces.

$$\left.\begin{array}{l} \Psi = \{a,b,c,d,e\} \\ \Xi = \{A,B,C,D,E\} \\ G = \{g \in G : g(\rho,\sigma)\} \\ P = \{p_1, p_2, p_3\} \\ \rho = \{A, B, p_1, p_2, p_3\} \\ \sigma = \{(A,B),(A,p_1),(A,p_2),(A,p_3)\} \\ \mathbf{O}(s) = \mathbf{P}(s)\cdot\mathbf{A}(s)\cdot\mathbf{B}(s) \\ \mathbf{X} = \{\chi \in X \subset \mathbf{G} : (\Psi \times \Xi) \mid \exists P \text{ \# may be fixed to some locations}\} \end{array}\right\} \quad (1)$$

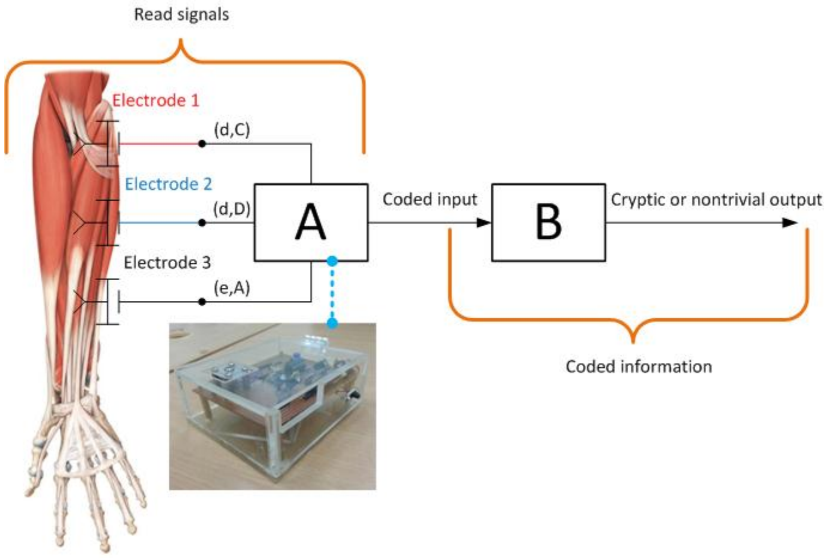

Fig. 3: The transducer has three electrodes linked to the circuitry in Block A. Block A collects the signals from the human arm and produces raw outputs. The system amplifies the raw signal outputs. Block B receives and processes them.

2.3. Modeling for Signal Coding

The communication between Block B and Block A may be realized through a middleware a message-based mechanism that manages the communication. At least one set of interface module presents when communication takes place. The steps for enabling access to Block B may begin when a signal requests to access Block B. Block B, in turns, only allow access because the signal is still raw. A module within the Block B will detect the class of the signal and process it.

We classify the signals as cryptic (CRYP), trivial (TRV) or non-trivial (nTRV). These depend on the preprogrammed instructions and is, therefore, being transformed into one of the classes of information—CRYP, TRV, or nTRV. If the information is CRYP, it will be transferred through a regular tunnel. Else, the transfer occurs through a secure tunnel.

The signal (S1) that comes from muscles that execute flexion or extension may be different to a signal (S2) that originates from the same muscles, which similar movements inclusive of subject's emotions. Now, S1 may be classified as TRV information, whereas S2 is nTRV due to additional emotion trait. Some signals are CRYP so that they become the biometric of a unique person.

Let S represents signals that emanate from the muscles. A signal is raw upon successfully extracted from the skin and is being filtered and amplified in Block A. So that equation (2) defines the process for signal extraction.

$$\text{SIG} = \forall\left\{S \mid (\text{raw}), s \in S \rightarrow \left[\tilde{\text{s}} \mid (\text{filter,amplify})\right]_{BLOCK-A}\right\} \tag{2}$$

Suppose Block B has received the raw signals from Block A. It just permits the signal to access the block. In the meantime, middleware routines will link and thus route the SIG to specific subroutines that will process it according to the class of signals. So that equation (3) defines the process of communication between Block A and Block B, and the SIG is being classified.

$$\text{COMM} = \text{REQ\_ACC}\left\{\left[\tilde{\text{s}}\right]_{BLOCK-A} \mid \exists\tilde{s} \rightarrow [\text{middleware}] \mapsto (\text{cryptic} \vee \text{trivial} \vee \text{non-trivial})\right\} \tag{3}$$

$$\left.\begin{aligned} \text{CRYP} &= \forall\left(\mathbf{O}(s) = \mathbf{P}(s)\cdot\mathbf{A}(s)\cdot\mathbf{B}(s)\right) \mid \exists\tilde{s} \text{ iff } (\text{SIG} \mapsto \text{unique} \because \text{biometric}) \\ \text{TRV} &= \forall\left(\mathbf{O}(s) = \mathbf{P}(s)\cdot\mathbf{A}(s)\cdot\mathbf{B}(s)\right) \mid \exists\tilde{s} \text{ iff } (\text{SIG} \mapsto \text{unique} \because \text{procedure}) \\ \text{nTRV} &= \forall\left(\mathbf{O}(s) = \mathbf{P}(s)\cdot\mathbf{A}(s)\cdot\mathbf{B}(s)\right) \mid \exists\tilde{s} \text{ iff } (\text{SIG} \mapsto \text{unique} \because \text{emotion}) \end{aligned}\right\} \tag{4}$$

The signals will have to pass through a filter and an amplification of Block A. Depending how one designs the circuitry, the kind of signals transmitted must possess some unique features. These characteristics may be directed to a separating pathway. The pathway may be a discriminating dividing circuit with parallel separating paths that split to feed to respective branches defined by equation (4). There exist at least three classifications; we suggest. We, therefore, propose that human may fuse with a synthetic system through myograph information that are CRYP, TRV, or nTRV.

3. Conclusions

We hypothesized that the recorded potentials from muscle activities may be regarded similar as to the signals that jump between synapses in the biological neurons. We suggest that these signals, instead of mere electrical in nature, their waveforms might include emotion characteristics from uniquely combined muscle activities and feeling. The system codes the signals where the newly created information may be made cryptic, trivial, or nontrivial depending on how they are going to be utilized in the synthetic systems. In doing so, each signal that emanates from the muscles must be treated according to how specific or how emotional it is being generated by the subject. So that the synthetic system could sense, for instance, the emotion of the human host.

4. Acknowledgements

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