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Proceeding Paper

Visualization of Multichannel Surface Electromyography as a Map of Muscle Component Activation †

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Abstract: The study of muscle activation patterns using surface electromyography (sEMG) provides critical insights into muscle coordination, enabling advancements in prosthetics, robotics, and rehabilitation by improving intuitive control, replicating human movements, and developing targeted therapeutic strategies. The study involved 15 healthy participants aged 20–27, using Trigno Avanti sensors to record sEMG signals from forearm muscles during specific gestures, with data processed into activation maps to analyze muscle activity and coordination for applications in rehabilitation and prosthetics. The results revealed distinct muscle activation patterns for each gesture, highlighting precise muscle coordination, with specific muscles like m. flexor carpi ulnaris and m. extensor digitorum showing varying levels of involvement depending on the movement, while m. brachioradialis remained inactive across all gestures. The study's findings enhance our understanding of motor control by revealing specific muscle activation patterns for different hand gestures, highlighting the selectivity of muscle coordination, and suggesting avenues for future research to improve prosthetic design and rehabilitation strategies.

Keywords: HD-sEMG; neurosignal; neuroimaging

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1. Introduction

The study of muscle activation patterns has important implications for advancing our understanding of human movement, developing innovative technologies in robotics [1,2] and prosthetics [3], and improving rehabilitation approaches [4,5]. Surface electromyography (sEMG) is a non-invasive technique that allows researchers to analyze muscle electrical activity during various tasks. By focusing on the forearm muscles, which are critical for fine motor skills, performance of daily tasks, and grip strength, we can gain information about muscle synergy—the coordinated activation of multiple muscles that work together to produce smooth, efficient movements [6].

By identifying patterns of muscle component activation, engineers will be able to design prosthetic limbs that are more intuitive for the user, speeding prosthetic habituation and improving the quality of life for people with limb loss. Moreover, in the field of robotics, understanding muscle synergy can inform the design of systems that replicate human movements and devices that are capable of performing complex tasks that require precise control and coordination. In the context of rehabilitation, knowledge of muscle activation is essential for the development of effective therapeutic strategies. On their basis, individualized programs can be developed to target specific muscle groups, facilitating recovery and increasing functional capacity in patients with movement disorders [7]. The ability to visualize and analyze muscle activation patterns allows medical professionals to monitor progress and adjust interventions in a real-time manner, ensuring optimal patient outcomes.

Modern methods of analyzing sEMG from a matrix of electrodes and with advanced computational methods [8] allow the creation of detailed activation maps of muscle groups and the identification of interactions between them. Such activity maps provide information about the formation of the overall muscle response, providing the basis for prostheses that would mimic natural movements and fine motor skills.

In contrast to typical state-of-the-art approaches that can provide information on the generation of complex muscle responses, this study aims to identify the localization of signals in specific muscles during the execution of different gestures. This allows for a more accurate understanding of muscle coordination and therefore the development of targeted rehabilitation programs and more effective bionic prostheses that meet the individual needs of users. By identifying the precise muscles involved in different movements, we can design targeted rehabilitation strategies that optimize muscle activation and coordination, leading to significantly improved functional outcomes. This deeper insight into muscle dynamics will drive advancements in rehabilitation techniques and prosthetic technology, ensuring they better align with users' physiological needs.

2. Materials and Methods

2.1. Participants

Fifteen healthy subjects without arm injuries aged 20–27 years, including seven females and eight males, participated in the study. The subjects were informed about the course of the study before testing and consent forms to participate in the experiment were signed. The entire study was conducted in accordance with ethical standards and on the basis of the Declaration of Helsinki. All procedures were approved by the Ethics Committee for Biomedical and Social Anthropological Research at Sirius University of Science and Technology.

2.2. sEMG

The electromyogram was recorded using Trigno Avanti sensors (Delsys Inc., Natick, MA, USA) placed in a circular arrangement on the superficial muscles of the forearm (m. flexor carpi radialis, m. palmaris longus, m. flexor carpi ulnaris, m. extensor carpi ulnaris, m. extensor digitorum, and m. extensor carpi radialis brevis/longus). Electrode locations were selected according to SENIAM and Barbero innervation atlas [9]. The signals were sampled at 1259 Hz and filtered using a band-pass filter of 20–450 Hz.

2.3. Experimental Procedure

The gestures chosen for the study were fist clenching, finger extension (open palm), and thumb raising. The subject's hand was comfortably placed on the table on soft pads in such a way as to avoid the pressure of sensors on the muscles and to keep the forearm in a relaxed state. For each gesture, instructions on its correct execution were given beforehand, and several trial attempts were performed for habituation for 2 min. After habituation, 10 successful attempts of each gesture were recorded, with each recording lasting between 2 to 4 s. At least 5 min were allocated for each gesture. During testing, the subjects had the opportunity to rest if they felt fatigue in their hand. The testing was conducted on one day without splitting into sessions, and the protocol time took 30 min.

2.4. Data Processing

EMG signals are analyzed using a multi-step process that includes preprocessing with artifact removal and normalization, smoothing with a sliding window method to remove noise, and visualization in the form of heat maps with normalized time scales to compare muscle activity during different movements. An interactive visual interface allows the user to flexibly adjust processing parameters and save results, simplifying and automating the analysis process.

3. Results

After analyzing the data associated with the muscle component activation maps for the 15 subjects, differences in the pattern of muscle co-activation can be observed depending on the gesture. Figure 1 shows the activation of muscles when performing the selected gestures (A–C). In all maps, we can see the absence of m. brachioradialis activation. During fist clenching (A), the greatest amplitude of contraction is observed in m. flexor carpi ulnaris, m. extensor carpi radialis brevis, and m. palmaris longus, while m. extensor carpi radialis longus and m. extensor digitorum were also involved to a lesser extent and m. extensor carpi ulnaris was involved when unclenching the fist. For finger extension (B), the most activity was observed in m. extensor carpi radialis brevis and m. extensor digitorum, while a small amount of activity was also present in m. flexor carpi ulnaris and m. extensor carpi ulnaris. Finally, for thumb elevation (C), m. extensor digitorum and m. flexor carpi ulnaris were most involved, and m. extensor carpi ulnaris and m. palmaris longus were also consistently active. Some muscles were activated in one gesture and were not activated in others, indicating precise muscle coordination for performing different gestures. There was no activation of the m. brachioradialis in any of the gestures, as this muscle is not involved in performing the selected gestures.

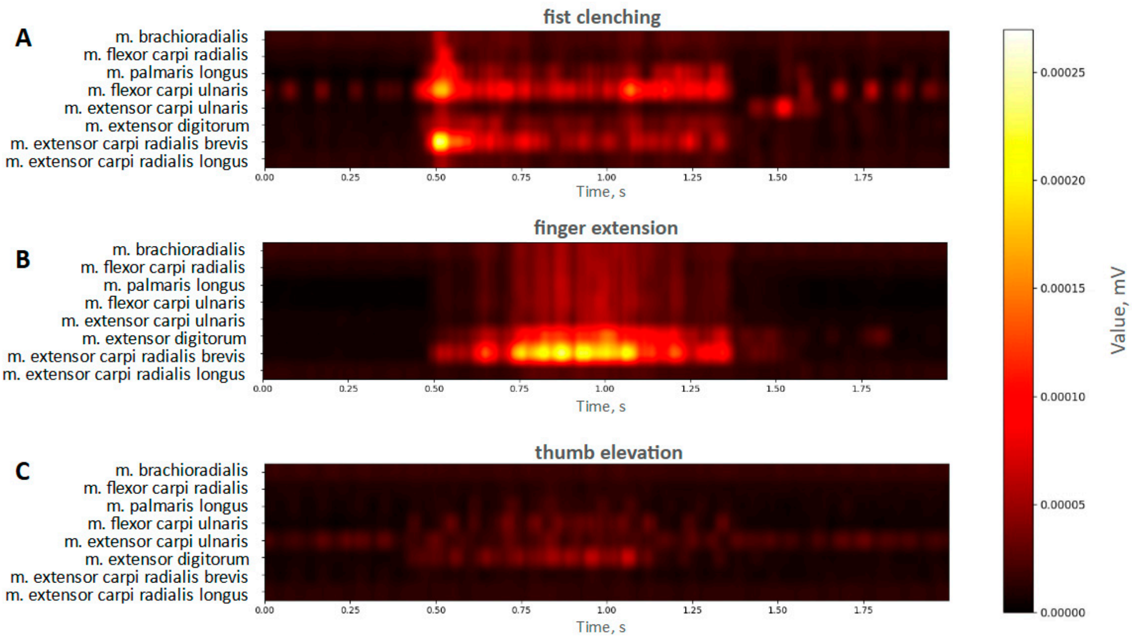

Figure 1. Motor activation map during gestures: (**A**) fist clenching; (**B**) finger extension; (**C**) thumb elevation. On the right is the color gradient scale on the map, where black means no activity and white means maximum activity.

4. Discussion

The present results of the analysis of muscle activation patterns during the performance of various hand gestures make an important contribution to the understanding of motor control mechanisms. The data obtained are in line with the results of previous studies, which also demonstrated the specificity of muscle activation depending on the nature of the movement [5,10–12]. However, in contrast to previous work, this study focuses on examining the signal from specific superficial muscles of the entire forearm, allowing for a more comprehensive view of the coordination of arm movements. One of the findings of this work is the lack of activation of the m. brachioradialis. Since m. brachioradialis is primarily responsible for elbow flexion rather than wrist or finger movements, its inactivity in the studied gestures is expected. This indicates the selectivity of motor control involved in the performance of the studied gestures.

5. Conclusions

The findings suggest that the current understanding of muscle synergy still needs to be expanded. Each movement activates its own unique set of muscles, which repeats from person to person. Previously, we have demonstrated alternative methods for signal registration [13]. Further research in this direction could include analyzing the influence of various factors, such as fatigue or pathological conditions, on muscle activation patterns. The segmentation of muscle signals by electrodes will also simplify signal acquisition for the classification of movements controlled by prostheses and may serve as a basis for the development of more effective rehabilitation approaches for various motor disorders. Decoding muscle synergies provides insights into how the brain orchestrates movement, enabling the development of highly personalized rehabilitation programs. This targeted approach can optimize recovery by concentrating on specific muscle groups critical for functional improvement. Thus, increasing the understanding of muscle synergy can greatly advance development in the fields of prosthetics and rehabilitation.

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Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests for access to the datasets should be sent to the author's e-mail address listed in Correspondence.

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