Analysis and Considerations of the Controllability of EMG-based Force Input

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Abstract. Using electromyography (EMG) measurements for user interfaces (UIs) is widely employed as an interaction method. Some advantages of using EMG-based input are that it does not require a physical controller and can be operated intuitively with small body movements. Existing work has explored different novel interaction methods for UIs using EMG. However, it is still unclear how precisely users can control the force and what kind of control pattern is easier for them to use. Thus, this paper analyzes the effect of EMG-based force input on control accuracy and mental workload. We constructed a pointer-tracking application that inputs force strength from forearm EMG. Tracking accuracy and mental workload were evaluated under the conditions of multiple tracking patterns and hand gestures. The results showed that EMG-based input accuracy was affected by the way in which the force was applied (e.g., strengthened, weakened, or fluctuated). We also found that hand gesture type did not influence accuracy or mental workload.

Keywords: Muscle–computer Interface, Electromyography, Force Input, Performance Evaluation.

1 Introduction

Electromyography (EMG) is a technique for measuring the change in muscle potential over time that is produced by skeletal muscles. There have been efforts to improve EMG measurement devices [1, 2]. In addition, multiple applications in various fields use EMG as input (e.g., entertainment, healthcare, and education [3]). In part, the use of EMG devices is popular because they can estimate the posture or specific body movements of users [4, 5]. For example, EMG-based input allows intuitive manipulation by small body movements without a physical controller [6–8].

Previous studies have analyzed the controllability of the force estimated from an EMG signal [9, 10]. The studies discussed the validity of input in the UI with EMG compared to physical input methods. However, it is not clear which hand gestures or methods of applying force (e.g., keep strong/weak force) enable a user to control the input force more accurately and with less strain.

Therefore, we investigated how a user can track different applied force patterns (e.g., ascending or descending lines) at different muscle activation levels under the next six hand gestures: fist, grip, pinch, and push on a surface with the index finger, thumb, and palm. The evaluation included qualitative and quantitative measures. To understand the accuracy, we computed how well users perform given force patterns. We also administered a six-question questionnaire to assess the mental workload. This experiment provides the first approximation of the relationship between performance force, accuracy, and mental workload.

Human–computer interaction (HCI) researchers can use these results to design new hand gestures at various performing strengths or with a dynamic force input (which changes over time). This can lead to a wider range of interaction methods for EMG-based applications.

The contributions of this paper are as follows:

- We are the first to analyze the effects of EMG-based force strength input on control accuracy and mental workload.
- We clarify the features that can accurately control EMG-based force strength.
- We clarify that certain hand gestures do not influence input accuracy or mental workload.

2 Related Work

In this section, we provide use cases of the muscle–computer interface and some foundational research for our paper. We then describe the literature that explores EMG-based input accuracy. We also point out that our experimental condition is novel compared to previous studies.

2.1 EMG-based Devices for User Interfaces

EMG signals enable intuitive UI operation in real-time. Thus, controlling user interfaces through EMG is widely practiced in HCI research. Becker *et al.* demonstrated the gradual adjustment of lamp brightness using EMG-based force strength [6]. Benko *et al.* realized a variety of sketching brush strokes using forearm EMG [11]. These studies utilized EMG amplitude information as the inputted strength.

Furthermore, EMG-based input enables human assistive activity. For example, Rosen *et al.* developed a powered exoskeleton system controlled by forearm EMG, which is naturally controlled by humans [12]. Rakasena *et al.* also proposed an electric wheelchair controlled by forearm EMG [13]. A variety of applications have used forearm EMG as an input method. In contrast, in this study, we analyzed the impact of different EMG-based input approaches on controllability and mental workloads.

2.2 Detecting Gestures with EMG-based Signals

The state of the human body can be estimated by extracting and learning the features of an EMG signal. The advantage of utilizing EMG is that it requires only simple measurements without large body movements. Much research has estimated human states, for example, gestures and behaviors, from EMG signals using machine learning [9, 14]. In addition, the human body is composed of many muscles; therefore, the muscles of the face, legs, arms, and other body parts have been utilized for estimations [15, 16]. Many studies have estimated body movements from EMG signal features. In this study, we analyzed continuous tracking accuracy measured from EMG potentials.

2.3 Continuous Tracking with EMG-based Input

The ideal interaction with a UI is that the user intuitively and comfortably controls the target object, as expected. Several studies have investigated the influence of the EMG-based force input of the forearm on tracking accuracy. Yamagami *et al*. performed a cursor-pointing task to analyze the controllability of the target trajectory [17]. The literature reports that EMG-based control showed higher accuracy than a physical controller. Lobo-Prat *et al*. performed a one-dimensional tracking task using EMG-, force-, and joystick-based interfaces [18]. Corbett *et al*. also conducted a similar tracking task to compare EMG and force-based interfaces [19]. Their results revealed that EMG-based operations have comparable or better controllability than other input methods. However, these studies examined accuracy under the conditions of a single gesture or a simple tracking pattern. To the best of our knowledge, this study is the first to consider multiple gestures and the way force is applied to evaluate tracking accuracy as well as mental workload.

3 Experiment

The main objective of this user study was to find the effects of EMG-based force input on control accuracy and mental workload. For that goal, we designed a two-factor repeated measures ANOVA on input accuracy and mental workload. We introduced the independent variables *gesture* and *control patterns*. As dependent variables, we evaluated input accuracy and mental workload scores using NASA-RTLX [20].

3.1 Apparatus

We built an application using Unity (Ver. 2020.3.15) to visualize the exerted EMG (Fig. 1, Fig. 2a). The application runs at 120 frames per second with a display resolution of 1920 × 1080 pixels. We used the same EMG measurement device as in [21] (Fig. 2c). The amplitude range of the device was –1.25 to +1.25 mv. The surface EMG signals were amplified 1000 times, and then, A/D conversion was applied to the signals. The measured signal was transmitted to the computer via serial communication at a sampling frequency of 1000 Hz. Two electrodes were attached 20 mm apart on the dominant forearm [22]. The reference potential was set by letting the participants grasp the wrench.

The general frequency range of EMG signals was from 5 to 500 Hz; therefore, we used the same frequency range in the experiment [23]. The signal filters used a high-pass filter to cut low-frequency noise below 5 Hz and a low-pass filter to cut high-frequency noise above 500 Hz. A band-pass filter was also applied to eliminate humming, with a cutoff frequency of 55–65 Hz (Table 1).

An EMG signal contains positive and negative amplitudes; thus, the measured EMG signal was rectified and smoothed. We used the percentage of the root mean square (%RMS), which is a widely used indicator for smoothing EMG [3, 24]. The %RMS represents the myoelectric potential ratio of the measured RMS to the maximum voluntary contraction (MVC). The window size was 300 ms, with an overlap of 299 ms. Each RMS value corresponds to the white pointer in the Unity application.

3.2 Hand Gestures

A variety of hand gestures are used to interact with a user interface [25]. It is important to compare the controllability and mental workload between multiple gestures to design interactions. Thus, we selected six types of static hand gestures that do not move the forearm: fist, grip, pinch, finger push (index finger), finger push (thumb), and palm (Fig. 2b). The advantage of these gestures is that they do not change the hand position compared to dynamic gestures (e.g., swipe, slide, and tap). In this study, we focused on static gestures that can be employed for a variety of UI operations.

The electrodes were affixed to the muscle position corresponding to the hand gesture. Specifically, we attached electrodes to the extensor digitorum muscle for the fist and grip conditions. The flexor carpi radialis muscle corresponded to the finger push conditions (index and thumb). The brachioradialis muscle corresponded to the palm condition. The flexor pollicis longus muscle corresponded to the pinch condition.

3.3 Task

The participant controlled a pointer to keep it within the area of a blue target figure moving from the right side of the screen. The pointer moved up and down, ranging from 0% to 100%, depending on the %RMS. Tracking accuracy was calculated for each of the six hand gestures. The target figure (control pattern), which refers to the method of applying force, was randomly shown from seven patterns (Fig. 3). The types of target figures are divided into the following categories:

- Straight line (L1: low, L2: middle, L3: high)
- Diagonal line (L4: uphill, L5: downhill)
- Curved line (L6: inverted U-curve, L7: U-curve).

The pointer was counted as correctly controlled if it was positioned inside the target diagram. Each diagram had a range of ±5% from the center (Fig. 3). The duration of each diagram was 5 s. The seven types of target figures flowed in random order, with intervals of 5 s. One trial took 70 s ((5-s tracking time + 5-s intervals) × 7 target figures).

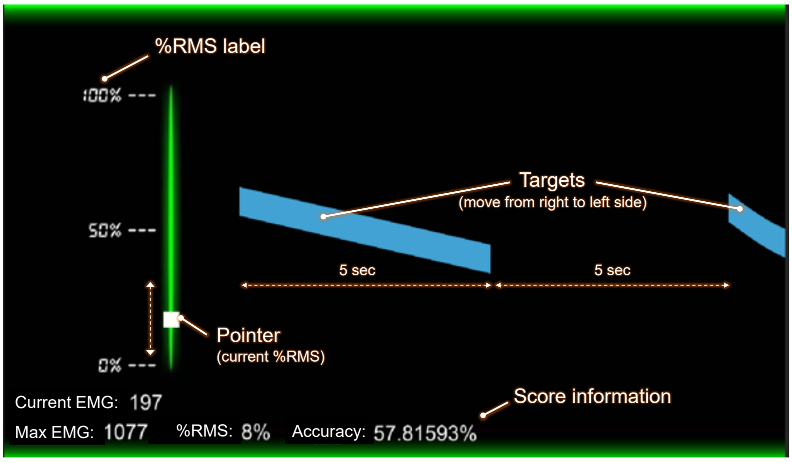

Fig. 1. The application for visualizing the input force used in the experiment. The participant adjusted the force strength so that the pointer stayed inside the blue target figure. The participants' maximum force strength was mapped to 100%.

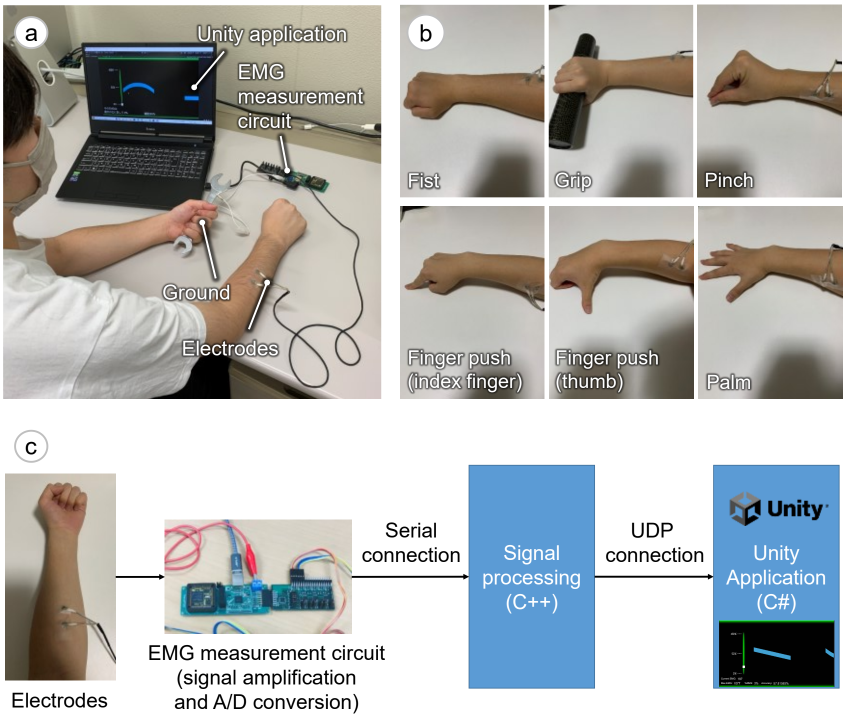

Fig. 2. Experiment setup. a) The participant controlled the strength of the force measured with EMG while viewing the measurement application. b) We set up six types of hand gestures: fist, grip, pinch, finger push (index finger), finger push (thumb), and palm. c) The measured EMG was sent to the application through the measurement device [21] and filter processing.

Table 1. EMG processing parameters.

Sampling frequency	1000 Hz
Window size	300 ms
Overlap window size	299 ms
Indicator	RMS
Filters	High pass: 5 Hz Low pass: 500 Hz Band-pass: 55–65 Hz

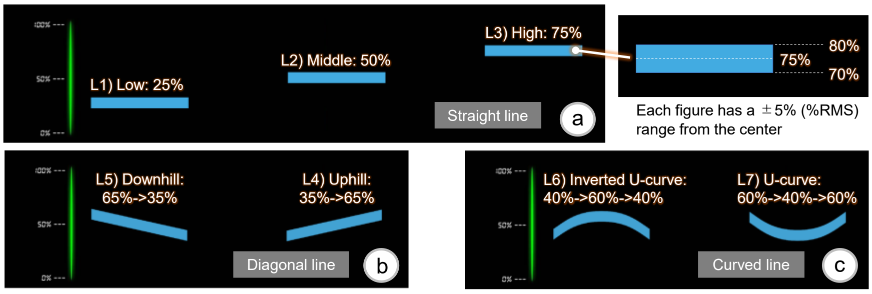

Fig. 3. The methods for applying force. A total of seven figures (L1–7) were presented per hand gesture task. The pointer was counted as correctly positioned if it was located within ±5% (%RMS) of the target diagram center.

The trial was repeated six times, which is the number of hand gestures. The accuracy of each target diagram was calculated by dividing the duration of the correct position by 5 s.

3.4 Participants

Twelve participants (four women, $\bar{X}$= 21.2 years old; 11 right-handed) volunteered. All participants were university students majoring in computer science.

3.5 Procedure

The experiment began with an instruction session. Participants were first given information about the experiment and signed a consent form. They were instructed to sit in a chair in front of the monitor, keep their back straight, and avoid bending forward. The participants were guided to place their elbows on the table so that they could relax their forearms. Floor mats were placed in the experimental area to block noise. For all gestures, electrodes were attached to the participants' dominant forearm, while the opposite arm held the wrench.

The instruction session was followed by the calibration session. The participants were asked to measure their MVC. They exerted their full strength for 2 s, and the average RMS was calculated as the MVC. This measurement was repeated for the six gestures. The measured MVC corresponded to 100% of the range that the pointer could move.

Once the participants concluded their task, we asked them to answer the NASA-RTLX questionnaire [26]. It contained six questions that assessed mental workload on a 20-point scale. The procedure was repeated until all hand gestures were evaluated, with sufficient breaks to avoid muscle fatigue. The order of the conditions was randomized. Finally, we conducted exploratory interviews to better understand the user experience. We collected 504 ratings (12 participants × 7 target figures × 6 gestures) on input accuracy and 72 ratings (12 participants × 6 gestures) on the NASA-RTLX score. The entire procedure took about 50 min.

4 Results and Discussion

The average tracking accuracy in each condition is shown in Fig. 4. The error bars indicate standard errors. The accuracy data were analyzed using a two-way ANOVA with *gesture* and *control pattern* factors. The statistical analysis revealed that the main effect of the *gesture* factor was not significant ($F_{(5,55)} = 1.588$, $p = .178$), and the interaction was not significant ($F_{(30,330)} = 1.079$, $p = .360$). In contrast, the main effect of the *control pattern* factor was significant ($F_{(6,66)} = 64.558$, $p<.001$). Furthermore, we employed a post hoc test using Holm multiple comparisons ($\alpha = 0.05$, two-sided test) for the *control pattern* factor and confirmed significant differences (Table 2).

The statistical analysis showed that the smaller the force strength, the higher the accuracy (L1, L2, and L3). The L6 conditions, which required force strength fluctuation, was as accurate as the L2 condition needed to maintain an intermediate force intensity. The L7 condition showed statistically higher accuracy than the L6 condition. Moreover, the task of relaxing the force (L5) showed higher accuracy than strengthening the force (L4). The results showed that the EMG-based force strength and the way in which the force was applied had an impact on tracking accuracy. The participants commented that maintaining a strong force (L3) made it difficult to track the diagram. This comment was reflected in the experimental results. However, the type of static hand gesture showed no statistical differences in tracking accuracy. This suggests that the muscle intensity and the way the force was applied had more influence on tracking accuracy than the posture of the hand.

The average NASA-RTLX scores for the conditions are shown in Fig. 5. A higher score represents a higher mental workload. The error bars indicate standard errors. The mental workload (NASA-RTLX) data were analyzed using a one-way ANOVA. As a result of the analysis, the main effect was not significant ($F_{(5,55)} = 1.912$, $p = .107$). The statistical analysis showed that mental workload did not differ regardless of the types of hand gestures. Therefore, Fig. 4 and Fig. 5 reveal that input accuracy depends on the method by which force is applied; however, the types of hand gestures did not influence the input accuracy or mental workload scores. Participants stated the following: “I feel fatigued in the fist condition compared to the other gesture because nothing is held,” and “In the grip condition, the gripped object is large and hard, so it makes me tired controlling it.” We could not conclude that the difference in the gestures could not be attributed to the mental workload. However, the comments suggested that the gripping condition of the object may have an impact on the mental workload.

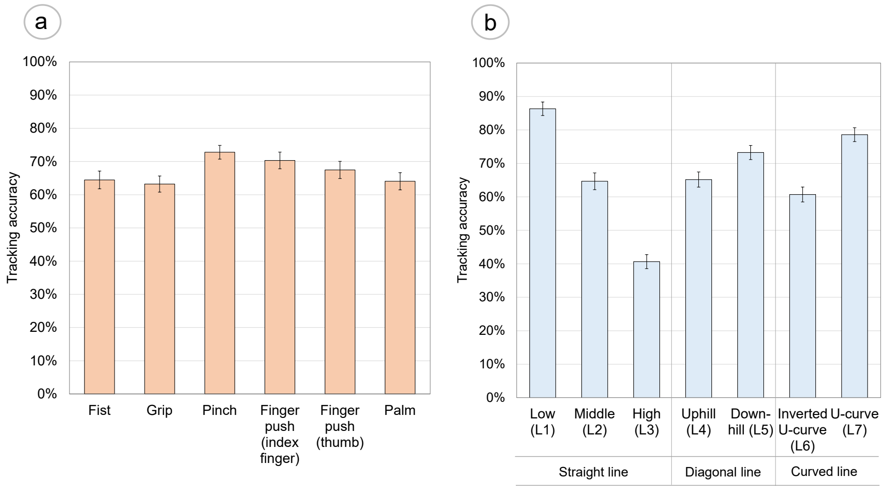

Fig. 4. Results of the experiment on input accuracy. We evaluated the input accuracy for each factor: a) gesture, b) target figure.

Table 2. Significance of the target figure. The highlighted values show significant differences.

	L1	L2	L3	L4	L5	L6
L2	<.001	N/A	N/A	N/A	N/A	N/A
L3	<.001	<.001	N/A	N/A	N/A	N/A
L4	<.001	.806	<.001	N/A	N/A	N/A
L5	<.001	.005	<.001	.009	N/A	N/A
L6	<.001	.217	<.001	.162	<.001	N/A
L7	.002	<.001	<.001	<.001	.120	<.001

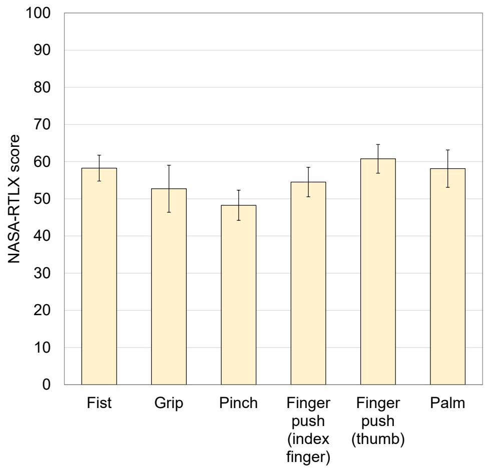

Fig. 5. Results of the experiment for the mental workload for each hand gesture.

5 Conclusion

In this study, we explored the input accuracy and mental workload of EMG-based force strength by measuring multiple hand gestures. We built an application to measure tracking accuracy from force inputs. We defined seven control patterns and evaluated the accuracy and mental workload for six types of hand gestures. Through the experiment, we demonstrated that (1) EMG-based input accuracy was affected by the way force was applied. Specifically, (2) the smaller the force strength, the higher the tracking accuracy, and (3) the task of relaxing the force showed higher accuracy than strengthening the force. We also found that (4) the types of hand gestures did not influence tracking accuracy and (5) the mental workload scores.

The experimental results may provide fundamental knowledge for designing user interfaces that use EMG as a force input. In future work, we plan to conduct a time-series analysis of the EMG data in this experiment. We are also interested in analyzing the controllability of force input with other body parts.

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