Experimental Results on the Accuracy of the Myo Armband for Short-Range Pointing Tasks

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***Abstract*—We analyze the accuracy of a Thalmic Myo armband in regards to short-range pointing interfaces. Through an experiment with multiple trials, we investigate the factors that could have an impact on the recognition rate. We found that removing the armband between sessions of use and a small spatial distance between pointing locations have a negative impact on the accuracy. By applying an exploratory approach, we found a configuration with a 97.3% recognition rate.**

Keywords— air pointing; pointing accuracy; Myo armband; experiment; wearables

I. INTRODUCTION

When analyzing pointing or gesture interfaces designed and built for Smart TVs, we can observe that an abundance of them use static devices to record the user's actions. For example, the Microsoft Kinect [12] device was used in the initial "Smart Pockets" [14] implementation to capture the human body and detect the hand's position in relation to the user's pockets and the TV set. Moreover, Khalaf *et al.* [1] conducted a comparative study using the Kinect device, a Leap Motion controller [15] and Intel's RealSense [9] to allow participants to perform hand gestures while playing an object collection game. Their conclusion suggests that not all gesture recognition devices are suitable for gesture-based video games.

However, as noted by Tsai *et al.* [16], using the Leap Motion controller can be restrictive since the user must stay in range of the device to capture their hand gestures. Therefore, they opted for a Thalmic Myo armband device instead. An example of a Virtual Reality system that used the Myo device is "Virtual Muscle Force" [11], which is an immersion system where the armband was used for performing interaction techniques.

The limitations posed by static devices to record the user's body or gestures are problematic for interfaces, as the user could be restricted from moving around or would need to always make sure that they are in the correct range to be detected by the equipment. Thus, having a device attached to the user's body would solve this issue. The Thalmic Myo armband is more suitable for these scenarios because it must be placed on the user's hand and it uses a Bluetooth connection, hence becoming more flexible in regards to where the participants could be performing the hand gestures. However, apart from detecting a set of gestures, the device also provides data about the hand orientation that could be used for controlling applications.

In this paper, we open with presenting other articles that use the Myo armband in their studies followed by the details of our experiment during which we employed multiple trials due to the restrictions found in the initial study concerning the position of the armband on the user's body. We continued with a discussion section were we further analyzed our results, drawing out a conclusion.

II. RELATED WORK

Given the sensors equipped on the Thalmic Myo armband [13], the device can be used for multiple purposes. With the 8 built-in EMG sensors, it can detect the electrical activity of the hand's muscles and recognize five default gestures. Also, with the embedded 9-axis IMU, the device is capable of providing hand orientation data. Therefore, the Myo armband has been used in applications from a variety of domains.

In the medical field, Montoya *et al.* [10] designed and developed a Virtual Reality video game that used the EMG sensors to capture the upper limb muscle activity and fatigue with the goal of helping patients during their muscle rehabilitation process. In the game, by contracting their muscles, the users were creating a protection field against a monster that was shooting them with acid. Also, the system detected the patient's muscle fatigue and adapted accordingly by lowering the required contraction level. Moreover, Zhang *et al.* [17] created "Bubble", a system that aimed to help people with hand disabilities to grasp and hold objects. The Myo armband was used to detect the arm contractions in order to trigger the inflation of the chambers placed on the user's fingers, which would stop when the arm muscles relaxed.

Some systems saw a more immediate application, such as "MuscleSense" proposed by Lim *et al.* [2] that would record and analyze the user's fatigue while they were doing different rounds of strength training with the purpose of enhancing the training efficacy in a session.

When analyzing the user interfaces created with Myo, we can see that it has been used in pair with a smartwatch by

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Kurosawa *et al.* [5], where the orientation and EMG data have been used to control a cursor displayed on the screen of the smartwatch. The orientation data was used to detect the direction in which the cursor should be moved, whereas the EMG data triggered the cursor to be moved in the pointed direction when the user applied force.

In regards to interfaces for controlling the TV, the Myo armband has been used to expand on the concept of "Smart Pockets" [14] by using the orientation provided by the device to detect when the user is pointing to the TV screen or has their hand in one of their pockets [8]. Moreover, Popovici and Vatavu [7] developed an application where the user could change the TV channel using the Myo device. The user could move the hand in front of their body to discover the nine available channels and once they found the desired channel, they could change it by applying a *fist* gesture. The applied NASA-TLX test showed that the application had a high workload that was mainly caused by the Myo's gesture recognition accuracy, but at the same time, it had good usability and high desirability. Kerber *et al.* [4] reported that the standard gesture accuracy rate is just 68%, which explains the high workload when trying to change the channels from the [7] paper, however, by proposing an improved recognition algorithm, they increased the number of gestures to 40 with an accuracy rate of 95%.

In relation to pointing interfaces, Popovici *et al.* [6] evaluated the user performance for recalling and pointing to nine mid-air locations. These mid-air locations defined the participant's nine most favorite channels. Their user study revealed that users had a recall rate of 80%, which for some participants reached to 100%. However, something to note is that some participants had difficulties in filling the list of nine channels. Also, the best configuration for both user and system accuracy was the one shaped as a matrix.

III. Experiment

A. Apparatus and Development Tools

The Myo armband is a wearable device that provides the hand's orientation at a time t in the form of a unit quaternion.

$$q_t = (w_t, x_t, y_t, z_t) \in [0,1]^4 \quad (1)$$

When using the device in pointing mode, the recorded quaternions must be corrected by applying an offset:

$$q_{offset} = (w_{offset}, x_{offset}, y_{offset}, z_{offset}) \quad (2)$$

The offset is a known fixed location captured for each user before recording any data. The offset is applied by multiplying the quaternion q_t (1) reported at a time t with the offset (2) as follows:

$$\begin{aligned} w_r &= w_{offset} \cdot w_t - x_{offset} \cdot x_t - y_{offset} \cdot y_t - z_{offset} \cdot z_t \\ x_r &= w_{offset} \cdot x_t + x_{offset} \cdot w_t + y_{offset} \cdot z_t - z_{offset} \cdot y_t \\ y_r &= w_{offset} \cdot y_t - x_{offset} \cdot z_t + y_{offset} \cdot w_t + z_{offset} \cdot x_t \\ z_r &= w_{offset} \cdot z_t + x_{offset} \cdot y_t - y_{offset} \cdot x_t + z_{offset} \cdot w_t \end{aligned} \quad (3)$$

To compute the distance between two corrected quaternions, we applied the following formula [3]:

$$d(q_1, q_2) = 1 - \langle q_1, q_2 \rangle^2 \quad (4)$$

Where $\langle q_1, q_2 \rangle$ is the inner product:

$$\langle q_1, q_2 \rangle = w_1 \cdot w_2 + x_1 \cdot x_2 + y_1 \cdot y_2 + z_1 \cdot z_2 \quad (5)$$

For example, if we have q_1 and q_2:

$$\begin{aligned} q_1 &= (0.1, 0.2, 0.3, 0.4) \\ q_2 &= (0.5, 0.6, 0.7, 0.8) \end{aligned} \quad (6)$$

The inner product is:

$$\begin{aligned} \langle q_1, q_2 \rangle &= 0.1 \cdot 0.5 + 0.2 \cdot 0.6 + 0.3 \cdot 0.7 + 0.4 \cdot 0.8 \\ \langle q_1, q_2 \rangle &= 0.7 \end{aligned} \quad (7)$$

Thus, the distance between q_1 and q_2 is:

$$\begin{aligned} d(q_1, q_2) &= 1 - 0.7^2 \\ d(q_1, q_2) &= 0.51 \end{aligned} \quad (8)$$

Although it is no longer produced by Thalmic Labs, support is still available and Myo remains a remarkable wearable device for rapid prototyping and evaluation.

We used the Myo JavaScript SDK provided for developers for implementing the communication between the device and the web page application. The application was built using HTML 5, CSS 3 and JavaScript and it ran under Google Chrome (v80.0.3987.122) on a laptop that was connected to a large, 55-inch Smart TV (Samsung UE55D).

B. Participants

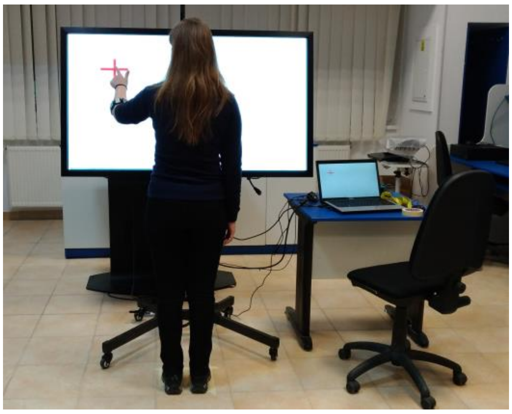

Fig. 1. Snapshot of a participant during the experiment. The participant was touching one of the 48 elements displayed on the Smart TV screen.

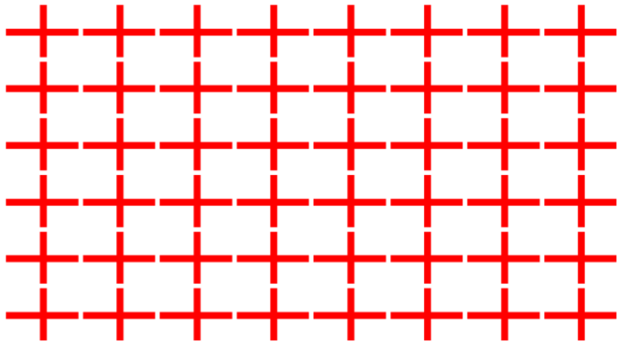

Fig. 2. Visual representation of all the 48 elements displayed at once.

We had ten (10) volunteers (5 male, 5 female) that participated in the experiment, ages between 20 and 28 (M=22.4, SD=2.41). One participant was left handed.

C. Task

The task that the participants had to accomplish was to touch 48 elements displayed one at a time randomly on the screen while wearing the Myo armband on their dominant and non-dominant hand. The elements were displayed in the form of a red cross and the volunteers were asked to try to touch the point where the two lines of the element intersect, see Fig. 1 and Fig. 2. Each element was displayed only once during a repetition.

At the beginning of the experiment, the participants were asked to stand in front of the Smart TV at a comfortable distance to be able to touch any element displayed on the screen. The initial position was marked and measured so that if the participant needed to take a break, they would be able to continue the experiment from the same location.

Half of the participants started with the Myo armband on their dominant hand and the other half on their non-dominant hand. The next step was to record the offset and have the participant touch the 48 elements displayed on the screen. This was repeated for 5 times and afterwards, the hand was switched repeating the whole process for the other hand. The participants were told that they can take a break whenever they needed to.

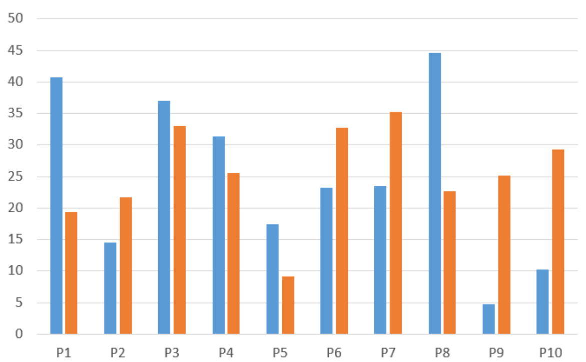

Fig. 3. Comparison of the recognition rate between the right and left hand for each participant. The bars colored with blue represent the recognition rate for the left hand and the orange bars are the corresponding recognition rates for the right hand.

D. Results

For the data captured for each hand, we applied a user-dependent training where we trained a classifier for each participant. We took this approach because the distance between the participants and the screen varied from 49cm to 61cm (M=52.3cm, SD=6.18cm), which means that the offset that was set at the beginning of the experiment had a different location for each participant. This distance varied based on the participant's height and hand length. Therefore, applying the classifier on the whole set of data would result in lower recognition rates.

When the participant touched an element on the screen, we captured the exact location provided by the touchscreen and the orientation from the Myo armband. Therefore, for each provided orientation we know which element should have been accessed and we can compare it with the result of a recognition algorithm. Thus, we created a classifier that would be used for calculating the recognition rate, which was implemented using the following pseudo-code:

```
for i = 1, participants, i += 1:
  for T = 1, 5 training repetitions, T += 1:
    for R = 1, 100, R += 1:
      *) pick T random samples for each element as the
         training set
      *) pick one random sample not selected
         previously for each element
      for candidate = 1, 48 elements, candidate += 1:
        *) classify the candidate based on the training set
           by finding the element with the minimum
           distance
        *) check if the provided result is correct
      endfor
    endfor
  endfor
endfor
```

The result was a recognition rate of 25.4% for the right hand and 24.7% for the left hand. Given that the recognition rates were so low, we conducted some smaller trials to analyze the possible issues. At the beginning of the trials, we recorded data for both dominant and non-dominant hands, the results can be seen in Fig. 3, however, given that the recognition rates were so low, we focused on increasing the overall value and continued the trials using only the right hand.

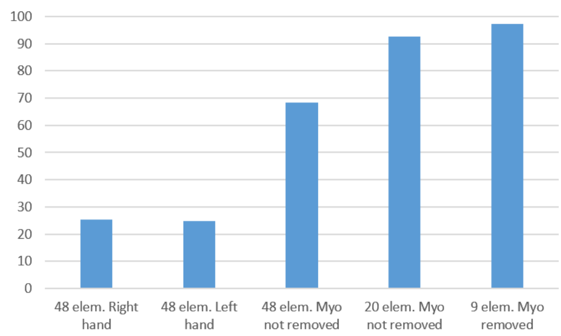

Fig. 4. Recognition rates for the experimental trials.

Initially, we ran a one participant trial for the right hand with the same procedure, but the Myo armband was not removed from the arm between the 5 repetitions. The result was that the recognition rate increased to 68.3%.

In the next trial, we kept the restriction of not removing the armband between repetitions and we decreased the number of elements to 20. The result was a recognition rate of 92.6%. However, not removing the device between sessions of use is not feasible, thus we conducted another trial where we had 9 elements and the participant had to remove the device between repetitions. The result was a recognition rate of 97.3%. We decreased to 9 elements as papers such [6] and [7] created interfaces using 9 mid-air locations.

As the number of elements decreased, their size changed. Given that the touchscreen had an active display area of 1209.6mm x 680.4mm, initially, each element had a size of 151.2mm x 113.4mm. When the elements decreased to 20, their size increased to 241.92mm x 170.1mm, and when the number of elements was 9, their size was 403.2mm x 226.8mm. Fig. 2. displays all the 48 elements at once, however, during the trials, each element was displayed by itself at random order.

IV. Discussion

When analyzing the recognition rate for the 48 elements from the initial trial in comparison to the second trial where the Myo armband was not removed, we can conclude:

- When trying to point to a fixed location in space using a device that offers orientation data relative to the user's body, the recognition rate will be low because the orientation might be different. The user is touching the same point, but it can be from different angles.
- Even when setting the offset and correcting the recorded quaternions, the differences in angles can still be substantial.
- Removing the Myo armband and placing it back on the arm could also provide differences in the hand orientation as the armband might not be placed on the exact initial location.

Moreover, when the number of elements was decreased to 20 and the restriction of removing the device between repetitions was still ignored, the recognition rate increased dramatically (from 68.3% to 92.6%). This further enforces the fact that the user may touch the same point but the hand is coming from different angles. Given that between the two trials the space allocated for each element increased 2.4 times in size, we can conclude that depending on the space that is used around the user, there must be a minimum spatial distance between each location, as pointed by Popovici *et al*. in [6].

This is further emphasized by the fact that when the number of points was decreased to 9, the recognition rate was high (97.3%), even though the Myo armband was removed between repetitions. This is a critical item as it is difficult to build a system where the device cannot be removed between sessions.

V. Conclusion

We presented an analysis of the Thalmic Myo armband in regards to its accuracy in short-range pointing tasks to find the best configuration for creating an invisible interface displayed in front of the body. We discovered that the device also poses some limitations as it can be placed in different locations between sessions and the hand orientation may be different depending on the angle from which a point is accessed.

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