Gesture Elicitation and Usability Testing for an Armband Interacting with Netflix and Spotify

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Abstract. Controlling home entertainment devices, like music and video, via an armband could free the user from using remote controls, but assessing their overall usability with mid-air and micro-gestures still represents an open research question today. For this purpose, this paper reports on results gained by jointly conducting and comparing two studies involving participants using a Thalmic Myo armband to control a NetFlix SmartTV and Spotify: (1) a gesture elicitation study to explore a richer set of user-defined gestures, to measure their effectiveness and the user subjective satisfaction of gesture interaction; (2) a System Usability Scale (SUS) to assess the overall usability of this setup and the subjective satisfaction for user-defined gestures.

Keywords: Gesture elicitation study · Mid-air gestures · Myo armband · Netflix · SmartTV · TV interaction · Wearable computing

1 Introduction

With modern technologies, new devices came up and are used in many daily life contexts of use, such as TV, recorder, communicating objects. There has been much research on how to control a TV using different modalities of interaction, ranging from the traditional physical remote control, to full-body gesture interaction [20]. With traditional remote controls the user is forced to always manipulate a physical device that may not be understandable, which is often inconsistent with another one, and which can be easily lost. When a new function is added to the TV, the remote control cannot be updated accordingly. *User-defined gestures* can be proposed by the end users themselves in order to

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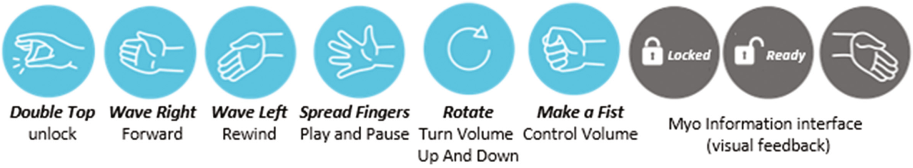

Fig. 1. Thalmic Myo Armband system-defined gestures.

come up with a consensus set of gestures [21]. It is not because these gestures emerge based on some consensus that they are simultaneously usable.

In this paper, we would like to investigate whether another interaction modality, i.e. an Armband based on electromyographic sensors (EMG) [7], could become a realistic alternative for interacting with common tasks based on a TV by combining a usability testing and a gesture elicitation study. The Myo Armband [7], is an off-the-shelf motion control device. It includes 8 EMGs able to measure electrical activity in the forearm muscles, thanks to which it detects and identifies the user's arm movements and/or gestures.

Two plugins were developed for this study. We also incorporate the control of Netflix thanks to the Netflix Connector: a free additional app built into Myo Connect (standalone Myo software) provided by Thalmic Labs and available in the official Myo Market. The Netflix Connector enables the control of the Netflix interface into the web browser. The control is set up through 7 standardized and non-changeable *system-defined gestures* (Fig. 1), which will be used for the navigation through both Netflix and Spotify. Our practical results consist in (1) an analysis of the agreement rates among the gesture proposals of the participants, (2) gestures comparison between TV interaction and music control with different positions, (3) usability testing scores about the predefined gestures of the Myo armband, (4) a comparison between the agreement rate pre- and post-experiment with the Myo armband, and (5) limits and discussion.

2 Related Work

This section discusses prior work on the Myo armband technology and reviews the principles of the gesture elicitation methodology in order to collect and understand the users preferences for mid-air gestures. Previous studies show several technological aspects of the Myo Armband in several domains of applications, such as: healthcare [16], virtual reality [17], music [5], and sports. For example, MyoGym [10] consists of an interactive application capturing up to 30 different physical exercises, monitor the movements of the end user, and reports on the progression over time. Another system [13] also relies on EMG to train the patient's muscles when they received a prosthetics. Squeeze gestures can be captured by the Armband in [14] by children suffering from cerebral palsy when they manipulate objects in virtual or mixed reality. Another research compared the use of the Nova bio-medical base sensor (a non-invasive wearable system which allows the measure of complex physiological phenomena) [13] and the

Myo Armband for muscle fatigue detection. The Myo armband could even be used in some limited medical scenarios where high accuracy levels of EMG are not required [13]. To expand the set of armband gestures, another gesture recognizer has been tested [8], which outperforms the original Myo algorithm with an overall accuracy of 95% compared to 68% for this gesture set. Instead of point-based recognizers, vector-based gesture recognizers also appear [18].

Understand, collect, and analyze users preferences with an interactive technology is the purpose of gesture elicitation. End users are not always consulted by designers when they create gesture interfaces [4]. Gesture elicitation, also known as "participatory design" [2] or "guessability studies" [21], is suitable for a large variety of sensing devices and domains [19], which could then be mapped into user interface design artefacts [12]. The outcome of a gesture elicitation study consists in a characterization of users' gesture input behavior with valuable information for designers, practitioners, and end users regarding the consensus levels between participants (computed as agreement or co-agreement scores [19–21]). The most recent formalization of the elicitation methodology was proposed in [20]. Gesture elicitation study also worked in a smart home as a larger environment [19]. For controlling television interaction showed, gestures are carried out in mid-air [4].

3 Research Questions

We divided our experiment into four phases in order to understand and test our research questions and hypothesis defined below: **RQ1**. What are the user's preferred gestures with an interactive armband for the TV interaction in their comfortable viewing position? Which gestures created by the participants are the most adapted to the requested action (referent)? Analysis and evaluation of gestures proposed under objective indicators (agreement rates) and a subjective questionnaire. **RQ2**. What are the user's preferred gestures for the use of an interactive armband to control music in a different active position? How many changes? Hypothesis 1: Users use the same gestures to control music as for the TV interaction. **RQ3**. What is the Myo usability? Learning and testing. What is the usability of the Myo for the Netflix interaction in a comfortable position? **RQ4**. What are the actions ultimately taken after the experiments? Compromise and justification of the use of the Myo bracelet.

4 Experiment and Methodology

We conducted a gesture elicitation experiment by following the methodology from the review of literature and a usability test was also conducted [9,15,20].

4.1 Participants

We interviewed 21 participants (10 female), aged between 15 and 71 years old ($M = 35.86$, $SD = 18.3$), who volunteered for our experiment. Two pilots and 19 for the main study. We had to exclude 2 outliers who did not succeed the pretest. The majority of the participants (16) were right-handed.

Table 1. Set of referents used for the elicitation experiment.

No.	Referent	Description	No.	Referent	Description
1	Unlock	Turn on the TV set	5	Rewind	Turn off the volume
2	Play	Turn off the TV set	6	Volume Up	Go to the next channel
3	Pause	Increase the volume	7	Volume Down	Go to the previous channel
4	Forward	Decrease the volume			

4.2 Apparatus

The experiments took place in two rooms set up to make the participant feel almost at home. In each setup there were a two-seat sofa and some blankets and cushions to enable a usual comfortable viewing position. We interviewed each participant at a time and the experiment lasted about 1 h. We used *Okja*, the South Korean-American movie, for all the Netflix phases and Michael Jackson's *Don't Stop 'Til You Get Enough* for the Spotify phases in order to stay neutral and avoid both choking scene and explicit lyrics. The participant wore armband on the dominant arm throughout the experiment. We informed the participant about the sensors included in the armband without showing any gesture and about the possibility to perform mid-air and finger gestures.

4.3 Procedure

Phase 1. After introducing the Myo Armband, we asked the participant to take a comfortable viewing position on the sofa with all the cushions needed (see Fig. 2). We presented the 7 referents they were going to elicit (see, Table 1). We allowed the participant to view all referents at once (after presenting the "unlock" referent alone) and they could revisit their gestures at any time. In doing so, we encouraged the participant to try out several possibilities for each referent. The participant had 5 min to think about his gestures. Then, we asked him to perform each referent by using his own suggested gestures and in the same time we controlled the computer to allow him to foresee the results. At the end, the participant was asked to complete a gesture questionnaire for each of his 7 suggested gestures and several subjective questions were asked.

Fig. 2. Positions.

Phase 2. The participant had to quit their comfortable position and stand up. They were asked to use the Myo Armband (using the same 7 referents) to navigate in Spotify instead of Netflix. They had 5 min to find out if they were going to use the same gestures as in the phase 1, change all the gestures or change some of them. Once again, we simulated the Spotify system to allow the participant to imagine the interactions related to their gestures. The aim of this phase is to observe the transferability of the suggested gestures during the first phase from one context of use to another.

Phase 3. We introduced the standardised Myo gestures for each referent and the armband manager gestures interfaces (see Fig. 1, right section). To allow the best recognition with the armband, we created a new profile for each participant by using a calibration step to teach the standardized gestures. Then, the participant was asked to lay back in their previous comfortable viewing position and to perform all the gestures for training. During the practice time we asked the participant to perform each action (randomly chosen) when asked, this phase lasted 5 min. The participant was asked to perform the standardized gestures following their own desires for 5 min. Then the participant completed a gesture questionnaire for each referent and a SUS test. During this phase we used the Armband instead of only simulate the results as previously.

Phase 4. The participant was asked to stand up as we asked them to use Spotify one last time. We asked the participant to figure out (after suggesting their own gestures, during the phase 1 and 2, and learning the standardized Myo gestures) what gestures they wanted to keep to perform the referent actions for Spotify. They also were aware they could suggest completely new gestures. Having taken 5 min to consider the matter, we asked the participant to perform each referent while we simulated the results (as it was the case during the phase 2). An IBM Computer Satisfaction Usability (IBM CSUQ) Questionnaire [11] was completed by the participant, and final open questions were asked.

4.4 Qualitative and Quantitative Measures

We employed measures to evaluate and understand the users preferred gestures and the users' performances in using the Myo Armband: **(1)** We asked the participants to assume a Viewing Position that they usually employed when watching TV at home. According to the results of the [5], we included the influence of a natural, comfortable position during the interactive test with Netflix. To assure a great ecological validity in our research, we will describe all different participants' positions and include their remarks if they had difficulties related to their positions. **(2)** A Creativity test was asked before the beginning of the experiment. It is made of 40 questions and gives a free assessment of one's level of creativity through 8 different metrics (abstraction, connection, perspective, curiosity, boldness, paradox, complexity and persistence)[1]. The participants needed a score higher than 55 to be part of the experiment. We rejected 2 participants because of a too low score. **(3)** We also conducted a Motor Skill test in order to select people for the elicitation step, we measured motor ability levels in fingers. The test was inspired by NEPSY test [9] and consisted of touching their

[1] http://www.testmycreativity.com.

thumb with the other fingers tip 8 times. **(4)** We calculated for each referent the central measure or the agreement rate (AR) as defined in [20] to understand the extent to which the participants agreed on each gesture. Proposed gestures for specified tasks are analyzed and used in comparison in order to predict the most suitable gestures. **(5)** A questionnaire with 7 subjective questions, on a 7-point Likert scale, was developed to allow the participants to rate the quality of a gesture. They could indicate the ease of execution, the memorability, the good correspondence or the enjoyability in performing [6]. **(6)** We used the SUS questionnaire [1,3] to measure the system usability. **(7)** Finally, the IBM CSUQ questionnaire [11] was used to relate the user satisfaction.

5 Results

5.1 Participants Viewing Position

We distinguished 16 different positions on 5 dimensions (Table 2). Some were in a semi upright position, some used different items like cushions and blanket and some put their feet on the couch. Participants were free to choose their own position as categorizing relaxed viewing positions is challenging.

Table 2. Overview of the participants viewing position.

Upper body	Feet	Back	Arm	Items
Sitting upright, sitting semi upright, lying on the couch, semi lying on the couch, sitting lying on the couch	On the couch with knees to right, on the couch with knees to left, on the couch with legs straight, on the couch with legs crossed, on the ground	On the back couch	Released on a cushion, released on the couch, released on the legs	On cushion and a blanket, sitting on a cushion, sitting with a blanket

5.2 Phase 1

We computed the agreement scores using the AGreement Analysis Toolkit tool (AGATe) [19,20]. The resulting gesture set – taking the gesture with the highest agreement rate for all participants – is presented in the left graph of Fig. 3. There are three referents for which there are very low agreement scores; for these referents, we have provided two or three elicited gestures in the Table 3. Except for the volume referents, we do not have a consensus on gestures proposals for other referents. These results could be explained by our observations. The participants were very creative during the elicitation test. Overall, we elicited 57 gestures for the 7 referents by the 19 people. Most of the elicited gestures are performed with the hand and the arm, only 4 out of 19 participants performed

Table 3. Set of referents used for the elicitation study.

Referent	Description of the elicited gesture (Phase 1)	Description of the elicited gesture (Phase 4)
Volume Up	Raise the arm vertically with the palm up	(1) Raise the arm vertically with the palm up; (2) Make a fist and rotate right
Volume Down	Put the arm down vertically with the palm down	(1) Put arm down vertically with the palm down; (2) Make a fist and rotate left
Rewind	(1) Move the arm and the hand to the left; (2) Wave right	(1) Wave left; (2) Move the arm and the hand to the left
Forward	(1) Move the arm and the hand to the right; (2) Wave right	(3) Wave right; (4) Move the arm and the hand to the right
Pause	(1) Extend your arm and point your hand face to the TV; (2) Get your hands down by tapping; (3) Make a fist	Spread fingers
Unlock	Snap	Double tap
Play	Extend your arm and point your hand face to the TV	Spread fingers

micro-gestures (with only fingers). Even if most of the gestures are spontaneous (less than 5 min for the conception) and natural, the variety of gestures is too wide and we cannot predict any agreement. Depending on their viewing position, the majority of the proposed gestures have been validated as easy to execute. The participants adapted their gestures to their position without any imposed constraint.

5.3 Phase 2

The vast majority kept all the gestures elicited for this test, 7 people changed their gestures to control music on Spotify. 18 gestures changed on all proposed gestures (133). According to the results provided by the elicitation of the gestures, we can confirm our hypothesis that people keep the same gestures set for the same referents for the navigation in both the video or the music.

5.4 Phase 3

When using the Myo system, the participants followed all the instructions and progressively (practiced) all the tasks we gave them. Calibration requires in

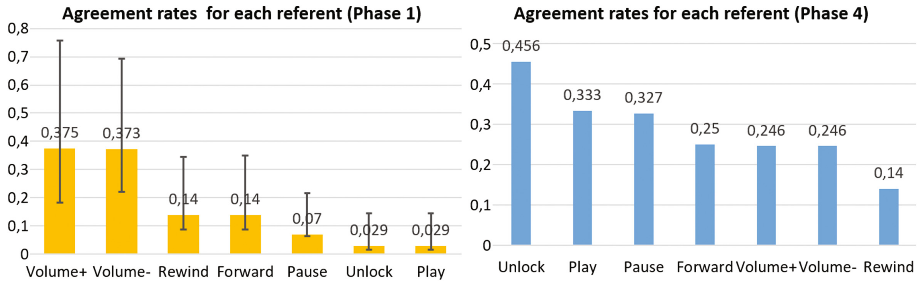

Fig. 3. Agreement scores as computed by AGATe [20]. Error bars show a CI of 95%.

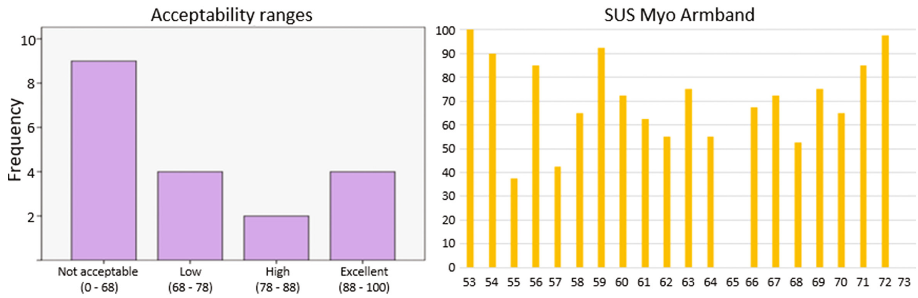

Fig. 4. Acceptability ranges and SUS score for Myo Armband.

general 5 min to define the profile. Thanks to the gesture memory cards, the participants used the predefined gestures easily. In each interview, we followed the whole experiment of the learning process. We completed the whole experiment with all the participants even if some signal recognition troubles appeared. In some cases, the gestures recognition's were not as precise as the natural users' interactions. Furthermore, we discovered a particular inversion in some gestures. For the Rewind and Forward referents as well as the Volume Up and Volume Down, it occurred that the actions were in the opposite direction to the one expected, even if the Myo gesture recognition interfaces (see right section of Fig. 1) were correct. In other words, in some cases the correct Rewind referent (by waving the hand to the right) and the correlated gesture recognition interface activated the Forward action. That inversion effect for the Rewind and Forward referents occurred for 14 participants, and for the Volume Up and Down it occurred 19 times (for all the participants). The total score of the SUS questionnaire is illustrated in the right graph in Fig. 4. The maximum score is 100 when the minimum score achieved is 37.5. The average score is 70.92. We considered score below 68 as not acceptable [1]. Thus, left graph in Fig. 4 demonstrates that 9 out of 19 participants had a not acceptable score. Half of the participants were not convinced by the Myo system in the proposed context. The other half of the participants sometimes very much appreciated the armband as presented. SUS results are to be associated with the series of subjective measures calculated

Table 4. Result of the subjective measures questionnaire.

Referent: Gesture	Good match		Ease of execution		Memorability		Enjoyable to execute	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Unlock: Double tap	5.47	1.83	5.39	1.81	6.16	1.42	5.39	1.88
Play: Spread fingers	5.68	1.49	6.11	1.34	5.84	1.38	5.66	1.55
Pause: Spread fingers	5.47	1.38	6.21	1.02	6	1.45	6.08	1.06
Volume up: Make fist, turn left	3.42	2.48	5.05	1.91	4.11	2.26	5.05	1.51
Volume down: Make fist, turn right	5.47	1.39	6.21	1.02	6	1.45	6.08	1.05
Rewind: Wave right	3.74	2.33	4.92	2.16	5.26	1.93	4.08	1.76
Forward: Wave left	3.84	2.19	4.68	1.85	5.32	1.97	4.08	1.66

on each gesture. In addition, the qualitative data and comments given during the experiment are also included in the analysis of the different criteria.

Good Match. Gestures proposals seem to have a good match for some referents like Unlock, Pause and Play. Right graph in Fig. 3 shows that referents like volume down-up and rewind-forward in a video sequence are to be discussed. Indeed, the vast majority of people were disturbed by the direction that worked. "Oh but it's upside down" was a common expression recorded for 9 participants during the experiment. Going back in the sequence linked to the wave left gesture was not interpreted in a natural way, as much as the gesture given to increase the sound by turning the fist to the left, which disrupted many participants. This comes from confusion about which gestures does what explained previously. Those gestures that actually worked during the experiment were in the opposite direction of what Myo had planned in the setup.

Ease of Execution. The participants measured their effort in the performance of predefined gestures and repeatedly highlighted the difficulty of wrist twist to the left or to the right. This average is lower than the other gestures (see, Table 4). Moreover, the participants repeatedly tried not to go too far in waving their wrist. Therefore it became more difficult to detect the executed gesture and made the users even more frustrated. About the execution of other gestures, they were rather positive. No difficulties were significant in the performance even if the armband sometimes did not have a precise answer or when the system misinterpreted the executed gesture. The participants just tried again until the system figured it out.

Memorability. When asked whether or not the gestures used in Netflix were memorable, participants did not really need extra help to be able to recall them. However, making a fist and turn left (to volume up) is less memorable for some participants (Table 4). Indeed, this gesture requires two particular movements with the hand to perform a single action.

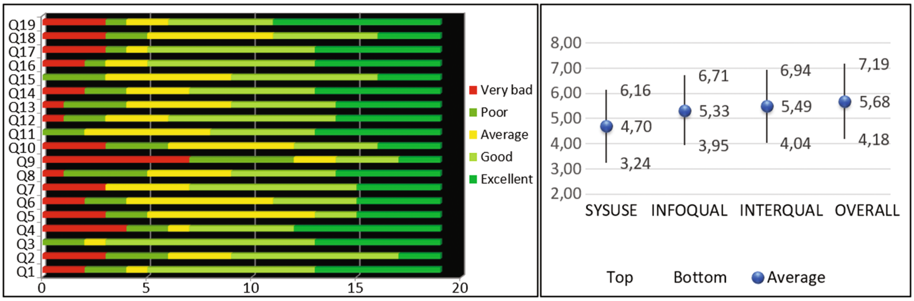

Fig. 5. Results from the IBM CSUQ questionnaire.

Enjoyable to Execute. A similar result was found with the ease of execution. It was the rewind and forward navigation gestures that did not entertain the participants. Stress for the execution of these gestures was constantly present. Figure 5 depicts the IBM CSUQ results. The study suggests that the global subjective satisfaction of the participants involved in the experiment follows a rather positive trend since Q19 ($M = 5.68$, $MD = 6$, $SD = 1.60$) is interpreted positively. Q9 ($M = 4.11$, $MD = 4$, $SD = 1.76$), the most negatively assessed question, raises a particular concern about the information quality to solve the users problems. During the experiment, the visual information guidance to solve problems recognition and to readjust the armband are not clear and helpful for the users. However, regarding the Q10 to Q15 the information quality system is evaluated positively. About the interaction quality (Q16-Q18, $M = 5.49$, $MD = 6$, $SD = 1.45$): all questions have some negative answers, but indicate that there is a positive agreement among the respondents. Finally, Q1 ($M = 5.68$, $MD = 6.0$, $SD = 1.45$) proposes that participants are satisfied with the process supported by the Myo system. Moreover, the most positively assessed question Q3 ($M = 6.05$, $MD = 6.0$, $SD = .91$) demonstrates that participants think that they completed the work correctly using the tool.

5.5 Phase 4

We computed specific agreement scores in which the participants would include all the Myo's system-defined gestures and the user-defined from the study. They exhibit higher agreement scores for each referent than the first one computed (right graph in Fig. 3). Myo's gestures were the most elicited for the Unlock, Play, Pause, Forward and Rewind referents (Table 3). System-defined gestures can feed an effective gestures set to satisfy most people using armband. People insisted on restoring the direction for the gestures: Rewind, Forward, Volume Up and Volume Down. They proposed a simplified gesture for the volume control to avoid making mistakes and created a new version of Wave gesture (left or right) to have less effort and more ease to execute the command. In our sample, 3 users out of 19 kept their own gestures that they defined at the beginning, without taking any system-defined gesture. They liked so much their own gestures that they could not choose any other. Other users reused one or many system-defined gestures. To reduce impact on recognition, participants often decided not to be as precise as the Myo system would recommend.

6 Conclusion

We presented the results of a gesture elicitation study combined with in an entertainment environment with an interactive Myo Armband. We also conducted a usability test in order to align the results between the gesture elicitation study (which returns the most preferred gestures for the tasks envisioned) and the usability study (which returns the most usable gestures for the tasks performed). During the experiment, we shaped a new hypothesis about the age and the ease of execution. The participants under 22 years have a deeper understanding of the proposed gestures and we suppose they adapted themselves to improve the gesture recognition's of the armband while the older users (+58) did not seem to adapt their own gestures. It requires future research to test this new proposal. We confirmed the usage of the same gestures for music and video control. Future studies should find out whether it is still the case when different rooms are used and whether the participant interacts the same way with the presence of other people near them, in a multitask context or in a smart environment. Again, this is the traditional debate of performance versus preference: participants may want to elicit some gestures that are not performant or not usable enough to be really incorporated in the final consensus set. Similarly, participants may return usable gestures (thus maximizing usability), but that are not also returning from the guessabiity study (thus minimizing the preference). Our findings revealed low agreement rates among our participants gesture proposals. Conversely, the participants went to a global higher agreement rate and satisfaction of use after learning and performing the predefined Myo gestures. The final consensus set resulting from this study expands the set of initial system-defined gestures. This new set could therefore become a candidate for an improved gesture recognition.

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