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Research Article

Development of an Interface for Real-Time Control of a Dexterous Robotic Hand, Using MYO Muscle Sensor

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Abstract

The learning curve of many prosthetic hands can be too difficult for users to grasp, this difficulty often leads users to stop using the prosthetic, especially if they have another hand which can pick up the slack. This paper created an interface controlled by a MYO Armband, which uses surface electrodes to detect ElectroMyoGraphic (EMG) signals in fore-arm muscles. The goal was to have participants take part in an experiment using the interface and track how well they can learn the process of moving a cursor across a 2D screen, the interface responds to four poses which control the cursors movement in left, right, up, and down motions. Two main variables were tracked, the time taken to complete a task and the accuracy on the cursor during the task, the poses being used were also tracked. All three participants had difficulties remembering the poses and controlling the cursor in the beginning, however after several attempts the participants saw improvements in time and accuracy. The improvements in time slow and even reversed in some instances, this is possibly because of fatigue in the arm being used, alternatively the accuracy continued to increase throughout the experiment for all three participants. There were two types of poses used, one type was using fingers "fist pose" and "spread fingers" pose, and the second type was using the wrist, "wave out" and "wave in" poses, two of the participants seemed to favor the wrist movements more than the finger movements. Conversely, the final participant favored the finger movements over the wrist movements, the reason for these differences could be comfort or possibly good/bad experiences during use in the early stages of the experiment.

Keywords: Human Robot Interface; Human Prosthetic Interface; ElectroMyoGraphy (EMG); User Interface; Upper Limb Prosthetics; Robotics

Introduction

There are 250,000 amputees in England and 10,000 amputations a year, with aroundone in four of these being upper limb amputations such as hands or arms [1]. While replacing some lost or damaged organs during transplant is not an uncommon sight in 2022, replacing a lost or damaged hand is. Dueto the strict conditions for anyone who wishes to be considered for a hand transplant only one in one hundred screenings lead to an attempted hand transplant [1]. Because of this, many amputees that wish to have a functioning hand must turn to prosthetics.

Prosthetics are not a modern technology, humans have been using materials toreplace lost limbs for many centuries, however it is only in the past few decades that we have begun to move away from lifeless restricting inanimate pieces of metal to articulated robotic prosthetics. These robotic prosthetics are capable of using a mixture of software and hardware to produce more natural feeling prosthetics which allow usersto perform more dexterous tasks such as grasping [2,3].

Robotic Prosthetic hands come in many shapes, from simple three-pronged grippers with just one or two degrees of freedom to fully dexterous hands with multi degrees of freedom, such as, for example, a Bebionic or an Handi Hand. The dexterous hands with many degrees of freedom are capable of replacing a human hand in many tasks such as grasping or gesturing [3-5]. However, these dexterous robotic hands need information from the user, this gathering of information via an interface between user and machine. This Machine-user interface has a limited bandwidth to communicate data to the prosthetic so interfaces with fewer data requirements are preferred. This limited bandwidth is considered a technological bottle-neck which requires innovation to overcome [6-9].

There are many different types of interfaces used in prosthetics, a broad categorization of the methods would be invasive and non-invasive. Invasive interfaces include Reinnervation, which involves repurposing nerves from a lost limb, and brain computer interfaces (BCI or BMI), uses intercranial sensors to get information from the brain [9,10]. Non-invasive interfaces such as non-invasive BCI uses electrodes on the scalp to get information [10]. Each of these processesare capable of supplying information to a robotic prosthetic, however one of the most widely used methods is electromyography (EMG). Using sensors to track EMG signals of contracting and uncontracting muscles can supply a non-invasive cost-effective method of controlling robotic prosthetics [11-13].

Using any interface to control a robotic prosthetic takes many hours of training to learn how each interface works and how to move the prosthetic device as intended. Due to this high amount of required training users are more likely to reject the prosthetic due to fatigue with the learning process [10,14]. To reduce the learning time, and in turn the fatigue, users must endue it is possible to reduce the amount on inputs a user must provide when controlling a dexterous robotic prosthetic. To provide low inputs from a user and have a robotic hand receive high inputs a process often referred to as reduced dimensionality is used [14]. One method of reducing the number of dimensions is called Principal Component Analysis (PCA), for a matrix dataset PCA uses weighted eigenvalues of the matrix to create a new data set by removing the lower weighted eigenvalues, thus leading to a reduction in the dimensionality of the original data set [14].

The aim of this project is to create an interface capable of receiving data from simple poses via MYO Armband - the armband can be seen in Figure 1 and uses EMG signals from the muscles - and provide a visual output on a computer screen so the user can see progress. An experiment will be conducted, and the participants will test the interface, the time, the accuracy, and the choice of pose over multiple attempts will be tracked and the data will be presented to determine if this interface is simple and intuitive to use, thus reducing any fatigue from the learning process.

This research paper will start with a Literature review to present what has already been done on the subject of interfaces for robotic prosthesis, from there themethodology will present how the research and experiment were carried out including information on tools used, such as MYO Armband and python programming packages, and the experiment procedure. Following the methodology, the results and discussion will discuss what happened during the experiment while presenting the data in graphs and explaining what it means. This research paper will then end with a conclusion and future research possibilities.

Materials

This section details the overall architecture of the system, reporting the mainHardware and Software components in Section A and Section B, respectively.

Hardware

The overall Hardware set up is made of a desktop PC and a wearable MYO Armband.

The MYO Armband

This sensor is a gesture recognition device, is uses medical grade surface electrodesto detect changes in electrical activity or stimulation of the fore-arm muscles, also calledElectroMyoGraphy (EMG). The device has on board software capable of processing information from the electrodes and providing pose classification for interaction with a computer. The armband uses a Bluetooth USB dongle to transmit data from the device toa PC, in this case a mid-range windows 10 PC is used. Figure 1 shows an image of the MYO Armband with the surface electrodes visible.

Desktop computer

A windows 10 PC with the following specification is used: AMD 5600X CPU, Nvidia GeForce GTX 1080 TI and 16GB of RAM. This PC is capable of providing sufficientcomputing power for the project. The monitor used has a 27-inch 1440P panel, howeverthe program accounts for the resolution of the screen so the size is irrelevant.

Software

The overall Software set up is made of a MYO-connect Dongle, an interface and a testing set-up combined with the design of an experimental protocol where the subject is performing some tasks by means of the above wearable system.

The Myo-connect

The software used to connect and receive information from the MYO Armband is the official MYO Windows referred to as "MYO-Connect". The software allows the communication between the MYO Armband and the included Bluetooth USB dongle, the Bluetooth USB dongle connects to a Windows 10 PC. The Myo-Connect application is used for the initial set up of the MYO Armband and also installs required drivers associated with the device.

The interface program

The interface has been written in the Python 3 Programming Language and used Microsoft Visual Studio Code Development environment. One of the main functions usedin this study is the "data pose" function. The "data pose" function is the interface which receives information from the MYO Armband, this is done using a "listening function" (which uses libraries provided by [15]). The "listening function" reads any information sent through the corresponding com port set up when the MYO-connectapp launches, so when a user's pose is classified by the MYO Armband it is then pickedup by the listener and the listener provides the "data pose" function with necessary dataabout which pose the user is currently holding. The "data pose" function then moves the on-screen cursor by a small percentage of the screen resolution in the direction which corresponded with the pose carried out by the user, once done the function goes back to listener until another pose is received from the user. The function produces a file which all poses carried out by the user are recorded in, this file will be overwritten if not moved after each attempt as the file name is not unique.

Testing board program

The second main function is called "create board" and this functions purpose is to create a testing board for the user to navigate during the experiment. The function creates a white grid image as the background with each square being the same "1-unit" horizontal distance and "1-unit" vertical distance wide (this is referred to as "1-unit"due to the distance changing depending on the resolution used thus 1-unit for each square is a simple way of comparing during this research project), then the function randomly adds a single green target to any of the intersections of the grid lines. The random location is generated by using a random number generator which generates a pair of numbers between 1 and 5, the numbers correspond to a location on the grid image with 1,1 being the first intersection (top left) and 5,5 being the last (bottom right), a loop checks if random number generator produces a 3,3 and rerolls the numbers as the center is the start location thus no targets should be there, see Figure 2 for the grid imagine with every possible location of the targets. Once the user moves the mouse cursor over the target the user will receive a message, and a sound, notifying them of completion, three seconds later the board will begin again but this time with a target in a different location. This cycle of reaching the target and creating a new one is repeated ten times at which point the function will end and the user will have completeda single attempt. This program records several variables during its use which are used for tracking progress of the user, a file which lists the variables is created by the program using the unique "participant number" followed by the current target number the user is on, for example the file name for participant 1 during the first target would be 1_1.txt. The following variables are recorded in the file: The location of the mouse cursor is recorded every 0.2s and the time when the program begins, and ends isrecorded.

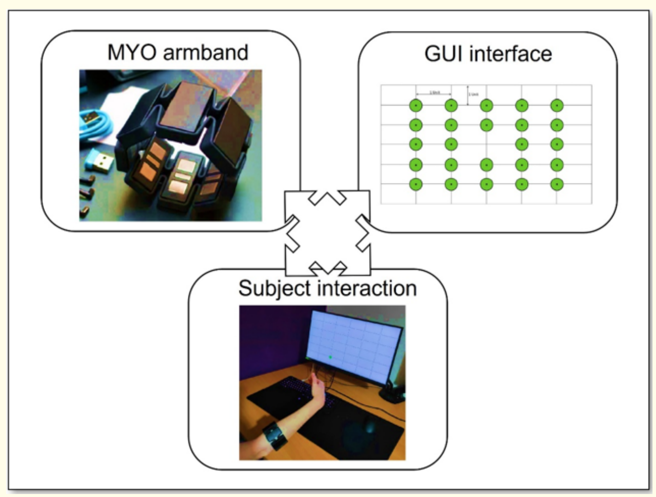

Figure 1: System architecture: the arm band provides driving signal for the user interface where a human subject perform motion task by means of forearm muscle contraction (i.e. the EMG signals).

The final program used is called the “main” function, this function does not require much explanation as this function is used to request a participant number from the user and then loops through the “create board” function ten times then closes on completion. Both this program and the Interface program run simultaneously however the interface program has a ten second delay before beginning to move the cursor, this is to allow the researcher time to start the “main” function.

The full code for all of these programs can be found in the appendix, each of them are under their corresponding titles.

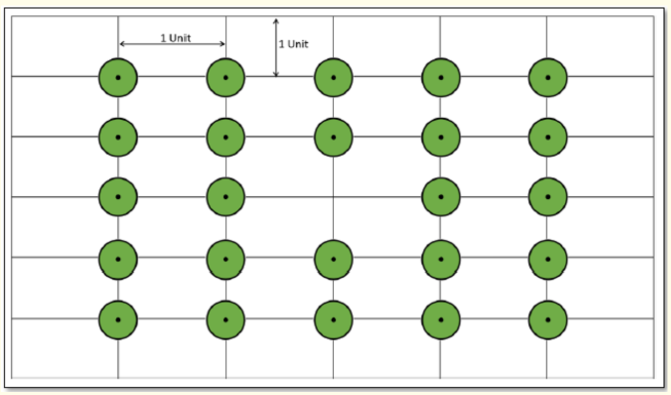

Figure 2: Grid with every possible target and unit size.

Experiment set-up

The experiment carried out will have three able-bodied participants, all three participants will complete the same task three times while wearing the MYO Armband and data during their use of the armband will be collected.

The task to be completed by the participants requires the user to navigate an on- screen interface by moving the mouse cursor using four different hand poses, fist, spread, wave in, wave out. The aim for the user will be to move the cursor over a target as fast as they can. After the user reaches a target, a message saying “completed” will show on screen and a sound will play, following the sound a new target will be presented in a different location. A total of ten targets will be presented and upon completion of the task the program will close. The task will be completed by each participant three times, this should be a sufficient number of attempts for the participant to use any experience gained and show improvement in the task.

While the task is being carried out, data on the participants actions will be gathered. Each of the data variables chosen have been carefully considered with the goal of tracking any improvement from the participant between each task attempt. What data will be gathered and the reasons for choosing this data are presented below.

- Time, tracking the time taken to complete a task will be one of the variables used to determine how much a user has improved over the previous task.
- Number of inputs, tracking the number of inputs is another variable which canshow user improvement. More concise movement of the user will result in better results.
- Tracking the position of the cursor, this will allow mapping of cursor movement during the experiment which will show how concise movements are of the participant, this will also show any favorable routes participants useto reach different areas of the grid.
- Recording every pose carried out. By recording the poses carried out by the participant it will be possible to determine some favored poses by the participant and could show which poses are easier to carry out.

Experimental protocol

The experiment procedure has been created to ensure each of the participants wear and use the armband correctly, this will reduce user error while wearing the armband and produce more reliable data. The tasks will be explained to the user and have been presented in the order they will be carried out.

Set up procedure

To acquaintance the subject on the experiment, the following stages were performed.

- Stage 1 - Show a short demonstration of the task
- Stage 2 - Show and present following instructions on how to wear the MYO Armband correctly (Figure 3):
    - Hold out arm
    - Orientate the logo on the band facing upwards (i.e., aligned with back of hand)
    - Slide arm band up forearm ensuring logo stays in correct position
    - Let armband sit at top of forearm 1-2 cm away from elbow joint
    - Ensure comfort of participant, if band too tight, wear further down the forearm (staying as close to the elbow as comfortably possible)

- Stage 3 - Give participant 1-2 minutes to familiarize themselves with poses being used. Explain how each pose is safely carried out and what each pose does:
  - swipe inwards – move cursor left
  - swipe outwards – move cursor right (i.e., hyperflexion at the wrist is not needed)
  - fist – move cursor down
  - spread fingers – move cursor upwards
- Stage 4 - Ensure the participant can perform all of the poses comfortably so that no injuries occur.

Experiments and trials

- Upon beginning the program, a participation number will be requested, theresearcher will input the participants given number (1, 2, 3, and so on)
- Once the participant is ready the researcher will press the "enter" key and have the participant complete the presented task three times.
- After each completion of the task the file "pose data" will be renamed to prevent over-writing of pose data, this will be carried out by the researcher.
- Once the task has been completed three times the participant will be thankedand asked to remove the arm band and leave the lab.

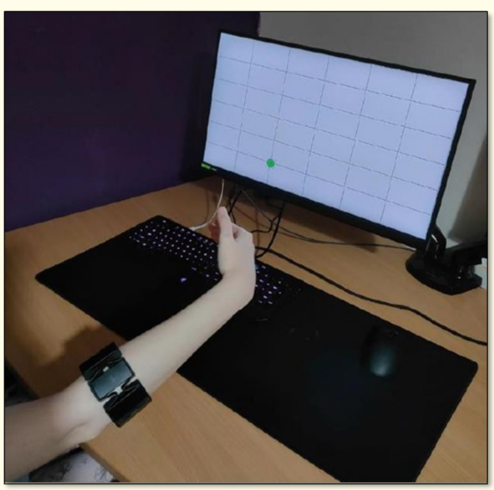

Figure 3: Participant carrying out the task.

Results and Discussion

This project designed a GUI capable of interfacing with the MYO Armband and tested the feasibility of learning to control such an interface effectively. Three participants wereasked to complete a single task three times, the task required the participants to hit targets on a 2D grid using hand poses (muscle movements in the forearm using the poses created with the hand) interpretated by the MYO Armband. This discussion sectionof the paper will be focused on the experimental results of the four variables which were tracked to measure improvement of the user over multiple uses, the variables recorded were: time taken, accuracy and poses used.

Time taken

The testing program recorded the time each participant took to reach a target, this data shows if the participant became faster over time. Because some targets are further from the starting point than others, there are four distances considered. The distances are measured using the lines of the grid image seen in Figure 2, each line is considered one unit of distance and so the four distances used are as follows: one unit, two units, three units and four units. The time taken has been presented using the average time taken to reach a target of given distance, for example the time taken to reach all targets of four units away will be presented together, this will allow accurate observations and comparisons between participants and targets of different distances.

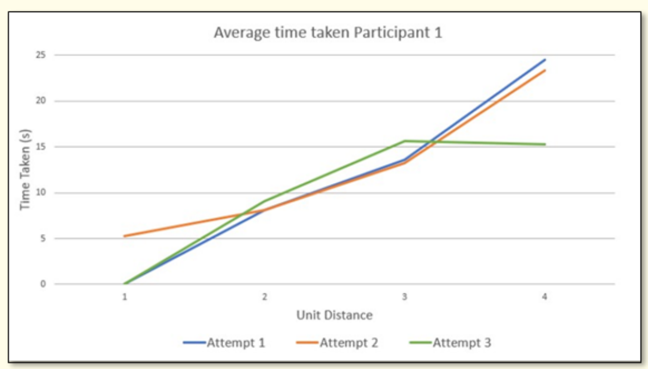

Figure 4: Average time participant 1 took in each attempt.

N. of units	1st trial	2nd trial	3rd trial
	time [s]		
1	0	5.24	0
2	8.14	8.11	9.05
3	13.62	13.21	15.60
4	25.51	23.31	15.28

Table 1: Average time taken by participant 1.

A graph showing the average time taken, in each attempt, for participant one is presented in Figure 4 and Table 1, the points on the graph which show zero are due to the participant not receiving any targets of that distance (this is because the targets are randomly generated), these zeros can be seen in the accompanying table. Similarly, participant one shows only a single target for 1 unit distance during Attempt 2, this is for the same reasons mentioned above, however comparisons can be made for targets of1 unit distance in the same attempt. Starting with targets of 1 unit distance, participant one managed small improvements during Attempt 2 with the first time taken being 7.1s however, this was quickly improved on with times of 4.4s and then 4.2s. 1 unit distance targets are the easiest to improve in as they require only a single pose to reach, this means once a participant is comfortable with a pose then it can be held indefinitely untilthe target is reached. All other unit distances do not benefit from this simplification and require two or more pose changes to reach a target. Figure 4 shows improvement for a unit distance of 2, the second attempt was fastest at 8.1s but had no noticeable difference from attempt 1 with 8.14s however, the third attempt was the slowest at 9s. Once again, the difference between attempt 1 and 2 is quite small when considering the unit distance of 3, with attempt 2 seeing a slight improvement of 0.5s over attempt 1, however attempt 3 saw no improvement with the time taken increasing by 2.5s. Participant 1 saw impressive improvements for the unit distance 4 targets starting at 24.5s during attempt 1 and improving for attempt 2 by 1.2s then finally reducing the time taken even further to 15.2s, this was the biggest improvement participant 1 achieved and is likely due to experience of holding the poses steady during large movements of the cursor across the grid.

Similarly to unit 1, targets of the first participant, the second participant (Figure 5 and Table 2) did not receive any in the first attempt. As discussed in the methodology this is because of

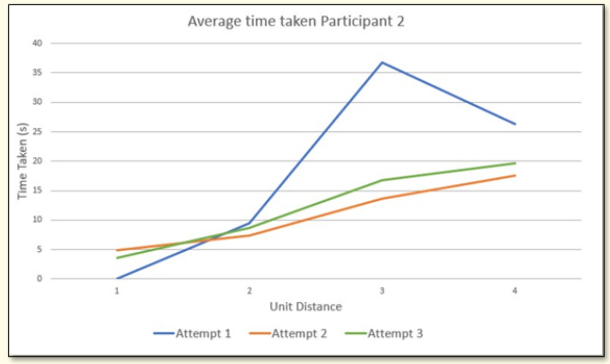

Figure 5: Average time participant 2 took in each attempt.

N. of units	1st trial	2nd trial	3rd trial
	time [s]		
1	0	4.83	5.93
2	9.45	7.43	8.67
3	36.75	13.59	16.81
4	26.30	17.57	19.70

Table 2: Average time taken by participant 2.

the randomly generated locations of the targets (leading to the 1-unit targets sometimes not being randomly selected) and because there are only four potential locations to spawn a 1-unit target, in comparison the 3-unit targets have eight potential spawn locations (the locations for every target can be seen in figure 3). Other than unit 1 targets participant 2 set reasonable times for a first attempt with the 2-unit targets being reached in 9.4s and the unit 4 targets being reached in 26.2s, however the 3-unit targets were the first three targets the participant had attempted, and it shows, with a much higher average of 36.7s. The reason for this was because of in-experience ofusing the MYO Armband but also due to the participant not performing the poses as directed which led to some miss-classification of which pose was being attempted, the participant did however correct the poses through trial and error and then proceeded tolower the time to 17s for the final unit 3 target. During the second attempt, participant 2showed impressive improvements over attempt 1 with the time taken being reduced in every unit of distance. The 2-unit targets improved by 2s, down to 7.4s, the 3-unit targets became consistent with the participant lowering the time to an impressive 13.5s and finally showing a 9s improvement in 4-unit targets to 17.5s. This level of improvement is almost certainly due to the extended time spent during the first attemptof 3-unit targets, this shows the participant clearly benefits from more practice with the MYO Armband, this also shows that being more mindful about the poses is beneficial. Finally, the 3rd attempt shows an improvement on the unit 1 targets of 1s but an increase in the times for all other units, with 2-unit targets increasing by 1.2s, 3-unit targets increasing to 16.8s and 4-unit targets increasing to 19.6s. This increase in time taken could be due to fatigue of the participant due to spending more time in the first attempt, however participant 1 also saw a decrease in the times from attempt 2 to attempt 3.

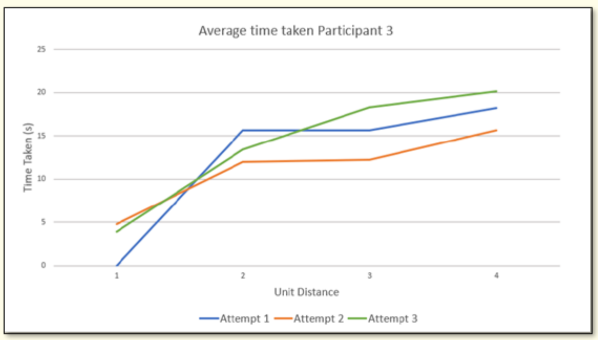

Figure 6: Average time participant 3 took in each attempt.

N. of units	1st trial	2nd trial	3rd trial
	time [s]		
1	0	4.79	3.89
2	15.64	11.96	13.42
3	15.68	12.24	18.30
4	18.23	15.65	20.16

Table 3: Average time taken by participant 3.

Much like the previous two participants the 1-unit targets did not spawn for the first attempt of participant 3 either (Figure 6 and Table 3). This does not have an effect onthe learning process as the location which the 1-unit targets would spawn are also locations which participants are required to move through to reach higher unit targets. During attempt 1 Participant 3 had some issues with 2-unit targets much like participant 2 did, however participant 3 noticed mistakes in their poses much quicker than participant 2 and due to this was able to recover quickly, lowering their time for 2- unit targets from a high of 22s down to the average shown in figure 8 of 15.6s. the participant had very consistent times for reaching 3-unit targets during the first attemptwith all times being close to the average of 15s. Similarly, to the 2-unit targets, 4-unit targets started high at 21.3 and lowered to 15s bringing the average to 18.22s. As expected, improvements were seen throughout the second attempt for participant 3, 1- unit targets were spawned, and the participant managed them in 3.5s and 6s leading to an average of 4.7s which is close to the average of the other 2 participants for this unit distance. The real improvements begin to show during the other unit distances, 2-unit targets have improved by 3.5s, down to 11.9s, but it is still above the average time for the previous two participants. Both the 3-unit and 4-unit targets saw improvements of 3s during the second attempt, 12.2s and 15.6s respectively, which is in line with improvements seen by the other two participants. During the 3rd attempt for participant 3 the 1-unit targets saw an improvement of almost 1s, conversely the average times for the other 3-unit distances have once again increased, 2-unit targets saw a small increase by 1.5s, however 3-unit and 4-unit targets saw increases of around 5s to 18.3s and 20s respectively.

All three participants performed as expected in their first attempt, some did better than others but overall, they set scores which were within the expect boundaries of a first-time user. That said, some participants took longer than others to control their hand poses sufficiently for the MYO Armband to classify, this was an error on the researcher's side as they had not explained to the participant that a conscious attemptto engage your muscles is sometimes required for correct classification, that being said all participants recovered quickly, and all three participants show impressive improvements during the second attempt. The second attempt for all three participants showed the most improvement, with all of them reducing their times through the four different unit distances. During the third attempt every participant's average time, for the three largest unit distances, increased compared to their second attempt. This increase is more significant in some unit distances such as the 3-unit and 4-unit targets. The increase in average time taken appears to be due to fatigue, all three participants were clearly showing signs of their arm becoming tired and their poses becoming "lazy".Because of these "lazy" poses the classifier was sometimes unable to determine the correct pose being carried out which could lead to the kind of increases in average time shown by each participant. Another possibility is that the participants had gotten too confident with their ability and become more relaxed, this would lead to more relaxedor unfocused muscle movements (or "lazy" once again) and perhaps effect the signals which in turn would affect the classifier on the MYO Armband, in the same way mentioned above.

Accuracy

The accuracy of all participants is presented in two types of graph, the first set of graphs will show a tracing of the cursor movement during each participant's worse result and best result (looking at cursor accuracy only), the second set of graphs will bea type of density graph which will show a tracing of every participants cursor movementfor a given unit distance target.

In Figure 7, top left panel, a diagram shows a tracing comparison of the mouse cursor during one of participant 1s the first attempts and a later attempt. In the figure, theearly attempt of participant 1 is in blue and it is clear that mistakes where made, the participant moved the incorrect direction, using the incorrect pose, and then needed to back track in the correct direction to reach the target, this is common during the opening few targets as the participant is just starting to create the association of a specific pose with a direction of movement. The red data points in Figure 7 panelrepresent an attempt made during the second attempt of participant 1, from this data it is clear that the participant did much better by heading directly to the target withoutany mistakes in choice of pose. However, they did miss-judge the position of the target and undershot the edge by a very small margin which led to the need for a third pose in order to reach the target, nevertheless this is a clear improvement in pose decision and accuracy brought on by practice and experience from the first attempt.

Another comparison of initial attempts and more experienced attempts is shown in Figure 7, top right panel. The figure shows Participant 2s struggle during the second target in attempt 1. The data in blue shows that after moving the cursor to the required x axis position participant 2 began moving downwards instead of upwards, this initially was due to incorrect pose choice however following this it was also caused by incorrect pose performance, this is what caused the cursor to go further leftwards. After some time figuring out what was going wrong participant 2 was able to move the cursor in thecorrect direction and son after reached the target, the difficulty participant 2 had duringthis attempt helped to improve the hand pose accuracy for future attempts, which the red data shows. The red data in the figure shows the best attempt made by participant 2,from this data its possible to see the almost perfect accuracy which participant 2 used toreach the target. Reaching the target in only two poses is the ideal number of poses used for this unit distance, the only improvement which could be made was changing the poses sooner which would result in reaching the target sooner. Comparing the two series of data in figure 11 shows the clear improvements participant 2 has made in the accuracy of the hand poses and the accuracy when controlling the cursor.

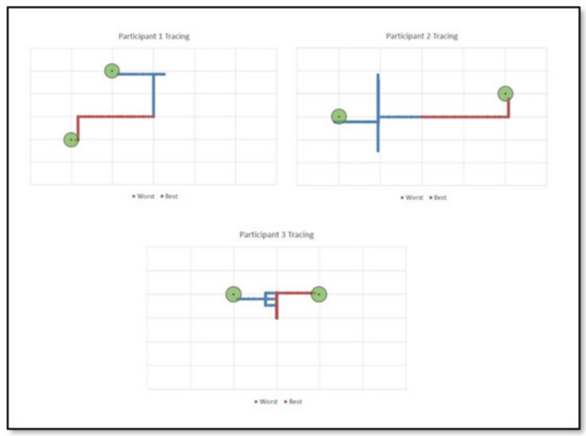

Figure 7: Participant 1, 2 and 3 tracing of worst attempt and best attempt (top left, top right and bottom panels, respectively).

A tracing of participant 3s worst attempt and best attempt has been presented in the bottom panel of the same figure (Figure 7). In this figure the worst attempt, in blue, can be seen moving in incorrect directions at times, this fork like direction was the participants attempt at correcting incorrect pose choices at the start, further mistakes were made following this due to the quick movements attempted after realizing the incorrect pose was used. This is what caused the up, down, and right movements, until finally the participant was able to calm down and focus on the correct pose and move to the target. Alternatively, the best attempt by participant 3 is shown in red and improvements can be seen immediately. This participant was able to complete this target in just two poses, which is ideal for this unit distance, and although not necessary,this participant consistently aimed at the middle of each target which shows impressive accuracy for such a short time using the interface. As seen with the other two participants this participant was able to grasp control of the cursor within two attempts and shows impressive improvements during their use with the MYO Armband and interface.

In Figure 8 a new type of graph is shown, this chart shows the location of all movement made by the three participants during 3-unit target attempts. In the graph its possible to see the routes participants took, with the routes travelled more often having more data points and thus have a denser path towards the target. The graph is very effective at showing early attempts and reaching targets, this is seen clearest in the bottom left section of the graph where many attempts have been made and two lines are clearly more travelled than others. This graph once again shows clear improvement for the three participants, as each participant became better at navigating the interface,they figured out the best route to take for each target and figure 13 shows this.

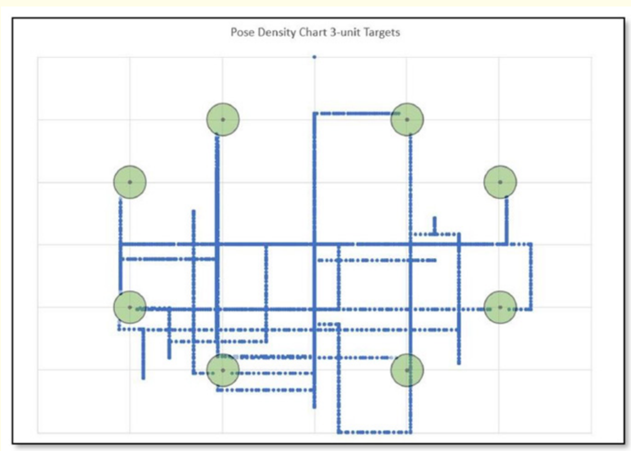

Figure 8: Pose density for the 3-unit targets.

As seen in the previous plots, all three participants struggled in the early stages of their first attempt. Their struggle was mainly focused around two things, using the correct corresponding poses for a given movement and engaging their muscles. However, from the figures mentioned its clear that all three participants learned to control these aspects of the interface with great success and improved their accuracy from several incorrect poses and incorrect movements of the cursor to reducing both down to the optimum movement for effective control of the interface. Similarly, the Pose density graph in Figure 8 shows the same improvements but for every attempt made at 3-unit targets.

Poses used

Tracking the most common poses used by all three participants present some valuable information about how comfortable some poses are compared to others. Although the pose choice for each target is limited, depending on the location of the target and the poses come in two directions, vertical movement, and horizontal movement, it is still possible to see over multiple attempts how often participants choose to do a particular pose over another by looking at the first poses carried out at the beginning of each attempt on a target. Although, it should be said that all poses chosen by the researcher are considered "comfortable" and any able-bodied person would be capable of carrying them out without any injury, some users will find some poses more comfortable than others (or have a reason for preference of a pose over another pose).

Participant 1 Pose Choice

First route taken	Attempt 1	Attempt 2	Attempt 3
target number	direction/pose	direction/pose	direction/pose
1	up	down	up
2	up	up	left
3	up	down	up
4	down	down	down
5	down	left	up
6	right	down	down
7	left	down	down
8	down	down	down
9	down	right	up
10	down	left	down

\# Red cells required one pose

Figure 9: First pose choice table for participant 1.

The table in Figure 9 shows the first pose chosen by participant 1 for each target, as there are some target locations which require a single pose to reach, they will not be included in this analysis since there is no choice in which pose will be carried out first, unless there are mistakes, but these mistakes will not be considered in this section. The cells shaded in red represent the single pose targets, some are 2-unit distance, and someare 1-unit distance. Looking at Figure 9 it is possible to see that participant 1 favors the

vertical axis which corresponds to the "fist pose" and the "spread fingers" pose, these two poses saw more success with some participants than others and participant 1 had seemed to grasp them quickly during the experiment. These poses engage the fingers and not the wrist so participant 1 may have found them more comfortable to carry out for this reason.

Participant 2 and 3 appeared to favor the horizontal axis more than the vertical axis, with participant 2 using the vertical axis as the first pose only twice and participant 3 using it only three more (Figures 10 and 11). The poses for vertical axis are the "wave out"

Participant 2 Pose Choice

First route taken	Attempt 1	Attempt 2	Attempt 3
target number	direction/pose	direction/pose	direction/pose
1	right	right	right
2	left	right	left
3	down	left	down
4	left	left	right
5	down	down	right
6	left	down	right
7	left	right	down
8	left	right	left
9	left	left	left
10	right	right	left

Red cells required one pose

Figure 10: First pose choice table for participant 2.

pose and the “wave in” pose, both poses use the wrist and not the fingers and are both the simplest poses to carry out due to moving only the wrists flexion and extension movements, conversely the movement of all five fingers is required for the other poses. It was predicted that these two poses would be the most preferred by the participants due to ease of carrying them out which shows in Figure 10 and 11.

Participant 3 Pose Choice

First route taken	Attempt 1	Attempt 2	Attempt 3
target number	direction/pose	direction/pose	direction/pose
1	up	right	right
2	up	down	right
3	right	down	down
4	down	right	left
5	down	right	left
6	right	left	right
7	left	right	up
8	up	up	down
9	right	down	down
10	down	right	right

Red cells required one pose

Figure 11: First pose choice table for participant 3.

Although it appears all three participants have poses which they appear to be more comfortable carrying out than others, there are some other possibilities which can affectthe choice of pose. The first alternative reason could be a bad experience, all three participants struggled at the start of the experiment with some poses working better forthem than others, this could have led to a subconscious bias towards the poses the participant deemed “easier” to carry out. Alternatively, each participant may prefer lining up the targets, perhaps some participants felt they could line up the cursor with the centre of the target easier on the vertical axis and others using the horizontal axis. However, these last plots show that it is really down to the individual user and what theyfind comfortable doing with their own body and their intentions.

When looking at all of the results from the experiment, the tracked variables show clear improvements made by all three participants. Participants improved their time to reach multiple unit distance targets, significantly in some cases, and began to slow towards the end of the experiment possibly due to fatigue, meanwhile the accuracy the participants continued to see increases up to the end of the experiment where some participant had managed to reach targets using almost perfect movements of the cursor.The choice of poses became almost perfect for all participants after the first attempt however the accuracy of the MYO Armband saw some fluctuation depending on how engaged the participant was during the attempt. Similarly, the choice of initial poses for each target fluctuated but generally participants preferred the use of the wrist movement over the figure movement, but this could be for a number of reasons, stated previously.

Conclusion

This paper recognizes the difficulties some users of prosthetics have when learning how to use one, this difficulty for many is what pushes them away from using their prosthetic. An interface was designed to allow for low input from the user thus simplifying the process of control, using this interface an experiment was carried out using three able-bodied participants. The experiment had the participants complete a series of navigations tasks on a 2D computer screen, three times, while wearing the MYO Armband. The device tracked poses held by the user and moved a cursor on the screen according to which pose was held by the user. During the process the timetaken, and accuracy were tracked to determine how well the participants learned to use the software. Throughout the experiment all three participants saw impressive improvements in time taken between the first attempt and the second attempt however in the third attempt the time taken had increased to above the second attempts time,this occurred for all three participants and it likely due to fatigue of using the armband as engaging the muscles for some poses could be tiering. Unlike the time taken, the accuracy saw increases in all the attempts for all three participants with some participants managing to complete the tasks with near perfect movement of the cursor.

With respect with previous analysis and controlling strategies as proposed in [14,16-18], this work presents for the first time a real-time interface which provides the tool for the development of the novel approach proposed in [10], namely the possibility of controlling a multi-dexterous prosthetic (or robotic device) by means of a low number of inputs (i.e. 2 inputs in the case of this study). From a different perspective, implementation of a similar, but reversed strategy, has been already shown in [19], where human subjects were asked to remap their multi degrees of freedom hand movements into a low degree of freedom geometrical environment. These latter results suggest that this type of mapping can be efficient and be learnt by the subject.

As this study did not look at controlling a prosthetic with the interface (yet), a logical futureresearch step would be to alter the output of the program and add real poses forprosthetic hand control using principal component analysis. Using this, a future researcher could then have participants take part in an experiment to determine how well this interface could be used to control a prosthetic hand and perhaps more importantly are the participants capable of learning how to control the hand in a reasonable time frame without becoming too fatigued or giving up. Further changes to the poses system used could also benefit from adding some choice to poses available for the user, adding finger poses for vertical movement or wrist poses for horizontal movement would allow for users who are more comfortable using their wrist for poses to provide all required inputs and the same for adding finger poses. Overall, these additions would create a more complete research into effective learning for new users of non-invasive prosthetics solutions, according to a variety of techniques which could be implemented (see for ex [20,21]).

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