Impact of Diverse Aspects in User-Prosthesis Interfaces for Myoelectric Upper-limb Prostheses

Diego Cardona, Guillermo Maldonado, Victor Ferman, Ali Lemus and Julio Fajardo

***Abstract*—Numerous assistive devices possess complex ways to operate and interact with the subjects, influencing patients to shed them from their activities of daily living. With the purpose of presenting a better solution to mitigate issues generated by complex or expensive alternatives, a test comparing different user-prosthesis interfaces was elaborated to determine the effects of diverse aspects in their amiability, including that of a version created for this work. A simplistic, anthropomorphic and 3D-printed upper-limb prosthesis was adapted to evaluate all the renditions considered. The chosen design facilitates the modification of its operational mode, facilitating running the tests. Additionally, the selected prosthetic device can easily be adapted to the amputees' lifestyle in a successful way, as shown by experimental results, providing validity to the study. For the interaction process, a wireless third party device was elected to gather the user intent and, in some renditions, to work in tandem with some sort of visual feedback or with a multimodal alternative to verify their impact on the user.**

***Index Terms*—Upper-limb prosthesis, Three-dimensional printing, Electromyography, User-prosthesis interface**

I. Introduction

In recent years, there has been substantial progress in high-technology prosthetic devices, offering the patients numerous alternatives, perks and characteristics to improve their condition. Most of the focus has been fixated on diverse methods to interpret the user intent to actuate bionic prostheses or investigating ways to make them more efficient. Nevertheless, most of these advances have not completely succeeded in providing the user with a simple and easy-to-use user-prosthesis interface (UPI), because the studies have been directed elsewhere.

Traditionally, research on upper-limb prosthesis control was focused on different techniques based on the processing of electromyography (EMG) signals to analyze the user intent and to operate it with a specific activation profile. Some solutions to this problem involve implants [1]–[3], which employ Bluetooth or radio channel waves. These assistive devices use wireless charging to function and must regulate the power dissipation to a safe value for human tissue to avoid damage. In a similar manner, several approaches opt for using Brain-Machine Interfaces (BMIs) as a means to control these devices. One of the most recent iterations is based on high-density electrocorticography (ECoG), which allows the user to control each finger individually [4]. These works show that, although implants may have promising results and help alleviate the discommodity of wired prostheses, they require challenging, intrusive procedures, that result in an expensive and complex product. Other projects show more creative approaches to analyzing the EMG signals, utilizing other members to drive the movements of the prosthetic limb, as shown on [5] and [6], which use the toes and the tongue, respectively. Such methods provide alternatives for other disarticulation types, such as the bilateral amputations, but are not so efficient for trans-radial amputees, because these they are not intuitive to the human body and they also affect the way some common activities of the daily living (ADLs) must be carried out, like walking and eating.

Several commercial prosthetic hands use state machines actuated by a single feature of a predefined subset of muscle activity, while the majority of sophisticated research assistive devices are based on pattern recognition algorithms with a multimodal approach. This method consists in taking a set of EMG features and complementing them with information from other types of sensors like inertial measurement units (IMUs), mechanomyography (MMG), accelerometers or even features detected by a microphone, showing a substantial improvement in classification rates [7]. Taking such a stance has been used, successfully, to improve the user control of prosthetic devices [8], like using a hybrid system with Radio Frequency Identification (RFID) tags on specific objects to reduce the cognitive effort to operate a prosthesis, and to address some of the well-known issues of EMG techniques, such as the limb position effect [9,10]. Similarly, other focuses have been taken into account with the use of these types of systems, such as utilizing voice-control, together with visual feedback through a touchscreen LCD, providing the users with alternatives to control their prosthetic limb in a different manner [11]. Other studies have been carried out to increase the functionality of multi-grasping upper-limb prostheses, utilizing an amalgam of EMG and deep-learning artificial vision systems. This works by associating a subset of objects to a specific kind of grasp based on the geometric properties of said target. The classification process is fulfilled via a convolutional neural network (CNN) employing an object classifier [12]–[14].

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This paper focuses on the evaluation of user-prosthesis interfaces employing a wireless module and comparing the impact of certain aspects in the interaction process. Since the utilization of Thalmic Labs' Myo armband has been shown to be an affordable and viable replacement for the medical grade sensors, even with subjects with a certain level of trans-radial amputation [4,15]–[17], it was selected for operating the versions in this project. This gesture-based system was elected, because it processes and classifies the surface EMG (sEMG) signals; plus, its small subset of contractions can be adapted to enact numerous actions. In addition to that, its utilization on all the interfaces facilitates the replication of the different iterations and removes any possible bias regarding the transductor to gather the user intent, evaluating only the UPI. Although the cost increases by using such a system, this results in a more comfortable device for the subject in comparison to implants or wired prostheses; besides, it helps to keep a modular design. On top of that, the contractions detected by the Myo permit creating an interaction process with a significantly greater number of expressions than similar alternatives.

The rest of this paper is structured as follows: Section II elaborates on the related projects replicated for the comparison of the interfaces. Section III informs about the UPI proposed for this work. Section IV describes the hardware used for all the versions and how the whole system is integrated. Section V describes the evaluation processes and their interpretations. Finally, the last section, Section VI, deals with the impact of the results.

II. RELATED WORK

To identify the aspects relevant for a user-friendly interaction, several interfaces were evaluated. This choice was not only established on different interaction processes, but also considering akin price ranges and physical characteristics. That is why the same hardware (shown in Fig. 1) was adapted to fit each individual rendition and the same array of sensors, Thalmic Labs' Myo armband, one of the more traditional research alternatives [9], was used on the patient's forearm, where the stump for transradial amputees is located, to create a natural operational mode.

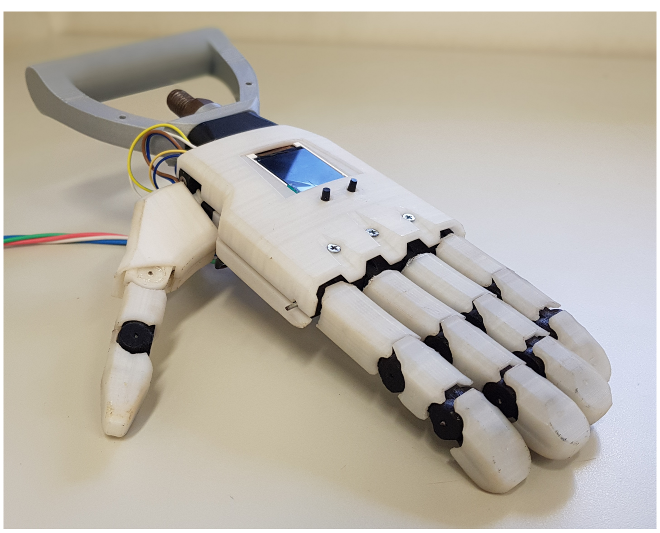

Fig. 1: Galileo Bionic Hand: anthropomorphic, 3D-printed upper-limb prosthesis.

A. Multimodal approach using buttons and Myo interface

The functionality for this version, similar to the work presented in [18], is illustrated in the Finite State Machine (FSM) in Fig. 2. Both, the muscle contractions subset, $Q = \{q_0, q_1, q_2, q_3\}$, corresponding to Thalmic Labs' "Myo poses", and the buttons, $B = \{b_0, b_1\}$ (which are installed on top of the hand's shell), are used to operate the prosthesis. Using "wave out" (hand extension), q_0, and "wave in" (flexing the hand), q_1, as well as b_0 and b_1, causes an alteration in the position of the menu displayed on a μLCD screen (shown in Fig. 3), i.e. forwards or backwards, respectively. These changes are taken place in the state S_1, indicating an alteration in the screen is occurring. Moreover, S_0 indicates that the prosthesis is resting in its default state, the fingers on the prosthesis are fully extended; while S_3, that they are completely flexed. It is relevant to note that, whilst on this last state mentioned, changing actions in the menu is prevented to the user. The reason for this is that the timing of the coiling and unfurling processes differ between actions and the finger timing may be detrimental for future behavior if this case arose.

On the other hand, S_2 and S_4 indicate that the prosthetic hand is currently closing or opening, correspondingly, processes that can be interrupted by each other if a correct command is received. Furthermore, to activate an action, q_2, "fist", needs to be received; whilst "double tap" (two swift, consecutive contractions) and "fingers spread" conform the contraction q_3, that deactivate it. The decision to use both gestures to deactivate the actions was taken according to the results shown in Section V. Finally, other relevant elements in the FSM representing the interface's behavior are the flags fl and t_r. The first one informs that all the fingers have reached their desired position when performing an action, whilst the second represents that the time required to fully open the hand has passed.

B. Multimodal approach based on object classification and detection

This version is a replica of the one used in [14], which uses a mobile application to interface the prosthesis and the patient. This rendition possesses a camera mounted on the top side of the shell, which takes pictures of objects that will interact with the assistive device, and suggests a grasp to the user via an app. The photographic module can also be replaced with the mobile device's own camera. By employing the Myo's default poses, the user can either accept, reject

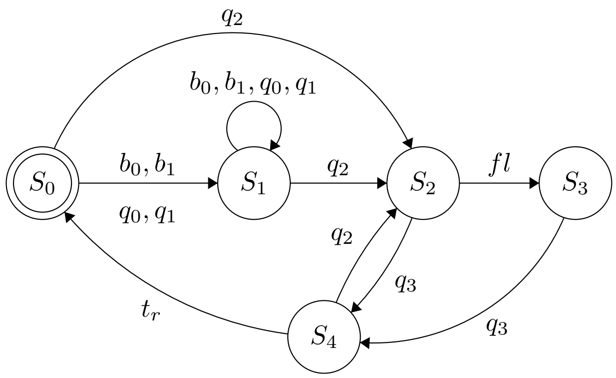

Fig. 2: Finite State Machine showing the behavior of the interface using buttons and the Myo to operate.

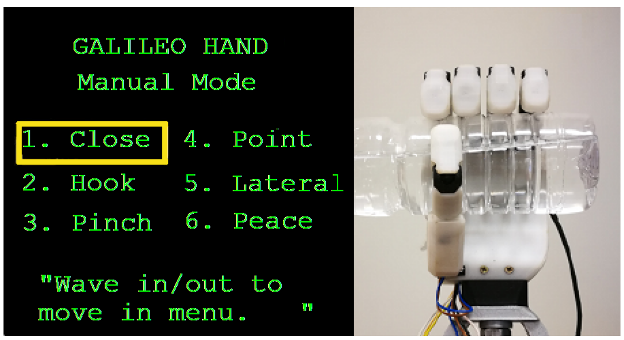

Fig. 3: Galileo Hand's graphical menu (left) and the prosthesis performing the action “Close“ (right).

or cancel the recommendations provided by the computer vision detection and localization algorithm. This process uses a bag of words method to assign its labels to the detected objects, where each each of them is associated to a specific, customized grasp.

The interface's operational mode is described in Fig. 4, where the contractions, $Q = \{q_0, q_1, q_2, q_3\}$, represent the following Myo poses, respectively: “fist“, “fingers spread“, “wave in“ and “‘wave out“, which are used to navigate along the states of the FSM. S_0 indicates that the prosthetic hand is completely open; S_1, that a picture is being taken; S_2, that a label for the detected object is being determined; while S_3, that the selected action is being executed. The remaining relevant elements in the FSM are the flags t and l. The first indicates a timeout in assigning a label, while the second informs it was successfully elected. The transition that occurs when q_1 is active, indicates that another image needs to be taken and cancels the action selection process. On the other hand, q_2 accepts the suggestion provided by the algorithm; while q_3, rejects it and another grasp is proposed.

C. sEMG pattern recognition

The following interface, based on [11], but utilizing the Myo's pattern recognition methods, consists in a simplistic

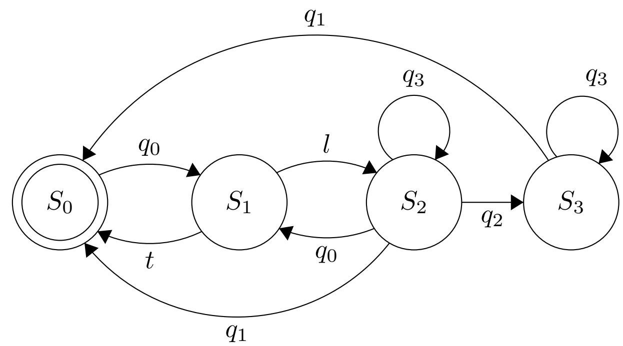

Fig. 4: Comportment of the UPI from the version based on object recognition.

system that maps each of the predefined “Myo poses“ to a gesture to be executed. The mapping was carried out as follows: “wave in“ to a pointing position; “wave out“ to carry out a lateral grasp; “double tap“ to a hooking stance; while “fist“ and “fingers spread“ to closing and opening all fingers, respectively. The gestures selected were the ones considered to be the most useful in the ADLs.

III. Myo-powered Interface with a Reduced Contractions Subset

The following iteration was created for this work, which, as aforementioned, also utilizes the Myo armband to recover the user intent. This interface behaves in a similar matter to the one explained in Section II-A, but without the incorporation of the buttons. Additionally, the contraction subset Q is reduced to three, utilizing “wave out“ to deactivate the action. This was decided to provide an alternative if one of the poses is inaccessible to the patient. Plus, a possibility to alter the amount of supported hand actions was incorporated, this, to fulfill the patients' unique necessities. This comportment is illustrated in Figure 5.

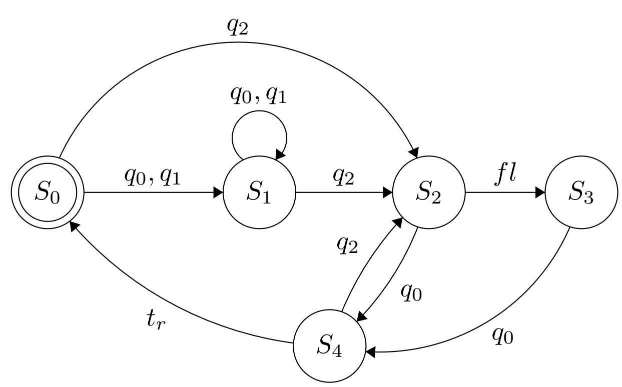

Fig. 5: Finite State Machine representing the UPI interaction process from the version with the Myo armband with the reduced contraction subset.

IV. SYSTEM ARCHITECTURE

A. Galileo Hand

The hardware selected, the Galileo Hand [11], consists in a lightweight (under $350g$), affordable (under \$350), anthropomorphic, modular and intrinsic 3D-printed, ABS shell. It encases 5 metal geared micro DC motors, one for each finger, plus an additional one with encoder for the thumb. Also, it has a main control PCB with an ARM Cortex M4 microcontroller unit (MCU) (Teensy 3.2), 3 TI DRV8833 dual driver motors and one 4D-Systems' 1.44" μLCD-144-G2 screen.

The five fingers are assembled via waxed strings, which, when coiling, close the fingers. They are also composed by surgical-grade elastics that permit the articulations to spring back open. The configuration of these artificial extremities provide 15 degrees of freedom (DOF) in total, 14 of which are comprised by each joint in the fingers to simulate flexion and extension; whilst the remaining DOF is in charge of rotating the thumb, which is at a 15° angle from the palmar to emulate both adduction-abduction and opposition-deposition movements. Besides, each finger possesses a motor, resulting in 6 degrees of actuation (DOA).

Because of the modularity of its design, it was possible to adapt an external unit to the Galileo Hand. It consists in a Bluetooth Low Energy (BLE) device, HM-10, and a secondary MCU, ATmega328P. This, to interface the Myo armband and the prosthetic hand, which was achieved with a similar process to the one proposed in [19].

B. Feedback current on/off controller

Each finger has an individual on/off controller to perform the flexion/extension movements, except for the thumb, which possesses, additionally, a quadrature encoder using a PI position one for its rotation. This way, the prosthesis has the ability to perform different predefined gestures, i.e. pointing, power grip, etc. The functionality for each digit is illustrated in the Finite State Machine in Fig. 6.

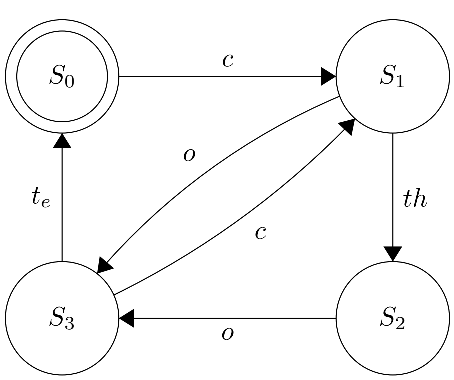

Fig. 6: Finite State Machine demonstrating the opening/closing behavior of each finger on the prosthesis.

The system starts with the finger fully extended (in an "open" position), modelled by the state S_0. The transition to S_1 happens when the command to move the finger, c, is received, activating the motor and causing the finger to start closing. While on this state, the RMS value of the current is monitored by the main MCU and, when a predefined threshold, th, is exceeded, the switch to S_2 happens. This parameter may be different for each individual finger, as each one has different size and, therefore, discrepant mechanical factors, so the calibration was carried out experimentally. At this point, the finger is considered to be fully closed and will start to reopen if the o command is issued by the user, as shown by the transition from S_2 to S_3. The alteration in state from S_3 to S_0 happens after the time, t_e, passes, which was determined in an experimental manner as well, as it is different from the time spent in S_1. This disparity occurs, because the elastic installed on each finger opposes itself to the coiling process, but favors the unfurling one. It is relevant to note that the closing/opening processes may be interrupted and reversed if the appropriate commands are received.

V. EVALUATION AND RESULTS

A. Myo Armband Efficiency

Since the array of myoelectric sensors is not fault-free, some actions are misclassified, a confusion matrix was elaborated to corroborate the results shown in [15] and to verify its feasibility for the project. It also served as a means to select which of the Myo armband-supported poses are the most adequate to be implemented as default actions to operate each interface. The data was obtained with the help of 10 volunteers, who had never used the armband before, to avoid biased results. The matrix is adjoined posteriorly (in Fig. 7), where the actions are numbered as follows: "wave out"

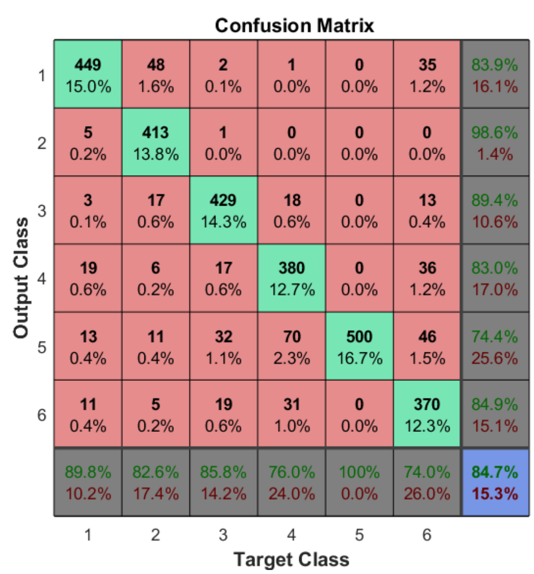

Fig. 7: Confusion matrix evaluating the default classifier of the Myo armband.

(1),“wave in“ (2), “fist“ (3), “double tap“ (4), “fingers spread“ (6) and (5) indicates a no operation (NOP), meaning the armband did not detect any pose. According to the results gathered by this experiment, the Myo poses were mapped to the operation actions in diverse manners to the different interfaces.

The first one, the one using the buttons, uses the gestures with the least successful rates to return the hand to its open position, since changing poses was designed to be blocked whilst performing an action. Additionally, considering that the most false positives for both “double tap“ and “fingers spread“ were each other, both poses were chosen to fulfill this purpose. Moreover, for assigning the remaining actions, it was decided to map them to the most natural ways, ergo the “waving in/out“ were chosen to change actions and “fist“ remained to activate a gesture.

On the other hand, the one using the artificial vision algorithms, was not modified from its original design proposed in [14]. The same gestures were kept to interact with the mobile application, since the actions chosen possessed apt success rates.

For the version described in Section II-C, the poses with the greatest success rates were mapped to the most useful ADLs, while also considering the naturality of the mapping (e.g. “fist“ to closing the prosthesis and “fingers spread“ to opening it).

Regarding the version created for this work, the array of gestures was selected in a similar manner as the version in Section II-A, but, for deactivating the hand gestures, “wave out“ was chosen. The reason for this is avoiding using the actions with poor success rates and replacing it with the most accurate one. This alternative is possible, since the menu is blocked during the performance of a gesture, so both hand extension and flexion are available to use to return the hand to its default state.

B. NASA Task Load Index Evaluation

Additionally, to effectively evaluate how amiable the interfaces are, a NASA Task Load Index (TLX) test was carried out, not unlike [20] and other works, like the ones mentioned in [21]. The selection of this scale to evaluate the interfaces was based on requiring a user testing, post-task evaluation method, since post-test evaluation techniques (like SUS), do not permit to evaluate different parts of the interface separately. Plus, methods like SEQ are not as thorough as the one implemented, since not many categories are considered during testing, providing a more binary result. Additionally, the test chosen has numerous research and industry benchmarks to interpret the scores in context, which can be helpful for future works. This index quantifies the effectiveness and performance of the workload to operate the device. The following categories are taken into account: mental, physical and time demand, performance, effort needed and the frustration evoked.

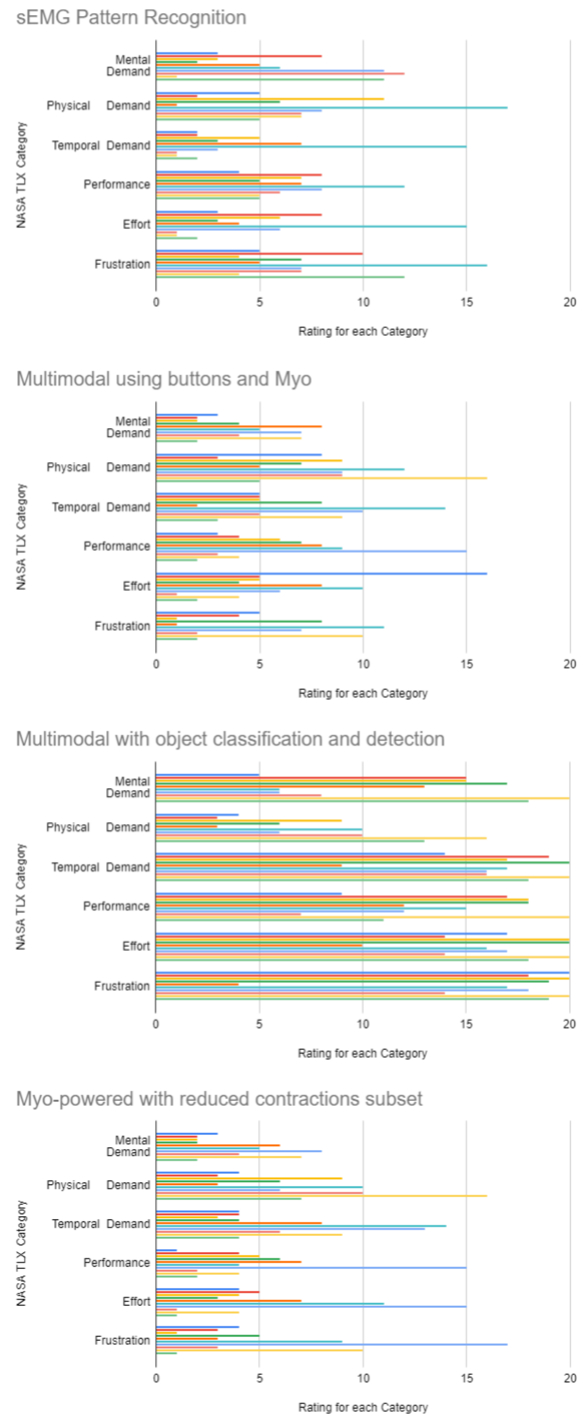

Fig. 8: NASA Task Load Index results for the four interfaces.

The test was passed to 10 volunteers, who were asked to rate each category in a scale from 1 to 20, with a lower score indicating a better result. The subjects consisted in 8 males and 2 females between the ages of 22 and 35. The evaluation process was carried out for all the UPIs previously mentioned and compared them to each other to notice their strengths and weaknesses and find out which one has a better rating. It consisted in performing four different gestures and utilizing some grasps to interact with their environment, i.e. they were asked to hold a wallet, a bottle and to press a certain key in a computer keyboard. The tasks were repeated thrice so that they could properly adapt to the operational mode.

The results are shown in Fig. 8, where each bar represents the choice for each individual subject. Their means are visualized in Fig. 9 along with their standard deviations. The figures reflect a great discrepancy in all categories between the version using the computer vision algorithms and the others, showing a poorer interface. Running a Factorial Analysis of Variance (ANOVA) test on the results, demonstrate a significant difference in comparison to the one elaborated for this project. The F statistic obtained was 132.4, when its critical value is 3.84 for an alpha of 0.05. This discards the main effect hypothesis, showing a significant inequality between interfaces.

The sEMG pattern recognition version shows the best results in physical and temporal demand, as well as the effort required to complete a task. Furthermore, the one using the buttons and the Myo together, resulted in the least frustrating interface, while the one with reduced contractions subset trumps the others in performance and mental demand. These three versions are proficient in different categories, but a clear superior one is not palpable with the previous graphs. Thus, an overall performance statistic was determined (Fig. 10), which calculates an average of all categories for each interface. This showed that they are user-friendly iterations with results around the upper 70% regarding the NASA TLX's scale. Since the means for the remaining interfaces are still very similar ((a) has a mean of 6.08; (b) one of 6.1; and (d) 5.75), more Factorial ANOVA tests were run on these iterations with the same alpha value. These evaluations were made comparing the version proposed in this work to the interfaces replicated to verify if the improvement is relevant. The results do not show a significant impact between them, showing that the different aspects in the interaction process do not affect in a relevant matter.

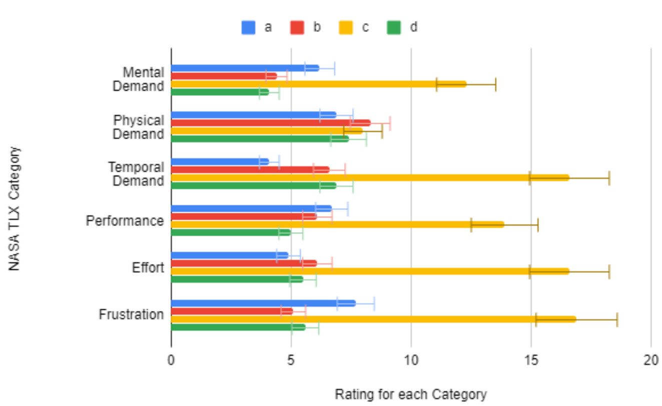

Fig. 9: Mean of the results gathered from the volunteers. Where (a) is the sEMG Pattern Recognition one; (b), the one using the buttons and the Myo; (c) is the version using the camera; and (d) is the iteration with reduced contractions subset.

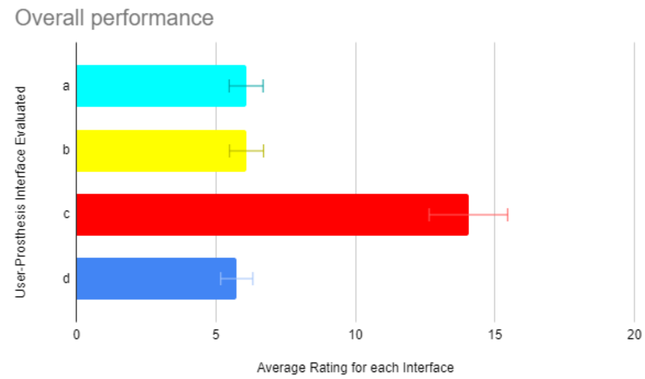

Fig. 10: Overall performance of the different versions. (a) is the sEMG Pattern Recognition iteration; (b) is the one with the buttons; (c) uses the computer vision algorithms; and (d) is the interface utilizing a reduced contractions subset.

VI. CONCLUSIONS

The UPI is an important aspect when selecting an assistive device, since it directly affects the interaction process with the prosthesis. For this reason, it is relevant to note if certain aspects tend to be favored or opposed when creating an interface. This study showed a tendency heavily tied between the execution time of the actions and its subjective evaluation, as shown by the poor reception of the version in Section II-B and the extensive operation time required to use the prosthetic device. This may reside in the process of taking a picture to select a grasp taking too much time, which became tedious to the users, evoking frustration and demanding more effort to achieve their goals. Plus, the users require the use of a healthy hand to operate the external device with the app, needing certain physical prowess not possessed by all patients, especially by bilateral amputees.

Furthermore, regarding the results in Fig. 9, the superiority of the interface in Section II-C lies in the swift selection of actions. This is because of the lack of a menu to interact with, therefore the physical demand is reduced and, hence, the effort required is also less. In contrast, the elevated mental demand and frustration for this rendition are caused by the need to memorize the actions mapped to the Myo poses, which does not come easily to the patients. However, this shows that a visual menu is not really necessary for the interface to be user-friendly, which may lead to a more simple, yet affordable alternative. Moreover, the lack of frustration for the iteration shown in Section II-A may be result of the sporadic inexactitude of the Myo classification process. Since this interface provides an alternative to navigate along the menu, the Myo is not strictly required to select an action, providing a fulfilling alternative.

Furthermore, the mental exertion needed to operate the interface proposed in this work, in Section III, results in the lowest, as the user does not have to memorize the mapping of the actions, nor need they ponder over the use of the buttons. Besides, the contractions subset is limited, so, by reducing the choices, this demand is also reduced. Additionally, the performance for this version showed to be the best along the interfaces. This may be caused by the larger gamut of actions at the patient's disposal and the accuracy of the poses used to return the prosthetic hand to its initial state.

On the other hand, an aspect noted after performing these trials was that a multimodal approach using mechanical input in addition to the wireless one did not result in a relevant improvement. The same conclusion applies to implementing a system using an extended contractions subset. This demonstrates that a more affordable and simple UPI evokes a similar interface to the user, but, by reducing the contractions subset, one can restrict the operation mode to fit each individual amputee's unique necessities. This prompts in permitting the user to employ the prosthesis even if they are unable (or unwilling) to complete certain of the Myo's poses. Furthermore, since the version elaborated for this project showed similar results to the one using sEMG Pattern Recognition, it is convenient to provide the patient with a larger gamut of actions to provide a more customized and practical prosthetic device.

The results gathered during this investigation shed a light on how some common approaches to interacting with upper-limb prostheses impact the amiability of the interface. This helps to find alternatives to ameliorating the price and the performance of these assistive devices, either by reducing the physical effort required to operate them, providing alternatives to do so or by reducing the complexity of the interaction process altogether.

REFERENCES

[1] E. Moutopoulou, G. A. Bertos, A. Mablekos-Alexiou, and E. G. Papadopoulos, "Feasibility of a biomechatronic EPP Upper Limb Prosthesis Controller," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2015, pp. 2454–2457.

[2] C. Miozzi, S. Guido, G. Saggio, E. Gruppioni, and G. Marrocco, "Feasibility of an rfid-based transcutaneous wireless communication for the control of upper-limb myoelectric prosthesis," 2018.

[3] A. Stango, K. Y. Yazdandoost, and D. Farina, "Wireless radio channel for intramuscular electrode implants in the control of upper limb prostheses," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2015, pp. 4085–4088.

[4] G. Hotson, D. P. McMullen, M. S. Fifer, M. S. Johannes, K. D. Katyal, M. P. Para, R. Armiger, W. S. Anderson, N. V. Thakor, B. A. Wester *et al.*, "Individual finger control of a modular prosthetic limb using high-density electrocorticography in a human subject," *Journal of neural engineering*, vol. 13, no. 2, p. 026017, 2016.

[5] W. T. Navaraj, H. Heidari, A. Polishchuk, D. Shakthivel, D. Bhatia, and R. Dahiya, "Upper limb prosthetic control using toe gesture sensors," in *2015 IEEE SENSORS*. IEEE, 2015, pp. 1–4.

[6] D. Johansen, C. Cipriani, D. B. Popović, and L. N. Struijk, "Control of a robotic hand using a tongue control systema prosthesis application," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 7, pp. 1368–1376, 2016.

[7] W. Guo, X. Sheng, H. Liu, and X. Zhu, "Mechanomyography assisted myoeletric sensing for upper-extremity prostheses: a hybrid approach," *IEEE Sensors Journal*, vol. 17, no. 10, pp. 3100–3108, 2017.

[8] M. S. Trachtenberg, G. Singhal, R. Kaliki, R. J. Smith, and N. V. Thakor, "Radio frequency identificationan innovative solution to guide dexterous prosthetic hands," in *Engineering in Medicine and Biology Society, EMBC, 2011 annual international conference of the IEEE*. IEEE, 2011, pp. 3511–3514.

[9] A. Fougner, Ø. Stavdahl, P. J. Kyberd, Y. G. Losier, P. Parker *et al.*, "Control of upper limb prostheses: terminology and proportional myoelectric control a review," *Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 5, pp. 663–677, 2012.

[10] A. Fougner, E. Scheme, A. D. Chan, K. Englehart, and Ø. Stavdahl, "Resolving the limb position effect in myoelectric pattern recognition," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 19, no. 6, pp. 644–651, 2011.

[11] J. Fajardo, A. Lemus, and E. Rohmer, "Galileo bionic hand: sEMG activated approaches for a multifunction upper-limb prosthetic," in *2015 IEEE Thirty Fifth Central American and Panama Convention (CONCAPAN XXXV)*. IEEE, 2015, pp. 1–6.

[12] G. Ghazaei, A. Alameer, P. Degenaar, G. Morgan, and K. Nazarpour, "Deep learning-based artificial vision for grasp classification in myoelectric hands," *Journal of neural engineering*, vol. 14, no. 3, p. 036025, 2017.

[13] N. Bu, Y. Bandou, O. Fukuda, H. Okumura, and K. Arai, "A semi-automatic control method for myoelectric prosthetic hand based on image information of objects," in *Intelligent Informatics and Biomedical Sciences (ICIIBMS), 2017 International Conference on*. IEEE, 2017, pp. 23–28.

[14] J. Fajardo, V. Ferman, A. Muñoz, D. Andrade, A. R. Neto, and E. Rohmer, "User-Prosthesis Interface for Upper Limb Prosthesis Based on Object Classification," in *2018 Latin American Robotic Symposium, 2018 Brazilian Symposium on Robotics (SBR) and 2018 Workshop on Robotics in Education (WRE)*. IEEE, 2018, pp. 390–395.

[15] M. Cognolato, M. Atzori, D. Faccio, C. Tiengo, F. Bassette, R. Gassert, and H. Muller, "Hand gesture classification in transradial amputees using the myo armband classifier* this work was partially supported by the swiss national science foundation sinergia project# 410160837 meganepro." in *2018 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob)*. IEEE, 2018, pp. 156–161.

[16] A. Phinyomark, R. N Khushaba, and E. Scheme, "Feature extraction and selection for myoelectric control based on wearable emg sensors," *Sensors*, vol. 18, no. 5, p. 1615, 2018.

[17] P. Visconti, F. Gaetani, G. Zappatore, and P. Primiceri, "Technical features and functionalities of myo armband: an overview on related literature and advanced applications of myoelectric armbands mainly focused on arm prostheses," *Int. J. Smart Sens. Intell. Syst*, vol. 11, no. 1, pp. 1–25, 2018.

[18] J. Fajardo, V. Ferman, A. Lemus, and E. Rohmer, "An affordable open-source multifunctional upper-limb prosthesis with intrinsic actuation," in *2017 IEEE Workshop on Advanced Robotics and its Social Impacts (ARSO)*. IEEE, 2017, pp. 1–6.

[19] F. Ryser, T. Bützer, J. P. Held, O. Lambercy, and R. Gassert, "Fully embedded myoelectric control for a wearable robotic hand orthosis," in *2017 International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 2017, pp. 615–621.

[20] D. Andrade, A. R. Neto, and E. Rohmer, "Human prosthetic interaction: Integration of several techniques," *Simpsio Brasileiro de Automao Inteligente*, 2017.

[21] S. G. Hart, "NASA-task load index (NASA-TLX); 20 years later," in *Proceedings of the human factors and ergonomics society annual meeting*, vol. 50, no. 9. Sage publications Sage CA: Los Angeles, CA, 2006, pp. 904–908.

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