Development of an advanced control module for context-aware upper-limb prostheses

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***Abstract*—Nowadays, upper-limb prostheses have reached an extraordinary level of sophistication. However, the limitations of the state-of-the-art myo-electric control algorithms are not capable to driving the large number of degrees of freedom (DOFs) that they present. The development of collaborative approaches, in which some of these DOFs are automated, is a trend in the last years. Yet, there are no evidences on how the combination of the control inputs has to be implemented in order to maximize the benefit of the users.**

With this study, we provide a sight into the effects that different control mixing schemes have on the time performance and the cognitive workload of their users, when performing reach-to-grasp tasks. To this aim, we have developed a semi-autonomous control system, a manual control system and three different control mixing schemes: a master-slave scheme and two simultaneous control approaches, namely, one in which the automation activates when there is manual control, and one independent of it.

We found that the simultaneous control, when the automation is independent of the user controlling any DOF, was the fastest option for all the participants, decreasing the task elapsed times up to 70% ($p<0.05$) when compared to manual control. Moreover, all the participants showed reductions in the cognitive workload of up to 82% respect to manual control ($p<0.05$). The master-slave scheme provided similar results. When the system required the participants to drive at least one DOF for the automation to happen, the automation did not provide benefit compared to manual control in terms of workload.

The differences shown across control mixing schemes, in the outcome measurements, demonstrate their implications require profound for the development of collaborative control systems.

***Index Terms*—control mixing, sensor data fusion, collaborative control, semi-autonomous control**

I. Introduction

Human hands play an essential role in the interaction with the environment. Their exceptional dexterity provides a wide range of possibilities regarding work, social and activities of daily living, to be performed with great ease . Therefore, their loss might have a dramatic effect on the individual's well-being [1].

To replace the missing function, myoelectric prostheses are the most widely chosen option (among active prostheses) [2]. These devices employ decoders that interpret acquired muscle signals in order to generate prosthesis control command. Even though their dexterity and technological sophistication keep developing over the years, one of four amputees that get the myoelectric hand replacement abandon it, and among those who maintain it, approximately one of three uses it only passively [5].

The literature indicates that beside physical features such as weight, comfort and appearance of the prosthesis [6] the transient effects of the input signals and the lack of intuitiveness of the state-of-the-art Human-Machine-Interfaces (HMIs) are the the main limiting factors for the acceptance of myoelectric prostheses [6] ,[7], [8].

The naure of HMIs' as limiting factors are well represented in the discrepancy between the state-of-the-art myoelectric control algorithms' capabilities and the potential offered by the most advanced devices in the field [2], [6], [7]: On the one hand, the state-of-the-art myoelectric control algorithms are capable of driving, in practice, a maximum of three degrees of freedom (DOFs) simultaneously [2]. On the counterpart, some of the state-of-the-art upper-limb prostheses exhibit outstanding dexterity offering more than 20 DOFs (i-Limb Ultra, from Touch Bionics) or the capability to perform up to 14 different grasping modes (BeBionic, from Ottobock).

Due to these limitations, the research community is shifting its effort towards developing systems that can assist the user of the prosthesis in the control of the overwhelmingly large number DOFs, by means of automation of some of them. There are two main trends to assist the user on adjusting the prosthesis DOFs: A first trend is constituted by the development of algorithms that predict user movements, based on the user's forearm muscles activity, in order to drive certain DOFs in a synergycally manner. A second trend is the development of multi-modal sensor-fusion algorithms that take advantage of the fusion of multi-modal inputs (e.g., computer vision, prosthesis feedback, inertial data, force and torque sensors) in order to provide to the system a certain level of awareness, from which it can generate control commands autonomously to support the user's task.

The interaction between both control schemes (autonomous and manual) is a paradigm that requires profound understanding. For instance, [14] proposed different control mixing approaches (in which the decisions of both control sources are fused) for an intelligent wheelchair. In this study, it was found that users who do not have access to a control plane (e.g. the device is completely autonomous) may suffer from frustration and anxiety. Similarly, if the user was restricted to only one of the control mixing options, it was less likely that the technology would be accepted. Noticeably, in situations of high cognitive load, even experienced users benefit from shared control [15]. Finally, in [16] it was shown that the performance of both systems associated was better than that of each individually, i.e., the influence of each part on each other translated into decreased task's elapsed times, respect to these situations in which these performed independently. Additionally, in the context of upper-limb prostheses, users prefer a certain degree of implication on the control, rather than being driven by a fully autonomous system [18]. Likewise, most studies propose to perform data fusion at the level of data acquisition, by means of machine learning algorithms, whereas few fuse control decisions from both agents to generate the command that drives the device [19].

Even though there is an existing trend in the literature of enhancing the control of complex prosthetic devices by means of collaborative approaches, the way in which such schemes should be developed must be explored. For upper-limb prostheses, there are multiple contributions that analyze the outcomes of such systems, e.g. [17], [18], [21], [22]. Yet, none provide insight on how the interaction must be carried out to maximize the user's benefit.

In the field of collaborative control approaches for upper-limb prostheses, the literature's focus is on the technical developments of these systems. Currently, there are multiple contributions that propose different ways to merge the control sources. In [10], [11], [12], the switching is based on the intention detection, i.e., it relies on identifying the intended action of the user to automate certain movements. In [17], the PACE system was proposed, which consists on a master-slave switching scheme. In this system, the device is driven by the manual control if control signals are generated, and it is driven autonomously otherwise. These publications focus on the autonomous -technical- implementations, and not on the control mixing strategy, even though this can presumably affect to the user's performance and cognitive workload. Furthermore, none of them analyzed the implications of their control mixing approach for the user (or any variations of it).

In this study, we evaluate the effect of different control mixing schemes on the subject's time performance and cognitive workload, during reach-to-grasp tasks. More specifically, we present three different control mixing approaches for the evaluation of the interaction between autonomous and a manual control schemes, in the context of upper-limb prostheses. These have been developed based on the literature, to cover the range of user's required level of participation in the control: a master-slave scheme and two simultaneous control approaches, namely, one in which the automation activates when there is manual control and one independent of it. To provide control signals to these schemes, both a manual and a semi-autonomous control system have been developed, according to their respective state-of-the-art approaches, yet based on ideal input data to circumvent the current drawbacks of such systems.

With the presented work, we seek to provide insight on how different levels of implication of the user (in the control) can affect the cognitive workload and the time performance, which aims to embark the research community into the understanding on the repercussion of these systems, beyond their technical implementation.

II. Methods

A. System overview

In order to analyze the effect that different control mixing schemes have on the performance and the cognitive workload of their users, a manual and a semi-autonomous control system have been developed, which comprise the base of the collaborative control system (Fig. 1). Remarkably, these have been developed according to the state-of-the-art, yet they have been implemented relying on ideal input data. This way, the technical effort which imply the development of collaborative control systems has been minimized to allow to place the focus on the effects of the different ways to mix their inputs. The systems were developed using Matlab 2019a (Mathworks, US), Simulink, Arduino Support from Simulink, the Real Time Windows Target (RTWT) toolbox, and the Closed Loop Control toolbox [24]. Implemented primarily in Simulink, it is built by connecting the different modules that constitute the control schemes. The system executes in real time by means of the RTWT.

The implementation is depicted in Fig. 1. The different modules connect to each other to constitute a prototype of a collaborative control system. This way, this generic approach can be modified to implement specific configurations (different control mixing approaches) in one-go.

B. Semi-Autonomous Control

The semi-autonomous control system (SA system) has been developed according to the state-of-the-art multi-modal sensor-fusion algorithms. Therefore, its input block provides the ideal artificial extereoception and proprioception information sources, from which it retrieves the contextual information, namely, the starting point of the movement, the targeted object and its position, and prosthesis tracking information. This is achieved by means of a motion capture system (MOCAP) (Qualysis, from Qualysis AB, Sweden), which sends the information to the control schemes by means of UDP communication, at 100Hz. Subsequently, this input module provides a stable and robust contextual information source.

Remarkably, to provide further stability to the data streaming by compensating for sudden -and short- tracking loses of the MOCAP system due to occlusion of the markers, the SA system integrates compensation of tracking failure by means of data extrapolation.

The semi-autonomous system is capable of driving three DOFs during the reach-to-grasp task using the input data, namely, wrist pronation/supination, wrist flexion/extension, and opening of the hand (the closing of it was reserved for the subject). Based on the contextual information, the system performs calculations of the three dimensional trajectory that the prosthesis (i.e., the user) is following, as well as an approximation of the distance until reaching the target, from which it determines the amount of movement that the subject will perform. Thence, the system is capable of identifying critical phases of the reach-to-grasp task (e.g., reaching phase).

Similarly, the speed at which the prosthesis is being moved by the user towards the target is computed, at a frequency of

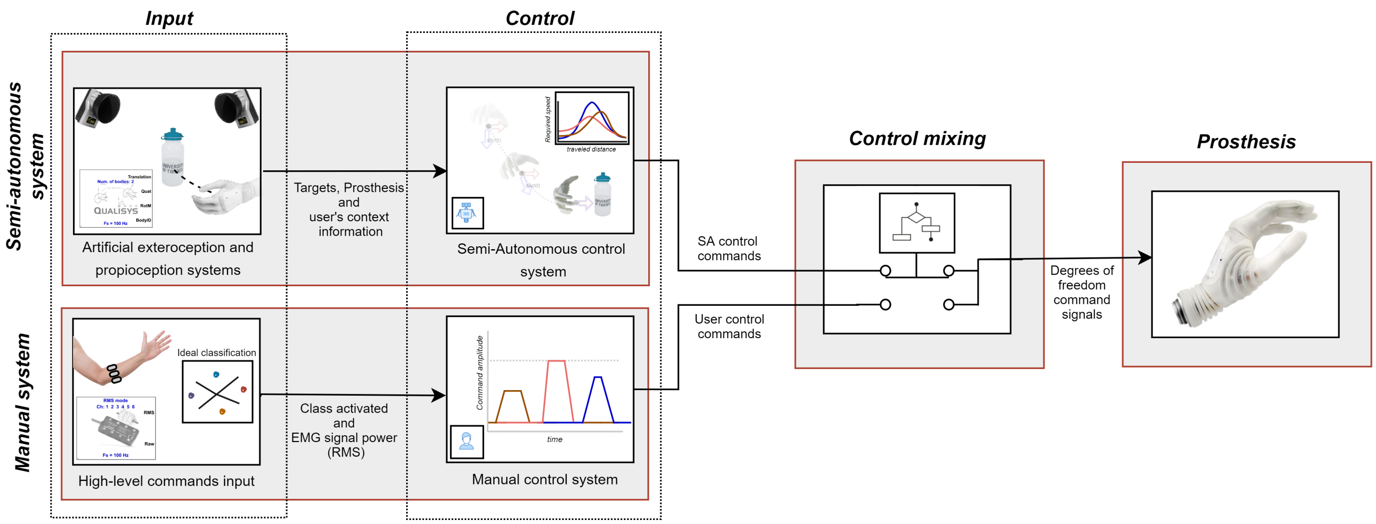


Fig. 1. The layout of the system, which allows configuring and testing collaborative control schemes for upper-limb prostheses. The semi-autonomous control system is capable to perform the prehsape (on the flight) during the reach phase, to provide automation of the desired DOFs during the task. These commands are calculated according to the input data retrieved from an ideal exteroception and propioception algorithms that provide context-awareness to the device. The manual system represents the interface between the prosthesis and the user. It is composed of an input module, in charge of providing the idealized high-level commands (perfect classification) from the user to the control algorithm to decipher them. The decision mixing module (center-right) includes the control mixing approach, in charge of mixing the control commands which are output by both control agents. Lastly, the prosthesis module (right) represents the prosthetic device and the sub-module in charge of translating high-level commands into low-level commands for the device.

25 Hz. After low-pass filtering it with a cut-off frequency of 3Hz, it is used to estimate the time remaining before reaching the target. In parallel, the required activations for each DOF (i.e., the difference between the current state of each DOF and their desired grasping configuration) are calculated. This configuration (restricted in mode to palmar grasp) depends on the targeted grasping side (left, right, front and top, respect to the user) and can be calibrated for each DOF, according to the user's preferences. Subsequently, based on this difference and the estimated time remaining, a required speed profile is generated for each of these DOFs, providing the speeds at which each of them should be driven throughout the reach phase. Therefore, the semi-autonomous system implements *adaptive speed capabilities*.

Finally, when the prosthesis has completed the reach phase and it is prepared to perform the grasping of the target, the SA compensates any further movements made by the user, in order to maintain the desired grasping configuration regardless any variation in his/her arm's position and/or orientatio.

C. Manual control

The manual control system has been developed to present a functioning principle which is analogous to the state-of-the-art pattern recognition, sequential, myoelectric control. In these algorithms, the myoelectric activity is classified in a set of classes that are later associated to control commands. For this, the presented control scheme includes a custom-made socket for able-body subjects, which integrates buttons on it to eradicate the prime inconveniences related to input signal

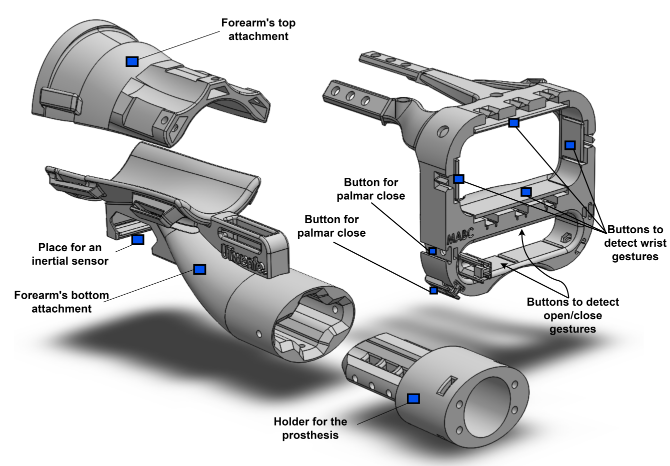


Fig. 2. Manual control system socket. The socket has embedded physical buttons which activate when the user performs certain gestures. These gestures have been selected to be morphologically consistent, e.g., when the user flexes the hand, the buttons which are then mapped to activate the flexion the prosthetic device are pressed. The mapping to the classes are customizable, and the activation depends on the power of the myoelectric signal, which also proportionality to the signal. The inertial sensor attachment (not used for the presented work) is aligned with the wrist rotation axis of the prosthesis. The holder for the prosthesis, shown in the image, allows three different positions to adjust the relative position of the prosthesis respect to the user. Likewise, the frame with embedded buttons allows adjustment with three positions. These three positions are calculated so, in the most proximal setup, a Michelangelo prosthetic device (Ottobock, Vienna) does not collide with the structure nor the hand.

features (EMG) [2]: non-stationary effects, tedious training/re-calibration sessions, need of big efforts to control more than two DOF, lack of consistency over time. . . .

This way, when the subjects perform gestures to activate the classes, their hand hit certain parts of the socket, activating certain switches and, therefore, providing the gesture that is being carried out. Thence, the buttons carry out the (idealized) function of the pattern recognition algorithm and provide the class activated. This way, the subjects do not suffer from the lack of robustness over time that characterize these algorithms when more than two DOFs are used.

Likewise, in the state-of-the-art pattern recognition, sequential myoelectric control, the power of the myoelectric signal is used to provide proportionality to the commands [3]. The developed control includes eight surface electrodes (Ottobock AC, Ottobock, Vienna) which provide the EMG signals of the forearm's muscles to the system, to calculate the Root-Mean-Square of the signal. With this information, the manual system seeks to (1) provide proportionality to the activated class, and (2) remove the "Joystick effect" from this control scheme, i.e., that the subjects press buttons to activate classes with no effort employed.

Ultimately, these features make that the manual control system's behavior adheres to its equivalent in the literature, yet avoiding the technical and performance drawbacks that these systems still present.

D. Control Mixing schemes

Three different control mixing schemes were developed. These cover different levels of required user's implication on the control of the prosthesis, implementing its functioning principle based on the state-of-the-art approaches (Fig 3).

On the one hand, similarly to the master-slave approach proposed in [17], a *Sequential* mixing scheme alternates between the manual and the SA systems as control input source; by default, the SA system has control of all the DOFs of the prosthesis, as long as there are not manual control signals. When the manual control generates commands, it drives the correspondent DOF, and the SA system is turned off until the manual control is idle again. While the prosthesis is being controlled by the SA system, the user has fundamental influence on it, as the SA system generates commands only while the prosthesis is being moved towards the target.

On the other hand, in accordance with the simultaneous control based on user intention detection proposed in [11], [12] and [13], two different levels of simultaneity (parallel control) have been developed, namely, the *Myo-Triggered Parallel* and *Continuous Parallel* mixing schemes.

Firstly, in the *Myo-triggered Parallel* scheme, the prosthesis is controlled simultaneously by the manual and the SA systems, only while the manual control is active. When this condition is fulfilled (e.g., the user is generating a command), the manual control system drives the correspondent DOF, while the rest are driven, in parallel, by the SA system. Hence, this approach presents a way of shared control between both, which occurs only while the user is actively controlling the prosthesis. The user has, thus, both indirect (movement condition) and direct (a command is being generated) influence on the ability of the SA to control the prosthesis.

Secondly, a *Continuous Parallel* mix makes the prosthesis to be controlled either by the SA system uniquely, or in a shared manner between both controls. Therefore, when the user generates a control signal, the correspondent DOF's control is switched to it, until the activation concludes.

Finally, as a common feature for all the Control mixing schemes, the switching process from one control source to another implemented temporal restrictions (switching thresholds). This way, when the manual control system ceased completely its activity, it had to remain like within time window (defined by the threshold), before switching to the SA system as driving scheme. This feature is necessary due to the fact that the manual control commands do not overlap in time (as it follows the state-of-the-art sequential, pattern recognition myocontrol approach). Therefore, when the user performs a sequence of movements, there are time windows with no commands in between them, as the user needs to relocate the hand to generate the next gesture. Thus, the implemented threshold copes with the *source bouncing effect* that the nature of the sequential control input might introduce.

III. Experimental Evaluation

To evaluate how different decision mixing schemes affect the performance and the cognitive workload, an experiment was conducted using the presented system. To this aim, two tasks had to be performed, namely, tracking a sound occurrence (primary task), and a reach-to-grasp task (secondary task).

A. Primary task

The primary task consisted on tracking monotonic sounds which played with fixed duration of 0.25 seconds. The user was asked to press -and release- a button as fast as possible, at each sound occurrence. Subsequently, the reaction time and the number of sound tracking failures could be analyzed, to compare the cognitive workload across conditions.

The frequency at which the sound occurred was arbitrary. This randomization was generated by means of a uniformly distributed random signal, generated in real time, yet ensuring that there is no repeatability across trials. The range of such distribution, which lastly represented the pause length between sounds, was from 0.8 to 1.7 seconds. Therefore, the arbitrary nature of the sound occurrence was set by the randomization of the pause length between consecutive sounds.

Remarkably, a sound occurrence was determined as 'failed' when there was either no button hit, or more than one hit within the *valid tracking window*. This temporal window was defined as an interval starting 140 milliseconds after the sound occurrence, and lasting for 660 milliseconds. The lower limit of the valid range is motivated by minimum reaction time that a human being can present after an auditory stimulus, which is 140 milliseconds [26]. The upper limit of the range, by the signal frequency of the sound occurrence, as after

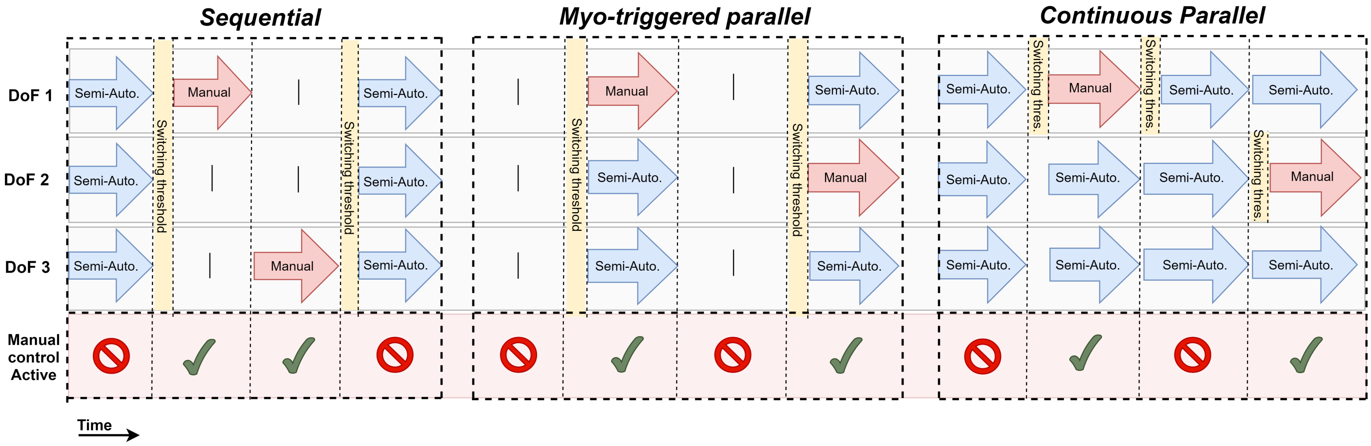


Fig. 3. The Control Mixing schemes for the incoming commands from the manual and the SA control systems. Firstly, The *Sequential* control mix (right) prioritizes the control inputs from the manual system (*Manual*). If these are non-existent, it allows the SA to control all the DOFs. The *Myo-triggered parallel* mix allows shared control of the prosthesis by both control systems, given that there are manual commands active. The DOFs that are not being controlled by the manual system are controlled by the semi-autonomous one. The *Continuous Parallell* mix (right) allows the SA system to have control of all the DOFs while there is no manual command. When the user generates it, the correspondent DOF is controlled by the manual system, while the SA has control on the unused DOFs. Remarkably, every time at which the control source changes for any DOF, a temporal threshold *Switching threshold* avoids possible bouncing effects in the input source selection.

800 milliseconds it would be possible that the next sound occurrence would happen.

Additionally, since the accuracy of the time measurement was critical for these outcome measurements, the computer's sound card output was attached to the speakers and to a data acquisition card (National Instruments PCI-6221, from National Instruments, US). The button activation was also measured with this device. Therefore, the effect of possible discrepancies between the time at which a sound was launched by the algorithm, and the time at which such sound would actually play on the speakers, was avoided.

Lastly, it is important to remark that there are two main reasons for the sound occurrence tracking task to be defined as the *primary* task. Firstly, the reach-to-grasp task proposed, would last just a few seconds. Therefore, launching the tracking of the sound occurrence in a interval so short could (undesirably) make it to be perceived as an startling event. Secondly, this way, it allows to compare, within each trial, the baseline for the subject's workload (during the time in which the subject uniquely performs the primary task) and the later effect of the secondary task. Therefore, such baseline is representative of the subject *throughout* the session.

B. Secondary task

As part of the secondary task, the subjects were asked to grasp an object, given specific instructions, and re-place it on another (predefined) position on the table. Then, the time performance (i.e., the time to reach and grasp the object as instructed) was assessed.

There were two different objects: a box (85x65x135 mm) and a cylinder (60x60x160mm). Additionally, there were three different positions on which the objects could be placed, being one empty and two occupied by the objects at each time. The targeted object and the grasping side were randomly selected, yet ensuring consistency in the number of repetitions of each of the variants. Subsequently, on each trial, the subjects had to move the prosthesis from the starting position, which was predefined, towards the instructed targeted object. Once reached, the participants had to grasp it from instructed side (right, left, front or top), and relocate it on the empty position on the table. After releasing the object, the subjects had to move the prosthesis back to the starting position before advancing to the next trial.

C. Experimental setup

Three subjects performed the four sessions on the experimental setup shown in Fig. 4. On each of these, five experimental conditions were evaluated, namely, manual control (MAN), Sequential control (SEQ), Myo-triggered parallel control (MTRIG), Continuous parallel control (CONT) and sound tracking task (Baseline).

The subjects accomplished sixteen trials for each of the experimental conditions, as they performed two times each combination of grasping side (four in total) and target (two in total). On each of the trials, the participants were in front of the table, on which there were two objects and the three possible positions for them (Fig. 4). A screen, placed in front of the user, displayed the instructions (target and grasping side), as well as the flag to initiate each of the parts of the trial, namely, the primary task uniquely (first ten seconds), and the period with both tasks in parallel (after the first ten seconds, until the relocation of the target).

D. Statistical analysis

The data collected during the experimentation sessions were processed to assess these measurements based on the period corresponding to the reach phase (i.e., from the initiation of the movement towards the target, until the grasping of it), for

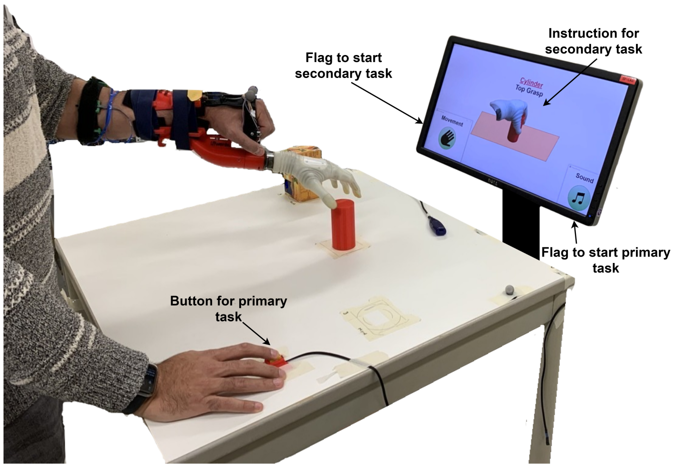


Fig. 4. Experimental setup. The subject stands in front of a table with three possible positions for objects. Two objects occupy two of these, at all times. The subject, using the custom-developed manual control socket for able-body subjects, is performing the secondary task, whose instructions are displayed on the screen. Two flags are displayed to provide information on when to start the primary and the secondary tasks.. Additionally, the subject presses the button with the index finger of his right hand on each sound occurrence (primary task).

each trial. If the participant started the preshape at the starting position, even without displacement, the time would initiate as well.

As for the time performance, it was calculated for each trial and condition. In order to test how the different control mixing approaches affect the time that the subjects required to complete the task, the results of each participant, under each of the conditions, were firstly subjected to a Wilcoxon rank sum test [25]. Subsequently, Bonferroni–Holm correction [24] was applied to each of the subjects.

Additionally, the cognitive workload analysis was performed by evaluating the number of *missed sounds* (i.e., the sound occurrence tracking failures). For each participant, the missed sounds were divided according to the condition under which they happened. Lastly, to subsequently evaluate if there are significant differences in the number of missed sounds of each condition for each participant, Wilcoxon rank sum tests were applied. Aftwerwards, the Bonferroni–Holm correction was applied to its results.

The analyses were carried out using Matlab 2019a (Mathworks, US).

IV. Results

A. Results of time performance

The results of the time performance for each subject on each of the conditions are shown in Fig. 5.

For all the participants in this study, CONT incurred a decrease of the median time of 47.37%, 42.86% and 69.23% (for the subjects 1, 2 and 3), with respect to MAN. These time performance improvements were significantly different for all the subjects ($p<0.05$).

Additionally, for the subjects 2 and 3, SEQ and MAN also provided significant difference ($p<0.05$), with SEQ presenting median time reductions of 47.86% and 65.49%, respectively.

Moreover, MTRIG and MAN did not show significance in their difference for two of the participants (subjects 1,2). For subject 3, MTRIG presented a significant reduction of 60.00% in the median time, respect to MAN. Lastly, the difference between SEQ and CONT was significant only for subject 1 ($p<0.05$). The CONT (the fastest for this subject) presented a median time a 28.13% below the median time for SEQ (the second fastest).

B. Results of cognitive workload

The results of the number of missed sounds for each subject, in each of the conditions, are shown in Fig. 6. The participants presented significant differences between their Baseline and MAN ($p<0.05$). For all of them, the median number of missed sounds for MAN increased by a 35.41%, 50.00% and 41.42% with respect to their Baseline. The difference between the Baseline and the MTRIG is also significant for all the participants ($p<0.05$), with increased median number of missed sounds of 28.57%, 50.00% and 20.83%.

Subject 2 presented a significant increase of the median number of failures for SEQ, respect to the Baseline ($p<0.05$), with an increase of 14.28%. Subjects 1 and 3 did not show significant difference between their number of failures for SEQ and their Baseline.

All the participants showed significant difference between MAN and SEQ ($p<0.05$). The SEQ condition incurred in reductions of 54.3%, 74.44% and 82.76% in the number of sound tracking misses, with respect to these for MAN. Lastly, none of the participants presented significant differences in their results for CONT and SEQ.

V. Discussion

In this study, an insight into how different ways of mixing control inputs from a SA system and a manual system has been explored, to assess the effects on the time performance and the workload of the users. The results retrieved, however, need to be further confirmed in studies involving bigger populations.

The results shown suggest that certain level of automation in the control makes the overall task faster and less cognitive demanding, as already claimed in the literature. Additionally, regarding the level of automation provided by a SA system, our results show no differences between the master-slave scheme (SEQ), and the simultaneous scheme in which the automation does not depend on the manual control (CONT). Even though the participants were not necessarily biased towards the SA control or the manual control due to their performance (as both presented ideal input data), they might have been biased in the sense of knowing that the SA control system was perfect regarding the calculation of the commands. This implies that the SA scheme could perform the same task repeatedly and accurately, with no errors. Therefore, the scenario in which the subjects had to intervene in the control because the prosthesis was not behaving as they expected was nonexistent. This fact

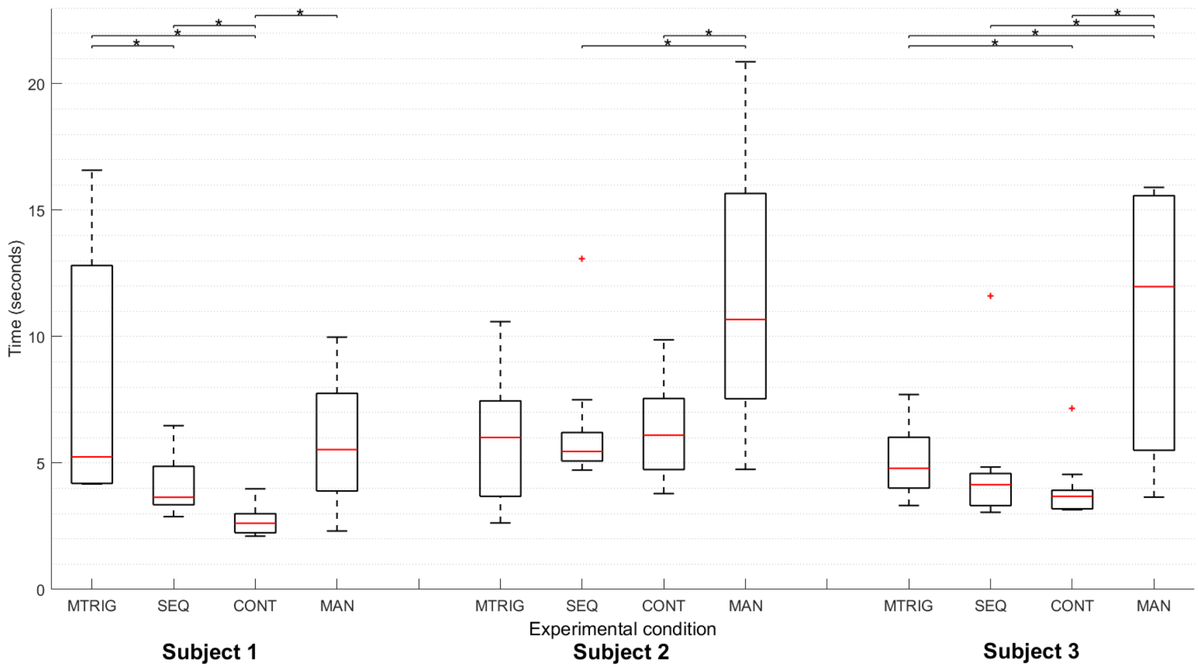


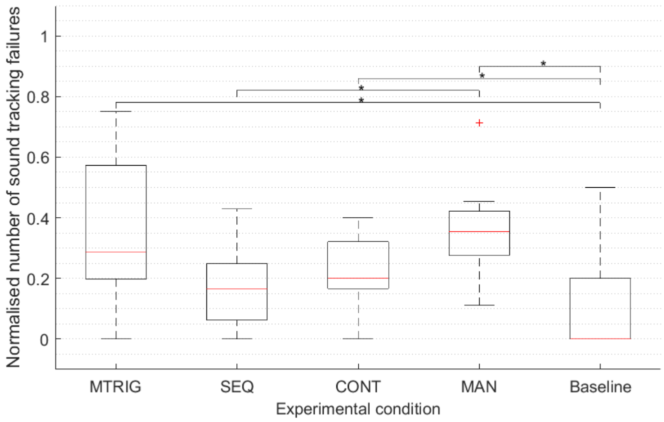
Fig. 5. Results of time performance of the three subjects for each condition (MTRIG: Myo-triggered Parallel mix, SEQ: Sequential mix, CONT: Continuous Parallel mix, MAN: Manual control, Baseline: primary task only). The data shown correspond to the time required by the participants to initiate the movement towards the target and grasp it, including appropriate prehsape of the prosthesis. A box represents the data for each condition, with the central mark the median, and the upper and lower edges of the box the 75th and 25th percentiles, respectively. The whiskers represent the extreme data points, and the plus signs the outliers. The indications of the asterisks correspond to these conditions which present significant difference with $p<0.05$.

could explain the lack of difference between the Sequential and the Continuous Parallel mix schemes in two of the three participants; if the SA would have been imperfect in its behaviour, it could have had generated decisions that deviate from the expectation. Then, the participants would have been forced to decide whether to correct them or to adapt to these. In such situation, the Sequential scheme would represent a trade-off between and increased effort (generating manual commands and also losing the automation of the other DOFs) and the amount of compensatory movements. In that case, it is likely that the discrepancies of different levels of automation would appear, as the Continuous Parallel scheme does not present such trade-off.

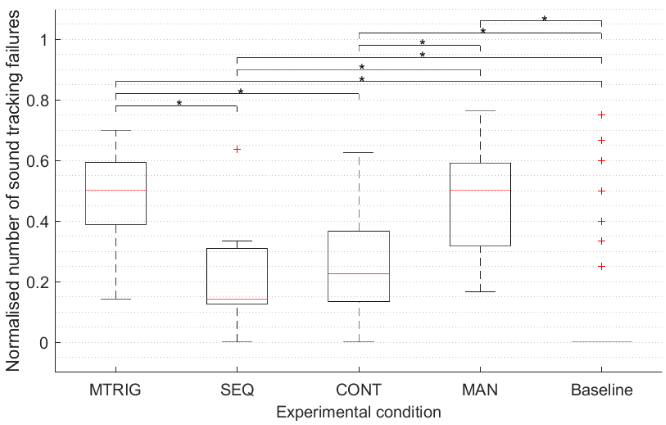
In addition, the necessity to actively enable SA control (MTRIG) did not show differences respect to the manual control (MAN) for two of the three participants. Moreover, this mixing scheme presented increases in the workload for all participants, with increments of between 20% and 50% of sound tracking failures, respect to their baselines. This indicates that they were not being benefit from the support provided by the SA system during the task, for this condition. This fact suggests that for the subjects it was not convenient that the SA system depended on their command generation to fulfill its functions. The literature suggests that the prosthesis users prefer to have control on when the autonomous decisions take place. Our results suggest that, moreover, it should not be required to be a continuous requirement. Therefore, the collaborative systems should integrate triggers to activate or deactivate the SA control rather than control signals that require to be active during the whole functioning of the device.

For all the subjects, the manual control (MAN) required the longest times to complete the task and it represented the condition with major cognitive workload. The manual control was the control condition which required more intervention by the participants (as the prosthesis was dirven uniquely by them). The fact that they had to perform the whole control sequence without support justify such results.

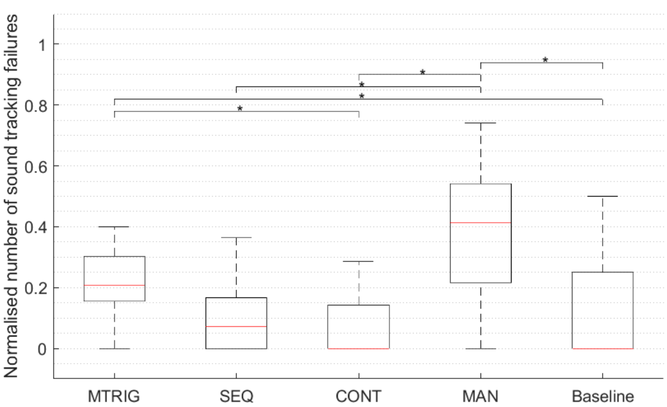
Similarly, our positive results with the mixing scheme that does not require direct control nor activation from the user (CONT) does not necessarily imply that the participants actually preferred a fully autonomous system. The SA system presented here featured adaptive speed of the DOFs, which required movement of the prosthesis towards the target in order to generate its commands. Therefore, the system integrated an indirect control condition (the movement of the prosthesis). Further research is needed to evaluate if the users preference of having access to the control plane is because they want to actively drive the prosthesis, or rather because this way it is ensured that they have access to it if the device does not perform as expected. These statements suggest that the collaborative control systems would benefit from *indirect* manners to activate the autonomous functions. The addition of eye-tracking devices for detection of the user intention could be a way for them to generate control flags that activate or deactivate the autonomous system in manners that do not require interaction with the control plane (e.g., blinking



(a) Results for subject 1.



(b) Results for subject 2.



(c) Results for subject 3.

Fig. 6. Results of the number of sound tracking failures for each of the conditions (MTRIG: Myo-triggered Parallel mix, SEQ: Sequential mix, CONT: Continuous Parallel mix, MAN: Manual control, Baseline: results of primary task alone). The results are normalized over the number of total sound occurrences within each condition. A box represents the data for each condition, with the central mark the median, and the upper and lower edges of the box the 75th and 25th percentiles, respectively. The whiskers represent the extreme data points, and the plus signs the outliers. The indications of the asterisks correspond to these conditions which present significant difference with $p<0.05$.

patterns to activate/deactivate the SA system).

Moreover, it is evident that the trends shown on the data are greatly influenced by the implementations of the control schemes. The SA system presented here relies on data streamed from a MOCAP setup. The robustness and accuracy is much superior to the devices used in the literature, where the context information is retrieved from mobile setups. The evaluation of the effect of such idealizations on the results can be carried out by introducing disturbances in a controlled manner.

Additionally, for the manual control, its functioning principle (idealized classification) has allowed to control the drawbacks of the transient effects of the EMG signals as control inputs. The addition of disturbances over time on this system could place it even closer to the its analogous from the state-of-the-art, and could lead the presented manual control system to be a modelled version of it, which allows to control variables that are not controllable otherwise, like the consequences of the transient effects of the EMG signals.

VI. Conclusion

In this study, we present how different ways of mixing control inputs from manual and semi-autonomous systems affect the cognitive workload and the time performance of users carrying out reach-to-grasp tasks.

An innovative implementation of a semi-autonomous system and a manual control system has been carried out, by relying on ideal input data, to circumvent the drawbacks that their analogous state-of-the-art implementations. This way, we have presented an scenario in which the participants were not biased towards the best (working) control scheme, but rather by their own preference on the control approach.

According to our results, the control mixing schemes in which the automation does not have to be activated by the user resulted on the best time performances and the lowest levels of cognitive workload with a probability of $p<0.05$. We did not observe significant differences between the two levels of simultaneous control (CONT and SEQ) for the majority of participants. The hypothesis of that such differences did not emerge as a result of the idealization of the control systems requires further research.

Lastly, the results indicate that a collaborative system in which the SA commands are only generated when the user is accessing to the control plane as well does eliminate the benefits of the automation regarding time performance and cognitive workload.

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References

[1] T. Feix, J. Romero, H. B. Schmiedmayer, A. M. Dollar, and D. Kragic, "The GRASP Taxonomy of Human Grasp Types," IEEE Trans. Human-Machine Syst., vol. 46, no. 1, 2016.

[2] Igual, Carles, Luis A. Pardo, Janne M. Hahne, and Jorge M. Igual. "Myoelectric Control for Upper Limb Prostheses." Electronics 8, no. 11 , 2019.

[3] A. Fougner, O. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. A. Parker, "Control of upper limb prostheses: Terminology and proportional myoelectric control: a review," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 20, no. 5, pp. 663–677, 2012.

[4] "i-Limb Ultra, Touch Bionics Inc." [Online]. Available: http://touchbionics.com/products/activeprostheses/i-limb-ultra.

[5] E. A. Biddiss and T. T. Chau, "Upper limb prosthesis use and abandonment: a survey of the last 25 years.," Prosthet. Orthot. Int., vol. 31, no. 3, pp. 236–257, 2007.

[6] F. Cordella et al., "Literature review on needs of upper limb prosthesis users," Front. Neurosci.,vol. 10, no. MAY, pp. 1–14, 2016

[7] D. Farina and S. Amsüss, "Reflections On The Present And Future Of Upper Limb Prostheses," Expert Rev. Med. Devices, vol. 4440, no. May, p. 17434440.2016.1159511, Apr.2016.

[8] T. R. D. Scott and M. Haugland, "Command and control interfaces for advanced neuroprosthetic applications," in Neuromodulation, 2001, vol. 4, no. 4, pp. 165–174.

[9] N. Jiang, S. Dosen, K. R. Muller, and D. Farina, "Myoelectric Control of Artificial Limbs: Is There a Need to Change Focus? [In the Spotlight]," IEEE Signal Process. Mag., vol. 29, no. 5, pp. 150–152, 2012

[10] Gandolla, Marta, et al. "Artificial Neural Network EMG Classifier for Functional Hand Grasp Movements Prediction." Journal of International Medical Research, vol. 45, no. 6, Dec. 2017, pp. 1831–1847, doi:10.1177/0300060516656689.

[11] M. V. Liarokapis, P. K. Artemiadis, K. J. Kyriakopoulos and E. S. Manolakos, "A Learning Scheme for Reach to Grasp Movements: On EMG-Based Interfaces Using Task Specific Motion Decoding Models," in IEEE Journal of Biomedical and Health Informatics, vol. 17, no. 5, pp. 915-921, Sept. 2013.doi: 10.1109/JBHI.2013.2259594

[12] P. M. Pilarski, T. B. Dick and R. S. Sutton, "Real-time prediction learning for the simultaneous actuation of multiple prosthetic joints," 2013 IEEE 13th International Conference on Rehabilitation Robotics (ICORR), Seattle, WA, 2013, pp. 1-8. doi: 10.1109/ICORR.2013.6650435

[13] D. Novak and R. Riener, "A survey of sensor fusion methods in wearable robotics," Rob. Auton. Syst., vol. 73, pp. 155–170, Sep. 2014.

[14] Viswanathan, Pooja et al. "A Wizard-of-Oz Intelligent Wheelchair Study with Cognitively-Impaired Older Adults : Attitudes toward User Control.", 2014.

[15] T. Carlson and Y. Demiris, "Collaborative control for a robotic wheelchair: Evaluation of performance, attention, and workload," IEEE Trans. Syst. Man, Cybern. Part B Cybern., vol. 42, no. 3, pp. 876–888, 2012.

[16] C. Urdiales et al., "A new multi-criteria optimization strategy for shared control in wheelchair assisted navigation," Auton. Robots, vol. 30, no. 2, pp. 179–197, Feb. 2011.

[17] M. Markovic, S. Dosen, D. Popovic, B. Graimann, and D. Farina, "Sensor fusion and computer vision for context-aware control of a multi degree-of-freedom prosthesis.," J. Neural Eng., vol.12, no. 6, p. 66022, 2015.

[18] C. Sherstan, J. Modayil, and P. M. Pilarski, "A Collaborative Approach to the Simultaneous Multi-joint Control of a Prosthetic Arm," IEEE Int. Conf. Rehabil. Robot., vol. 2015-Septe, pp. 13–18, 2015.

[19] Herrera-Luna, E. J. Rechy-Ramirez, H. V. Rios-Figueroa, and A. Marin-Hernandez, "Sensor Fusion Used in Applications for Hand Rehabilitation: A Systematic Review," IEEE Sens. J., vol. 19, no. 10, pp. 3581–3592, 2019.

[20] C. Cipriani, F. Zaccone, S. Micera, and M. C. Carrozza, "On the shared control of an EMG-controlled prosthetic hand: Analysis of user-prosthesis interaction," IEEE Trans. Robot., vol. 24, no. 1, pp. 170–184, 2008.

[21] S. Došen, C. Cipriani, M. Kostić, M. Controzzi, M. C. Carrozza, and D. B. Popovič, "Cognitive vision system for control of dexterous prosthetic hands: Experimental evaluation," J. Neuroeng. Rehabil., vol. 7, no. 1, p. 42, 2010

[22] M. Markovic, S. Dosen, C. Cipriani, D. Popovic, and D. Farina, "Stereovision and augmented reality for closed-loop control of grasping in hand prostheses," J.Neural Eng., vol. 11, no. 4, 2014

[23] S. Dosen, M. Markovic, C. Hartmann and D. Farina, "Sensory Feedback in Prosthetics: A Standardized Test Bench for Closed-Loop Control," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 23, no. 2, pp. 267-276, March 2015. doi: 10.1109/TNSRE.2014.2371238

[24] Holm, Sture. "A Simple Sequentially Rejective Multiple Test Procedure." Scandinavian Journal of Statistics 6, no. 2 (1979): 65-70

[25] Wilcoxon, Frank. "Individual Comparisons by Ranking Methods." Biometrics Bulletin 1, no. 6 (1945): 80-83. doi:10.2307/3001968.

[26] Thompson PD, Colebatch JG, Brown P, Rothwell JC, Day BL, Obeso JA, et al. Voluntary stimulus-sensitive jerks and jumps mimicking myoclonus or pathological startle syndromes. Mov Disord. 1992;7:257–62