EMG-driven bilateral therapy for hand rehabilitation: Evaluation of the influence of an EMG-based visual biofeedback on the users' performance

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Abstract

Background: The development of rehabilitation robotic systems has experienced significant growth in recent years. Electromyography (EMG) is commonly used to drive this kind of robots. Although there are some studies that have assessed the effectiveness of EMG biofeedback in neurorehabilitation, none of them has applied this technique in combination with robotic platforms.

Objectives: Our goal was to evaluate the influence of EMG biofeedback on the user performance, when individuals were asked to perform different hand gestures (open, rest and close) using an EMG-driven robotic hand exoskeleton rehabilitation platform.

Methods: A total of 18 healthy subjects were enrolled in the study. The subjects were asked to perform 1-minute randomly generated sequences of hand gestures in four different conditions resulting from the combination of using or not (1) EMG-based visual biofeedback (2) kinesthetic feedback from the exoskeleton movement

Results: The subject performance was statistical significantly better when the EMG-based visual feedback was present, while kinesthetic feedback did not improve their performance. The performance when both sources of feedback were present did not resulted in any enhancement, indicating that the kinesthetic feedback overrides the effect of the electromyographic one.

Conclusion: The EMG-based visual feedback enables subjects to increase their control over the movement of the robotic platform by assessing their muscle activation in real-time. This type of feedback could benefit the patients in learning faster how to co-activate the motions of the rehabilitation robot, which may increase their motivation.

Background

The incidence of stroke is growing because of the ageing population. Although the stroke mortality has been reduced, the increase of stroke survivals results in a raising number of adults with disabilities, and therefore, the demand of stroke rehabilitation services is also growing [1]. This aspect has elicited considerable scientific interest in motor recovery using rehabilitation robotic systems.

A major challenge in developing rehabilitation robotic systems is to enable a natural human-robot interaction (HRI). The selected strategy for intention detection is crucial for a transparent and friendly HRI. Some rehabilitation robotic platforms use bio-signals as an intention recognition source. Electromyographic signals are the most used since they are closed related to the human motion [2]–[4]: they represent the electrical activity produced by the skeletal muscles responsible for performing the intended gestures and actions [5]–[13]. Several studies have reported the influence of the learning effect on the user performance after repeated used of the intention detection strategy implemented in the robotic platform [14]. Hence, providing some feedback about EMG activity may help the user to learn

faster how to control the device because it could improve the user's motor control. This way, the user's learning time may be shorter and consequently, their motivation may be enhanced.

The biofeedback approach was introduced more than forty years ago in rehabilitation settings [15]. It consists of providing the user with information about their physiological activity in real-time that would otherwise be unknown. EMG biofeedback is the most widely method of biofeedback and it is usually provided to the user by visual or auditory signals [16], [17]. Although EMG biofeedback techniques appear promising there is limited and contradictory evidence about its effectiveness in musculoskeletal and neurological rehabilitation [16]–[18]. However, studies that have tried to assess the effectiveness of EMG biofeedback did not used this technique in combination with robotic rehabilitation platforms [19]–[40].

For this reason, we aim to evaluate whether the inclusion of EMG biofeedback enable users to gain control over the movement of EMG-driven robotic rehabilitation platforms by better assessing their EMG responses and therefore, to learn self-control of these responses. For this assessment we used RobHand, an EMG-driven robotic hand exoskeleton for neuromotor rehabilitation. The EMG was visually fed back to the user. Furthermore, the EMG-based visual biofeedback was designed specifically for this study with the aim of being as simple as possible using a visualization based on two variable length bars and two colors. Its effectiveness was investigated by comparing the user performance. Furthermore, we investigated whether the kinesthetic feedback from the own exoskeleton movement also induces an enhancement over the robot control.

Methods

Participants

A study has been conducted with 18 subjects, all legal age (mean age was 23 ± 3.4) and students of Valladolid University. All subjects were healthy, with no neurological or orthopedic impairment, and volunteered to participate in the study by providing written informed consent. None of the subjects had previously used EMG-driven robotic devices. The study was undertaken during the month of January of 2022, using the RobHand rehabilitation platform.

Robotic rehabilitation platform

The RobHand (Robot for Hand rehabilitation) robotic neurorehabilitation platform is based on a hand exoskeleton which allows performing EMG-driven bilateral therapies. The exoskeleton assists the hand fingers in the flexion and extension movements, and it is based in a direct-driven under-actuated serial four-bar linkage mechanism [41]. The bilateral therapies are carried out by recognizing the gesture of the healthy hand (open, rest or close) and replicating that gesture on the hand exoskeleton which is placed on the paretic hand. For this purpose, the electromyographical signals of the extensor digitorum (ED) and flexor digitorum (FDS) are recorded by a custom-made low-cost EMG acquisition system. The recorded EMG are processing in real-time in a microcontroller to detect the hand gesture. The EMG signals are recorded at a sampling rate of 200Hz, and notch-filtered at 50 Hz, high-filtered at 10 Hz, rectified by

calculating the root mean square (RMS) with a moving window (50 ms duration) and low-filtered at 2 Hz. The rectified signals are normalized with respect to the maximum voluntary contraction (MVC), which are determined in a previous calibration. The gesture recognition is threshold-based, and it depends on the normalized signals of the ED and FDS muscles and two EMG threshold calculated in previous calibration [42],[43].

Experimental protocol

The subjects were comfortably seated in a chair in front of a table, looking into a computer screen positioned approximately 50 cm away. The positions for the placement of the EMG electrodes were determined by palpating and visually observing muscle contractions in the dominant forearm. The hand exoskeleton is placed on the non-dominant hand (Fig. 1). The dominant arm was held in a self-selected comfortable position (e.g., on their leg or on the table). The principle of hand exoskeleton operation was explained, and EMG calibration procedure is performed before starting the experimental trial.

All subjects performed four experimental tasks. Each task has a duration of one minute and there was a 3-minute break between tasks to eliminate the effects of possible muscular fatigue. The four tasks were randomly performed to eliminate the possible learning order effect. The task consisted on performing and maintaining a hand gesture (rest, open and close) with the dominant hand following the sequence of gestures indicated by visual and sound information from a computer program. The gestures were randomly generated each three seconds.

In tasks A and B, the hand exoskeleton is operative and moves the non-dominant hand of the subject according to the analysis of the EMG signals collected. Hence, there is a kinesthetic feedback due to the exoskeleton's own motion in the tasks A and B. On the contrary, in task C and D, the hand exoskeleton is not operative and therefore, it does not make any movement, remaining continuously in the resting position. In addition, in tasks A and C, the EMG-based visual feedback is visible on the computer screen, while this is hidden in tasks B and D. Table 1 shows the feedback configuration for each task.

Table 1
Task configuration

Task	Kinesthetic feedback	EMG-based visual feedback
A	(✓)	(✓)
B	(✓)	(x)
C	(x)	(✓)
D	(x)	(x)

The EMG-based visual feedback consists in two variable length bars which represents the instantaneous value of the normalized signals from the ED and FDS muscles. The bars are labeled as 'Opening force' and 'Closing force' so that the user can easily understand what they mean. The bars turn red or green to indicate whether the gesture recognition module has detected the hand is at rest (both bars are red), is

opened (opening force bar is green while closing force bar is red) or is closed (opening force bar is red while closing force bar is green). As previously said, the computer screen also incorporates the gesture to perform by the user. Figure 2 shows the configuration of the computer screen with and without EMG-based visual feedback.

Data analysis

The target sequence of gestures to be performed by the user (red signal called “Target” in Fig. 3) and the sequence actually performed by the user (blue signal called “Generated” in Fig. 3) are saved on the system database at 20 Hz (T_s = 0.05s) during the experiments (Fig. 3. a). The generated signals are determined by the EMG-based gesture recognition module. It is important to remark that the sequences of generated gestures are delayed with respect to the sequence of target gestures due to the user response time (from the beginning of the visual and audio information to the onset of the hand movement) and the motion selection time (time needed by the controller to determinate the hand gesture, [42]). Therefore, for each task both discrete-event time series are time-synchronized (Fig. 3. b) using the lag in which the cross-correlation of both sequences are the highest, which will be referred to hereafter as delay time (T_d). The cross-correlation of two time series x and y is computed using Eq. 1, where h is the lag and * denote the complex conjugate. Data analysis were performed using Matlab 2021a software (MathWorks) licensed to University of Valladolid. The mean time delay for different tasks and individuals was 0.8791 ± 0.139 s.

$$r_{xy}\left(h\right)=\begin{cases}\sum_{n=0}^{N-h-1}x\left(n+h\right)y^{*}\left(n\right)0\leq h\leq N-1\\ r_{yx}^{*}\left(h\right)-\left(N-1\right)\leq h\leq 0\end{cases}$$

1

The performance of the subject in each task is measured computing the L2 distance (squared Euclidean distance) between the target and the synchronized user generated time series. Thus, considering the order of states “Open < Rest < Closed” (coded by “Open”=-1, “Rest”=0 and “Close”=1), the distance between “Open" and “Closed” is twice that of either and “Rest”. In addition, the quadratic cost penalizes the type of error more than other distances such as the L1 norm, also known as Manhattan distance, that is the sum of the absolute vector values. This is relevant because in practice a confusion between open and closed can lead to more serious consequences than either of them at rest.

Besides, when calculating the distances between signals, it is important to take into account that the synchronized signals are shorter than the reference length (one-minute task) and, moreover, that the differences between the lengths of the signals generated by each individual with each task depends on the time delay (T_d). Therefore, the target signal is cut off at the end to make it equal in length to the synchronized signal made by the individual.

Formally, let us denote by $x = (x_i)_{i=0}^{n_{samples}}$ the generated sequence for a particular individual and task, for which the time delay is T_d and $n_{samples} = [60 - T_d]T_s$, where T_s is the sampling period. If we denote by $x^* = (x_i^*)_{i=0}^{n_{samples}}$ the target signal (truncated by the end, following previous observation), then the L2 distance between the two sequences can be computed according to Eq. 2.

$$d_{L_2}(x, x^*) = \sqrt{\sum_{i=0}^{n_{samples}} (x_i^* - x_i)^2 T_s}$$

2

Results

All the statistical analysis in this section were carried out using the software R (https://cran.r-project.org/). To detect significant effects in the performance of the subjects, a Multifactorial additive ANOVA for the L2 distances was performed from explanatory variables task, order and individual (Table 2). Note that the consideration of individual as a factor was included in the model in order to block its effect.

Table 2
Results from multifactorial additive ANOVA for the L2 distances.

	Df	Sum Sq.	Mean Sq.	F value	Pr(> F)	Significance
Task	3	3.366	1.1221	4.028	0.0124	*
Order	3	1.037	0.3456	1.241	0.3054	
Individual	17	20.933	1.2313	4.420	2.43e-05	***
Residuals	48	13.373	0.2786			
**** Denotes significance at the (< 0.001) level and * at the (< 0.5) level.*						

From these results, we can conclude that there are no significant differences in the order of the tasks. What is relevant is that, in terms of subject performance, significant differences are found in the type of tasks taken (p-value 0.0124). More precisely, in Fig. 4 we can see the differences in the distributions of the L2 distances conditionally given the type of task. L2 distances were 3.39 ± 0.70, 3.43 ± 0.75, 2.89 ± 0.71, 3.17 ± 0.73 for task A, B, C and D, respectively. Specifically, subjects perform better in task C than in the other tasks A, B and D, the differences between the latter three not being statistically significant. This can also be seen through the pairwise comparisons using Duncan's multiple range test (Table 3). Importantly, the results of such a test show that the performance of the individual at task C is significantly better than at task B (p-value 0.038) and task A (p-value 0.051). Finally, all the results are supported by the fact that homoscedasticity has been checked.

Table 3
Results of Duncan's multiple range test.

	A	B	C
B	0.877525	-	-
C	0.049675*	0.041183 *	-
D	0.355697	0.312118	0.245101

**Denotes significance at the (< 0.5) level.*

Discussion

In the present study, performance of the subjects was better in task C. Thus, EMG-based visual feedback has enhanced the motor control of the user and has significantly improve accuracy during the trials. This feedback allowed the subjects to monitor their EMG activations levels during the tasks and compare them with the activation threshold predefined in the previous calibration in a simple way. This enable subjects to regulate their EMG activity with respect to these threshold levels and to better control the movement of the hand exoskeleton.

On the other hand, the kinesthetic feedback does not provide significant improvement in the performance of the subjects. Neither does it improve when both feedbacks are present. This result may be related to the fact that subjects do not need to conscious pay attention to kinesthetic activity, as it is more straightforward and intuitive than the visual EMG feedback.

The main factor behind these findings is the instant of time at which each feedback modality is provided to the user. The EMG-driven control of the RobHand robotic platform works as follows (Fig. 5): the recorded EMG signals are rectified ($rEMG_{ED}$ and $rEMG_{FDS}$) and normalized ($nEMG_{ED}$ and $nEMG_{FDS}$). The gesture recognition module determines the hand gestured based on the values of the normalized signals and the thresholds calculated in the calibration. The position controller generates the control signal (u) in function of the detected gesture so that the actuators move to reach that gesture. Hence, EMG-based visual feedback provided to the user is earlier in time than the kinesthetic feedback. Therefore, the performance of the subject is better when he/she is provided with the visual feedback as it has a longer reaction time than when the feedback is kinesthetic.

In fact, the real-time visual EMG feedback allows the user to modulate the exerted force at that very moment and thus, directly influence the position controller input. In contrast, with the kinesthetic feedback, the user modulates the exerted force once he/she has felt the movement performed by the actuators of the exoskeleton so that the force modulation is not instantaneous.

Furthermore, the hand motion generation process is not instantaneous. The hand motion is achieved by muscle contraction and this motor control signal is delivered from the central neural system. For any

intended motor action which implies muscle contractions, it is well known that there is a time delay between the onset of the EMG signal and the onset of force production. This time delay is known as the electromechanical delay (EMD) and is about 10–300 ms [44], [45].

In addition, the electromechanical characteristics of the actuators should be also considered: (1) The dynamic response (time interval from the instant the actuator receives a position command to the onset it starts to move) is low (2) The speed is not too high due to the type of application (rehabilitation) and its maximum speed is the maximum mm/s. The time delays of the RobHand system that are considered relevant to the human-robot interaction were determined in [42]: the Motion-Selection Time (MST) is 0.55 ± 0.6 s, the Motion-Completion Time (MCT) is 1.90 ± 1.65 s, varying from 0.98 s (close to rest movement) to 3.42 s (open to close movement).

With the visual feedback the subject modulates their force from the data of the gesture recognition module (nEMG signals and detected gesture) and anticipates the exoskeleton movement response. However, with the kinesthetic feedback the user modulates their force once the action has been performed by the exoskeleton. If the user perceives that the movement performed by the exoskeleton does not correspond to their intention, the subject can modulate their muscle activity to correct it but it takes much longer than if he/she had corrected it based on the real-time EMG visual feedback.

Methodological aspects

Inferences in this study are based on differences in performance with and without the two proposed feedbacks. There are some limitations of the current study in the following aspects. For attaining reliable EMG, the experimental tasks were very constrained and standardized However, the surface electrodes placement has a direct influence on the performance.

Another limitation of the present study is the possibility of muscular fatigue during the trials, which will deteriorate the user’s performance. Three-minute breaks were included between task to avoid it.

It was possible, although highly unlikely due to the low number of repetitions, that the learning effect on the user performance could appear during the trials. No statistically significant differences were observed in the results in function of the order in which the tasks were performed.

For the calculation of the L2 distance that is used to performance evaluation, it is necessary to previously synchronize the generated and the target signals. The time delay between these two signals has been considered constant throughout each task, although in may vary between gestures.

Experimental trials have been performed on healthy subjects, so they cannot be extrapolated to patients who have suffered damage affecting their cognitive abilities. The patient with impaired cognition and perception may become confused and distracted with the EMG biofeedback, resulting in deterioration of task performance.

Furthermore, the EMG monitorization was carried out in a simple way and there was no need to have any knowledge about electromyogram. Furthermore, no additional visual information that may distract the user was provided apart from the target hand gesture. There were two bars (one for opening and one for hand closing) of variable length (proportional to the muscle activation) and two colors (exceed or not the predefined threshold). Thus, evidence has been found of effectiveness on this type of EMG-based visual feedback but cannot be applied with other types. Further studies should be undertaken to confirm if other types of EMG feedback have the same positively effect and whether its combination with other virtual objects (exergames based on virtual reality) has also this type or effect or the user gets distracted.

Conclusion

The incorporation of a real-time easily understandable EMG-based visual feedback enhanced the performance of the subjects. This feedback allowed the subject to monitor their muscle activation in real-time and thus, modulate the exerted force. In contrast, kinesthetic feedback does not improve performance due to lag times and eliminates the positive influence of the EMG feedback if both are present. EMG-based visual feedback can be very useful in the learning stage so that the user could more quickly learn how to modulate his or her muscle activation so that the rehabilitation robot moves according to their intention. This could result in an improvement of the motivation of the patient for the rehabilitation process with the assistance of robotic platforms.

Abbreviations

EMG
Electromyography
HRI
Human-robot interaction
ED
Extensor digitorum
FDS
Flexor digitorum
RMS
Root mean square
MVC
Maximum voluntary contraction
MST
Motion-Selection time
MCT
Motion-Completion time

Declarations

Ethics approval and consent to participate

The Ethics Committee of the University of Valladolid specified that its approval was not necessary since the trial was non-invasive and participants were healthy. All participants volunteered and signed the written consent form to participate in this study.

Consent for publication

Written informed consent for publication was obtained from the participants involved in the study.

Availability of data and materials

Data and materials can be made available upon request to the authors.

Competing interests

The authors declare no conflicts of interest.

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Authors' contributions

A.C. developed the application for the trials and performed the data analysis. P. G. conducted the statistical analysis. J.P.-T and J.-C-F. made a substantial contribution to the to the design of the experiments. D.S. was responsible for conducting the trials. All authors contributed to the organization of the paper, writing, and proofreading. All authors read and approved the final manuscript.

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Figures

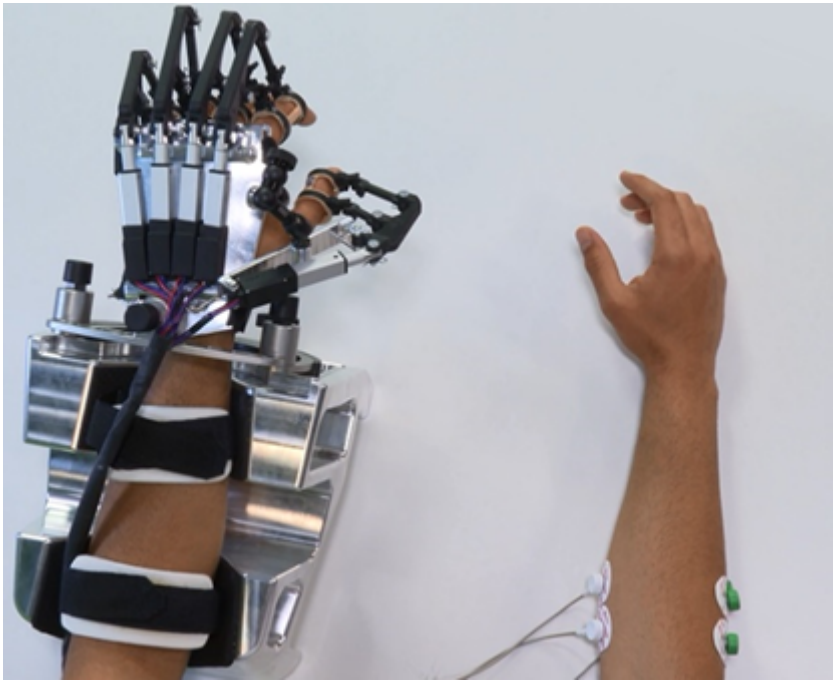

Figure 1

Experimental setup of the experiments. Surface electrodes are connected to the dominant ED and FDS muscles, while the exoskeleton is placed in the non-dominant hand of the subject

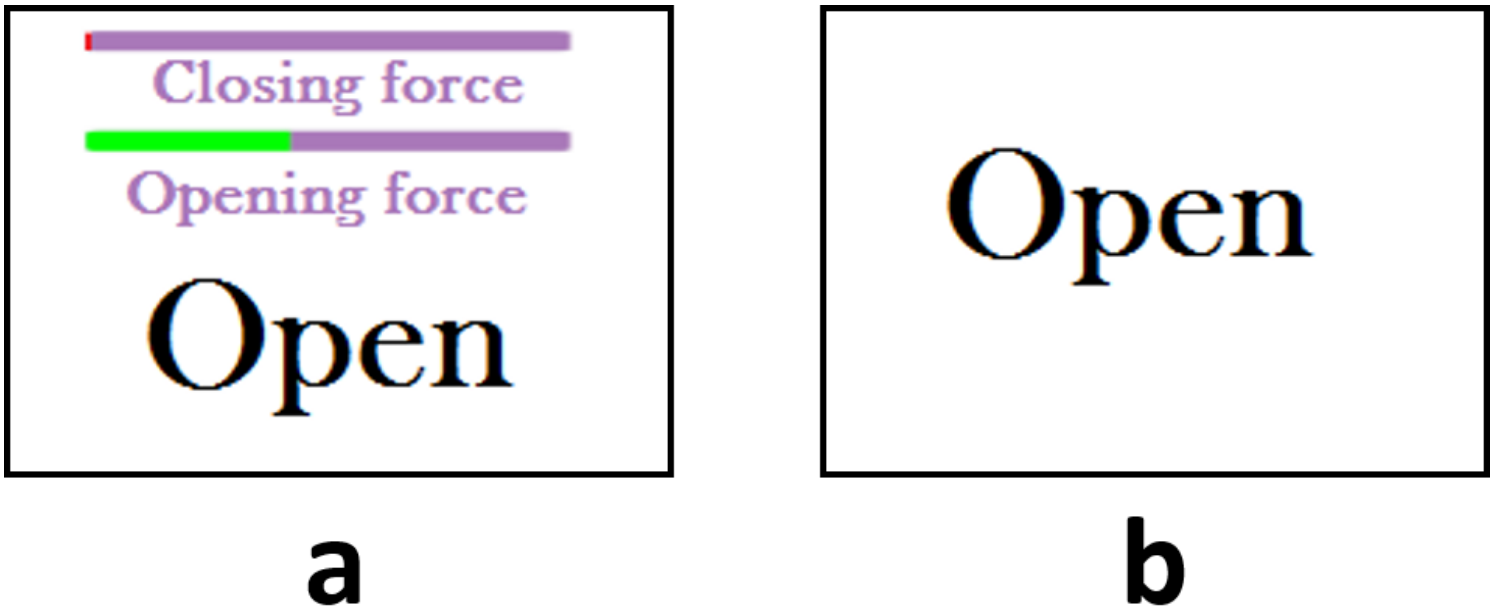

Figure 2

Computer screen (a) with and (b) without EMG-based visual feedback.

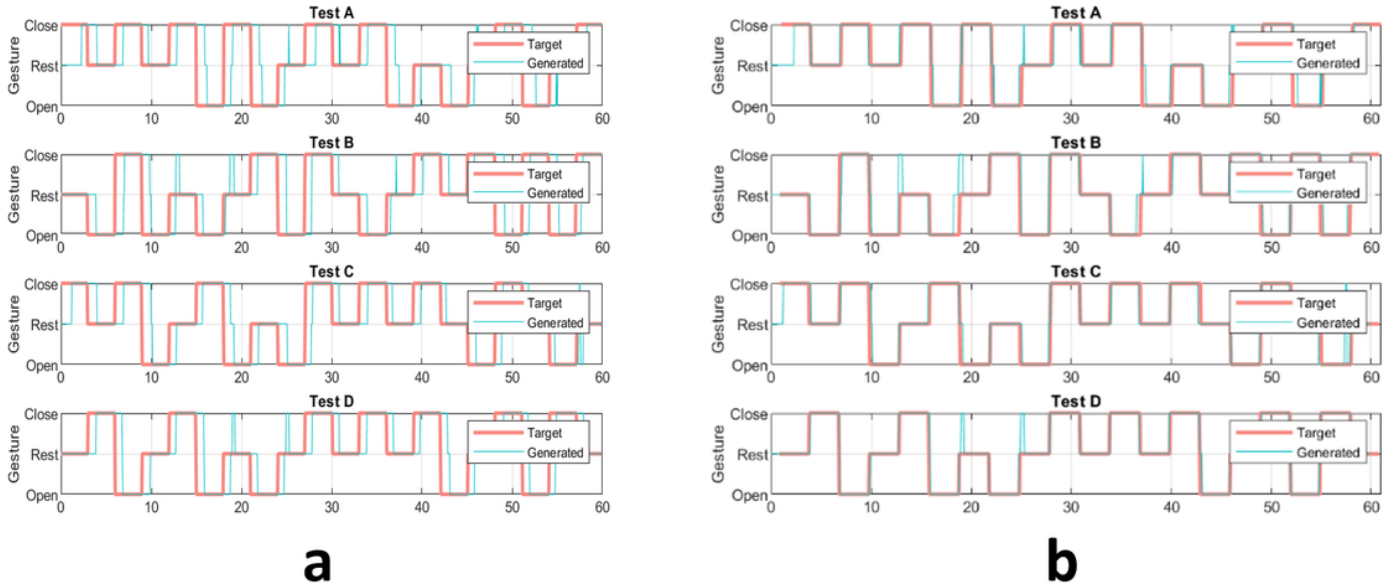

Figure 3

Target and generated sequence of gestures of one task. (a) Raw data (b) Data after synchronization

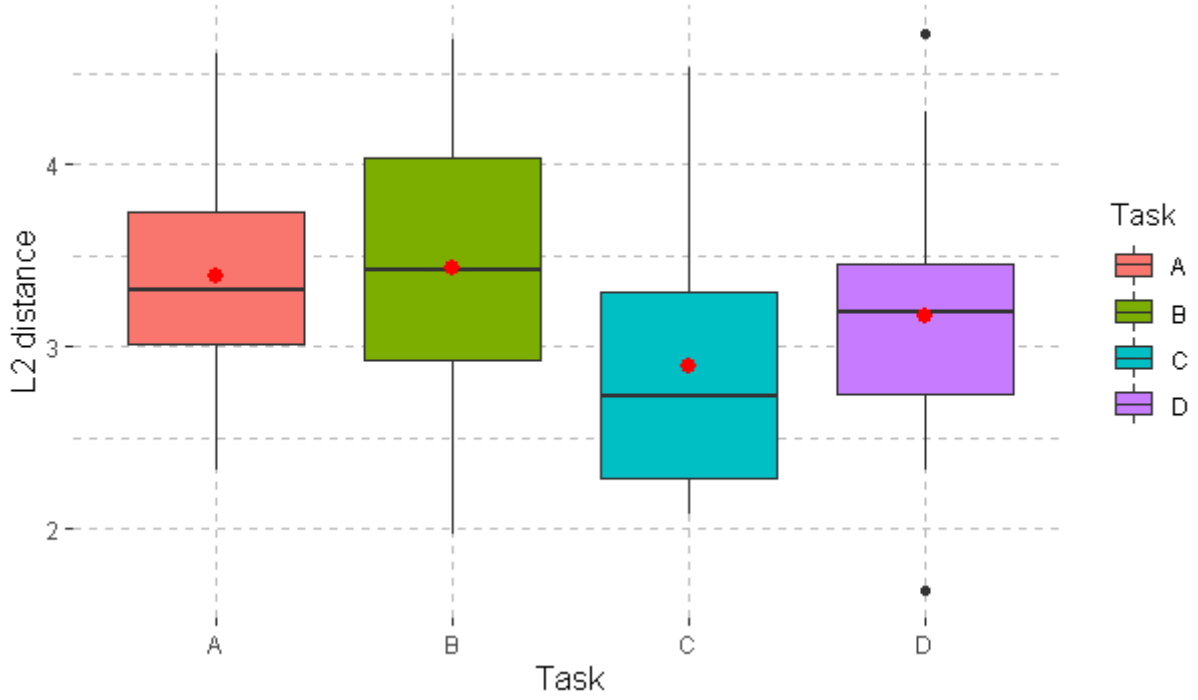

Figure 4

Boxplot of the L2 distances for the four performed tasks

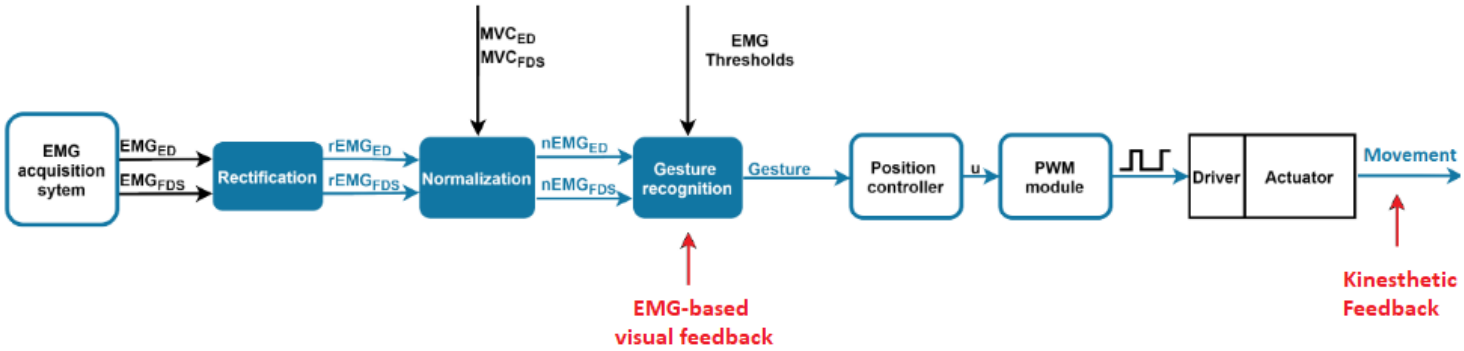

Figure 5

Control loop for the threshold EMG-driven control of the RobHand indicating the feedbacks.