# Human-Robotic Collaborative Intelligent Control for Reaching Performance

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**Abstract.** In most human-robot interfaces, the user completely controls the robot that operates as a passive tool without adaptation capabilities. However, a synergetic human-robot interface where both agents collaborate could improve the user's performance while reducing the cognitive and physical workload. Specifically, when considering this framework applied to rehabilitation, we examined a shared collaborative control between a human user and an adaptive biologically inspired neurocontroller in order to perform reaching movements with a simulated prosthetic arm. When this neurocontroller was enabled, it progressively learned from the user to control the prosthetic arm, increasing its role in the shared performance and facilitating the user's reaching movements. This resulted in the user's performance enhancement and in a reduction of his/her cognitive workload. The long term goal of this work is to contribute to the development of the next generation of intelligent human-robotic interfaces for rehabilitation.

**Keywords:** Human-machine/robot collaborative performance, intelligent control, adaptive systems, arm reaching, assistive technology, prosthetic arm, rehabilitation.

## 1 Introduction

Currently, in most human-machine interface applications, the user fully controls every aspect of the machine performance, which is thus considered as a passive tool

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controlled in a unidirectional manner with no or very limited capability of adaptation to the user and/or to the environment. However, a more optimal interaction between the user and the machine, such as a robotic limb (e.g., a human controlled robotic arm or finger), would be a dynamic, active and bidirectional process. Therefore, developing a symbiotic human-robot interaction where both the user and the robot can co-adapt and/or cooperate could provide several advantages such as the reduction of ergonomic challenges due to physical and cognitive load, while improving efficiency, quality and safety. Specifically, in the area of rehabilitation, the robotic device that interacts with human can take the form of an assistive device such as a prosthetic limb.

Generally, the working principles of prosthetics as well as many assistive technologies for severely disabled individuals are based on the decoding of available biosignals (e.g., muscle, brain activity, eye, head, tongue movements). These signals are recorded from the user and quantified in order to control the device of interest (e.g., [1-9]). The optimal patient specific interface guides the selection of biosignals that may be employed; e.g., eye, head and tongue movement, and muscle or brain activity [2,5,6,8,9]. Regardless of the interface and the type of biosignals, the user is generally expected to adapt his signal of command in order to unilaterally control the prosthetic while the control system of the device has no or very limited adaptive capabilities [10,11]. While the final aim is to maximize the recovery of motor functions, the available biosignals offer a limited channel of communication to control the prosthesis and/or the assistive device resulting in tedious training, increase of user's fatigue, frustration and cognitive workload as well as a decrement in performance [1,9-12]. It seems reasonable to expect that a prosthetic or an assistive device that would incorporate some adaptive capabilities would reduce the user burden while improving human performance.

Although several investigations proposed adaptive systems to control wheelchairs (e.g., [13,14]), only a few studies have examined biosignals-based intelligent interfaces to control upper limb prosthetics that are critical for the user to perform reaching and grasping task in order to regain interaction with his/her environment. Notably, few previous works have proposed to integrate adaptive elements in the interface to facilitate the decoding process of the control biosignals [10,11]. For instance, Sanchez et al. (2009) employed a reinforcement learning method to adapt the decoding process of invasive brain signal to enhance the control of a robotic arm by a rat [10]. Also, Pilarski et al. (2011) used a similar approach to enhance EMG decoding from human muscles to control a robotic arm [11]. Although very interesting, these previous studies were centered on the decoding process per-se without focusing on the downstream processes related to the controller of the prosthetic device itself. As such, there is a need to develop intelligent collaborative control between the user and a prosthetic arm controller itself. In this regard an adaptive bio-mimetic neurocontroller offers a promising area for developing enhanced human-shared collaborative performance.

Therefore, we propose a human-robotic adaptive collaborative control scheme that provides emergent assistance to the user while performing a reaching task with a virtual prosthetic arm displayed on a computer screen. Using head motion as the biosignal to control the virtual prosthetic arm, an adaptive biologically inspired neurocontroller will progressively learn to compute the inverse kinematic of the prosthetic limb in order to perform reaching movements towards multiple targets. We predict that the user's performance will be facilitated with concomitant reduction in cognitive workload and frustration as the neurocontroller learns to control the prosthetic arm autonomously. The implications of this approach in the context of intelligent human-robotic interfaces for rehabilitation are discussed.

# 2 Material and Methods

## 2.1 The Human-Robotic Interface

The human-machine interface was composed of two elements. The first component acquired the signals from two infrared sensors placed on the head (one on the forehead and one on the chin) of the participants. The movements of the forehead sensor provided the up/down and right/left desired direction from the user whereas the chin sensor was used for selecting/confirming the target acquisition by opening the mouth. Through the movements of these two markers, a motion capture camera-based system (Optotrak™) detected the selection of the target and the desired directional displacement from the user. This information was then used to move a virtual prosthetic arm in a two dimensional workspace displayed on a computer screen that was placed in front of the participant (Fig. 1). It must be noted that as a first step, this study considered a virtual prosthetic arm that was modeled at the kinematic level. However our approach can be employed including an enhanced model of the kinematics and dynamics of the prosthetic arm. In order to ensure consistency, the same targets (same positions, same sequence) were presented to all participants. Once the target was selected by the user, he/she executed (up, down, left or right) head movements that were decoded and provided to the prosthetic arm that moved in the corresponding directions in order to reach the selected target.

The second component of this human-robotic interface included a biologically inspired neurocontroller that functionally reproduces the premotor/motor cortical regions in order to learn an inverse kinematic mapping. In particular, this neurocontroller was able to provide an accurate, robust and efficient inverse kinematics computation reproducing similar kinematics to those observed in human during arm/finger reaching task, while efficiently handling tools, unexpected perturbations, online reacquisition of the targets during simple single reaching motion, as well as more complex movements. These results were obtained with anthropomorphic arms including multiple degrees of freedom as well as with fingers having a mechanical coupling of the last two joints. Although, a simple planar arm with two degrees of freedom arm was considered, this type of neurocontroller can efficiently operate with simulated as well as actual robotic systems such as humanoid arms and fingers that include more complex kinematic mechanisms [15-21].

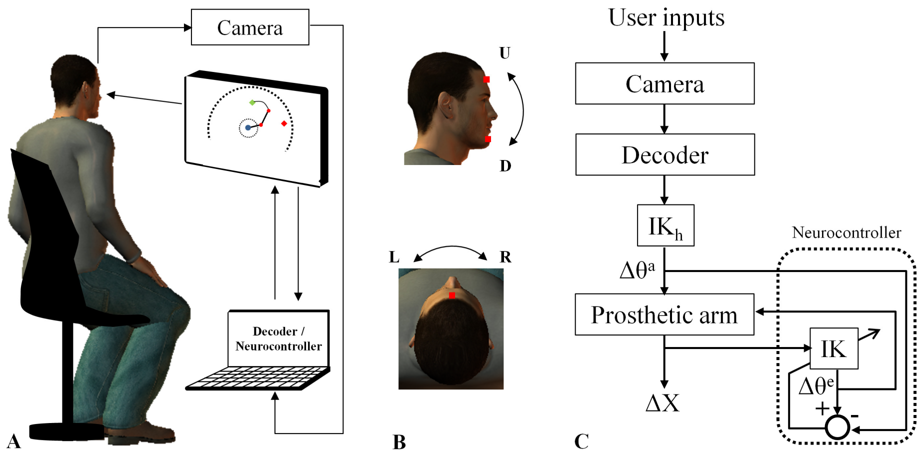


**Fig. 1.** Working principles of the human-robotic interface. (A). Experimental set-up with the user facing the virtual prosthetic displayed on a computer screen. (B) Marker placed on the forehead to detect the upward (U), downward (D), left (L) and right (R) direction as well as the marker placed on the chin to select the target (C). Human-robotic interaction scheme that allowed adaptive shared control. $\Delta\theta^a$; $\Delta\theta^e$, $\Delta X$ represent the actual joint, the estimated joint and the spatial displacement of the prosthetic arm, respectively. IK: Inverse kinematic (h: heuristic).

When considering the present human-robotic framework, the general computational principle of this neurocontroller is to learn an internal representation of the inverse kinematics (i.e., inverse model) of the virtual prosthetic arm by progressively encoding a mapping between its spatial and joint displacements. Thus, when the user moved his/her head, the corresponding (horizontal or vertical) movement directions were decoded and provided to a local inverse kinematics heuristic in order to obtain the corresponding joint displacements and move the virtual prosthetic arm. Simultaneously, the corresponding joints and spatial displacements of the prosthetic arm were provided to the neurocontroller in order to learn the inverse kinematics representation as the user executed reaching movements. As the user moved the prosthetic arm in the workspace, this neurocontroller performed action-perception cycles during which it generated an estimate of the motor commands to move the prosthetic arm in order to reach the targets selected by the user. As the session progressed, the number of movements performed by the user increased and provided further information to the neurocontroller that gradually learned the internal inverse kinematic model of the prosthetic arm by integrating visual (spatial position of the prosthetic arm), and proprioceptive (joint angles of the prosthetic arm) information, as well as internal information related to the neurocontroller. Based on these spatial displacements, the cortical model estimated the joint angles that were compared to the corresponding actual joint movements, providing an error signal that guided the adaptation of the cortical network (for further details see, [15-19]).

### 2.2 Participants and Reaching Task

Fourteen healthy individuals participated in this study composed of a primary reaching and a secondary cognitive task under various conditions. Only the reaching task that was performed under two conditions will be presented. During the first and second conditions, the subjects had to control, through limited head motion, the prosthetic arm to reach multiple targets while the adaptive neurocontroller was disengaged (i.e., passive prosthetic mode) and engaged (i.e., active prosthetic mode), respectively. Thus, in the first condition (or passive mode), the user exerted traditional control over the prosthetic since he/she fully controlled the prosthetic device that could be considered as a passive tool. During the second condition (active mode), by integrating the user's performance data, the adaptive neurocontroller of the prosthetic arm progressively learned to perform reaching movements towards the targets.

Before starting the experiment and in order to minimize any training or adaptation effects from the user; all the participants went through a familiarization stage where they had to move the virtual prosthetic arm with the neurocontroller disabled and enabled until they felt comfortable in controlling the device. Then, the participants completed two sessions, each of them corresponded to one of the conditions. The condition chosen for the first and second sessions was randomly selected and counterbalanced among the participants. In both sessions, a target (red diamond) to reach was presented on the computer screen within the 2D workspace to the subjects. They had to: i) select/confirm the target acquisition (the target turned green once selected) and then ii) guide the prosthetic arm towards the selected target. Once the participants reached the selected target, the subsequent target was presented and all the information from the previous trial was erased. Each session included 60 trials. To ensure consistency between the two sessions, the sequence of targets to reach was the same during the two sessions (although different from the target set employed during the familiarization phase). The information related to the performance was analyzed throughout each session and for each trial.

In order to assess the quantity of information provided to the prosthetic from the user, the occurrence of head movements were quantified as control signals. Also, the movement time was recorded, the smoothness of the movement path was assessed by means of the jerk [22] and both the linear and angular kinematics of the prosthetic were analyzed. Once each session was completed, participants were requested to complete the NASA TLX questionnaire in order to assess the level of task difficulty and cognitive workload for each task [23]. The indicators of reaching performance (occurrence of head movements, movement time, jerk and the weighted respective role in the performance) were tested using ANOVA. The Huynh-Feldt correction was applied when sphericity was violated [24]. The NASA TLX questionnaire scores were contrasted using paired *t-test* or *Wilcoxon* depending if the assumption of normality was violated or not.

# 3 Results

## 3.1 Reaching Performance

Overall, the findings revealed that the user's reaching performance with the prosthetic arm in the passive condition (i.e., neurocontroller disengaged) was inferior to that during the active condition (i.e., neurocontroller engaged).

When comparing the respective roles of the human and of the neurocontroller performance, it appears clearly that the human kept full control of the prosthetics arm in the passive mode and thus produced the entire trajectory (see Fig. 2, upper row). In the active mode, the neurocontroller became progressively dominant in generating the trajectory to reach the targets (see Fig. 2, lower row) and thus gradually reduced the need for user intervention from early to late learning (compare the black and gray portions of the path in Fig. 2). When comparing to the active mode, the passive mode revealed more jerky and irregular movement's paths (Fig.2). Namely, the occurrence of head movements, movement time and jerk values were larger in the passive compared to the active mode ($p<0.001$; Fig. 3A-C).

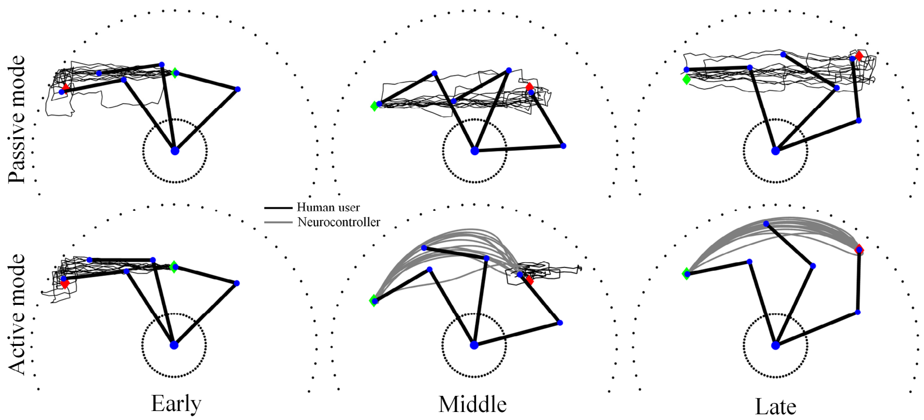


**Fig. 2.** Reaching performance with the prosthetic arm in the passive (upper row) and active (lower row) mode. The red and green diamonds represent the starting target and the target to reach, respectively. The dotted circular shapes represent the outer and inner limits of the workspace. The black and gray lines represent the portion of the trajectory generated by the human user and by the neurocontroller, respectively.

When focusing on the changes within the session itself, the findings revealed that in the passive mode, the performance was generally stable although towards the end of the session the movement time and smoothness increased and decreased, respectively. The same analysis, conducted in the active mode revealed that the occurrence of head movement required to control the prosthetic arm as well as the movement time were significantly reduced whereas the smoothness of the movement was significantly increased ($p<0.001$; Fig 3A-C). When comparing the respective roles of the human and of the neurocontroller during reaching with the prosthetic arm in the active mode, the role of neurocontroller, which learned from the user, became progressively preponderant in generating the trajectory to reach the targets. In turn, this resulted in a gradual reduction of the role of the user in controlling the trajectory. Thus towards the end of the session, the user mainly had to control the target selection while the trajectory was generated by the neurocontroller (Fig. 3D). During the passive mode, no change was observed since the users fully control the prosthetic arm at all time.

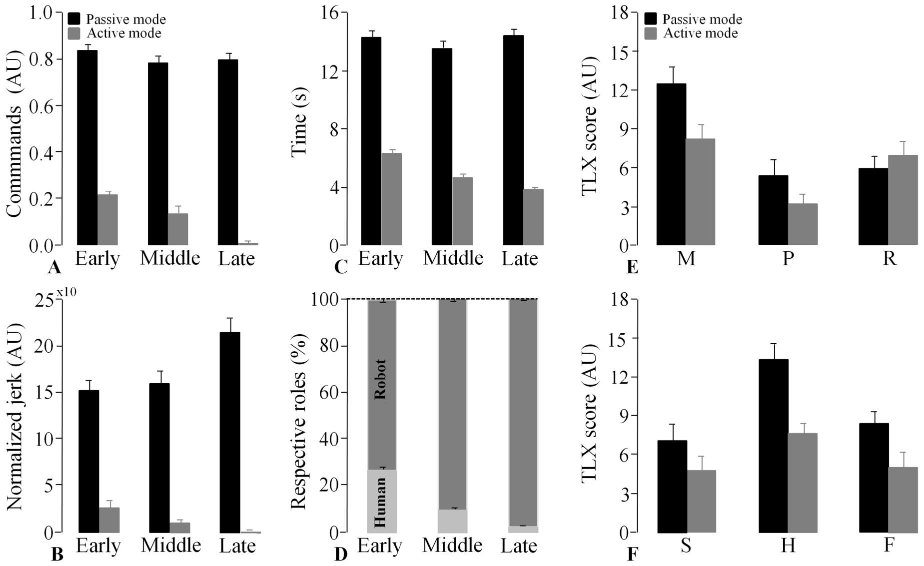


**Fig. 3.** Indicators of reaching performance along with the cognitive workload and task difficulty assessment during the control of the prosthetic arm in the passive (black color) and active (gray color) mode for the early, middle and late session. (A) Occurrence of head movements, (B) Movement smoothness, (C) Movement time, (D) Respective role in the control of the prosthetic arm during reaching movements, (E-F) NASA TLX scores to assess the mental (M), physical (P) demand, the sensation of being rushed (R), of performing successfully (S), of the task difficulty (i.e., hard or not; H) and the level of frustration (F).

## 3.2 Cognitive Workload and Task Difficulty

Overall, the NASA TLX results revealed higher scores for the passive compared to the active mode. Specifically, compared to the active mode, the mental demand, the perception to perform successfully, the difficulty to perform the task and the level of frustration were all significantly higher ($p<0.05$). Also, a tendency showed that the physical demand tended to be higher for the passive compared to the active mode ($p=0.06$). The same comparison did not reveal any significant difference between the two modes for the sensation of being rushed ($p>0.73$).

## 4 Discussion and Conclusion

Overall, the findings suggest that, the cognitive (e.g., mental workload, task difficulty, frustration) and physical effort from the user were reduced whereas the performance was considerably increased (e.g., reduced movement time, increased smoothness) when the neurocontroller was engaged (active mode) compared to the condition where the user fully controlled the prosthetic (passive mode). This finding is in agreement with previous studies that revealed that a collaborative control scheme for wheelchair navigation improved the performance while decreasing the cognitive workload of the user [13, 14].

Specifically, when this adaptive neurocontroller was enabled, throughout the entire session it learned, from the participant, to progressively control the prosthetic arm resulting in an emerging increased assistance to the user to reach the targets. Although the control was shared between the user and the neurocontroller during the entire task, the weights of their respective role evolves as the neurocontroller learned to control the prosthetic arm and thus gradually changed the dynamic of the collaborative effort. Thus, at the beginning of the session, the role of the user in this collaborative framework was predominant since he/she had to control both the target selection and the trajectory of the prosthetic arm. However, as the cortical architecture learned to control the prosthetic device, the roles of the user and of the robot in controlling the trajectory were progressively reversed (i.e., reduced and increased, respectively). Thus towards the end of the session, the user mainly controlled the target selection (i.e., the goal) while the neurocontroller generated the trajectories. In other words, the lower-level aspects of the task, such as the control of the trajectory, were progressively outsourced from the user to the neurocontroller whereas the human user maintained the control of higher-levels aspects of the task such as target selection/movement initiation. Such outsourcing from the human to the robot translated into enhanced performance while the user's cognitive and physical load was reduced. This approach has several implications for users employing prosthetics and assistive devices. First, prosthetics/assistive devices that are based on decoding of biosignals offer a limited communication channel since the recording and interpretation of these biosignals can be complex [1,9]. In addition, the control of such devices generally require long training hours, elevated cognitive workload, and sustained concentration [1,10,12]. By outsourcing some lower-level control features of the task, such as trajectory control, our approach has the potential to develop prosthetic control systems that allow more complex performance while limiting the control of the user to the higher level aspects of the performance (e.g., control related to the goal). This would allow: i) execution of ecologically valid complex movements by the collaborative robot and ii) maintaining a low level of the user's cognitive workload. This is in accordance with previous studies that suggested that the goal control method is a promising option to increase the utility of neuroprosthetics [9, 25, 26]. Second, in daily life, even if the user can correctly control the prosthetic device, this may be at a very high cognitive cost thus reducing cognitive reserve. Under such conditions, the user would not be able to maintain a conversation or deal with unexpected events (e.g., someone inadvertently pushes the prosthetic arm; the prosthetic arm collides into an unseen obstacle) that may occur in the environment [27, 28].

It must be noted that employing adaptive control in the prosthetic control loop does not systematically guarantee a better performance and/or a reduced cognitive workload. For instance, after the study, personal interviews with the users revealed that if a target was not reached in the active mode, it was sometimes awkward to switch back to the traditional (passive) mode in order to regain control of the prosthetic arm and reach the target. This illustrates how the implementation of the synergistic control between the user and the robot is critical. In this regard, a biologically plausible neurocontroller trained on-line may provide a better user-robot functional merging. This also emphasizes the need for future works that include the development of improved switching modes, more complex tasks and enhanced bio-mimetic control systems that incorporate both kinematics and dynamics characteristics of the prosthetic device. The long term goal of this work is to develop intelligent collaborative human-robotic systems to improve rehabilitation.

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