Simultaneous Control of 2DOF Upper-Limb Prosthesis With Body Compensations-Based Control: A Multiple Cases Study

Mathilde Legrand, Charlotte Marchand, Florian Richer, Amélie Touillet, Noël Martinet, Jean Paysant, Guillaume Morel, and Nathanaël Jarrassé

***Abstract*— Controlling several joints simultaneously is a common feature of natural arm movements. Robotic prostheses shall offer this possibility to their wearer. Yet, existing approaches to control a robotic upper-limb prosthesis from myoelectric interfaces do not satisfactorily respond to this need: standard methods provide sequential joint-by-joint motion control only; advanced pattern recognition-based approaches allow the control of a limited subset of synchronized multi-joint movements and remain complex to set up. In this paper, we exploit a control method of an upper-limb prosthesis based on body motion measurement called Compensations Cancellation Control (CCC). It offers a straightforward simultaneous control of the intermediate joints, namely the wrist and the elbow. Four transhumeral amputated participants performed the Refined Rolyan Clothespin Test with an experimental prosthesis alternatively running CCC and conventional joint-by-joint myoelectric control. Task performance, joint motions, body compensations and cognitive load were assessed. This experiment shows that CCC restores simultaneity between prosthetic joints while maintaining the level of performance of conventional myoelectric control (used on a daily basis by three participants), without increasing compensatory motions nor cognitive load.**

***Index Terms*— Prosthesis control, body compensations, physical human–robot interface.**

I. Introduction

SIMULTANEITY between joint motions is a natural feature of arm movements. Reproducing this ability with an upper-arm robotic prosthesis is far from being straightforward. Although mechatronic features of current prosthetic devices are available to offer such a possibility, their controller is not yet appropriate. The main control approach, conventional myoelectric control, only allows sequential movements [1]–[3]. The motions of each joint (e.g., hand closing/opening, wrist pronation/supination or elbow flexion/extension) are governed by the activity of two antagonist muscles of the stump. To manage multiple degrees of freedom (DOF), a finite state machine is implemented; each DOF corresponds to a different state. To switch from one DOF to the other, the prosthesis user has to co-contract both muscles, or in some cases, to modulate the contraction level. This scheme is the most widespread one, due to its robustness and simplicity of implementation, but the slowness and the sequential nature of the performed motions give rises to recurring complaints from prosthesis users [4], [5].

To remove the need for co-contraction switching and extend control possibilities, pattern recognition-based methods have been proposed: classification or regression algorithms are trained to identify intended motions from muscular activation patterns of amputees' remaining muscles [6]–[8]. These algorithms can be trained to allow simultaneous motions [9]–[11]. Yet, the total number of motions is limited: an increasing number leads to a less effective and less robust control algorithm (see [12] for instance) and requires more muscular activity information and thus more recording sites (i.e. more electrodes) [3]. Simultaneous prosthetic motions with pattern recognition-based control have thus been mainly implemented for two DOF (hand opening/closing and wrist pronosupination) and for transradial prosthesis, even if some works with a third DOF (wrist flexion or different grasping types) can also be found [12]–[14]. To increase the number of accessible recording sites, targeted muscle reinnervation, which proposes to transfer residual nerves from the amputated limb to new muscle targets that have lost their function [15], [16], can be considered, but with the downside of a complex surgery and extended rehabilitation.

Moreover, myoelectric control is hardly scalable, in the sense that controlling more active prosthetic DOF requires additional efforts and attention from the user. When acting with their natural upper-limbs, human subjects generally use all the limb joints in coordination to perform the task, the wrist being used to shape and orient the hand whereas proximal DOF, such as the shoulder and elbow, are used to

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(a) The prosthesis user wants to pick the clothespin, which requires simultaneous wrist pronation (around z_w) and elbow extension. (around z_e).

(b) With an initially still prosthesis, the user starts mobilizing task-oriented upper arm and torso compensations (in red).

(c) Compensations are detected and used to generate adequate prosthesis motions (in green), which naturally leads the user to cancel compensatory motions.

Fig. 1. Illustration of compensations cancellation control functioning.

transport the hand to the target location [17]. With current myoelectric control approaches, be it conventional or based on pattern recognition, the prosthesis user has to learn specific control instructions to actuate each joint independently. The more the active prosthetic DOFs, the more complex the control sequence.

To remove the need for voluntary control instructions, we have proposed in [18] and [19] to control upper-limb prostheses by cancelling the body compensations of the user. This approach relies on natural behaviours of prosthesis users, i.e. the body compensations, and avoids dealing with the known signal processing issues of electromyograms. Previously validated for the control of single DOF prostheses, we here generalize this method to control several intermediate joints of a transhumeral prosthesis (wrist pronosupination and elbow flexion/extension). We expect that it will allow simultaneous motions of the prosthetic joints in a continuous and unconstrained way, close to the natural human movements, without increasing the control complexity and thus associated cognitive load.

II. Compensations Cancellation Control

As presented in [18] and [19], Compensations Cancellation Control (CCC) aims at cancelling the compensations exhibited by the user with prosthesis motions, through a kinematic coupling created between the human and the prosthetic device (see Figure 1). It operates in three steps: (i) analysis of the body posture to evaluate whether the user is currently compensating for an inadequate prosthesis configuration; (ii) when a body compensation is detected, computation of a new desired position of the prosthesis that cancels the compensation; (iii) servoing the prosthesis joint positions to this desired value with a secondary loop. The prosthesis user merely has to focus on the end-effector task, while the device is in charge of his/her posture. The general control law is:

$$\dot{\mathbf{q}}_{p,c} = \boldsymbol{\lambda} Z_{q_0}\left(\boldsymbol{\epsilon}_p\right) \tag{1}$$

with $\dot{\mathbf{q}}_{p,c}$ the vector of prosthetic joint velocity commands, $\boldsymbol{\epsilon}_p$ the prosthesis angular position errors obtained from the user's body compensations, Z_{q_0} a deadzone function and $\boldsymbol{\lambda}$ a gain that tunes the rate of correction. Instead of looking for an exhaustive measure of body compensations to compute $\boldsymbol{\epsilon}_p$, we propose to gather body motions in one metric: the stump position and orientation. Assuming that the hand is correctly placed by the user (through body compensations) and that the role of the prosthesis is to move the stump back to a reference (non-compensatory) posture, we consider the device *backwards*, with the hand as the base body and the stump as the end-effector (see Figure 2). In that case, we can write

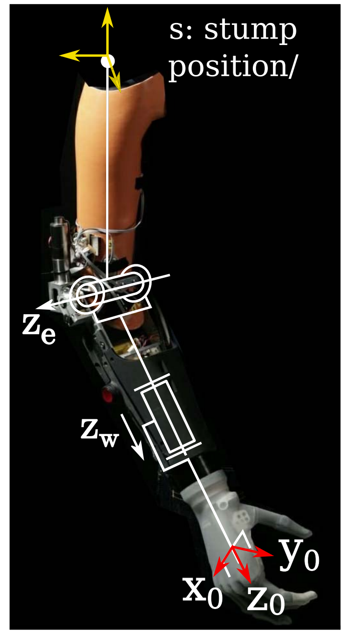


Fig. 2. Prosthesis model used to obtain the prosthesis position error from the stump orientation.

$$\dot{\mathbf{q}}_p = \mathbf{J}(\mathbf{q}_p)^{+}\dot{\mathbf{s}} \tag{2}$$

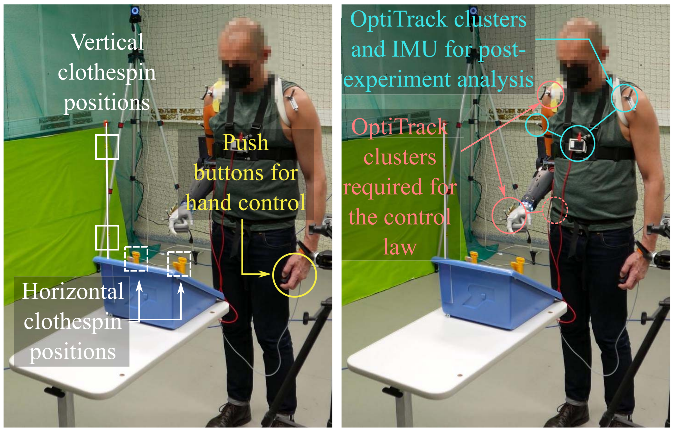
with $\mathbf{J}(\mathbf{q}_p)$ the natural jacobian matrix of the prosthetic arm and $\mathbf{s}$ the stump position and orientation vector. Within the framework of small displacements, we have

$$\boldsymbol{\epsilon}_p = \mathbf{J}(\mathbf{q}_p)^{+}\boldsymbol{\epsilon}_s \tag{3}$$

This general formulation can be used whatever the number of prosthetic DOF. In the particular case of this study, prosthetic joints (wrist and elbow) are revolute; we decided to work with orientation only, since it allows to work in a 2D space. We thus have $\mathbf{J}(\mathbf{q}_p) = \begin{pmatrix}\mathbf{z}_w & \mathbf{z}_e\end{pmatrix} \in \mathbb{R}^{3\times 2}$, with $\mathbf{z}_w$ and $\mathbf{z}_e$ the axes of rotation of the prosthetic wrist and elbow respectively. $\boldsymbol{\epsilon}_s$ was chosen to be the rotation of the hip-acromion vector and was projected in the 2D-base $(\mathbf{z}_w; \mathbf{z}_e)$. In that frame, $\mathbf{J}(\mathbf{q}_p)$ becomes the identity matrix and the mapping is merely:

$$\boldsymbol{\epsilon}_p = \begin{pmatrix}\theta_{z_w}\\ \theta_{z_e}\end{pmatrix} \tag{4}$$

with $\theta_{\mathbf{z}_w}$ and $\theta_{\mathbf{z}_e}$ the rotation of the hip-acromion vector around $\mathbf{z}_w$, the wrist pronosupination axis, and $\mathbf{z}_e$, the elbow flexion/extension axis, respectively (see Figure 1(a)).



(a) Adapted Refined Rolyan Clothespin test, with remote hand control

(b) Sensors for control and post-experiment analysis

Fig. 3. Experimental set-up of the refined rolyan clothespin test adapted to transhumeral amputated people.

III. Materials and Methods

To evaluate CCC ability to offer an intuitive control of a 2-DOF prosthesis (wrist pronosupination and elbow flexion/extension), four transhumeral amputees participated to the experiment, performed in accordance with the recommendations of Université Paris Descartes ethic committee CERES, which approved the protocol (NIRB: 20163000001072). The participants gave their informed consent, in accordance with the Declaration of Helsinki.

A. Task

Participants were asked to perform the Refined Rolyan Clothespin test [20], [21]: three clothespins are moved from a horizontal rod onto a vertical rod (and vice versa), changing the orientation in the process. The protocol was slightly modified to adjust to the restrained reachable space of transhumeral amputated people: instead of moving three clothespins, the participants were asked to move only two of them (see Figure 3). The task was completed six times for each prosthesis control mode (12 trials in total, see also *Prosthesis control* paragraph).

B. Prosthesis Prototypes

The first participant was our pilot for the Cybathlon 2020 Global Edition, who wore a prosthesis prototype especially developed for him and this competition. The three other participants were patients from the Institut Régional de Réhabilitation - UGECAM Nord-Est in Nancy. They wore a prototype designed in the lab for validation experiments which could be easily mounted on their socket connector in replacement of their own prosthesis. These two prototypes have a polydigital hand (Quantum from Touch Bionics / Ossür©), an Ottobock© motorized wrist (for pronosupination) and a motorized elbow (for flexion/extension). They are controlled by a Raspberry Pi3©, through a DC motor driver. The Cybathlon prototype elbow joint velocity can go up to 120 deg.s^{-1}, while the other one is limited to 60 deg.s^{-1}, but this difference had no influence for the present experiment.

C. Prosthesis Control

The prosthetic intermediate joints (wrist and elbow) were successively controlled by a conventional on/off myoelectric control, using the contraction of the biceps and triceps as inputs (MYO), and by CCC. MYO was implemented with a trapezoidal velocity profile for each joint; co-contraction was required to switch from the wrist control to the elbow one and vice-versa. CCC law was the one described in Equations 1 to 4. Hand orientation, hip and acromion positions, required in the control law, were measured with a motion capture system OptiTrack© (NaturalPoint, Inc.), and sent in real time to the prosthesis. Following the tuning performed in [19], λ was taken as 2s^{-1} for the elbow, and to homogenize wrist and elbow velocity during the task, λ was taken as 4s^{-1} for the wrist. The deadzone threshold vector $\mathbf{q}_0$ was $\begin{pmatrix}5\\5\end{pmatrix}$ deg.

The control of the prosthetic hand was chosen to be the same for the two control modes. Like most of upper-limb prostheses functional assessments, the Refined Rolyan Clothespin test involves hand grasping. Yet, as the evaluation of the control of this function is out of purpose here, it was decided to set it apart, with a simplified control: the fingers of the polydigital hand were preliminarily positioned in a pinch posture and the closing/opening of the hand was controlled with two push-buttons held in the contralateral hand of the participants. Functional assessment thus focused on wrist and elbow mobility only and was not biased by the difficulty of myoelectric grasping.

The Refined Rolyan Clothespin test was performed six times with both modes; MYO and CCC were alternated to avoid any effect of task learning with one of the two modes.

D. Participants' Experience in Prosthesis Control

Our Cybathlon pilot was used to conventional myoelectric control but without co-contraction; he had thus to adapt to the co-contraction switching implemented for the present experiment. He had also tested CCC for one DOF and knew the general principle of the concept. The three other participants were used to conventional myoelectric control with co-contraction switching (daily-basis use) and did not know anything about CCC. It has yet to be noticed that the second and fourth participants do not use an active prosthetic elbow in everyday life: the myoelectric control they are used to was transferred from hand-and-wrist control to wrist-and-elbow. Usual myoelectric control of one of the participants (P4) had also to be adapted for the experiment: one of the activation threshold was increased because of unintentional biceps contraction when the shoulder was mobilised. Wrist pronation and elbow flexion were thus a bit more difficult to perform than usual.

Participants thus represent a variety of cases: P1 would reflect the case study of an expert user with the two control methods; P4 would reflect the case of someone still learning to use both control modes - since his myoelectric control has been

TABLE I
SUMMARY OF THE EXPERIMENTAL SET-UP

		Trial 1		Trial 2		Trial 3		Trial 4		Trial 5		Trial 6		After
Main Task (Rolyan)	CCC	x		x		x		x		x		x		
	MYO		x		x		x		x		x		x	
Double task	Serial 3 subtraction							x	x	x	x			
	Serial 7 subtraction											x	x	
Raw-TLX														x

substantially changed -; P2 and P3 would reflect users expert with MYO but new to CCC.

Participants were given few minutes to test the elbow-wrist myoelectric control before starting the experiment (with no specific task to perform). The participants who did not have any previous experience with CCC (P2, P3 and P4) did not have any familiarization with this control method; they were just explained the main working principle.

E. Cognitive Load Assessment

CCC takes as input the body compensations of the prosthesis user, which are natural behaviours [22]–[24], and discharges the user from managing voluntarily the multiple prosthetic joints. We thus found worthwhile to compare the cognitive workload required to control multiple DOF prosthesis with CCC and with conventional myoelectric control, which asks for muscle contractions and with which the prosthesis user has to manage independently the multiple joints. The cognitive load was evaluated with both objective and subjective methods. The objective measure was a double task, performed in parallel to the Rolyan test: participants were asked to perform serial 3 or 7 subtraction [25]. The serial 3 (resp. 7) subtraction consists in subtracting from a random number by 3 (resp. 7); the outcome is the number of errors produced and the number of subtractions performed. Serial 3 subtraction was performed in parallel of the Rolyan during the fourth and fifth trials of each control mode; serial 7 subtraction during the last trial. Subjective measure was the Raw-TLX score [26], [27], in which the participants rate six categories (mental, physical and temporal demands, frustration, effort and performance) after completing the task; the final score is the sum of the six sub-ratings. Each control mode is given a score and the smaller the score, the less demanding the control mode. Table I provides an overview of the entire set-up.

IV. RESULTS

We chose to base the assessment of the control strategies on three complementary aspects:

- task performance, measured here by the time of the task, which is a classic metric to evaluate the Refined Rolyan Clothespin test;
- joint motions, evaluated through joint trajectories and simultaneous activation timing;
- body compensations, evaluated through the time average of the absolute value of trunk angles. Since compensatory motions are used as input of the controller, it is crucial to check that they are not exaggerated by the user to activate the device.

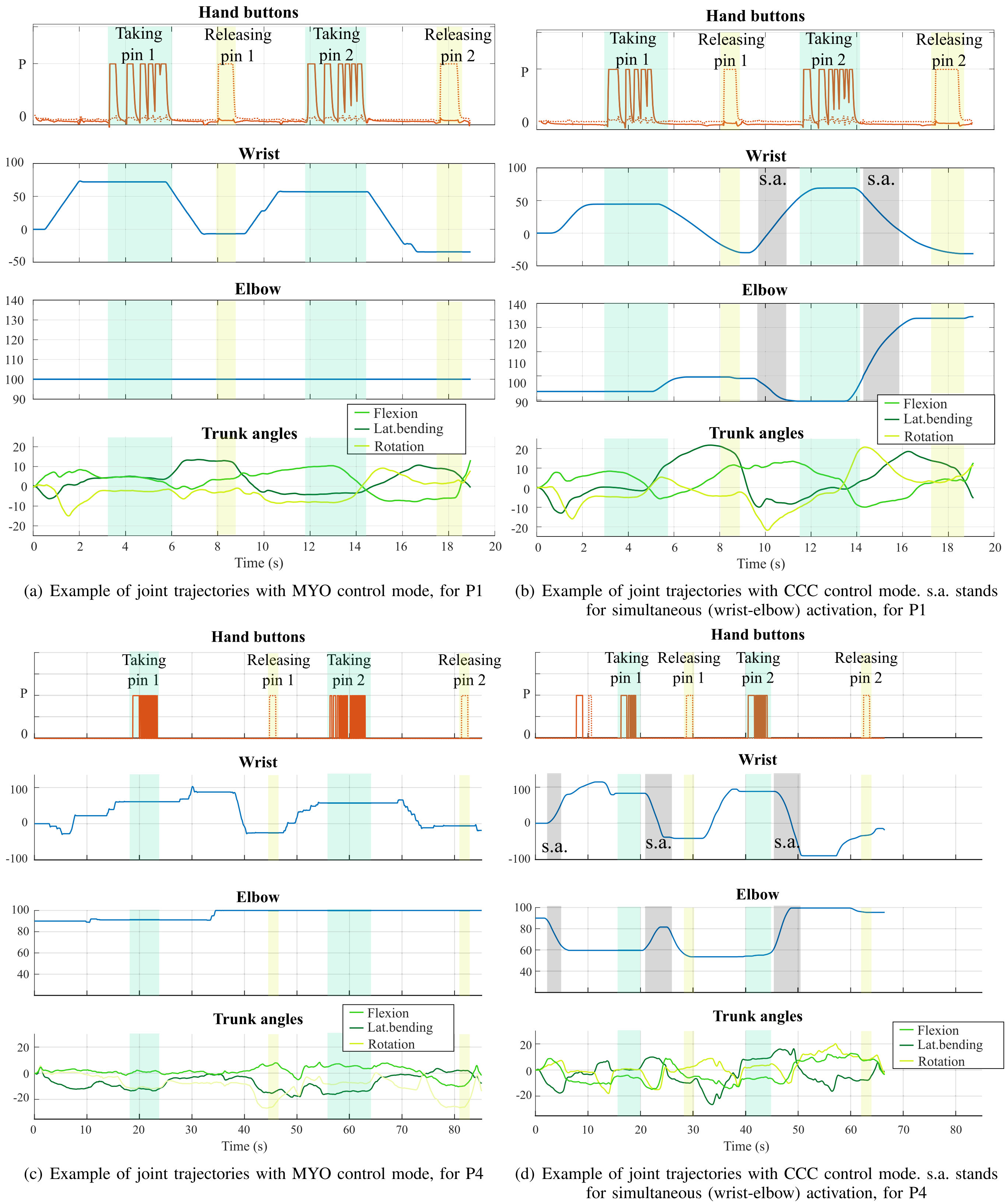
In the Refined Rolyan Clothespin test, subjects first move the pins from the horizontal to the vertical rod (upwards motion), then from the vertical to the horizontal rod (downwards motion). As upwards and downwards motions could call for different motion strategies and thus different performance, they are disassociated for the aforementioned metrics. In addition to the three aspects listed above, and as described in the previous Section, the cognitive load was also assessed, through a double task and a Raw TLX questionnaire. Due to the small number of participants, no statistical analysis was conducted. The results are presented for each participant individually, since the inter-subject variability is high.

A. Example Trial

Figure 4 shows one example of upwards motion from P1 and one from P4 (expert and beginner resp.), which allows to visualize the first main points of our analysis.

For P1, we see that the time of the task is similar when the prosthesis is controlled by MYO or by CCC (around 19s). Then, we can observe the absence of elbow motion with MYO (Figure 4(a)): P1 avoided co-contractions and focused on the most useful joint, the wrist rotation. There is also a clear separation between hand and wrist activation, despite the possibility to move both at the same time, offered by the push buttons-based hand control. With CCC (Figure 4(b)), the hand opening to release the clothespin is performed while the wrist is still moving. Wrist and elbow motions are also simultaneous (black areas labeled "s.a."), during clothespin transport. Finally, trunk motions show a common pattern between both control modes, which confirms that the input of CCC is a natural behaviour, already exhibited with MYO. However, in this example, trunk motions have a higher amplitude with CCC: lateral bending goes up to 20 deg instead of 10 deg with MYO and rotation is between -20 and $+20$ deg while it is between -10 and $+10$ deg with MYO. The coupling created by CCC between trunk lateral bending and wrist pronosupination is also visible.

For P4 (see Figures 4(c) and 4(d)), the time of the task is much longer than the time of P1 ($\approx$+60s with MYO and $\approx$+40s with CCC); it is also longer with MYO than with CCC (+18s). Contrary to P1, P4 moves a bit the elbow with MYO, which could explain the longer time (need for co-contraction switching). Hand and wrist activation are also well separated with MYO but also with CCC, which tends to show that a simultaneous hand-wrist activation is not immediately mastered by a beginner with CCC. However, we do observe simultaneous activations of the wrist and the elbow joints. Finally, there is no clear



(a) Example of joint trajectories with MYO control mode, for P1

(b) Example of joint trajectories with CCC control mode. s.a. stands for simultaneous (wrist-elbow) activation, for P1

(c) Example of joint trajectories with MYO control mode, for P4

(d) Example of joint trajectories with CCC control mode. s.a. stands for simultaneous (wrist-elbow) activation, for P4

Fig. 4. Example of joint trajectories and hand activation from one upwards motion of P1 (a and b) and one upwards motion of P4 (c and d).

common pattern of trunk motions with MYO and with CCC. Trunk motions with MYO are quite small: P4 favoured the use of MYO rather than a fast task performed with body compensations.

These examples highlight the sequential character of prosthesis motions with MYO and, in contrast, the simultaneity allowed by CCC, between wrist and elbow but also between wrist and hand (for the most advanced user). To strengthen

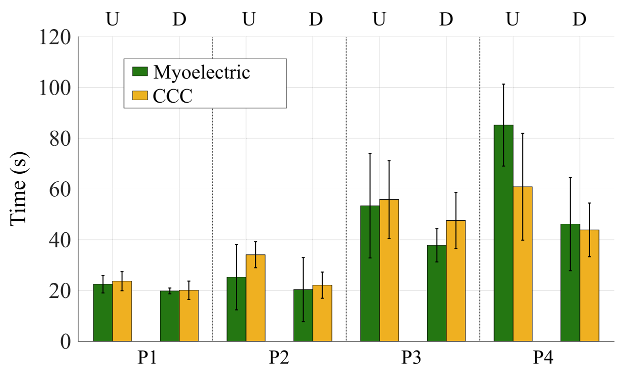


Fig. 5. Time of the task (mean over trials and standard deviation) for each participant. U: upwards; D: downwards motions.

this first insight, results from all trials of the four participants are now analysed.

B. Task Performance

Figure 5 shows the time of the task, averaged over trials, for each participant. A great variability can be noticed between participants (from 22s to 85s with MYO for instance), surely due to the difference in their individual learning stage. For a same individual, there is no clear difference between MYO and CCC (overlapping of standard deviations); both control modes allow completing the task with similar performance.

C. Prosthetic Joints

In this experiment, both prosthetic wrist and elbow were active. Many points can be raised on the strategy developed by the participants with CCC and MYO, be it for individual joint motions or for simultaneous prosthetic joints or prosthetic-and-human joints activation.

Wrist and elbow angular trajectories are shown in Figure 6. Focusing first on pronosupination (Figure 6(a)), we can notice that there is a common CCC trajectory pattern (two successive bell-shapes, reflecting wrist motions for the two clothespins) for every participants, even if the range of motion can differ. For upwards motions, this pattern is similar to the one with MYO for the first three participants (P1, P2 and P3). As for Participant 4 (P4), the wide range of motion with MYO is due to the implemented myoelectric control, which made pronation difficult and led P4 to preferentially use supination, sometimes up to 300 deg. For downwards motions, CCC and MYO trajectories have similarities for P1. For P2 and P3, MYO trajectories seem less smooth and repeatable than CCC.

Considering elbow angular trajectories (Figure 6(b)), we can see that P1, P2 and P4 barely used their elbow joint with MYO: P1 used it only once (light green), P2 did not used it at all and P4 moved it of few degrees only. On the contrary, the elbow joint was activated during every trials, in a repeatable way, with CCC. P3 adopted a different strategy, both with MYO and CCC. With MYO, P3 easily mastered myoelectric switching and thus activated the prosthetic elbow in a useful way, during each trial. When using CCC, P3 extended the elbow once at the beginning of the task, and then kept it still to focus on the wrist rotation. P3 stayed focus on individual prosthetic joints even with CCC.

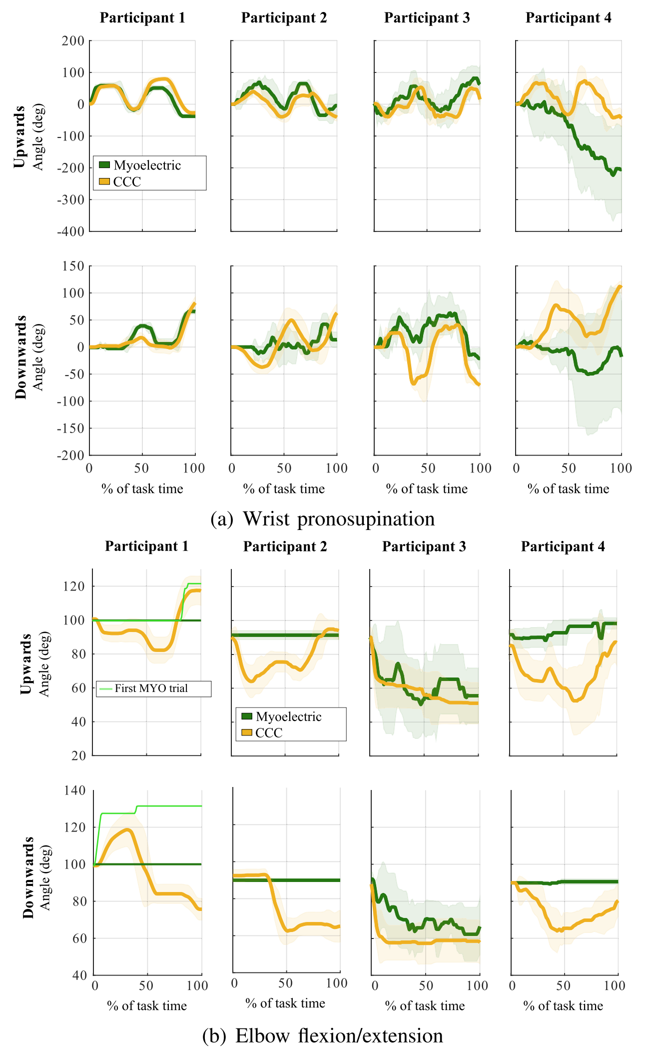
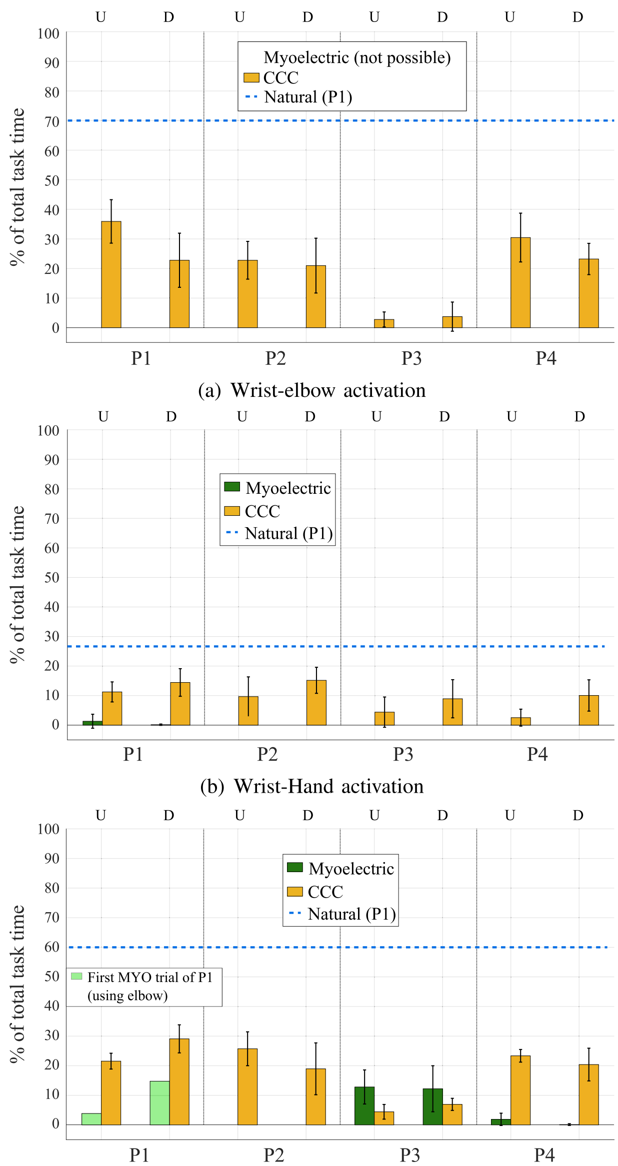


Fig. 6. Prosthetic joint angular trajectories, normalized in time and averaged over trials.(a) Wrist pronosupination. (b) Elbow flexion/extension. For P1, the first trial is set apart (light green), since it was the only one for which the elbow was activated.

Besides angular trajectories, we analysed whether wrist and elbow were activated together with CCC during the task completion. Figure 7(a) shows the time of simultaneous wrist-and-elbow activation, expressed as a percentage of the total task time (joints were considered as active when their angular velocity was higher than 3 deg.s^{-1}). There is no result for MYO, since this feature is not achievable. Natural data are obtained from one participant (P1) performing the Rolyan Clothespin Test with his sound arm (the result is the average over the three trials he performed). It can be observed that natural wrist and elbow joints are moved simultaneously during $\approx$70% of the task. With CCC, wrist and elbow prosthetic joints were moved simultaneously for P1, P2 and P4, during around one quarter of the task. Concerning P3, there is nearly no simultaneity between wrist and elbow motions, since, as observed before, this participant used CCC like MYO and decomposed arm motions into individual joint motions.

It is also of interest to look at a similar simultaneity index for prosthetic hand and wrist motions. CCC does not directly allow for hand grasping motions, since the latter cannot be



(a) Wrist-elbow activation

(b) Wrist-Hand activation

(c) Shoulder-elbow activation

Fig. 7. Simultaneous activation of prosthetic and prosthetic-and-human joints: (a) wrist and elbow, (b) wrist and hand, (c) shoulder and elbow. For P1, the first trial is set apart (light green), since it was the only one for which the elbow was activated. U: upwards; D: downwards motions.

compensated by any other joints, but it discharges myoelectric control which can then be fully dedicated to the control of the hand. For the experiment considered here, we recall that a pair of push-buttons supplanted myoelectric control of the hand, to avoid being particularly biased by the control of the grasping in the task assessment. The prosthetic hand is thus considered as activated when one of the push-button is pressed. For natural data, the hand activation was defined when thumb and index fingers moved towards and away each other. We can see on Figure 7(b) that, even if simultaneous hand-wrist activation was possible with both MYO and CCC due to remote hand control with push-buttons, the participants only made use of it with CCC. With the latter, hand and wrist were moved simultaneously during 5 to 20% of the total time, which gets closer to the 27.5% of the natural task. Myoelectric control actually requires the user to focus on the individual joint s/he is moving, whereas CCC is built to allow prosthesis user to focus on the end-effector, which eases coordinated hand-and-wrist motions.

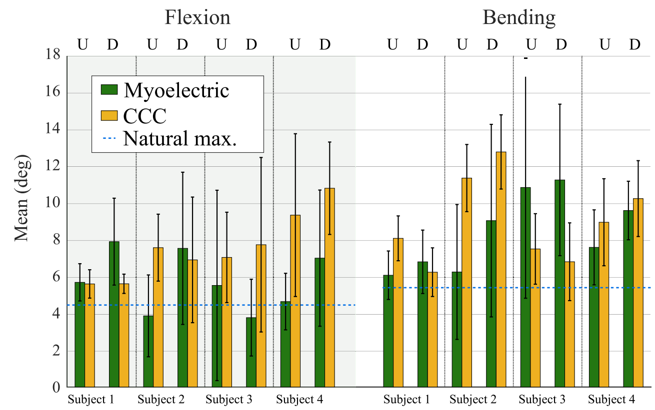


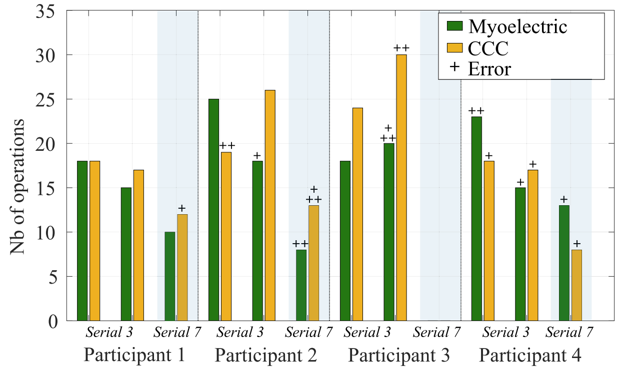
Fig. 8. Time average of trunk compensatory motions (flexion and lateral bending). U: upwards motions; D: downwards motions.

Finally, simultaneity is not only important between prosthetic joints but also between prosthetic and human joints. Indeed, transhumeral myoelectric users often struggle to move their prosthetic arm in coordination with their residual limb, which leads to a global motion in two steps: (i) prosthesis motion followed by (ii) human motion [22], which is inefficient. The natural coordination between joints is missing. The same simultaneity metric as for prosthetic joints is thus considered, but between the prosthetic elbow and the human shoulder (see Figure 7(c)). When the task is performed with the sound limb, the shoulder-elbow simultaneity is around 60% of the total task time. With the prosthesis, we can again observe a difference between P1, P2, P4 and P3. For P1, P2 and P4, CCC allows some recovery of shoulder-elbow coordination; with MYO, as there were few elbow motions, the shoulder-elbow simultaneity is nearly absent. For the MYO trial of P1 using the elbow joint, we see that the time of simultaneous activation between human shoulder and prosthetic elbow is much smaller than the mean over trials with CCC (1.7% vs 14.6% for upwards motions and 8.1% vs 20.9% for downwards motions). As for P3, the prosthesis-user simultaneity with CCC is very low (less than 8%), since this participant extended the elbow once at the beginning of the task, in a totally asynchronous way. With MYO, the shoulder-elbow simultaneity is noticeable for this participant (around 12%) but still remains lower than the one with CCC for the other participants.

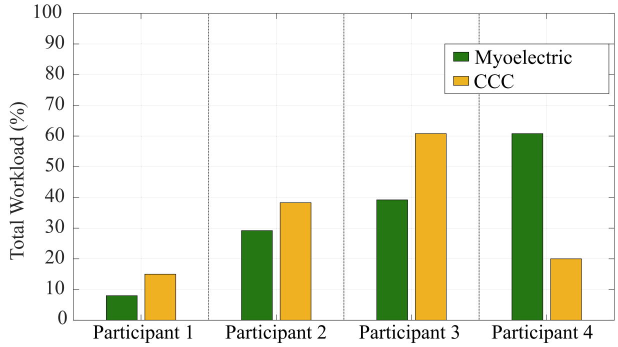
D. Body Compensations

Due to the use of body compensatory motions as controller input, the assessment of the performance allowed by CCC requires to analyse the amplitude of the compensations exhibited by the participants. CCC upper body motions are compared to the one exhibited with MYO, and to the maximum of body motions when P1 performed the task with his non-amputated limb.

Since shoulder motions and trunk rotation are functional joints for the Refined Rolyan Clothespin test, compensatory



(a) Double task: serial 3 and serial 7 subtractions



(b) Raw TLX score

Fig. 9. Cognitive load assessment. (a) Double task: participants were asked to perform serial subtractions in parallel to the Rolyan Clothespin Test. Participant 3 did not perform the serial 7 subtraction trial. (b) Raw TLX questionnaire.

motions are analysed through trunk flexion and lateral bending. The time average of the absolute value of these motions for upwards and downwards motions are shown Figure 8. Three main points can be raised:

- there is no clear difference between compensations exhibited with MYO and those exhibited with CCC. Those tend to be higher than natural trunk motions;
- there is a high inter-subjects variability: no common compensation patterns stands out between participants;
- there is also a high intra-subject variability (for P2, P3 and P4 particularly): the standard deviation is more than 2 deg and can go up to 6 deg when the highest mean value is 13 deg.

E. Cognitive Load

As stated above, the cognitive load required by CCC and the one required by MYO were measured with a double task of serial subtractions and a Raw-TLX questionnaire (see Figure 9). Figure 9(a) shows the results of the double task: the number of operations performed during a complete updwards-downwards cycle, and the number of errors (if any). If the prosthesis control scheme requires the participant to be focused on the control, s/he will be less able to perform the double task. Thus, the lower the number of operations and the higher the number of errors, the higher the cognitive load. It can be observed that there is no clear difference between MYO and CCC with this metric, for every participants. With the Raw TLX questionnaire, filled at the end of the experiment, the participants gave a score for each control mode. The higher the score, the higher the perceived cognitive load. We can see on Figure 9(b) that MYO was given a lower score than CCC by P1 (-7%), P2 (-9%) and P3 (-21%) while P4 gave a much higher score to this mode ($+40\%$).

V. Discussion

The complementary metrics presented above show that the proposed control scheme allows to perform a complex task, the Refined Rolyan Clothespin test. With CCC, the task performance (measured by the time) is similar to the one obtained with the myoelectric control, while requiring no training. After six trials only, CCC was mastered by all four participants. Yet, even if the task performance of both control modes are comparable, the deployed motion strategies differ. The results of P1, P2, P4 on one side, and those of P3 on the other side, will be analysed distinctly, since P3's behaviour shows some particularities.

A. Joint Motions

Results of P1, P2 and P4 show that these participants neglected prosthetic elbow motions with MYO: they tended to avoid co-contractions whenever possible to minimize the global effort, and focus on the most helpful joint, the wrist. With CCC, the activation of the prosthetic elbow requires no additional effort from the user: the absence of voluntary switching allows a simple use of multiple prosthetic joints. Moreover, albeit the percentage is not yet as high as during natural task performance, CCC restores simultaneous and synchronous joint motions (as shown in Figure 7): wrist and elbow are moved together during $\approx$25% of the task; hand is opened while wrist is still moving; human shoulder and prosthetic elbow retrieve coordination. It could yet seem curious that the simultaneous joint motions do not reduce the time of the task with CCC. This is due to the wrist velocity which is smaller with CCC than with MYO. It could be speed up by increasing the gain λ in the control law but with possible stability issue for the human-robot system. Regarding body compensations, one can wonder why the increased use of the elbow joint with CCC does not decrease the amount of compensatory motions. A more detailed analysis of kinematic metrics characterizing the different motion strategies should thus be conducted to better understand this result.

Contrary to most of transhumeral amputated subjects, P3 used a lot the elbow joint with MYO, despite the co-contraction switching. He had also an important shoulder mobility despite the constraints applied by its strapped socket, which made his compensatory motions different from the three other participants and from most of transhumeral amputees. The definition of compensations used in CCC implementation was not fully adapted for him. After one trial, he thus chose to control prosthetic joints individually with CCC, mimicking the strategy used with MYO. When moving the prosthesis with CCC, P3 decomposed the arm motion and considered the joints one-by-one, instead of focusing on the end-effector only, as we had expected. This led to sequential elbow and wrist motions, with the elbow extended once at the beginning of the task. This way of using CCC is not optimal since the upper body motions exhibited to move the prosthesis are not natural task-based compensations, and the benefit of simultaneity is removed. Through this participant's results, it is thus shown that, as expected, body compensations vary between prosthesis users according to the residual mobility of the subject, and that the choice of the compensations used in CCC implementation is crucial to provide an efficient and beneficial control scheme. An important limitation of the current implementation of CCC is thus the generic and constant definition of compensatory motions. To overcome this issue, we recently proposed to update in real time the reference (non-compensatory) posture [28], through an optimisation process on a human model. Body compensations would be then defined as deviation from a regularly updated reference. In [28], a preliminary validation of this proposition has been presented: the optimised posture is obtained with inverse kinematics methods, with some imposed constraints on joint motions. We proposed a null-space optimisation approach with a RULA inspired score [29], an approach then validated with non–disabled participants. Next steps are planned to apply this optimisation method to compute individual body compensations for CCC.

B. Cognitive Load

According to the double task assessment, CCC and MYO are as demanding for this experiment. This is a significant result since CCC required no specific learning nor extended training, contrary to MYO. Participants managed to control their prosthesis with CCC in few minutes, without being more focused than with their usual myoelectric control scheme (which often require an extended training of several weeks or months). For P1, P2 and P4, the similar cognitive load is even more valuable since simultaneous motions of prosthetic joints were achieved (including the elbow), while only the wrist was activated with MYO. Multi-joint motions with CCC thus does not require more mental charge than one joint motion with MYO, which is acknowledged not to be highly demanding when the user is well trained [1]–[3]. The Raw TLX questionnaire brings additional information. P1 and P2 gave close score to CCC and MYO, confirming the results of the double task. P3 scored more CCC than MYO, which could be explained by the unexpected way he used CCC compared to his advanced expertise in myoelectric control. Finally, P4 gave a much higher score to MYO than to CCC. This tends to confirm that MYO is perceived as very demanding when the subject is not well trained, while CCC is easy to handle from the first uses. The assessment of cognitive load of this experiment gave a first insight but could be supplemented by more quantitative measures relying, for example, on the recording of electroencephalograms [30], [31].

C. Perspectives

This experiment validates the benefit that CCC could bring for upper-limb prosthesis control but a long term study would be necessary to strengthen this hypothesis. We have indeed only observed the discovery phase, except for P1 who had previous experience with CCC. While it is interesting to study the easiness of discovery, a next step would now be to study long term use, together with the influence of additional training for CCC. It could also allow us to analyse CCC performance with other tasks. More participants could be included in the experimental campaign, to strengthen the results presented in this paper. Another point of interest is the tuning of CCC. CCC parameters ($\boldsymbol{\lambda}$ and $\boldsymbol{q_0}$) were here kept identical for all participants, to show the generalization of the control method. Yet, it would be valuable to analyze the influence of a fine and personalized tuning of CCC on the performance.

In this work, CCC has been compared to conventional myoelectric control but not to a pattern recognition-based approach. The later has been mostly studied for hand and wrist control, more than for wrist and elbow. Yet, a CCC vs pattern recognition comparison could genuinely complement our study.

Another enhancement for future works is the switching from motion capture system to embedded sensors for compensations measurements. Motion capture was chosen because of the easy body reconstruction and the precise measure of motions it provides. This allows to focus on the preliminary validation of the CCC concept without addressing at the same time the particular issue of body motions measurement in ecological situations. However, a motion capture system such as OptiTrack is completely unsuitable to daily life environments. There is an imperious need to replace it with a wearable alternative. A widespread option is to use IMU, which are low cost, small and lightweight. Many works indeed explore the feasibility to track human motions with IMU [32], [33]. In upper-limb prosthetics, these sensors can even be integrated into the socket or the prosthesis.

VI. Conclusion

Existing control schemes for upper-limb prosthesis do not provide efficient control for multiple degrees of freedom simultaneously, in any situation. The suggestion of this paper is to extend Compensations Cancellation Control, previously validated on single prosthetic DOF [18], [19], to transhumeral amputees controlling simultaneously two joints, the wrist pronosupination and the elbow flexion/extension. This concept lets the user focus on the end-effector task, while prosthesis motions aim at correcting human posture and cancelling body compensations. Tested on the Refined Rolyan Clothespin test, with four transhumeral amputated participants, CCC was quickly mastered by all participants. Compared to conventional myoelectric control, it allows to correctly perform the task, with a simultaneous activation of wrist and elbow when necessary, while not affecting negatively the overall cognitive load nor enhancing compensatory strategies. Nevertheless, to ensure optimal performance, the definition of compensatory motions in CCC implementation should not be generic nor constant, to suit each individual. This aspect is the principal next work to address to enhance the possibilities of CCC. Besides easiness of use and multi-joint motions, a major strength of CCC is its scalability: the addition of active prosthetic DOF does not increase the control difficulty and does not require any major change in the control algorithm. The mapping between body compensations and prosthesis motions is readily adaptable for more than two degrees of freedom, which opens wide perspectives for advanced prosthesis control. The simplicity of implementation, with no algorithm training or user learning, is also a great benefit which supports further works on CCC.

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References

[1] D. Farina *et al.*, "The extraction of neural information from the surface EMG for the control of upper-limb prostheses: Emerging avenues and challenges," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 797–809, Jul. 2014.

[2] P. Parker, K. Englehart, and B. Hudgins, "Control of powered upper limb prosthesis," in *Electromyography: Physiology, Engineering, and Non-Invasive Applications*. Hoboken, NJ, USA: Wiley, 2004.

[3] G. Li, "Electromyography pattern-recognition-based control of powered multifunctional upper-limb prostheses," in *Advances in Applied Electromyography*. Rijeka, Croatia: IntechOpen, 2011, pp. 99–116.

[4] F. Cordella *et al.*, "Literature review on needs of upper limb prosthesis users," *Frontiers Neurosci.*, vol. 10, p. 209, May 2016.

[5] C. Castellini, "Design principles of a light, wearable upper limb interface for prosthetics and teleoperation," in *Wearable Robotics*. Cambridge, MA, USA: Academic, 2020, pp. 377–391.

[6] G. N. Saridis and T. P. Gootee, "EMG pattern analysis and classification for a prosthetic arm," *IEEE Trans. Biomed. Eng.*, vol. BME-29, no. 6, pp. 403–412, Jun. 1982.

[7] M. Oskoei and H. Hu, "Myoelectric control systems—A survey," *Biomed. Signal Process. Control*, vol. 2, no. 4, pp. 275–294, Oct. 2007.

[8] 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, Sep. 2012.

[9] J. M. Hahne, M. A. Schweisfurth, M. Koppe, and D. Farina, "Simultaneous control of multiple functions of bionic hand prostheses: Performance and robustness in end users," *Sci. Robot.*, vol. 3, no. 19, Jun. 2018, Art. no. eaat3630.

[10] S. Amsuess, P. Gobel, B. Graimann, and D. Farina, "A multi-class proportional myocontrol algorithm for upper limb prosthesis control: Validation in real-life scenarios on amputees," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 5, pp. 827–836, Oct. 2014.

[11] X. Yang, J. Yan, Y. Fang, D. Zhou, and H. Liu, "Simultaneous prediction of wrist/hand motion via wearable ultrasound sensing," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 4, pp. 970–977, Apr. 2020.

[12] M. Connan, R. Kõiva, and C. Castellini, "Online natural myocontrol of combined hand and wrist actions using tactile myography and the biomechanics of grasping," *Frontiers Neurorobot.*, vol. 14, p. 11, Feb. 2020.

[13] A. J. Young, L. H. Smith, E. J. Rouse, and L. J. Hargrove, "Classification of simultaneous movements using surface EMG pattern recognition," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 5, pp. 1250–1258, May 2013.

[14] D. Yatsenko, D. McDonnall, and K. S. Guillory, "Simultaneous, proportional, multi-axis prosthesis control using multichannel surface EMG," in *Proc. 29th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2007, pp. 6133–6136.

[15] T. A. Kuiken, G. A. Dumanian, R. D. Lipschutz, L. A. Miller, and K. A. Stubblefield, "The use of targeted muscle reinnervation for improved myoelectric prosthesis control in a bilateral shoulder disarticulation amputee," *Prosthetics Orthotics Int.*, vol. 28, no. 3, pp. 245–253, Dec. 2004.

[16] P. Zhou *et al.*, "Decoding a new neural–machine interface for control of artificial limbs," *J. Neurophysiol.*, vol. 98, no. 5, pp. 2974–2982, Nov. 2007.

[17] E. B. Torres and D. Zipser, "Simultaneous control of hand displacements and rotations in orientation-matching experiments," *J. Appl. Physiol.*, vol. 96, no. 5, pp. 1978–1987, May 2004.

[18] M. Legrand, N. Jarrassé, F. Richer, and G. Morel, "A closed-loop and ergonomic control for prosthetic wrist rotation," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2020, pp. 2763–2769.

[19] M. Legrand, N. Jarrassé, E. D. Montalivet, F. Richer, and G. Morel, "Closing the loop between body compensations and upper limb prosthetic movements: A feasibility study," *IEEE Trans. Med. Robot. Bionics*, vol. 3, no. 1, pp. 230–240, Feb. 2021.

[20] A. Hussaini and P. Kyberd, "Refined clothespin relocation test and assessment of motion," *Prosthetics Orthotics Int.*, vol. 41, no. 3, pp. 294–302, Jun. 2017.

[21] A. Hussaini, W. Hill, and P. Kyberd, "Clinical evaluation of the refined clothespin relocation test: A pilot study," *Prosthetics Orthotics Int.*, vol. 43, no. 5, pp. 485–491, 2019.

[22] M. Merad *et al.*, "Assessment of an automatic prosthetic elbow control strategy using residual limb motion for transhumeral amputated individuals with socket or osseointegrated prostheses," *IEEE Trans. Med. Robot. Bionics*, vol. 2, no. 1, pp. 38–49, Feb. 2020.

[23] A. J. Metzger, A. W. Dromerick, R. J. Holley, and P. S. Lum, "Characterization of compensatory trunk movements during prosthetic upper limb reaching tasks," *Arch. Phys. Med. Rehabil.*, vol. 93, no. 11, pp. 2029–2034, Nov. 2012.

[24] A. Hussaini, A. Zinck, and P. Kyberd, "Categorization of compensatory motions in transradial myoelectric prosthesis users," *Prosthetics Orthotics Int.*, vol. 41, no. 3, pp. 286–293, Jun. 2017.

[25] R. M. Williams *et al.*, "Does having a computerized prosthetic knee influence cognitive performance during amputee walking?" *Arch. Phys. Med. Rehabil.*, vol. 87, no. 7, pp. 989–994, Jul. 2006.

[26] S. G. Hart, "NASA-task load index (NASA-TLX); 20 years later," in *Proc. Hum. Factors Ergonom. Soc. Annu. Meeting*, 2006, vol. 50, no. 9, pp. 904–908.

[27] S. Said *et al.*, "Validation of the raw national aeronautics and space administration task load index (NASA-TLX) questionnaire to assess perceived workload in patient monitoring tasks: Pooled analysis study using mixed models," *J. Med. Internet Res.*, vol. 22, no. 9, Sep. 2020, Art. no. e19472.

[28] A. Poignant, M. Legrand, N. Jarrassé, and G. Morel, "Computing the positioning error of an upper-arm robotic prosthesis from the observation of its wearer's posture," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2021, pp. 10446–10452.

[29] L. McAtamney and E. N. Corlett, "RULA: A survey method for the investigation of work-related upper limb disorders," *Appl. Ergonom.*, vol. 24, no. 2, pp. 91–99, 1993.

[30] J. V. V. Parr, "Evaluating and alleviating the cognitive burden associated with myoelectric prosthetic hand control," Ph.D. dissertation, Dept. Sport Exerc. Sci., Liverpool Hope Univ., Liverpool, U.K., 2018.

[31] S. Deeny, C. Chicoine, L. Hargrove, T. Parrish, and A. Jayaraman, "A simple ERP method for quantitative analysis of cognitive workload in myoelectric prosthesis control and human-machine interaction," *PLoS ONE*, vol. 9, no. 11, Nov. 2014, Art. no. e112091.

[32] A. Filippeschi, N. Schmitz, M. Miezal, G. Bleser, E. Ruffaldi, and D. Stricker, "Survey of motion tracking methods based on inertial sensors: A focus on upper limb human motion," *Sensors*, vol. 17, no. 6, p. 1257, Jun. 2017.

[33] M. Sierotowicz, M. Connan, and C. Castellini, "Human-in-the-loop assessment of an ultralight, low-cost body posture tracking device," *Sensors*, vol. 20, no. 3, p. 890, Feb. 2020.