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Closed-loop multi-amplitude control for robust and dexterous performance of myoelectric prosthesis

Marko Markovic, Marc Varel, Meike A. Schweisfurth, Arndt F. Schilling, and Strahinja Dosen, *Member, IEEE*

***Abstract*—In the case of a hand amputation, the affected person can use a myoelectric prosthesis to substitute the missing limb and regain motor functions. Unfortunately, commercial methods for myoelectric control, although robust and simple, are unintuitive and cognitively taxing when applied to an advanced multi-functional prosthesis. The state-of-the-art methods developed in academia are based on machine learning and therefore require long training and suffer from a lack of robustness. This work presents a novel closed-loop multi-level amplitude controller (CMAC), which aims at overcoming these drawbacks. The CMAC implements three degrees-of-freedom (DoF) control by thresholding the muscle contraction intensity during wrist flexion and extension movements. Unique features of the controller are the vibrotactile feedback that communicates the state of the controller to the user and a scheme for proportional control. These components allow exploiting the full dexterity of the prosthesis using a simple two-channel myoelectric interface. The CMAC was compared to a commonly implemented pattern-recognition method (linear discriminant analysis – LDA) using clinically relevant tests in 12 able-bodied and 2 amputee subjects. The experimental assessment demonstrated that CMAC was similarly fast as LDA in dexterous tests (clothespin and cube manipulation), while it was somewhat slower than LDA during a simple, single DoF task (box and blocks). In addition, in all the tasks, LDA and CMAC resulted in a similarly low error rate. On the other hand, to an amputee that could not generate six distinguishable classes using LDA, the CMAC still enabled the control of all the prosthesis DoFs. Importantly, the overall setup and training time in CMAC were significantly lower compared to LDA. In conclusion, the novel method is convenient for clinical applications, and allows substantially higher control dexterity compared to what can be normally achieved using conventional two channel EMG. Therefore, CMAC provides performance comparable to advanced machine-learning algorithms and the robustness and ease of use that is characteristic for the simple two-channel myoelectric interface.**

***Index Terms*—myoelectric control, pattern classification, multi-amplitude control, vibrotactile feedback, functional tasks**

I. Introduction

ELECTRICALLY powered hand prostheses are the contemporary state of the art in substituting the functions of the amputated limb. The current commercial prostheses are multi-articulated and offer several controllable DoFs that are operated by means of electrical muscle activity. The user generates distinguishable electromyographic (EMG) signals in the residual muscles, which are then mapped to the movements performed by the artificial limb. However, the implementation of a myoelectric human-machine-interface (HMI) is not always straightforward primarily due to lack of residual muscles, which could be used as control inputs [1]. In fact, it is largely considered nowadays that it is the HMI and not the mechatronics that is the bottleneck to the prosthesis performance and usability [2].

A popular method for the implementation of myoelectric control is the use of machine learning to estimate user motor intention from a multichannel EMG recording. In this approach, the controller is trained to assign inputs (i.e., muscle activity) to outputs (i.e., prosthesis function) based on the examples that demonstrate the desired mapping (training dataset). This requires that the user produces reproducible and stable myoelectric patterns in order to train the system to perform a reliable input-output association. Traditionally, pattern recognition has been the method of choice [3] but it allows activating only one specific movement at a time (e.g., wrist flexion followed by hand closing) [4]. More recently, regression algorithms have been tested to enable simultaneous and proportional control of several DoFs (e.g., wrist flexion while closing the hand). However, these methods are so far limited to a maximum of three DoFs in virtual tests [5], [6], and only two DoFs in functional tasks with a prosthesis [7], [8]. In general, machine-learning based control approaches perform well offline as well as in laboratory conditions. The reported classification accuracy is usually > 95% for up to six classes

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[9], [10]. However, it has been demonstrated that the offline accuracy is a poor predictor of the online control performance [2], [11] and that the lack of a broader commercial implementation is primarily caused by the poor reliability in daily use. Namely, the non-stationarities like transient changes, electrode shift, and variation in limb positioning or load [1], [12]–[14] alter the muscle patterns generated by the user and this can significantly deteriorate the performance of machine learning algorithms from day to day [2], [11]. Despite decades of research, first commercial systems for prosthesis control based on pattern classification have been introduced only recently [15], [16]. Altogether, so far the lack of robustness of pattern classification and regression is "limiting its clinical applicability and acceptance" [17].

Consequently, the control of most commercial prostheses still relies on the direct proportional and sequential control scheme, which was invented decades ago [10], [18]. In this approach, a monopolar myoelectric signal determines the velocity of prosthesis movement in a specific direction (e.g., hand closing). Therefore, at least two muscles are needed for proportional control of a single DoF (e.g., hand closing and opening). This scheme can be easily extended to multiple DoFs by using a dedicated switching signal, such as a co-activation of both muscles, to change the function. However, such control is slow and tedious for the multifunction prostheses, because the user needs to switch sequentially through all the DoFs. Grouping related functions in a state machine can improve the performance [19], [20], [21]. Alternatively, the signal amplitude can be divided into several ranges, where each range is associated to a specific function, which is known as multi-amplitude (MAC) or amplitude-coding control [22], [23]. For example, light flexion can activate closing in palmar and strong flexion in lateral grasp. The advantage of this approach is that the user can directly activate a function, without the sequential switching. However, the number of functions that can be controlled is limited since it can be difficult for the user to modulate the muscle activation across the amplitude levels. In literature as well as commercially, MAC has been used with at most two levels per electrode [22], [23]. In addition, proportional control can be challenging with MAC, because the signal needs to be modulated within a narrow amplitude. If the signal comes out of the range, the subject inadvertently switches the function.

Hence, the users' discontent with commercial HMIs in terms of their speed/intuitiveness in case of direct control or poor reliability in case of machine learning solutions motivate the implementation of novel control schemes. Here, we present a novel approach for the closed-loop multi-amplitude control (CMAC) using only two EMG channels to accommodate three DoFs, namely, grasping, rotation, and flexion/extension of the wrist in an advanced myoelectric prosthesis. The main novelty of CMAC, compared to conventional MAC, is the integration of vibrotactile feedback and a proportional control scheme. Importantly, the vibrotactile stimulation did not transmit the state of the prosthesis as usually done in literature [24], [25]; instead, the role of feedback was to communicate the state of the CMAC controller to the subject. These novelties allowed reliable selection as well as proportional control of six prosthesis functions, which would not be possible using conventional MAC.

In the present study, we compared the performance of CMAC versus commonly used pattern classification controller (linear discriminant analysis, LDA). The results demonstrated that CMAC performed similarly to the more advanced LDA controller in dexterous functional tasks. Additionally, CMAC had substantially shorter setup and training time than LDA. Therefore, the novel method provides the robustness of a simple, commercial two-channel control combined with the dexterity of machine learning algorithms developed in academia. Thereby, the new system closes the gap between the user's needs for robust control and feedback, and the limitations of the state of the art pattern-recognition control.

II. Materials and Methods

A. Experimental setup and hardware implementation

The experimental setup for evaluating CMAC prototype in able-bodied subjects consisted of components shown in Fig. 1: 1) a Michelangelo prosthesis with three degrees of freedom (Ottobock Healthcare GmbH, Vienna, Austria) coupled with a control unit and two dry EMG electrodes with integrated amplifiers (type: 13E200, Ottobock Healthcare GmbH, Vienna, Austria), 2) a feedback component including three C2 tactors (Engineering Acoustics, Inc., Casselberry, Florida, USA) generating vibrotactile stimulation, and 3) a desktop PC (Dell Optiplex 7010, Intel i5, Windows 7).

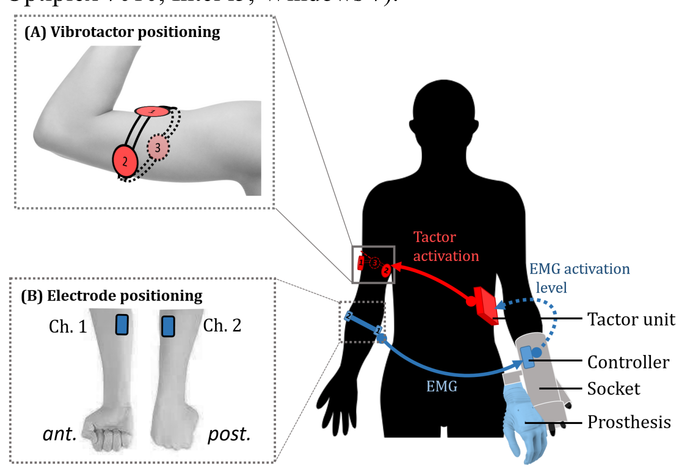

Fig. 1. The setup for evaluating CMAC prototype. Two-channel EMG signal is recorded and transmitted to the controller. After the muscle activation level has been classified into one of the three sub-ranges, the signal is sent to the tactor unit generating vibrations to indicate the selected functions and provide EMG biofeedback. (A) Vibrotactors are positioned at the ventral (1), medial (2) and lateral (3) side of the upper arm. (B) The anterior and posterior view of the lower limb together with the positioning of EMG electrodes, Channel 1 and 2, at the flexor carpi radialis and extensor carpi ulnaris, respectively.

In able-bodied subjects, a left-hand Michelangelo prosthesis was attached to a socket covering the subjects' left forearm (Fig. 1, grey component). The CMAC used two electrodes (Fig. 1B) placed on the dorsal and volar side of the forearm above the hand and wrist flexor (Channel 1) and extensor muscles (Channel 2), respectively. Due to the lack of space, the electrodes as well as the vibration motors were placed on the contralateral side. This was only a matter of convenience and, in the normal use, all the system components are supposed to be on the ipsilateral side, ideally integrated in the prosthesis socket. The vibrotactors were strapped equidistantly and circumferentially around the upper arm using a rubber band: tactor 1 was placed on the ventral side, tactor 2 on the medial, and tactor 3 on the lateral side of the upper arm (Fig. 1A). In amputee subjects, the prosthesis was connected to a custom-made socket with embedded EMG electrodes. The socket was placed on the residual limb and the vibrotactile feedback was, due to the space constraints, positioned on the ipsilateral upper arm, proximal to the elbow at one third of the upper arm length. Therefore, even though the vibrotactors were not integrated in the socket the setup in amputees closely resembled the envisioned application of the system.

The experimental setup in LDA condition differed from CMAC only in the number of electrodes (eight dry EMG electrodes in LDA) and the absence of vibrotactile feedback.

Importantly, although Michelangelo prosthesis was able to perform lateral grasp, this preshape was not utilized in the present experiment. Introducing an additional class would make the control less reliable, and we decided to prioritize system robustness over dexterity. Put differently, the primary goal was that the prosthesis operates in a stable and reproducible manner. Furthermore, when mapping available classes to prosthesis commands, we prioritized the wrist function with respect to hand dexterity. This decision was based on our own experience but also on the recent scientific evidence which demonstrates that in the context of prosthesis control, having a dexterous wrist could be more relevant for activities of daily living than having dexterous fingers [26], [27].

B. Algorithm implementation

1) CMAC system

The CMAC control was based on amplitude thresholding. The two electrodes with integrated pre-amplifiers were used to record surface EMG signals. To obtain the level of muscle activation, the root mean square (RMS) of EMG was computed over the sliding window (150 ms) with 80% of overlap and low-pass filtered using a 2nd order Butterworth filter with the cutoff frequency at 2.5 Hz. The RMS from both EMG channels was normalized by linearly mapping the values between the baseline activity and the maximal prolonged voluntary contraction (MPVC, [3]) to the range 0-100%. To produce MPVC, the subjects were asked to activate the muscles strongly but at the level that they could maintain for 10 seconds. The control signals were normalized to MPVC (instead of MVC) in order to ensure that the subjects did not need to produce excessive muscle contractions when controlling the prosthesis. The baseline RMS activity was heuristically adjusted to minimize the chance for accidental prosthesis activation. The MPVC was measured five times and the smallest value was adopted as the MPVC to minimize the chances that subjects would get fatigued during the experiment. During online control, the normalized myocontrol channel with the higher activation was compared against the thresholds at 35% and 80% in order to determine the amplitude range, and each range was associated to a specific prosthesis function (Table I). Since the system operated with two electrodes and three ranges per electrode, it could control up to six prosthesis movements (i.e., three DoFs). A light contraction of the wrist flexor muscles activated wrist pronation, a medium contraction closed the hand in pinch grip and a strong contraction led to wrist flexion. The contraction of the wrist extensor muscles actuated the same DoFs in the opposite direction. Furthermore, the majority-voting filter of 180 ms (150 ms overlap) was applied. The prosthesis function was activated only if 70% of the samples were from the same class.

TABLE I
MAPPING BETWEEN ACTIVATION RANGE, PROSTHESIS MOVEMENT AND VIBROTACTORS ACTIVATION

Muscle activation (% of the normalized RMS)	**Prosthesis activation**		**Feedback**
	Medial EMG (wrist flexor)	Dorsal EMG (wrist extensor)	
AR[a] 1: < 30	Pronation	Supination	Ventral tactor
AR 2: 30 - 85	Fine pinch	Hand open	Medial tactor
AR 3: > 85	Flexion	Extension	Lateral tactor

[a]AR: Amplitude range

The prosthesis was velocity controlled (Fig. 2). The wrist was operated using gated-ramp controller [28] and hand opening/closing was based on classic proportional control scheme. The gated-ramp control was therefore implemented in amplitude range 1 (wrist pronation/supination) and 3 (wrist flexion/extension). When the myoelectric signal was in these ranges, the prosthesis started rotating/flexing in the selected direction at a minimum velocity. The velocity was then linearly increased with time (constant acceleration) until a predefined maximal velocity was reached. The minimum and maximum velocity as well as the acceleration (slope) were adjustable parameters. In the present study, the maximum speed was reached in 0.9 s from the movement onset. Contrary to this, the prosthesis control in the amplitude range 2 (hand opening/closing) was proportional to the muscle activation to allow fine and reliable control of grasping force; the muscle activation in this range was mapped linearly to the prosthesis velocity, i.e., 85% of the normalized RMS corresponded to maximum closing speed and thereby maximal grasping force. The proportional controller was activated when the user entered the amplitude range 2 by increasing the muscle activation (transition from range 1 to 2). However, in order to avoid the sudden hand opening/closing at the maximum speed, the transition from range 3 back to 2 did not activate proportional control but instead it triggered the gated-ramp controller (same operation as when controlling the wrist).

Three vibrotactors were activated according to Table I. The currently selected range (prosthesis function) was indicated to the user by activating the respective vibrotactors, i.e., ventral, medial and lateral for the amplitude range 1, 2 and 3, respectively. Therefore, by modulating his/her muscle activation the subject perceived a vibration pattern, which was moving circumferentially around his upper arm from ventral over medial to lateral tactor for increasing and in the opposite direction for the decreasing muscle contraction. Since the overall control loop incorporated both mechanical (e.g., inertia of the prosthesis actuators) and signal-processing delays (e.g., majority voting filter) the selected amplitude range was perceived by the user not only before the prosthesis actually moved but also even before the control algorithm reached the decision. Therefore, the user was directly aware of his/her myoelectric command (EMG biofeedback [28], [29]) and he/she could use this to act predictively. For example, by sensing that the vibration "jumps" between two adjacent tactors he/she could anticipate the switching of the prosthesis function and modulate his/her muscle activity towards the range (function) that he/she actually wants to activate. When amplitude range 1 or 3 was triggered, ventral or lateral tactors, respectively, vibrated at the maximal intensity. However, when proportional control in amplitude range 2 was active, the vibration amplitude was modulated between 30% and 100% of the maximal intensity. In this case, the feedback indicated both the selected function (hand open/close) and the actual amount of prosthesis speed. Therefore, the subjects could use this information to finely adjust prosthesis force. The vibration frequency was set to 230Hz.

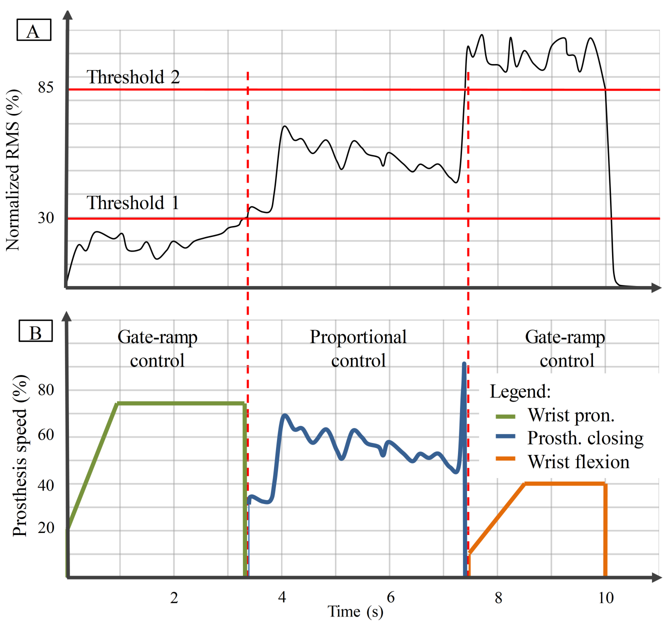

Fig. 2. Example of an input signal for CMAC controller, namely, filtered and normalized RMS of EMG of wrist flexor muscle, (A) and the corresponding velocity command generated by CMAC and sent to the prosthesis (B) plotted against time in seconds. Threshold 1 and 2 (red lines) depict the myoelectric control thresholds that switch between prosthesis functions (red dotted lines). Note that proportional control is available only in the middle amplitude range, which corresponds to prosthesis opening/closing (see Table I).

2) *LDA classifier*

LDA classifier used eight EMG electrodes and the Hodgins time-domain feature set (Hudgins, Parker, & Scott, 1993), which is considered as a benchmark for pattern classification prosthetic control [29], [3]. The features of the EMG were extracted using a time window of 150 ms with an overlap of 120 ms, the control module operated at a sample rate of 33 Hz. The classification was performed for seven movements (rest, fine pinch, hand opening, wrist pronation, supination, flexion and extension). The majority-voting filter computed the 'winning class' using a sliding window of 180 ms (150 ms overlap). For the decision to be reached, at least 70% of the samples (i.e., four out of six) had to belong to the same class. A second order low-pass Butterworth filter with a cut-off frequency of 2.5 Hz was used to smooth the control signal sent to the prosthesis.

C. Experimental evaluation: comparison between CMAC and LDA

1) *Subjects*

The study was approved by the Ethics committee of the University of Göttingen (22/04/2016). All experiments were conducted in accordance with the declaration of Helsinki, and the subjects signed an informed consent form prior to participation in the experiments. A total of twelve able-bodied (age: 25±5; 3 females, 9 males) and two amputee subjects were recruited (age: 59 and 61 years old, both males). Nine subjects were right handed, four left handed, and one was ambidextrous. Nine out of twelve subjects were naïve to myoelectric prosthesis control.

2) *Experimental tests*

Three tests of gradually increasing complexity were conducted to assess the practical applicability of the novel myoelectric control system (Fig. 3). In addition to these, subjective workload and feedback perception were evaluated using questionnaires.

Test 1: Box-and-Blocks Test (BOX). The BOX, first described in Cromwell (1976), is a standardized test in which the subjects are given 60 seconds to transfer as many blocks (size 2.5cm3, maximally 32 blocks) as possible from the left to the right compartment of a wooden box (Fig. 3A) (Cromwell, 1976). This was defined as one run. Therefore, the subjects needed to control a single degree of freedom – opening and closing of the hand. The test protocol was implemented as in [30], except that we allowed the subjects to get familiar with the procedure before starting the test.

Test 2: Clothespin-Reallocation Test (PIN). This method assesses the capabilities of dexterous manipulation of an object while maintaining a stable grasp [31]. Here, it has been slightly modified: the task was to relocate four, instead of three, plastic clothespins as quickly as possible from a horizontal to a vertical bar (Fig. 3B). Hence, two DoFs had to be controlled to accomplish the task (i.e., hand closing/opening and wrist rotation). The four pins were modified with two different spring resistances (two red pins: min. force = 13N, max. force = 23N; two blue pins: min. force = 29N, max. force = 38N). In addition, they have been equipped with a switch and a small LED (Fig. 3B) [32]. Applying too much force on a pin led to triggering the switch and activating the LED, which simulated the breaking of the pin. Therefore, the subjects had to apply the appropriate amount of grip force to open the pin. Dropping a pin or activating the LED resulted in a repetition of the complete trial from the beginning.

Test 3: Cube-and-Block-Transportation Test (CUBE). CUBE test was based on the design of [29] for evaluating the dexterity of control in transradial amputees. Here, the task has been adapted in order to assess the control performance for three DOFs. The subjects transported two objects, a cube (5 cm3) and a block (15 cm x 5 cm x 3 cm), sequentially. First, the cube was transferred from the left side of an upper shelf to a lower shelf (Fig. 3C1) performing the following sequence of prosthesis movements: flexing the wrist before grasping the cube, supinating the wrist at ~180 degree, extending the wrist and placing the cube within the marked area by opening the hand. Then, the block lying flat on one side in the lower shelf was transported to the upper shelf in an upright position (Fig. 3C2). In this case, the subjects pronated the wrist at ~180° and slightly flexed, if necessary. After grasping the object, the wrist was supinated at ~90°, the block was placed within the marked area on the upper shelf and released by opening the prosthesis. Dropping the object during the manipulation resulted in repeating the trial from the beginning.

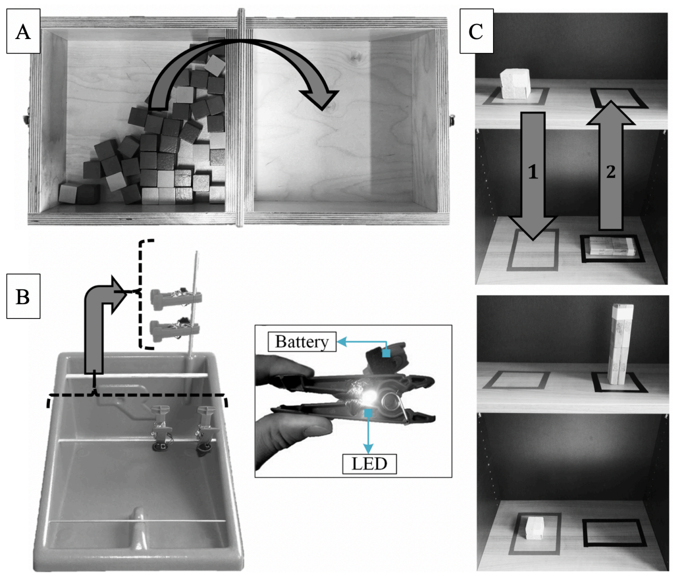

Fig. 3. (A) Box-and-Blocks Test. The subjects transported as many blocks as possible from the left to the right box within 60 seconds. (B) Clothespin-Relocation Test. The subjects needed to relocate four pins from the starting (horizontal bar) to the final positions (vertical bar). The clothespins are equipped with an LED indicator that lights up when too much force is applied. (C) Cube and Block Transport Test. The subjects were asked to reallocate the two objects from the starting positions on the left to the final positions on the right-hand side.

3) *Experimental protocol*

All able-bodied subjects performed the full experimental protocol in two control conditions (LDA and CMAC). Three able-bodied subjects additionally performed full experiment using CMAC without vibrotactile feedback to assess the importance of feedback (MAC condition). Each experimental condition was performed in two sessions - one practice and one evaluation session. One amputee subject used CMAC and LDA with a reduced number of classes (hand open/close and wrist pronation/supination) since he could not produce six distinguishable muscle activation patterns. The other amputee used CMAC and LDA both with full (LDA-6) and reduced number of classes (LDA-4). The CUBE task was not performed with LDA-4, as the task required the full dexterity. The order of conditions was pseudo-randomized across subjects (Fig. 4).

The practice session was used to train the myoelectric control and become acquainted with the experimental tests, while the outcome measures were collected in the evaluation session. The break between two adjacent sessions was between one and three days. The sessions lasted between 90 and 150 minutes. The experimental protocol was divided into five phases (Fig. 4): I) control introduction, II) calibration, III) training, IV) tests introduction, and V) testing phase (performed only in the evaluation session). Both sessions followed this protocol except that the practice session did not include the testing phase (V) and the evaluation session did not include the control introduction (I).

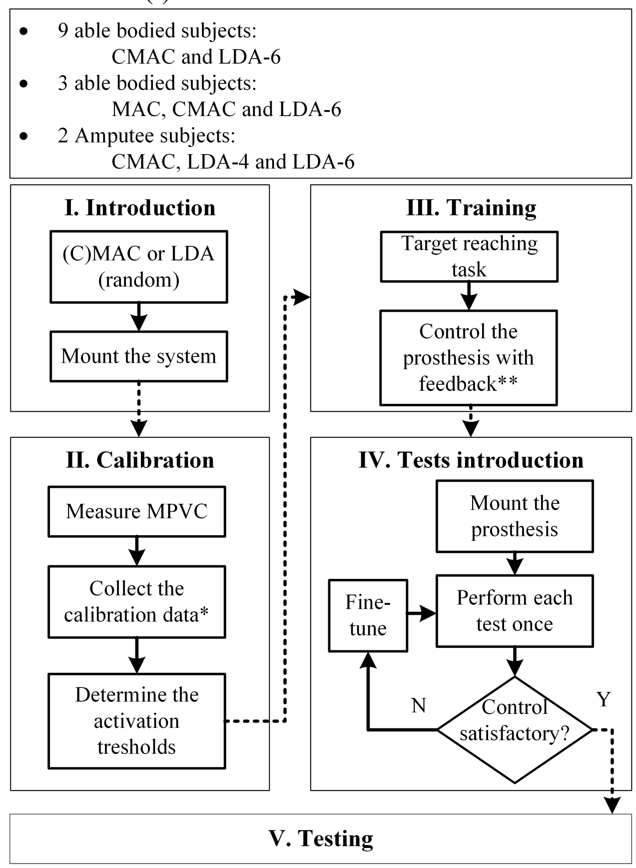

Fig. 4. Experimental protocol during evaluation session for three control methods – MAC, CMAC and LDA. The protocol was divided into five phases: I) introduction, II) calibration, III) training, IV) tests introduction and V) test phase. *The recording of the calibration data in phase II is done in LDA condition only. **The feedback testing was performed in CMAC condition only.

<u>*I) Control introduction.*</u> The CMAC was introduced in two steps. First, the visual feedback depicting the preprocessed and normalized RMS signals was shown to the subject (Fig. 2A). This visual feedback was used to explain how modulating muscle contraction triggers different activation ranges (AR) and how they relate to prosthesis functions. Then, the vibrotactile feedback was explained. The participants received a combination of visual and vibration feedback in order to learn how to utilize the vibrotactile coding scheme. Finally, the visual feedback was removed, and the participants focused on the vibration only.

In LDA, the introduction included training subjects to generate distinct muscle activation patterns for the six movement classes. This was achieved by visually inspecting a polar plot showing the RMS of EMG acquired from each electrode as a vector [33].

<u>*II) Calibration phase*</u>. In CMAC, the MPVC was measured for two motions: wrist flexion and wrist extension. The subjects

were instructed to activate the muscles strongly to the level that could be comfortably maintained for 3-5 s, five times in a row. Then, the minimum and maximum myocontrol activation thresholds that were used for RMS signal normalization were gradually adjusted until the user was satisfied with the overall controllability and no accidental activations of the prosthesis functions were observed.

In LDA, the MPVC was determined for six motions: wrist ulnar and radial deviation, hand and close, wrist flexion and extension; these motions were used in phase IV to control the respective prosthesis functions, where wrist abduction and adduction were mapped to wrist pronation and supination. LDA was calibrated as recommended in the literature [9], [34]. The subjects performed each movement at three activation levels (30%, 50%, and 80% of MPVC) by tracking a reference trajectory shown on the computer screen. Since the electrodes for able-bodied subjects were placed on the contralateral side, the subjects did not need to move the arm during the functional tests in phase V. Therefore, it was not necessary to train the algorithm in more than one arm position. However, for amputee subjects who wore electrodes on the ipsilateral side the training was performed in three arm positions to accommodate for the limb-position effect [35].

III) Training phase. The training phase consisted of a target-reaching task, performed on a computer screen. The task was to reach a pre-defined target by moving a cursor, which was controlled by a selected control method (CMAC or LDA). The subject had six seconds to reach the target area and then maintain the cursor within the target for at least one second (dwell time). The targets were presented in random order and they required activation of different DoFs (all DoFs included). The runs were repeated until the average success rate of 85% was reached across the last three runs.

In CMAC, the subjects had to perform additional training with the feedback in order to demonstrate that they were able to discriminate between the tactors and stimulation levels and utilize it for prosthesis control. The subjects were asked to select randomly chosen prosthesis functions (determined by experimenter) by relying only on vibrotactile feedback (eyes closed). Only upon repeatedly demonstrating that they can reliably activate every prosthesis DoF, the subjects could proceed further with the tests introduction phase.

IV) Tests introduction. In this phase, the participants tried the experimental tasks (BOX, PIN and CUBE) with the prosthesis. The control parameters were optimized if subjects had trouble in actuating the prosthesis during the test. In CMAC, the adjustable parameters were the activation threshold and the maximal muscle activation level. In LDA, the same parameters were adjusted but for each class separately.

V) Testing phase. The experimental tests were presented in the order of increasing complexity (BOX, PIN and CUBE). The BOX test was repeated six times, whereas PIN and CUBE were performed until six successful trials (no drops/breaks) were recorded. All tests were performed in an upright standing position in front of a table or a shelf. The height of the table and shelf were adjusted to the hips and shoulder level of the subject, respectively. The subjects filled in the NASA-TLX questionnaire after each test. The sensory feedback questionnaire (SFQ) was presented once at the end of the experimental session in each condition.

4) *Experimental outcome measures*

The primary outcome measures were the number of successfully transferred blocks (BOX), the time to accomplish the trial (i.e., reallocate 4 clothespins in PIN) and the total time to transport both objects (CUBE). The secondary outcome measure was the error rate, defined as the number of dropped blocks (BOX) and the number of repeated trials (PIN and CUBE).

The NASA TLX questionnaire was used to assess the task-specific workload according to mental, physical, and temporal demand as well as performance, effort and, frustration [36], [37].

A sensory feedback questionnaire (SFQ) has been developed in order to assess the subjective impressions about vibrotactile feedback. The SFQ was divided in two parts. Part A was completed once after each control condition (CMAC and LDA). It consisted of three questions evaluating the overall benefit of implicit feedback sources, i.e., visual feedback, sound and vibration of the prosthesis as well as proprioceptive feedback from the muscles. Under muscle proprioception, we regarded the ability of the subject to perceive his/her muscle contraction intensity and its effect on the prosthesis control. Part B was applied in CMAC condition only and it included four additional questions evaluating the usability of the vibrotactile feedback (benefit, comprehension, concentration, and sensation). A visual-analog scale between 0 to 100 points (in steps of five) was used to evaluate the questions.

Finally, the cumulative training time (CTT) was measured during the evaluation session only. It reflected how much time was needed to mount, train, test (using target reaching task) and fine-tune the prosthesis control with each of the systems (CMAC or LDA). The CTT was measured from the beginning of the evaluation session until the start of the experimental tests (phase IV).

5) *Data analysis*

The performance was computed for each subject by averaging the primary outcome measures and the error rate across six successfully performed trials and over all unsuccessful trials, respectively. Due to the oversight, two participants in CMAC and LDA condition did not fill out the SFQ questionnaires. Therefore, the SFQ and NASA TLX outcome measures were collected and analyzed for ten out of twelve subjects.

As the data did not pass a normality test (Kolmogorov test), the results are reported as median (interquartile range). The Friedman test was used to assess statistically significant differences within a control condition (CMAC, LDA). For the pairwise comparison, Tukey's honestly significant difference criterion was applied. The Wilcoxon signed rank test was employed to compare the results across the conditions. The threshold for statistical significance was set to $p < 0.05$.

III. Results

1) *Able-bodied subjects*

Fig. 5 depicts the primary (A1, B1, and C1) and the secondary outcome measures (A2, B2 and C2), as well as the

NASA TLX results (A3, B3 and C3) and questionnaires (D, E) in two control conditions (CMAC and LDA).

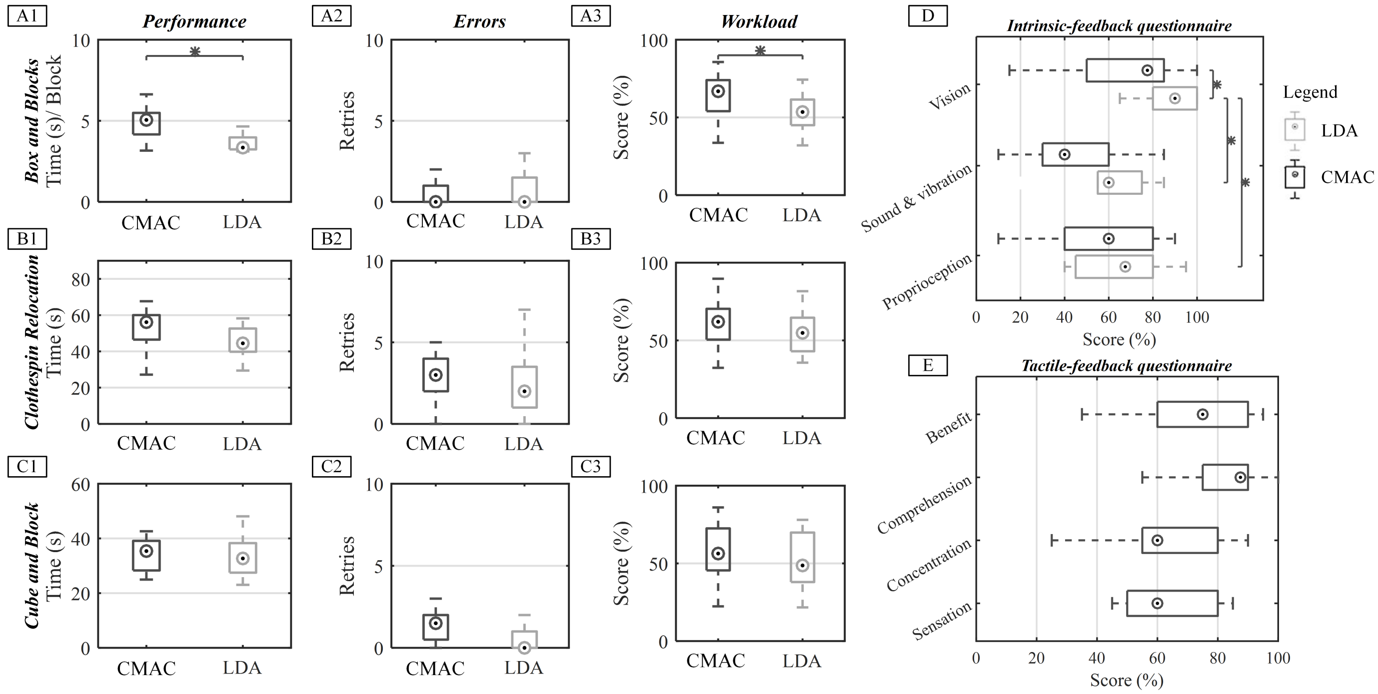

Fig. 5. (A, B, C) Average trial completion time (primary outcome), errors (secondary outcome) and workload score across the experimental tests (BOX, PIN, CUBE) and conditions (CMAC, LDA). The performance of CMAC was similar to that of LDA in PIN and CUBE tasks. (D,E) Sensory feedback questionnaire (SFQ) results. The ratings are between 0 and 100%. The boxplots depict the median (circles), interquartile range (boxes), maximal/minimal values (whiskers).

The average time to transfer a block in BOX was 5 (2) s with CMAC, and this was significantly slower compared to LDA (3 (1) s / block; p = 0.009). The error rate in both conditions was similar. Participants rated the overall workload significantly higher when using CMAC than when using LDA (Fig. 5A3; 67% (20%) vs. 53% (16%); p = 0.0327). In PIN test, there was no statistically significant difference in the time to accomplish the task between CMAC and LDA (Fig. 5B1; 56 (14) s vs. 44 (14) s). Additionally, neither the error rate (Fig. 5B2; CMAC 3 (2), LDA 2 (2)) nor the workload (Fig. 5B3; CMAC 62% (20%), LDA 55% (21%)) differed significantly between the conditions. The users exhibited similar performance with LDA and CMAC in CUBE test in all the outcome measures, including the time to accomplish the task (Fig. 5C1; CMAC 37 (10) s, LDA 33 (10) s), error rate (Fig. 5C2; CMAC 1(1), LDA 0 (1)) and workload (Fig. 5C3; CMAC 56% (27%), LDA 49% (32%)).

The summary results from the questionnaire about the use of implicit sensory feedback are shown in Fig. 5D. The subjects relied on the visual assessment of the prosthesis state significantly more in LDA (90% (20%)) than in CMAC (77% (35%), p = 0. 0078). Moreover, during LDA and in contrast to CMAC, the vision was perceived as the dominant feedback source as it was rated significantly higher than both sound and vibration cues of the prosthesis motor (60% (20%)) as well as muscle proprioception (67% (35%)). Overall, the subjects rated the supplementary vibrotactile feedback (Fig. 5E) as beneficial (75% (30%)), comprehensive (87% (15%)) and pleasant (60% (30%)). However, with a minimum of 25%, a maximum of 90%, and a median of 60% the subjects displayed a high variability in rating the concentration effort necessary for integration and utilization of the vibrotactile feedback.

The cumulative training time (CTT), was significantly lower in CMAC (40 (15) minutes) compared to LDA (50 (20) minutes, p = 0.03).

In the MAC in which the feedback was unavailable, the performance was substantially worse than in the CMAC condition (BOX: 8 (1) s / b; PIN: 72 (14) s; CUBE: 55 (14) s).

2) Amputee subjects

TABLE II
RESULTS FROM AMPUTEE SUBJECTS

	Amputee 1					
	LDA-4 classes		LDA-6 classes		CMAC	
	Perf.	Work.	Perf.	Work.	Perf.	Work.
BOX	3 ± 0.4 s/block	X	5 ± 0.4s s/block	56	4 ± 0.4 s/block	60
PIN	57 ± 8s 2 errors	X	58 ± 1s 0 errors	38	60 ± 9s 2 errors	61
CUBE	X	X	45 ± 8s 0 errors	62	45 ± 3s 0 errors	16
	Amputee 2					
BOX	3 ± 0.2 s/block	32	X	X	6 ± 0.5 s/block	38
PIN	38 ± 4s 2 errors	35	X	X	61 ± 8s 6 errors	48
CUBE	X	X	X	X	67 ± 6s 5 errors	74

The summary results for amputees are presented in Table II. For amputee 1, the overall trend was similar to that observed in able-bodied subjects. The performance was similar with CMAC and LDA-6 in both primary and secondary outcome measures. When he used LDA with four classes, the performance improved in BOX test. The second amputee, who could not control six classes with LDA, was able to exploit the full dexterity of the prosthesis with CMAC. He successfully performed all three tasks. When using a reduced number of classes (LDA-4), he was substantially better compared to CMAC, but he could not perform the CUBE task, which required wrist flexion/extension. The workload slightly increased in CMAC in most of the cases. It was substantially higher in PIN test in amputee 1 but also substantially lower compared to LDA-6 in CUBE test in the same amputee.

IV. Discussion

This study presents a novel myoelectric interface based on closed-loop multi-level amplitude control (CMAC) using two-channel EMG and three-channel vibrotactile feedback. CMAC was implemented as a proportional controller capable of controlling three prosthesis DoFs using three amplitude ranges per EMG electrode, while simultaneously transmitting the current activation level back to the user (biofeedback). The novel control scheme was compared to the conventional MAC as well as to the commonly used pattern-recognition algorithm (LDA) in able-bodied and amputee subjects, who performed functional tasks with increasing level of complexity. The evaluation addressed both objective and subjective performance measures.

The CMAC and pattern classification are substantially different approaches to prosthesis control both in terms of hardware and data processing (e.g., 2 versus 8 EMG channels). Nevertheless, they provide the same functionality, that is, direct, sequential control of prosthesis DoFs. The CMAC uses the same number of EMG channels as the SoA myocontrol but eliminates the need for manual switching through prosthesis functions (e.g., cocontraction). The switching is not only tedious but also extremely slow for multi-DoF prosthesis control. Two recent studies demonstrated that LDA substantially outperformed two-channel control with switching [29], [38] Therefore, although in the present experiment the CMAC was not directly compared to the SoA two-channel myocontrol, it is highly likely that it would be substantially better especially in terms of task execution speed, which was the primary outcome measure in this study.

1) *CMAC allows dexterous control using simple myoelectric interface and feedback.*

The provision of vibrotactile feedback was fundamental for the effectiveness of CMAC control. The feedback provided the information on the current level of muscle activation, thereby allowing the subjects to modulate the muscle activity across the three amplitude ranges in reliable and controlled manner. Indeed, removing the feedback in the MAC condition resulted not only in substantially worse performance (decrease of between 30% to 40% across all tests) but the subjects also reported that it was very difficult and frustrating to navigate the 3-level MAC control without the feedback information. This led to higher number of errors, such as involuntary object drops, and we consequently decided not to proceed with this experimental condition after assessing it in three able-bodied subjects. Therefore, in CMAC, the feedback assists the subject in function selection (levels 1-3) as well as in proportional control (level 2), and the present experiment shows that both were important (CUBE and PIN tasks, respectively). However, in the PIN task, the individual contributions of the two feedback mechanisms to the subject performance cannot be clearly separated.

Thanks to closing the loop and the use of range-specific controllers (gated ramp and proportional scaling) CMAC scheme provides the level of control dexterity that substantially surpasses the capabilities of the conventional two-channel methods such as sequential switching, and conventional open-loop MAC. CMAC allows direct activation of six prosthesis functions, which could be provided so far only using machine learning. However, since CMAC reduces the stimulation range that is available for proportional control (in order to allow feedback-driven function selection), it could happen that LDA and/or two-channel SoA interface would provide better proportional control in some tasks, especially if they are also supported by the feedback.

Due to the nature of CMAC operation, the tactile feedback was dynamic: short periods of stimulation that was jumping from tactor to tactor. This has minimized the habituation that is typically observed during a prolonged constant stimulation [39]. And indeed, none of the tested subjects reported any difficulties in feedback perception and/or interpretation. In addition, the vibrotactile interface did not interfere with EMG recording and myoelectric control.

2) *CMAC is similar to the state of the art machine learning in dexterous tasks.*

Overall, the performance of CMAC in able-bodied subjects and one amputee was comparable to that of LDA with six classes in the two complex tasks (PIN and CUBE) in terms of both speed (time necessary to complete the task) as well as reliability (number of errors). There was no clear advantage for either of the two methods regarding the perceived workload reported by the subjects. Therefore, not only that CMAC provides the same number of commands as LDA, but it also allows these commands to be activated by the user in a fast and reliable manner, despite the fact that it uses a simple scheme that is not based on pattern classification. This simplicity is an important advantage. Those subjects that cannot produce enough commands through pattern classification, like amputee 2 in the present study, can still utilize full prosthesis dexterity by using CMAC. Importantly, the implementation of LDA was substantially more complex compared to CMAC since it used 1) more EMG features: root mean square, zero crossing rate, slope sign change and wave length; 2) more EMG electrodes (eight vs. two); and 3) more complex computation (matrix multiplication vs. simple amplitude thresholding).

The fact that CMAC performed worse than LDA in the simplest, single DoF task (BOX) can be easily explained by the specific implementation used in the present study. Namely, BOX relies on a seamless activation of a single DoF, prosthesis opening and closing. However, in CMAC control scheme, these functions were associated to the middle activation ranges (Table I). Therefore, the user needed to activate and maintain the flexor and extensor muscles between 30 and 85% of the normalized RMS. This is a more difficult task then simply activating the flexors and extensors at any level above the resting threshold, which was enough to close and open the hand in LDA. Therefore, CMAC introduced control overhead that resulted in a significant increase of the workload during the BOX task (Fig. 5C1). Nevertheless, this could be easily corrected by rearranging the mapping between the ranges and functions in Table I (e.g., allocating opening/closing to the range 1); however, optimal mapping was outside the scope of the present study and remains to be investigated in the future.

Finally, during all the tests CMAC was as reliable as LDA with the same number of classes: the number of errors was similar in both conditions, independent of the task complexity. This result is specifically relevant in PIN. Here, the need for precise and fast myoelectric control is crucial for task success since closing the prosthesis too fast would lead to “breaking” the clothespin. Therefore, CMAC not only allows for dexterous switching between the DoFs but also for proportional myoelectric control, in which the user can regulate the prosthesis movement velocity. The vibrotactile EMG biofeedback enabled the subject to modulate the muscle contraction within the second range (proportional control) despite the fact that the range was limited by both lower and upper threshold (30-85% of the normalized RMS). Such constrain does not exist with LDA where the full range from zero to maximum was available for the modulation of the speed within each of the classes.

3) CMAC substantially decreases the training and setup time.

The CTT reflected the total time needed to mount, train and calibrate the control system. When compared to the LDA this time was approximately 10 minutes lower in CMAC condition. Since in both experimental conditions, we used dry EMG electrodes that were placed in an elastic band, which is simply strapped around the lower arm - a process that takes well below one minute to complete - the difference in CTT could be traced back to the system training and calibration and not to the electrode placement time. Moreover, the setup time of the CMAC system, although very short, was certainly longer than that of LDA since it required mounting of additional feedback component and careful placement of the EMG electrodes on the wrist flexor and extensor muscles. Indeed, the shortening of the training and system calibration time is important since myoelectric control is inherently unstable and prone to the influence of non-stationarities. Therefore, it may happen that the recalibration needs to be performed often (e.g., on a daily basis) [13]. While an amputee using LDA would need to retrain the movements that are not functioning, the recalibration of CMAC system is straightforward and does not differ much from calibrating the conventional two-channel myoelectric control. In addition, contrary to LDA, which requires a long initial training (data collection), the CMAC includes a minimal setup. This setup reduces to measuring the baseline activity and MPVC to determine the activation thresholds, followed by fine-tuning of the thresholds and vibration intensities, which is the likely reason behind 10 minutes difference in CTT.

4) CMAC decreases the reliance on the visual feedback

The results of the implicit feedback questionnaire (Fig. 5D) suggest that the subjects in LDA condition relied predominantly on visual cues. Thus, the control loop was primarily closed through vision. In CMAC condition, this trend has changed as the subjects payed less attention to visual cues. This can be explained by the fact that vibrotactile feedback in CMAC communicated the selected prosthesis function even before the prosthesis started moving, as explained in section II.B. Therefore, the subjects did not need to focus that much on the prosthesis itself. In LDA, the movement of the prosthesis was the only way for them to confirm they have successfully activated the proper class. This kind of perceptual shift (from visual to supplementary feedback) is already observed in our recent studies [32], [40]. Therefore, the subjects integrated the vibrotactile feedback into their control scheme. This was confirmed additionally by the high subjective rating of the vibrotactile feedback (Fig. 5E) regarding benefit (75 (30)) and comprehension (87 (15)).

In conclusion, the presented study demonstrated that a reliable dexterous control can be achieved by using a simple method that is easy to setup. Compared to LDA, CMAC requires substantially shorter training and yet provides similar performance in dexterous tasks. Therefore, we demonstrate that methods based on non-intuitive mapping between muscle activations and prosthesis functions can still lead to a good performance, as also shown in the studies with myoelectric abstract decoders [41], [42] and postural control [43]. The control loop is closed by transmitting the (bio) feedback to the prosthesis user. The EMG biofeedback is a novel and versatile paradigm in prosthesis control, recently proposed by us [44], [45] and developed further by other groups [46], [47]. The present study is a demonstration of how this feedback method can be used to substantially improve the performance of a simple control approach (multi-level thresholding) to the level that it becomes comparable to the state of art pattern classification. In principle, similar feedback could be also integrated in the control methods based on pattern classification and/or switching, however, this is outside the scope of the present study.

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