Extending mode switching to multiple degrees of freedom in hand prosthesis control is not efficient

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Abstract— **In recent years, many sophisticated control strategies for multifunctional dexterous hand prostheses have been developed. It was indeed assumed that control mechanisms based on switching between degrees of freedom, which are in use since the 1960's, could not be extended to efficient control of more than two degrees of freedom. However, quantitative proof for this assumption has not been shown. In this study, we adopted the mode switching paradigm available in commercial prostheses for two degree of freedom control and we extended it for the control of seven functions (3.5 degrees of freedom) in a modern robotic hand. We compared the controllability of this scaled version of the standard method to a state of the art pattern recognition based control in an applied online study. The aim was to quantify whether multi-functional prosthetic control with mode switching outperformed pattern recognition in the control of a real prosthetic hand for daily life activities online. Although in simple grasp-release tasks the conventional method performed best, tasks requiring more complex control of multiple degrees of freedom required a more intuitive control method, such as pattern recognition, for achieving high performance.**

I. INTRODUCTION

Recent developments of multifunctional prosthetic hands for commercial and research purposes [1] have led to the emergence of numerous advanced control strategies to provide answers to the increased demand of multi degrees of freedom (DOF) control schemes. These include statistical learning approaches and other machine learning methods based on surface EMG recordings [2], [3], as well as other strategies including direct control through intra muscular recordings [4], [5], implanted electrodes [6], specialized surgical procedures [7] and by linear combinations of single muscle recordings [8]. The current commercial state of the art in prosthesis control usually employs two surface EMG electrodes, one placed on the extensor and one on the flexor side of the residual limb. Activations of either of the electrodes can directly be mapped to control two functions of a prosthetic hand, e.g. opening and closing. In order to extend the use of two electrodes to the control of multiple prosthetic functions, the most common ways are the so called 4-channel control and mode switching (MSW) [9]. In the 4-channel control, still only two electrodes are utilized, but fast signals are used to govern the control of one DOF (e.g. rotation) and slow signals to control another DOF (e.g. opening and closing). In MSW, a switching impulse causes a state machine to change its current state. Commonly, co-contractions are used to generate such switching signals. The user has to quickly and strongly activate both flexor and extensor muscle groups in order to achieve the desired switching signal. The 4-channel control scheme allows the direct control of 2 DOF without switching, however it takes significantly more practice to learn, is prone to false activations (e.g., in a fast reflex situation, were quick release of an object is required, it would erroneously result in wrist rotation) and cannot be extended easily to multi DOF control. MSW is easier to learn and can technically be extended to accommodate the use of multiple functions. Since the MSW method is well accepted for the control of 2 DOF in many commercial prostheses, in this study we analyzed the extension of this method to the control of a prosthetic device with 3.5 DOF. To our knowledge, no quantitative assessment of the scalability of this classic approach has been provided yet. However, this analysis is substantial for supporting the need of highly advanced control mechanisms. Consequently, in this study we investigated the control performance by the MSW method extended to the control of 3.5 DOF and compare it to a well accepted pattern recognition method in online, applied tests of different levels of difficulties with naïve users. Most importantly, in this study a physical prosthesis was controlled by the subjects in real time, allowing to draw direct conclusions about the usability of the investigated control strategies.

II. MATERIALS AND METHODS

A. Subjects and test procedure

Nine able-bodied subjects (age 28.6 ± 3.2 years, three female, six male) with no limb deficiencies participated in this study. All subjects were dominant right handed. The experiments were approved by the local ethical committee. Participants signed an informed consent form after being instructed about the study protocol. Two subjects had previous experience in using the classic 2 DOF MSW paradigm for controlling computer screen cursors, but none of the subjects had previously experienced control of multiple DOF by either of the investigated methods and none of the subjects had experience in controlling and using a physical hand prosthesis attached to their arm to accomplish grasping

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Fig. 1. A subject wearing the Michelangelo prosthesis with the able-bodied adapter.

and object manipulation tasks. Prior to starting the tests, a Michelangelo hand prosthesis equipped with a wrist rotation and flexion extension unit was attached to the subjects' left arms using an able-bodied adapter, see Figure 1.

B. Control Methods

As representative of machine learning methods for the control of multi-functional prostheses, the well accepted and extensively studied linear discriminant analysis (LDA) classifier was selected. The MSW control method was extended to allow the use of a multi-functional prosthesis.

1) LDA: The LDA was chosen as the classifier [10] since it has found great acceptance as the state of the art in pattern recognition for myoelectric control in both online and offline performance studies [2]. The Hudgins time domain feature set was used and a majority vote of 7 was applied to the classification stream [11], which was found to yield the best trade-off between performance gain and reaction delay in pilot experiments. In order to add additional information about the contraction strength to the classification stream, a proportional speed control value was extracted from the mean of all RMS values and scaled to the maxima determined during the data recording phase.

2) eMSW: The extended version of the mode switching (eMSW) method applied in this study allowed access to all 3.5 DOF the used prosthesis. A state machine with four states was implemented: Wrist pronation/supination, wrist flexion/extension, lateral grip/hand open and tripod pinch/hand open. To switch from one state to the next in a circular manner, one co-contraction had to be performed. Therefore, a maximum of 3 co-contractions was necessary to switch between any two DOF and the fourth co-contraction would result in returning to the starting DOF. This approach thus represents the straight forward multi-DOF extension of the classic control scheme, where one co-contraction is used to switch between two control states. For each successful switch, the subject received acoustic feedback. All four control states were enabled during all tests. A switching diagram is provided in Figure 2, which was also visible for the subjects throughout the experiments for support.

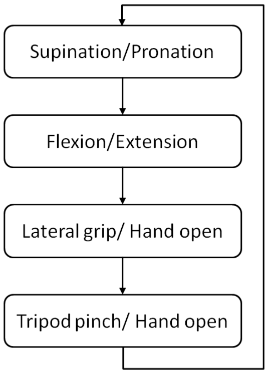

Fig. 2. Switching diagram of the extended mode switching (eMSW) control method. The same diagram was available for the subjects at all times for consultation during the tests. Switching from one state to the next was achieved by performing one co-contraction.

C. Signal Acquisition and Processing

The data acquisition protocol as described in [12] was used. Eight Otto Bock surface EMG electrodes (13E200=50AC Otto Bock Healthcare Products GmbH, Vienna, Austria, pre-amplified, filtered and 10-bit AD converted at 1kHz sampling rate) were placed around the circumference of the subject's forearm. For LDA control, all eight sEMG signals were used. For the eMSW control, two of the eight electrodes were selected. They were chosen to be above the flexor and extensor muscle groups, which were identified by palpation. For the training of the classifier, sEMG signals corresponding to the movements of wrist pronation/supination, wrist flexion/extension, hand open, lateral grip and tripod pinch were recorded. Additionally, data representing no muscle activation were recorded. Each movement was performed three times in a trapezoidal activation curve at three plateau force levels: 30%, 60% and 90% of the maximum long term voluntary contraction, defined as the contraction force that could be maintained over 30 s. Thus, a total of 72 movements were recorded. Each move lasted for 5 s and transient movement phases were not excluded from the training set [13]. With sufficient pauses to prevent fatigue, data recording required approximately 25 minutes. For eMSW no training data were necessary. The classifier was trained with the pre-recorded data, which were segmented in windows of 128 ms with 96 ms overlap (new classification every 32 ms). From those windows, four time domain features were extracted per channel: the root mean square (RMS) value, the number of signal zero crossings and slope sign changes, and the wavelength [10]. For the eMSW control, only the RMS values were extracted. The electrode gains, the movement thresholds and the co-contraction thresholds were adjusted for each subject to yield reliable control. The ”largest signal wins” strategy was adopted. Subjects had to pass the co-contraction thresholds with both signals within 80 ms, which is a standard value in commercial prostheses [9].

The sEMG electrodes were attached to the subjects' right arms, and the prosthesis was attached to the left arm via

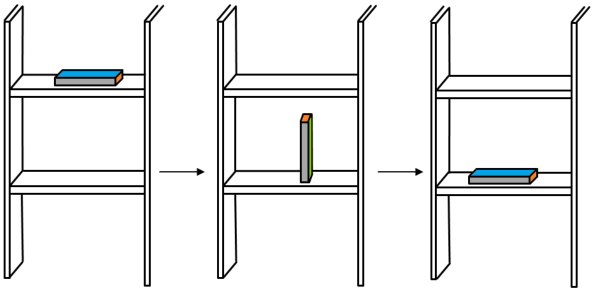

Fig. 3. Sequence of performing the block turn test. The block was to be picked up from above, turned, placed in the shelf, picked up again with the lateral grip and put back down in its original orientation.

an able-bodied adapter(Figure 1), which impeded mounting the electrodes and the prosthetic hand on the same side due to space constraints as well as that the left hand carrying the prosthesis was not freely moveable anymore without interfering with the movements of the prosthetic hand. In preliminary experiments, this contra lateral mounting did not result in any additional burden for the subjects.

D. Real Time Tests

For the evaluation of the usability of the two control methods, each subject was asked to complete three tests of increasing complexity in the following order.

1) Box&Blocks test: The first test was the box and blocks test [14]. The tests consists in transferring as many wooden cubes (2.5 cm edge) as possible from one box to another in 1 min. After explaining and showing the subjects how to perform this test, they were granted a familiarization phase, during which they learned how to pick up and release the cubes with the prosthetic hand with either of the control methods.

2) Clothes pin test: The second standardized test was the clothes pin test, as introduced in [15]. The time required for picking up three clothes pins clipped to a horizontal bar, rotate them and place them on a vertical bar was measured. This test thus required control over at least 2 DOF (open/close of the hand and wrist rotation in both directions). The Rolyan®Graded Pinch Exerciser [16] was used with red clothes pins (around 1 kg grip force) in our experiments.

3) Block turn test: For the last test, a new assessment method was developed, enforcing the use of all degrees of freedom available in the prosthetic device. A wooden block of the dimensions 15.8 cm x 5.7 cm x 1.7 cm was used for this test. It was placed on a shelf, approximately at shoulder level of the test subject. The subject was asked to pick up the block (wrist flexion, tripod pinch), rotate it by 90° (supination) and put it back in the shelf at waist level (extension, hand open). The subject then had to pick up the block again with the appropriate grip (lateral grip), rotate it again and place it back in the shelf, face up (pronation, hand open). The turning sequence is graphically demonstrated in Figure 3. As with the box and blocks test and the clothes pin test, this test was repeated three times per subject and control method.

E. Statistical evaluation

The statistical significance of algorithm performance differences was analyzed through an ANOVA analysis for repeated measures with two levels. To analyze the within effects, a Tukey-HSD test was performed *post hoc* to ascertain differences between the two control methods.

III. RESULTS

The ANOVA test for repeated measures revealed that there was a significant difference between the two control methods ($p < 10^{-3}$) for all the tests investigated. Pairwise comparisons were therefore made for each test separately.

A. Box and blocks test

In this test, which required only the opening and closing of the hand with one grip type, the eMSW method provided very good results. With an average of 24.0 ± 5.8 transferred blocks in 60 s, this approach outperformed LDA based control ($p < 10^{-3}$), with which subjects achieved an average score of only 15.9 ± 3.5. It was observed that with the LDA control method, several erroneous activations of wrist rotation occurred, requiring subjects to stop from time to time and rotate the wrist back to a position which allowed picking up the blocks again. With eMSW, due to the fast opening and closing alternations, sometimes a false co-contraction was detected, requiring the subject to discontinue the test and switch back to the hand open - close state, but in general this situation rarely happened, explaining the superior results for eMSW in this test.

B. Clothes pin test

In this test, which required to control wrist rotation and hand opening/closing, the pattern recognition control approach revealed clear advantages over the eMSW approach. On average, subjects required 27.3 ± 7.3 s for transferring the three clothes pins from the horizontal to the vertical bar. This was significantly faster than with eMSW ($p < 10^{-3}$), with which the average performance was 55.1 ± 18.5 s, and thus more than twice as slow.

C. Block turn test

The last and most demanding test was the block turn test. As in the clothes pin test, also in this assessment pattern recognition based control clearly outperformed the extended state of the art method ($p < 10^{-3}$). While with eMSW the average completion time was 46.8 ± 10.2 s, subjects only required 34.1 ± 16.5 s when using LDA as control method. However, concerning the number of drops of the wooden block during the test, eMSW proofed to yield more reliable control. With this method, during the three repetitions of the test, subjects dropped the wooden block 0.26 ± 0.27 times, significantly less than with LDA (0.74 ± 0.27 times, $p < 0.02$). In LDA control mode, the block was dropped mainly due to false activations of hand open. In eMSW, drops occurred either due to mistakes of the subject counting the number of performed switches, ending up in the wrong state or due to badly performed co-contractions which resulted in

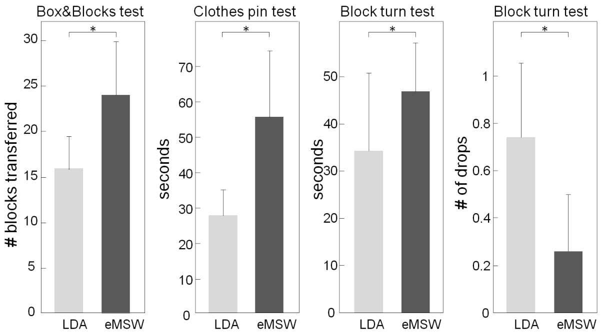

Fig. 4. Results of the box and blocks test (more is better), the clothes pin test (less is better), and the wooden block turn test (less is better) for the LDA and eMSW control methods. LDA outperformed eMSW in the more complex tasks, even though subjects dropped the wooden block more often. In simple grasping and releasing tasks, eMSW yielded better performance. All compared differences were significant, $p < 0.02$ for all.

an abrupt hand open activation. The latter reason accounted for the majority of drops, attributable to lack of concentration and training of the subjects.

The results of all tests are summarized in Figure 4.

IV. DISCUSSION

We investigated whether a commercial state of the art method in prosthesis control could be extended to allow the control of a modern multi DOF prosthetic hand. This strategy is commonly used for the control of up to 2 DOF. In the current investigation the same method was applied to the control of 3.5 DOF and compared to a simple but well accepted state of the art pattern recognition control strategy. It was found that for simple gripping tasks requiring only hand open/close, the classic control method can be successfully used even by naïve users with very little experience. However, when multiple DOF were involved in the control, the straight forward extension of the switch mode method was very cumbersome, unintuitive and slow. The quantitative results presented in Section III mirror the subjectively reported impressions of the subjects. All subjects reported that they quickly got lost in the four states of the eMSW state machine, even though they were provided with acoustic feedback for each DOF switch and had a switching map available for consultation at all times. These results are surprisingly clear, considering that the extension was done from the generally well controllable 2 DOF to only 3.5 DOF control. In the direct comparison, all subjects preferred the pattern recognition based control over the eMSW for the functional tasks investigated. In the more complex tasks, LDA was only inferior in performance in the number of drops of the wooden block turn test. This was due to some misclassifications to hand open, mostly confused with wrist extension when wanting to place the block in the shelf in the middle of the test. A more sophisticated control method or modification of LDA might overcome these limitations [12], [17], although this was not the focus of the current study. In the present study, a prosthesis offering seven functions was used. In research prototypes and also in some commercial hand prostheses, more functions may be offered, e.g., individual finger control. It can be expected that for such devices the extension of the classic control method is even more unsuitable for control and more intuitive methods need to be developed.

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