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Context-Dependent Upper Limb Prosthesis Control for Natural and Robust Use

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***Abstract*—Pattern recognition and regression methods applied to the surface EMG have been used for estimating the user intended motor tasks across multiple degrees of freedom (DoF), for prosthetic control. While these methods are effective in several conditions, they are still characterized by some shortcomings. In this study we propose a methodology that combines these two approaches for mutually alleviating their limitations. This resulted in a control method capable of context-dependent movement estimation that switched automatically between sequential (one DoF at a time) or simultaneous (multiple DoF) prosthesis control, based on an online estimation of signal dimensionality. The proposed method was evaluated in scenarios close to real-life situations, with the control of a physical prosthesis in applied tasks of varying difficulties. Test prostheses were individually manufactured for both able-bodied and transradial amputee subjects. With these prostheses, two amputees performed the Southampton Hand Assessment Procedure (SHAP) test with scores of 58 and 71 points. The 5 able-bodied individuals performed standardized tests, such as the box&block and clothes pin test, reducing the completion times by up to 30%, with respect to using a state-of-the-art pure sequential control algorithm. Apart from facilitating fast simultaneous movements, the proposed control scheme was also more intuitive to use, since human movements are predominated by simultaneous activations across joints. The proposed method thus represents a significant step towards intelligent, intuitive and natural control of upper limb prostheses.**

***Keywords*—Prosthesis control, simultaneous control, user centered testing, physical prosthesis control, proportional estimation**

I. Introduction

NATURAL movements are dominated by simultaneous activities across multiple joints and the fluency of movements was found to be a key factor for their perceived human-likeness [1]. Furthermore, it was reported [2] that fast, coarse positioning movements followed by fine and slow adjustment movements were the key factors for emulating human-like movement in robots. From these findings on robotic research, we hypothesized that also the control of prosthetic limbs should be characterized by fluent, dexterous movements, while facilitating optimized control for coarse limb positioning as well as for precise fine control in the terminal phase of a task. This claim is supported by studies on upper limb prosthetic device abandonment [3], [4], where shortcomings in device technology, appearance and ease of use were reported as main factors for secondary prosthesis rejection. In [5], the wish of "Could do coordinated motions of two joints at the same time" was ranked second out of ten possible answers to the question "I would like my preferred prosthesis better if…" in a study of a total of 2,477 returned user questionnaires.

In order to allow for the efficient control of modern upper limb prostheses, several efforts have been made during the past 4 decades [6]–[8], mainly focusing on classification of myoelectric signals for inferring user intent for prosthetic control. One drawback of pattern classification however is that it inherently only allows for the control over one degree of freedom (DOF) at a time (they are therefore summarized as sequential estimators, SEQ-E, for the remainder of this paper). In order to overcome this issue, direct control of multiple DOF through intra-muscular EMG recording [9], [10] has been proposed. Improved direct simultaneous control was also achieved with the targeted muscle re-innervation surgical procedure [11], although this technique is usually applied in cases of high-level amputations and reliable simultaneous control still cannot always be guarantied [12]. The use of surface EMG without the need of additional surgical procedures is the most convenient way for EMG signal acquisition, but it also poses the most challenging technical problems, due to signal cross talk [13] and other influencing factors (sweat, electrode shift, etc.). Regression techniques are being investigated for enabling simultaneous, proportional control from surface EMG (simultaneous estimators, SIM-E) [14]–[17]. Unfortunately, it has been shown that only 2 DOF can be controlled reliably using these techniques [18] and that the control is not always very accurate [19], thus compromising precise movements. Reliable control across many DOF as well as precise single-DOF activations are however achievable using SEQ-E. For example, the risk of erroneous dropping or squeezing a bottle while rotating the wrist to pour liquid into a cup is minimized using a SEQ-E, whereas SIM-E are known to produce inadvertent combined movements, increasing the risk of task failure. Table I summarizes the strength and weaknesses of SEQ-E and SIM-E based controls.

In this table, the complementary strengths and weaknesses

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TABLE I. COMPARISON OF SEQUENTIAL AND SIMULTANEOUS ESTIMATORS FOR PROSTHETIC CONTROL

Feature	SEQ-E	SIM-E
Precise single-DOF control	✓	✗
Intuitive movement planning	✗	✓
Control of many DOF	✓	✗
Simultaneous, natural appearance of movements	✗	✓
Proposed schemes for wrong movement suppression	✓	✗
Well suited for estimating dynamic activations	✗	✓

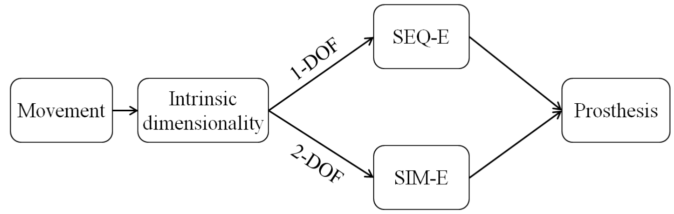

Fig. 1. Schematic representation of the proposed system. For a feature vector originating from a given movement, first the intrinsic dimensionality of the user intent is estimated. Depending on the result, the feature vector is forwarded to a specialist for estimating sequential (1-DOF) or simultaneous (2-DOF) movements. The resulting output is used for controlling the prosthesis.

of SEQ-E and SIM-E become apparent. Based on it and aforementioned necessity of different movement qualities in initial and terminal phases of a movement, the assumption was made that a situation and context dependent combination of SIM-E and SEQ-E methods could result in an improved control scheme over using each specialized estimator alone. In this study we describe the implementation and evaluation of such a system. A crucial step of this control paradigm is the successful separation of simultaneous from sequential movements. Several candidates for achieving this task are presented and the best approach is determined in an offline evaluation. Subsequently, the full control method was implemented in a framework capable of real-time control of a physical prosthesis. The evaluation was made in online tests performed by both able-bodied and transradial amputee subjects.

II. MATERIALS AND METHODS

In this work we propose the contextual optimized movement estimation by exploiting advantages of expert estimators for different movement situations. While SIM-E methods are suitable for fast and natural coarse positioning of the hand, SEQ-E are useful for precise single-DOF control. For each movement, following conventional 4 time domain EMG features extraction [20], as described later in this section, we propose to initially determine whether the movement originated from the intent of performing a single-DOF or combined-DOF movement. We refer to this step as estimating the movement's intrinsic dimensionality (intrinsic dimensionality estimator, IDE) which is done using a dedicated algorithm. After this step, the EMG feature values are forwarded to the respective specialist for sequential or simultaneous movements, whose output is ultimately used to drive the prosthesis in the desired manner. The schematic overview of the proposed system is shown in Figure 1.

A. Intrinsic Dimensionality Estimation

The estimation of the intrinsic movement dimensionality is crucial for the subsequent movement estimation. For the supervised training of both the SIM-E and SEQ-E methods, only EMG data of single-DOF tasks were recorded. Recording all possible combinations of movements at various contraction levels quickly becomes infeasible with the number of DOF and force levels involved. Therefore, for training the IDE, only data from single-DOF movements were used. The common concept behind all IDE methods investigated was to exploit the fact that only training data of single-DOF movements had been recorded. Any new feature vector could be compared to data seen during the training phase. If a high match to the known data was detected, it was assumed that this feature vector had to be of single-DOF origin. Otherwise it had to be from a combined movement. This assumption is reasonable, since it has been shown previously that a feature vector containing information from two distinct movement classes lies just between those two base classes [21], [22]. The mixture is approximately linear, which is also exploited when applying linear regression models for estimating the exerted force per DOF from the EMG [14], [15].

The problem of attributing an unknown feature vector to either a set of previously observed training data or not is commonly referred to as one class classification [23] or novelty detection [24]. Among several proposed novelty detection methods, the following were selected and investigated as the most promising:

1) OCSVM: One class support vector machine (OCSVM) was proposed by Schölkopf *et al.* [23] and uses the kernel trick to map the training data to a high dimensional space such that they are compact and well separated from the origin in that space. That is, the smallest hypersphere in that space, which encloses all training data, is identified. For a newly applied sample it is evaluated whether it is inside or outside that hypersphere (for details see [23]). This method is referred to as the gold standard solution in novelty detection. An implementation in *Lib-SVM* was used for the experiments [25].

2) KNFST: The Kernel Null Foley-Sammon Transform (KNFST) was proposed by Bodesheim *et al.* [26]. It computes the Fisher linear discriminant analysis (LDA) transformation, while maximizing the between-class distance in the null space of the within-class scatter matrix i.e. the data are projected to a single point [27]. This is only achievable in a high-dimensional space, such as obtained by applying a kernel transformation [26]. In essence, the novel feature vector is mapped to the high dimensional space and the minimum Euclidean distance of the transformed point to any of the trained class points is taken as the measure for novelty. An empirically determined threshold to that distance gives the decision for novelty or not. KNFST describes each trained base class individually and does not assume that all training data stem from the same class. In the present problem, multiple heterogeneous classes (training data per movement class) formed one super class of single-DOF movements. However, the major draw-

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back of KNFST is that it requires computation of the full kernel matrix with all training data, thus requiring considerable computation time and memory during the application phase. The implementation as available in [28] was used for this study. Only every 4^{th} training point could be used, otherwise an $OutOfMemoryException$ occurred when calculating the kernel matrix (PC with Intel i7 core, Windows 7 64 bit, 6 GB RAM and Matlab 2012a).

3) MD: A relatively simple technique is to calculate the minimum distance of a given feature vector to any of the training classes similarly to KNFST, but directly in the input space and without the Fisher transformation [24]. As distance measure the Mahalanobis distance (D_{Mahal}) is suitable, assuming Gaussian distribution of each class. The D_{Mahal} of a feature vector $\boldsymbol{x}$ to class i with the class mean vector $\boldsymbol{\mu}_i$ and covariance matrix Σ_i is calculated as [29], [30]:

$$D_{Mahal} = (\boldsymbol{x} - \boldsymbol{\mu}_i)^T \Sigma_i^{-1} (\boldsymbol{x} - \boldsymbol{\mu}_i) \qquad (1)$$

In contrast to the kernel based methods described above, this approach is computationally inexpensive and does not require hyperparameter optimization. However, a threshold for D_{Mahal}, above which a feature vector is classified as novel, has to be determined. In this approach the same threshold for all classes was chosen. We refer to this approach based on the Mahalanobis distance as MD approach.

4) MD-IND: This minor variation is mostly identical to the MD approach described above, with the difference that a novelty threshold for each movement class was determined individually.

5) MD-LDA: Another variation of the MD method, uses LDA transformation of the feature data before calculating the D_{Mahal} in the transformed space. This was included to investigate whether the Folley-Sammons transformation (identical to LDA) of KNFST was a critical step for successful novelty detection.

6) kNN: Rather than assuming an underlying Gaussian distribution of the class data and fitting the corresponding parameters as done with the MD based approaches, the non-parametric kNN approach was proposed for novelty detection [24]. The approach is almost identical to MD, but rather than evaluating the minimal Mahalanobis distance of the feature vector to all classes, the minimal euclidean distance to any set of k neighbors was considered. Again, a threshold based novelty detection rule was applied. The parameter k was set to k=5. A straightforward implementation (time complexity $O(Nd)$ for N training points of dimensionality d) was applied.

7) CSP-PELL: A further measure for recognition of known data can be extracted from the common spatial patterns proportional estimator (CSP-PE), introduced in [31]. As part of the computation, the likelihood (CSP-PELL) of each estimation is obtained. This can directly be used as the estimate for novelty. Again, a simple threshold between 0 and 1 had to be determined.

8) LDA-LL: Similar to CSP-PELL, the classification likelihood of an LDA classifier trained on the single-DOF data was applicable. Similarly as in [32] where it has been used for rejecting classification results of an LDA classifier with low likelihood for correctness (= low match to training data).

B. Identifying the optimal IDE

An offline evaluation was performed preceding the online experiments described later. For this purpose, 6 able-bodied subjects were recruited and sEMG data corresponding to 7 active single-DOF movements wrist supination (WS), wrist pronation (WP), wrist flexion (WF), wrist extension (WE), hand open (HO), tripod pinch (TP), lateral grasp (LG), and a rest class along with data from the 4 combined movements WS+WF, WS+WP, WP+WF and WP+WE were acquired. One run contained, all movements repeated 3 times (at 30%, 60% and 90% MLVC) and in total 3 runs were recorded. For the combined movements, subjects were asked to perform both of the partial movements equally at the prompted contraction level, as they would also like to use it in an online application. The 8 IDE methods introduced above were trained with two runs of the single-DOF data only, and the withheld run as well as all 3 runs of the combined movements were tested. This was repeated until all runs were withheld once from training and served as test data (3-fold cross-validation). The percentage of correctly recognized single-DOF and combined-DOF data was analyzed. The thresholds were optimized for each of the methods individually in 1000 steps. For KNFST this resulted in a grid search, since for this method also the kernel width required optimization. This was done in steps $[2^{-1} \dots 2^7]$. For OCSVM, the Gaussian kernel was chosen. The hyperparameters ν (determining the fraction of data which are allowed to be support vectors) and the bandwidth of the kernel σ had to be optimized. Both were varied in grid search in steps of $[2^{-10} \dots 2^0]$.

C. Statistical Analysis of IDE Methods

In order to determine the statistical difference between the investigated methods, a Kruskal-Wallis test was conducted. In case of statistically significant influence of the method, pairwise Wilcoxon rank sum tests with Holm correction for repeated tests [33] were conducted to determine significant differences between the methods. The significance level for all analyses was set to $p < 0.05$.

D. Results with IDE

The run time of each of the algorithms varied significantly. For estimating all 2160 feature data per run of the single-DOF movements and the 3240 vectors of multi-DOF data, the IDE algorithms required between 0.01 s (MD-LDA) and 190 s (kNN). The average estimation time for each feature vector on a PC running Microsoft Windows 7 64bit, Intel i7 1.73 GHz, 6 GB RAM and Matlab 2012a is shown in Figure 2.

The classification accuracies of feature vectors of single and combined movements were assessed according to the following equations:

$$Acc_{single} = \frac{\text{\# of classified as single-DOF}}{\text{\# of single-DOF feature vectors}} \qquad (2)$$

$$Acc_{comb} = \frac{\text{\# of classified as combined-DOF}}{\text{\# of combined-DOF feature vectors}} \qquad (3)$$

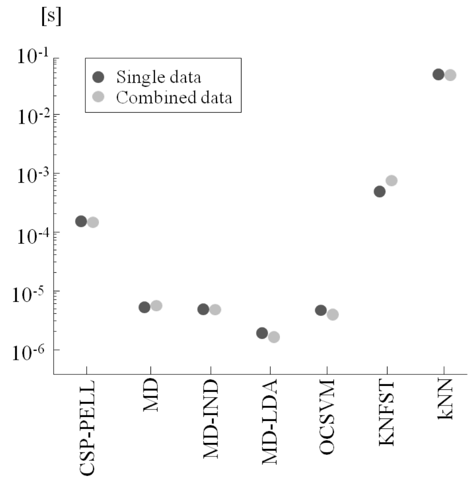

Fig. 2. Runtimes of IDE methods. Dark gray circles: average time in seconds for estimating one feature vector of single-DOF. Light gray circles: the same for combined data feature vectors. For KNFST only every 4^{th} training vector could be used due to memory constraints.

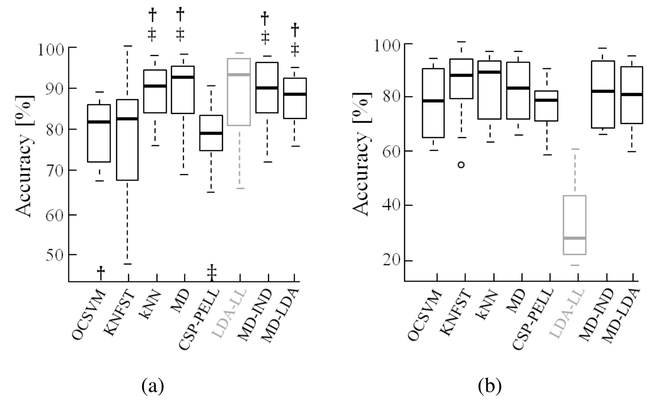

Fig. 3. Accuracies of IDE methods. (a): single-DOF accuracy - the percentage of single-DOF movements recognized as such. (b) combined-DOF accuracy: Percentage of combined-DOF data recognized as such. It is important to consider both accuracies at the same time. Due to its bad performance in the combined accuracy, LDA-LL had to be excluded. Significant differences between methods are marked with their respective symbols.

Regarding the classification accuracies of the IDE methods, it was found that LDA-LL did not yield acceptable classification accuracies for Acc_{comb} (<30% on average, as shown in Figure 3). Since it is indispensable that the IDE method of choice yielded high recognition accuracies for *both* single and combined motions, LDA-LL had to be excluded from all further evaluations (indicated in Figure 3). In the statistical analysis, it was found that the algorithm had a significant influence on Acc_{single} ($p < 10^{-3}$), but not on Acc_{comb} (after excluding LDA-LL, $p = 0.16$). It was therefore proceeded to perform pairwise comparisons between methods for Acc_{single}. While kNN, MD, MD-IND and MD-LDA were not significantly different among each other, they all outperformed OCSVM and CSP-PELL. KNFST performed also slightly worse, but this differences was not statistically significant.

As a result of this statistical evaluation it was concluded that the computationally fast and easy to implement methods based on the calculation of the Mahalanobis distance to the training data were the best candidates for online experiments. For simplicity of parameter tuning, MD was preferred over MD-IND and MD-LDA, since for this method only one threshold needed to be determined. This threshold was determined empirically by the experimenter before the start of the real-time experiments, so that the subject could reliably achieve sequential and simultaneous control.

E. Online control of physical prostheses

Following the identification of the most suitable IDE method to be MD, the rest of the system was implemented as shown in Figure 1. For the SEQ-E, CSP-PE [31], [34] was chosen, which has been shown to outperform classical LDA classification during online control of a physical prosthesis. For the SIM-E, linear regression was picked. Since linear regression was shown to work well with 2 DOF only, control of wrist rotation and wrist flexion/extension was done using this estimator for natural positioning of the hand. CSP-PE was capable of controlling all functions of the prosthesis. It is noteworthy that in principle any specialist estimator for single and combined movement estimations could be used and also different motions can be chosen for the simultaneous control part. The obtained task and user intent context dependent movement estimation paradigm will be referred to as context dependent estimator (CDE) for the rest of this paper.

For the online control part of this study, 5 able-bodied subjects (2 female, 3 male, age 28±1.9 years, all right hand dominant) and 2 traumatic transradial amputees with medium residual limb lengths were selected. The amputees (Amp1, Amp2) had already undergone substantial training in pattern recognition control of prostheses (40-60 hours) in research studies and scored optimally in a patient capabilities assessment test for pattern recognition control previously proposed by our group in [35]. However, none of these two subjects had any pattern recognition system for home trials or any experience in regression based simultaneous and proportional control of a prosthesis. Both amputees exhibited stable residual limb volume and had sufficient, sustainable residual muscle contractions allowing solid control of all phantom limb movements required for this study. For each amputee, a custom made experimental prosthetic socket was manufactured by a certified prosthetist.For able-bodied subjects a bypass adapter for attaching the prosthesis to their left arms was used.

These sockets were fitted with a commercially available Michelangelo hand prosthesis (Otto Bock HealthCare Products, Vienna, Austria), equipped with prototypes of actuated wrist rotation and flexion/extension joints. With two different grip types coupled to one hand open function, and the 2 DOF actuated wrist, this prosthesis had 3.5 DOF controllable

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by the user. Along with the Axon®bus system prosthesis, eight Otto Bock raw signal electrodes 13E200=50AC were used and placed equidistantly around the forearm, app. 8 cm distal from the elbow epicondyles. The EMG signals were preprocessed by the electrodes (filter, amplification) and digitized at 1kHz sampling rate with 10 bit depth. The raw signals were transferred to a PC via bluetooth. Here, the main processing took place, including extraction of root mean square (RMS), zero crossings, slope sign change and waveform length features [20] as well as the estimation of all 8 motions as described above. The movement commands were then sent back to the prosthesis via the same Bluetooth link.

For supervised training of the methods, as mentioned above, only data from eight single-DOF movements (see Section II-B) were recorded. For each movement, subjects were asked to follow a trapezoidal force profile (t_{rise} = t_{fall} = 1 s, $t_{plateau} = 3\,s$). During this tracking task, a visual feedback has been provided in a form of a running dot whose vertical displacement was correlated with the amount of exerted force as approximated by averaging the RMS values of all 8 electrodes in 128ms time windows. The profile plateaus were set to be at 30%, 60% and 90% of a calibrated maximum for each movement. Thus, one run consisted of 8 movements × 3 force levels = 24 trials. Three runs were recorded per subject.

Once the system had been trained, the participants were introduced to the simultaneous control scheme, which they had not experienced before, by asking them to mimic movements of the experimenters and mirror movements with their own, sound arms. Subsequently, subjects were given around 30 minutes to explore and get comfortable with the control on their own.

F. Online test procedures

1) SHAP test: Both amputee subjects completed the Southampton Hand Assessment Procedure (SHAP) test [36]. This comprehensive test included both precision manipulation tasks of objects in different shapes, sizes and weights, as well as activities of the daily living (ADL), such as pouring a cup of water, cutting a piece of plastic modeling mass with a knife, opening buttons on clothes, picking up coins from a table top, etc. For all tests and the exact test procedure, the reader is referred to [36] and in summary to Tables II and III. The conduction of this test was supervised by trained clinicians of the AKH Vienna General Hospital.

With able-bodied subjects, the evaluation focus was laid on tests with well-defined grading of difficulty for systematic evaluation.

2) Box and blocks test: The easiest conducted test was the box and blocks one [37], [38]. The subjects are asked to transfer as many wooden cubes (2.5 cm edge length) as possible from one box to the other in 60 s. This test required precise and fast hand opening and closing, but no wrist activations. We report the average number of seconds required to transfer one block, averaged over three test repetitions, in order to have a consistent *less is better* evaluation across all tests in this study for convenient interpretation.

3) Clothes pin test: The clothes pin test was conducted as introduced in [11] and the Rolyan graded pinch exerciser [39] was used with red clothes pins. In this test, subjects had to transfer 3 clothes pins clipped to horizontal rods to a vertical rod as fast as possible. Again, the average time of 3 repetitions is reported. Although strictly this test required only control over hand open/close and wrist rotation, it is important to note that with slight wrist flexion/extensions, subjects could clip the clothes pins more conveniently, and thus potentially faster.

4) Block turn test: This test was originally described by Amsuess et. al. [31]. It takes only around 30 s to be completed and yet enforces the use of all 3.5 DOF of the prosthesis used in this study. A wooden block (15.8 cm × 5.7 cm × 1.7 cm) initially lying flat on a start position at shoulder height was to be grabbed (tripod pinch), rotated and placed like a book in a shelf at waist level. It was then to be picked up once more (lateral grasp) and put back down. Again, the average completion time of 3 trials was reported.

G. Compared methods

The test results achieved by able-bodied subjects in this study were compared to test results achieved by the same subjects reported in [31], where CSP-PE was used as the only SEQ-E controller. The current study was conducted 6 months after the first one. In the meantime none of these subjects had used any machine learning based prosthetic control.

The use of several applied real-time tests as well as the inclusion of able-bodied and amputee subjects facilitated a comprehensive evaluation of the proposed method.

H. Statistical Evaluation of Online Tests

The online test results of able-bodied subjects were evaluated with paired t-tests to determine statistical differences between the performance of CSP-PE and CDE control. To ascertain the normal distribution of the data, the Shapiro-Wilks test was performed prior to the t-tests. Normality was confirmed with $p > 0.11$ for all time distributions.

III. RESULTS

A. Amputee SHAP results

The SHAP test results are detailed in Table II and Table III for Amp1 and Amp2, respectively. The overall score of function was 58 for the first and 71 for the second subject. Amp1 combined 20.1% of all wrist rotations with wrist flexion/extensions, and 24.5% of all wrist flexion/extensions were combined with wrist rotation movements. Exemplary activations for Amp1 are shown in Figure 4. With a total of 38.2% of all rotations being combined with flexion/extensions and 27.1% of all flexion/extensions that were combined with wrist rotations, Amp2 made noticeably more use of the possibility to combine wrist movements than Amp1.

In order to examine the origin of the different overall SHAP scores of Amp1 and Amp2, the individual sub-test results were compared to each other. Two of the tests were substantially different between the subjects: 11.62 s vs. 25.31 s for rotating

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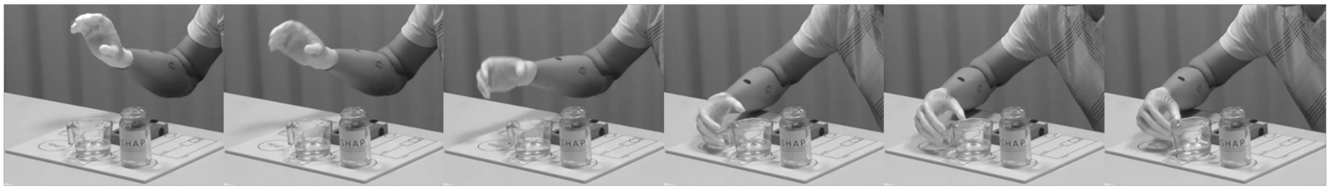


Fig. 5. Exemplary sequence of Amp2 performing simultaneous wrist flexion and supination followed by a pinch grip to grasp the mug of the SHAP test.

TABLE II. SHAP TEST RESULTS FOR AMPUTEE SUBJECT AMP1

Abstract Objects			
Light Sphere:	2.66 s	Heavy Sphere:	4.78 s
Light Tripod:	3.56 s	Heavy Tripod:	3.53 s
Light Power:	3.25 s	Heavy Power:	3.22 s
Light Lateral:	2.81 s	Heavy Lateral:	5.31 s
Light Tip:	2.88 s	Heavy Tip:	4.47 s
Light Extension:	3.88 s	Heavy Extension:	4.88 s
Activities of Daily Living			
Pick Up Coins:	22.25 s	Lifting a Heavy Object:	10.37 s
Button Board:	35.20 s	Lifting a Light Object:	4.15 s
Simulated Food Cutting:	22.47 s	Lifting a Tray:	7.25 s
Page Turning:	11.97 s	Rotate Key:	4.25 s
Jar Lid:	3.93 s	Open/Close Zip:	10.59 s
Glass Jug Pouring:	12.37 s	Rotate A Screw:	25.31 s
Carton Pouring:	11.35 s	Door Handle:	3.53 s
SHAP Scores			
Functionality Profile			
Spherical:	85.00	Tripod:	40.00
Power:	45.00	Lateral:	74.00
Tip:	56.00	Extension:	51.00
Index of Function Score			
Index of Function:	**58.00**		

TABLE III. SHAP TEST RESULTS FOR AMPUTEE SUBJECT AMP2

Abstract Objects			
Light Sphere:	3,60 s	Heavy Sphere:	4.03 s
Light Tripod:	3,94 s	Heavy Tripod:	3.98 s
Light Power:	3,22 s	Heavy Power:	3.50 s
Light Lateral:	4.66 s	Heavy Lateral:	5.20 s
Light Tip:	3.75 s	Heavy Tip:	4.59 s
Light Extension:	3.08 s	Heavy Extension:	4.22 s
Activities of Daily Living			
Pick Up Coins:	26.82 s	Lifting a Heavy Object:	4.53 s
Button Board:	19.80 s	Lifting a Light Object:	2.80 s
Simulated Food Cutting:	30.10 s	Lifting a Tray:	2.55 s
Page Turning:	6.96 s	Rotate Key:	4.97 s
Jar Lid:	4.40 s	Open/Close Zip:	6.47 s
Glass Jug Pouring:	13.12 s	Rotate A Screw:	11.62 s
Carton Pouring:	17.97 s	Door Handle:	2.59 s
SHAP Scores			
Functionality Profile			
Spherical:	78.00	Tripod:	38.00
Power:	54.00	Lateral:	76.00
Tip:	54,00	Extension:	74,00
Index of Function Score			
Index of Function:	**71.00**		

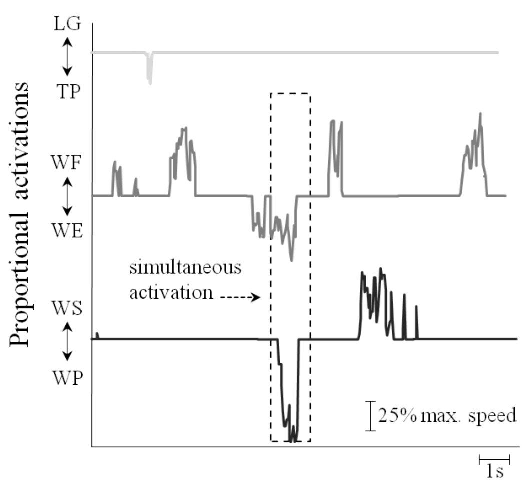


Fig. 4. Exemplary motor activations of the first amputee participating in the SHAP test (WS/WP wrist supination/pronation, WF/WE wrist flexion/extension, LG/TP lateral grasp/tripod pinch). It is shown that the subject chose to activate most of the movements sequentially, but also simultaneous movements were possible and used by the subject (dashed frame).

the screw and 19.80 s vs. 35.20 s for the button board. Overall, Amp1 was faster than Amp2 in 13 of the 26 SHAP sub-tests and slower in the other half. All direct result comparisons are shown in Figure 6.

B. Results of the able-bodied subjects

Subjects required 3.11 ± 0.62 s on average to transfer each block with the proposed CDE method, which was not significantly different from the 3.25 ± 0.62 s subjects needed with CSP-PE control alone ($p = 0.52$). The difference between the two compared methods was however significant in both more complex tasks - the clothes pin test and the block turn test. In the clothes pin test, subjects reduced the average completion time from 23.4 ± 4.66 s with CSP-PE to 16.4 ± 3.35 s with CDE, a decrease by 30% ($p < 10^{-3}$). Also in the block turn test, a substantial improvement was found. The average completion time was decreased from 23.2 ± 4.94 s to 16.0 ± 3.59 s, representing a significant decrease of 31% ($p < 10^{-3}$). During all tests, able-bodied subjects combined 14.5% of all rotation movements with wrist flexion/extension, and 26.7% of all flexion/extensions were combined with rotations.

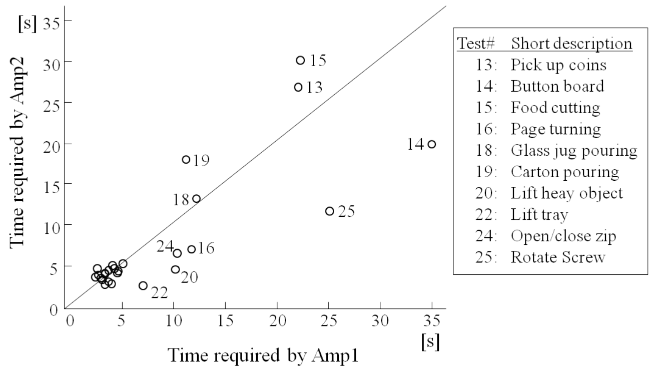
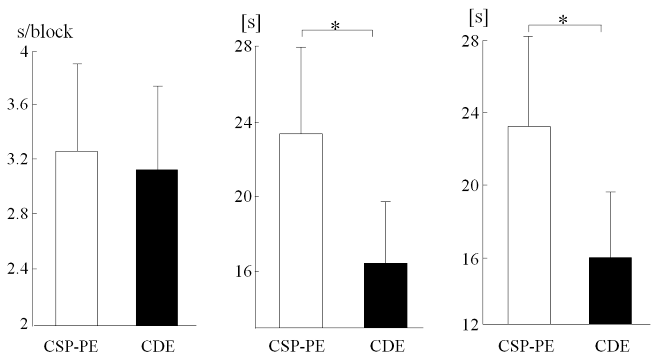


Fig. 6. Comparison of the SHAP sub test results between Amp1 and Amp2. The upper half of the plot represents tests were Amp1 performed faster than Amp2, while in scores shown in the lower half Amp2 was faster than Amp1. For tests with substantial differences between the subjects, the SHAP test number is added next to the data point.



(a) Box and blocks (b) Clothes pin (c) Block turn - Time

Fig. 7. Results of CDE compared to CSP-PE. In the simple box and blocks test, the advanced control mechanism with simultaneous wrist movements did not result in a significantly different performance compared to the sequential CSP-PE, since only hand open and close were required. However, in the two more difficult tasks, which required activation over several DOF, the simultaneous wrist and sequential hand activation control method resulted in a significant performance increase. * denotes significant difference ($p < 0.05$).

IV. Discussion

A new concept of context-dependent myocontrol for upper limb prostheses using surface EMG has been introduced and extensively validated. In previous studies concerning human-like robotic motions it was described that fast, coarse positioning of the hand followed by fine grained grasping motions in the terminal phase of a task were essential to emulate human movements. Here, the concept of this control was adopted and a dedicated algorithm facilitating context-dependent prosthetic control was introduced. The human-like behavior was obtained by combining algorithms suitable for either sequential or simultaneous movement estimation from the EMG. The switch between one control type to the other was automatically determined by the online analysis of dimensionality of the raw EMG signals. In a series of real-time control experiments, the operation of a physical prosthesis, using the proposed scheme, was proven to be feasible.

In the first part of this paper, various methodologies for differentiating single-DOF activations from multi-DOF activations from surface EMG have been investigated. This first step was fundamental for the proper functioning of the entire system. It was shown that a very simple approach based on calculating the minimum Mahalanobis distance to any of the movement classes was very well suitable for this task and outperformed other, more sophisticated methods. Generally, in the offline analysis it was shown that none of the methods investigated could guarantee recognition rates above 85-90%. However, in the online control part of this study, this accuracy proved to be sufficient for providing reliable control. It is important to note that a mistake in the estimation of the intrinsic movement dimensionality did not automatically result in a wrong movement of the prosthesis. It only meant that e.g. an intended simultaneous movement was performed sequentially or vice-versa. Since unintended simultaneous movements were more detrimental to the control than unintended sequential movements, the manually set threshold for the MD approach was selected to favor the SEQ-E estimation slightly. This had to be adjusted to the liking of the subject and would therefore be difficult to automatize. This challenging problem, likely solvable by an autonomously unsupervised adaptive algorithm, will be the focus of future studies.

After identifying the most suitable IDE method, the entire system was evaluated in a real-time control study. We focused on the control of physical prostheses in challenging tasks performed by both able-bodied and amputee subjects. The control was setup such that the 2-DOFs of wrist were controllable simultaneously and all 7 prosthetic functions sequentially. It is noteworthy that any combination of 4 movements could have been selected for simultaneous control. Also, the same principle of control could be applied to a prosthesis with less actuated functions, permitting simultaneous control of a bigger fraction of the total available DOF.

The involved tests represented a large variety of scenarios - from simple pick-and-place actions to complex tasks, such as cutting food or opening buttons of a shirt. The evaluation can therefore be regarded as representative for clinical practice. In able-bodied subjects, systematic analyses with tests of increasing difficulty were performed and compared to test results obtained with sequential control only. The proposed context-dependent control significantly outperformed the purely sequential control in more complex tasks. The latter method was recently shown to provide better results than both the academic (classic pattern recognition) and the clinical state-of-the-art [31]. In tasks requiring only precise single-DOF control (box and blocks test), the methods performed equally well, emphasizing the optimized context dependent control, enabling simultaneous control when desired, but without compromises in precise single-DOF control. The most likely explanation of faster completion times in complex tasks is that subjects had to spend less time in movement planning and the control was reported to be much more intuitive. Consider the example of a task requiring wrist supination, followed by wrist extension. Using the sequential control algorithm, subjects were instructed to perform the movement sequence *wrist supination*

- back to neutral position (relax) - wrist extension. Relaxing between movements was crucial, otherwise the sequential controller could not properly interpret the EMG data. This was due to the fact that during recording of the training data the subject always started from the neutral position. Contrary to the clear indications and repeated training, subjects tended to omit this return to the neutral position during the course of the tests, because this allowed them to intuitively mimic the observed position of the prosthetic hand (which of course did not return to neutral position during relaxation). In such a case, while a pure SEQ-E would fail, the proposed CDE still managed to recognize the intended motion by applying the SIM-E to the data, resulting in good estimation.

With amputees the extensive SHAP test was preferred over the tests less relevant for daily activities conducted with able-bodied subjects. The long duration of this test however prohibited testing of multiple conditions, so no data of pure sequential control were obtained. Able-bodied subjects were notconsidered for SHAP testing since employing a bypass adapter brings inconsistencies which are hard to account for and therefore compare. Direct comparability to able-bodied performance without a prosthesis is guaranteed by the SHAP test, which has a normed scale from 0-100, where 0 represents no function at all and 100 unimpeded able-bodied capabilities. However, comparing the achieved test results to others in the literature permits estimation of the relative performance. Dalley *et al.* [40] reported an index of function of 52 using the iLimb (Touch Bionics, Edinburgh, UK), controlled by an able-bodied subject. Bouwsema *et al.* [41] reported indices of function between 17 and 71 for 6 experienced transradial amputees using their clinical prostheses. Sobuh *et al.* [42] reported scores between 37 in the first session and 67 in the 5^{th} session for able-bodied participants using a prosthesis emulator. Atkins *et al.* [43] reported a score of 56 for one transradial amputee. Stein and Walley [44] reported scores around 30 for transradial amputees. Fougner *et al.* [45] reported scores of approximately 40 for two able-bodied subjects using a prosthesis emulator for the first time. In the light of these comparative data and considering the fact that this was the first time the subjects performed the SHAP test with this test prosthesis, the SHAP results obtained in the present study are promising. This result is also important in respect to an expected improvement with training. For example, Fougner *et al.* [45] reported that subjects still did not reach a plateau in performance after 5 repetitions of the SHAP test.

Subjectively the study participants stated that they favored the control which enabled simultaneous movements for its natural appearance. However, no structured questionnaire was completed. The quantitative results presented in this study showed the superior performance of context dependent movement estimation over pure sequential control. In this study, only experienced amputee subjects participated. Preliminary results with one additional transradial amputee (male, left side short residual limb, traumatic amputation 35 years ago) showed that this novice user, who had never participated in a machine learning controlled prosthesis experiment before, also achieved reliable and, as the subject stated - “excellent” control over all functions, including simultaneous wrist control, in the first session after less than half an hour. However, no prosthetic socket was available for this user, therefore functional scores could not be assessed.

Given the observed outcomes as well as literature reports, potentials of extending this approach to higher level amputees in combination with TMR surgery are present. Though, the number of simultaneously controlled DOFs would have to be carefully chosen.

In summary, the proposed method yielded favorable control over a purely sequential controller, which had been shown to outperform conventional pattern recognition in [31]. In future investigations, more amputee subjects with diversified background will be included for a more comprehensive evaluation of the benefit provided by the proposed method.

V. Conclusion

A novel concept for estimating prosthetic movement from multi-channel surface EMG has been introduced and evaluated. The proposed method allowed the users to perform precise, fine controlled sequential movements as well as simultaneous activations across 2 DOF for increased speed and intuitive use. For each motion output to the prosthesis, it was evaluated whether the user intended a combined-DOF or single-DOF movement. The algorithm allowed for seamless switching between two expert methods for estimating the respective movement situation, resulting in highly functional, fast and accurate control of a transradial hand prosthesis, tested in applied scenarios close to real life situations.

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