Wrist and grasp myocontrol: simplifying the training phase

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***Abstract*—The term "myocontrol" denotes, in the assistive robotics / machine learning community, the feed-forward control of a dexterous prosthetic device enforced by a disabled human subject, typically an amputee, using the activation of remnant muscles. Myocontrol relies on a human-machine interface (HMI), which converts muscle activation signals of diverse nature into control commands for the prosthetic device. Although novel kinds of HMIs are being explored, the traditional basis for myocontrol is surface electromyography (sEMG), a technique which records the electrical field emitted by the muscles when contracting. Due to the complexity of the HMI, it is desirable to shorten the calibration procedure as much as possible whenever the prosthetic device has two or more degrees of freedom (DOFs).**

In this paper we extend the Linearly Enhanced Training (LET) procedure, already employed in myocontrol of single fingers and their combinations, to myocontrol of two DOFs of the wrist plus the action of grasping (hand opening and closing). The LET principle, according to which combined simultaneous activation of more than one DOF are artificially modelled using a simple linear combination of single-DOF activations, was tested on six intact subjects engaged in wrist flexion, extension, pronation and grasping. The experimental results show that LET can solve this problem with a similar level of accuracy as in the case of single fingers. As well, the LET hyperparameters are shown to be invariant across subjects.

I. Introduction

The loss of the upper limb, whether by accident or by planned surgery, partial or total, and mono- or bilateral, constitutes a dramatic degradation of the quality of life of a human being. Daily-living functions are severely hampered and an assistive device (a prosthesis) is in that case needed. Modern self-powered arm and hand prostheses can to a certain degree restore the lost function, but the road to a decent solution to this problem is still long to go. In particular, the problem can be split in two: building a functional prosthesis, which adheres to the typical requirements of an amputee (e.g., limitations on weight and power consumption, robustness, aesthetic appearance, and so on), and letting the subject properly control it. With the advent of multi-fingered hand prostheses and mechanical wrists, elbows and shoulders, the situation has improved from the mechatronic point of view; nevertheless, at the time of writing the control part is still lacking, to the point that up to one third of amputees fitted with expensive self-powered upper-limb prostheses reject the device after the initial enthusiastic phase [1], [2]. It seems that right now, proper control of an advanced upper-limb prosthesis is still an open problem.

The main avenue to improve control is that of *simultaneous and proportional* control (s/p control), in which one or more degrees of freedom (DOFs) of the prosthetic device are directly controlled in torque (force, current) independently and at the same time [3]. The approach leads in principle to a more natural integration of the mechanical limb into the subject's body, since it enables control over an infinite manifold of force configurations. The application of machine learning (ML) to body signals which characterise the muscle remnants' activity (human-machine interface, HMI) in principle guarantees that the subjective experience is natural, i.e., the prosthesis acts "upon the subject's will". However, as opposed to the more traditional signal classification schema, one clear drawback of s/p control is that as the number of DOFs to be controlled in the prosthesis rises above two or three, the calibration phase ("training phase" in the ML lingo) grows unfeasibly; this is due to the necessity of calibrating the system not only on single-DOF activations, e.g., the flexion of the wrist or the opening/closing of the hand, but as well on their *combinations*. Given n DOFs, the number of possible combinations is obviously exponential in n, and it is unrealistic to expect the subject to reliably produce signals for all of them.

To ease this problem, in 2009 Jiang et al. [3] proposed to use a linear signal decomposition schema based upon Non-Negative Matrix Factorisation (NMF) [4] to obtain multi-DOF combinations from single-DOF ones; the approach was later on extended in [5] by incorporating a decision system to either use traditional classification in case the signal resembled single-DOF activations, or NMF whenever the Mahalanobis distance between the current signal and any previously stored single-DOF cluster was large enough. Alternatively, in [6], [7] we proposed to augment the dataset representing single-DOF activations with artificially modelled multi-DOF signals, obtained by linearly combining single-DOF ones in a very simple way, and then using the ML method of choice on this new dataset. The procedure therein introduced was called Linearly Enhanced Training (LET), since multi-DOF activations were created using a one-parameter linear combination of single-DOF activations. The LET procedure showed promising results on the problem of

978-1-4799-1808-9/15/$31.00 ©2015 IEEE

combining single-finger activations into multi-finger ones.

In this paper we extend the LET procedure to the control of two DOFs of the human wrist (pronation and flexion/extension) plus the ability of opening/closing the hand. Control of the wrist combined with grasping is deemed essential for daily-living activities (see, e.g., [8]). In a psychophysical experiment six healthy subjects were asked to perform several wrist and hand activations, as well as combined activations. sEMG data was gathered during these activations from the subject's proximal forearm. The experimental results reveal that an incremental, space-bounded machine-learning method for myocontrol, namely Ridge Regression with Random Fourier Features, achieves on LET-augmented data sets an accuracy in regression which is comparable to that found in the experiments concerned with single fingers [6], [7]. The hyperparameters needed to apply LET are found to be invariant across subjects, as it happened in the previous works. If proved successful in the large and on amputees engaged in a real online control task, the LET procedure could constitute a viable way to enforce reliable and dexterous s/p control for dexterous upper-limb prostheses.

II. The LET procedure

Data collected from the input space (i.e., sEMG) are arranged in *data clusters*, which are represented by matrices containing n samples of a d-dimensional sEMG signal, i.e. $\boldsymbol{X}_i \in \mathbb{R}^{n \times d}$. The index i stands for a specific activation, e.g. wrist flexion. Introducing the index j, e.g. wrist pronation, $\boldsymbol{X}_j$ represents the sEMG data gathered during wrist pronation. Furthermore, $\boldsymbol{X}_{ij}$ represents the sEMG data of a combined activation of DOF i and j, in this example a simultaneous flexion and pronation of the wrist. The central assumption of the LET procedure is that by choosing an appropriate *model function* $\mathcal{F}$ we can approximate the multi-DOF activation $\boldsymbol{X}_{ij}$ using the single-DOF activations $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$.

$$\boldsymbol{X}_{ij} \approx \mathcal{F}(\boldsymbol{X}_i, \boldsymbol{X}_j) \tag{1}$$

For $\mathcal{F}$ we test two different functions that have been applied in [7] as well, namely the single-α-model function $\mathcal{F}_1$ and the multi-α-model function $\mathcal{F}_\mathrm{m}$

$$\begin{aligned}\mathcal{F}_1(\boldsymbol{X}_i, \boldsymbol{X}_j) &= \alpha_{ij} \cdot (\boldsymbol{X}_i + \boldsymbol{X}_j)\\ \mathcal{F}_\mathrm{m}(\boldsymbol{X}_i, \boldsymbol{X}_j) &= \alpha_{ij}^i \cdot \boldsymbol{X}_i + \alpha_{ij}^j \cdot \boldsymbol{X}_j\end{aligned}$$

One can see that the $\mathcal{F}_1$ only has one parameter α, while $\mathcal{F}_\mathrm{m}$ has several, one for each DOF involved in the multi-DOF activation. Since the model function can be seen as a projection onto a lower dimensional space, the α-parameters can be determined analytically, if sEMG data from the single- and multi-DOF activations is available. The resulting formulations for α for $\mathcal{F}_1$ and $\mathcal{F}_\mathrm{m}$, respectively, are the following

$$\mathcal{F}_1: \ \alpha_{ij} = \frac{\bar{\boldsymbol{X}}_{ij} \cdot \left(\bar{\boldsymbol{X}}_i + \bar{\boldsymbol{X}}_j\right)^T}{\left(\bar{\boldsymbol{X}}_i + \bar{\boldsymbol{X}}_j\right) \cdot \left(\bar{\boldsymbol{X}}_i + \bar{\boldsymbol{X}}_j\right)^T} \tag{2}$$

$$\mathcal{F}_\mathrm{m}: \ \boldsymbol{\alpha}_{ij} = \left({\boldsymbol{\mathcal{X}}_{ij}}^T \cdot \boldsymbol{\mathcal{X}}_{ij}\right)^{-1} \cdot {\boldsymbol{\mathcal{X}}_{ij}}^T \cdot {\bar{\boldsymbol{X}}_{ij}}^T \tag{3}$$

with the α-parameters of $\mathcal{F}_\mathrm{m}$ arranged in a vector $\boldsymbol{\alpha}_{ij} = \left[\alpha_{ij}^i \ \alpha_{ij}^j\right]^T$ and the "basis" vectors of $\mathcal{F}_\mathrm{m}$ arranged in a matrix $\boldsymbol{\mathcal{X}}_{ij} = \left[{\bar{\boldsymbol{X}}_i}^T \ {\bar{\boldsymbol{X}}_j}^T\right]$.

In order to train a ML algorithm on the respective sEMG data we furthermore need corresponding target values or ground truth. An approach that proved to be very effective in myocontrol is to use the information from the stimulus as target values [9], [10]. Furthermore, sEMG data is only gathered during full activation of a DOF. Hence, training only occurs on full or no activation. These two states are simply represented by values of 1 or 0 for each individual DOF. Using this notation a training data set $\boldsymbol{D}_{ij}^\mathrm{SD}$ for two different DOFs i and j would result in the following

$$\boldsymbol{D}_{ij}^\mathrm{SD} = \{(\boldsymbol{X}_0, (0,0)), (\boldsymbol{X}_i, (1,0)), (\boldsymbol{X}_j, (0,1))\}$$

where $\boldsymbol{X}_0$ indicates rest, which can as well be seen by the two following zeros representing no activation of DOF i and j. Using $\boldsymbol{D}_{ij}^\mathrm{SD}$ for training a ML algorithm would allow the user (for most ML algorithms) to activate DOF i or DOF j, but not DOF i and j at the same time. The superscript SD stands therefore for *single-DOF*, since only single-DOFs can be actuated. By extending $\boldsymbol{D}_{ij}^{SD}$ by the LET training data (Eq. 1) we obtain the LET-augmented training data set $\boldsymbol{D}_{ij}^\mathrm{LET}$

$$\boldsymbol{D}_{ij}^\mathrm{LET} = \left\{ \begin{array}{c} (\boldsymbol{X}_0, (0,0)), (\boldsymbol{X}_i, (1,0)), (\boldsymbol{X}_j, (0,1)), \\ (\mathcal{F}(\boldsymbol{X}_i, \boldsymbol{X}_j), (1,1)), \end{array} \right\}$$

In the following we want to compare the performance of the LET-augmented data sets, $\boldsymbol{D}^\mathrm{LET1}$ and $\boldsymbol{D}^{\mathrm{LET}m}$, to the performance of $\boldsymbol{D}^\mathrm{SD}$ and $\boldsymbol{D}^\mathrm{MD}$. $\boldsymbol{D}^\mathrm{MD}$ is the training data set containing the actual sEMG data from the multi-DOF activation

$$\boldsymbol{D}_{ij}^\mathrm{MD} = \left\{ \begin{array}{c} (\boldsymbol{X}_0, (0,0)), (\boldsymbol{X}_i, (1,0)), (\boldsymbol{X}_j, (0,1)), \\ (\boldsymbol{X}_{ij}, (1,1)), \end{array} \right\}$$

III. Experiment description

The goal of the experiment is the evaluation of the applicability of the LET procedure to combined activations of the wrist and hand. We aim on evaluating the performance of the LET procedure in an offline comparison between SD, MD, LET1 and LET*m* training data. Furthermore, we optimise the parameters required for both model functions, as well as a hyperparameter for the ML algorithm we use. To this aim we engaged six healthy subjects to perform several wrist and hand activations and collected the respective sEMG data for further analyses.

A. Setup

The most essential component of the setup are the ten *MyoBock 13E200* sEMG electrodes from *Ottobock Healthcare GmbH*. The electrodes were fixed on a hook-and-loop strap using custom 3D printed housings and placed at the proximal end of the subject's forearm, see Figure 1.

Fig. 1. Ten *Ottobock* sEMG electrodes placed around a subject's proximal forearm

Data from the sensors was acquired at approx. $64Hz$ using a *National Instruments* data acquisition card (chassis: *NI cDAQ-9181*; card: *NI9205 (DSUB)*). The already amplified, rectified and low-pass filtered signal from the electrodes was transmitted via Ethernet to a Windows laptop, where a further filtering step was performed (1^{st} order Butterworth filter with a cut-off frequency of $1Hz$). The sampling frequency is the result of the machine learning method we use. Each sample is processed incrementally after it has been gathered. The duration of the incremental update depends on the computational power and the complexity of the method and leads to a sampling frequency of approx. $64Hz$.

A further component of the setup was a 27-inch screen, which provided visual information to the subjects as well as to the experimenter. In particular, the information consisted of a virtual hand model indicating the desired hand/wrist activation to the subject and a pattern displaying the currently recorded sEMG signal.

B. Protocol

In order to investigate how the multi-DOF sEMG signal of hand and wrist activations relates to the single-DOF sEMG signal, we chose a set of four different activations for our experiment, i.e. power grasp, wrist pronation, wrist extension and wrist flexion (the latter two are mutually exclusive). Based on these activations we asked the subjects to perform several single-, double- and triple-DOF activations, which can be found in Table I, and collected the sEMG expressed while performing these activations. The total number of activations per repetition was 11, while the number of repetitions asked of each subject was four. The whole data collection lasted on average approx. $13min$.

We were able to engage six healthy subjects in this experiment (age: 21 to 42 years; two women, four men).

TABLE I
ROUTINE IN CHRONOLOGICAL ORDER DEPICTING THE DOFS ACTIVE IN EACH ACTIVATION

#	Pow. Gr.	Wr. Pro.	Wr. Ext.	Wr. Flex.	abbreviation
1	1.0	-	-	-	SD1
2	-	1.0	-	-	SD2
3	-	-	1.0	-	SD3
4	-	-	-	1.0	SD4
5	1.0	1.0	-	-	DD1
6	1.0	-	1.0	-	DD2
7	1.0	-	-	1.0	DD3
8	-	1.0	1.0	-	DD4
9	-	1.0	-	1.0	DD5
10	1.0	1.0	1.0	-	TD1
11	1.0	1.0	-	1.0	TD2

One subject was left handed, but all participants were asked to perform the activations with their right arm. A description of the experiment in written and oral form was provided to the subjects prior to the experiment. After all questions were answered the subjects signed a written consent form. Before the experiment started the subjects were seated in front of the screen and asked to adjust their chair to assure a comfortable position throughout the experiment. During the experiment the previous mentioned virtual hand model showed the activations from Table I and the subjects performed the respective motion with their right hand. Enough time was provided to the subjects to assure a correct performance of the partly unintuitive activations.

This experiment is partly compliant with the World Medical Association's Declaration of Helsinki, regarding the ethical principles for medical research involving human subjects, last version, as approved at the 59th WMA General Assembly, Seoul, October 2008. Non-compliance refers especially to the following points: (section B-16) No physician will be supervising the experiment. Data collection from subjects was approved by the institutional board for protection of data privacy and by the work council of the German Aerospace Center.

C. Analysis

For both variants of the LET procedure, the data gathered during the experiment was used to evaluate the optimal α-parameters using Eqs. 2 and 3. Once the LET-modelled multi-DOF activations were added to the training data set, we employed *Ridge Regression with Random Fourier Features* (RR-RFF), already successfully employed in myocontrol in [10]. RR-RFF is a Least-Squares Support Vector Machine [11], [12] in which, instead of the classical Gaussian kernel, a finite-dimensional approximation of it, based upon Fourier coefficients, is used [13], [14]. This kernel being finite-dimensional implies that the size of the models generated by RR-RFF is independent of the number of samples in the training set — in our case this is of paramount importance, since LET, while keeping the training short for the subject, will indeed generate an augmented training set, which is still exponentially large in the number of single-finger activations selected. While using RR-RFF there is only one hyperparameter to be tuned, namely the standard deviation of the Gaussian kernel to be approximated, $\sigma > 0$. To find its optimal value, we performed a grid search in the interval $\sigma \in [0.05, 6.0]$ with variable step size ($\Delta\sigma = 0.05$ for $\sigma \in [0.05, 1.0]$, $\Delta\sigma = 0.1$ for $\sigma \in [1.0, 3.0]$ and $\Delta\sigma = 0.2$ for $\sigma \in [3.0, 6.0]$). This was done using a 4-fold repetition-wise cross-validation. As an error measure we used the normalised root mean squared error (nRMSE).

Furthermore, we conducted a performance comparison between the two LET methods, the SD and MD method. This was done for each of the seven multi-DOF activations from Table I (DD1 to TD2). Here as well, we used the nRMSE as an error measure and performed a 4-fold repetition-wise cross-validation. All four different methods are tested against the real sEMG data for the multi-DOF activations to determine the quality of the prediction. Therefore, we can assume that the MD method performs best, since training occurred on actual multi-DOF sEMG data, and the SD method performs worst, since no training at all occurred on multi-DOF sEMG data. The essential point of this comparison is to answer the question, how close to the performance of the MD method can the LET methods get.

For all statical analyses the one-way ANOVA test with a level of significance of 0.05 was used. The *Tukey*-test was performed as a post-hoc test [15].

IV. Experimental Results

The α-parameters for the single- and multi-α-model were determined using Eq. 2 and 3 and can be found in Figure 2 and 3, respectively, visualised with means and standard deviations across subjects. Explicitly, the means and standard deviations of the α-values for the single-α-model are

$$\alpha_{\mathrm{DD1}} = 0.7728 \pm 0.2357 \qquad \alpha_{\mathrm{DD2}} = 0.7741 \pm 0.1408$$
$$\alpha_{\mathrm{DD3}} = 0.4404 \pm 0.1503 \qquad \alpha_{\mathrm{DD4}} = 0.8465 \pm 0.2798$$
$$\alpha_{\mathrm{DD5}} = 0.7366 \pm 0.1978 \qquad \alpha_{\mathrm{TD1}} = 0.5377 \pm 0.0584$$
$$\alpha_{\mathrm{TD2}} = 0.3980 \pm 0.1239$$

The means and standard deviations of the α-values for the multi-α-model can be found in Table II. This arrangement was chosen to give a better overview of the values.

In Figure 2 brackets with an asterisk indicate significant difference, while brackets without asterisks are used to group α-values with the same interactions. In Figure 3 α-values marked with an asterisk are significantly different from the α-values marked with two asterisks.

The optimisation of hyperparameter σ using a grid search lead to $\sigma^{\mathrm{SD}} = 0.5866$, $\sigma^{\mathrm{MD}} = 0.5885$, $\sigma^{\mathrm{LET1}} = 0.3875$, $\sigma^{\mathrm{LET}m} = 0.5262$ for the four different training methods. Not only the σ-values with minimal nRMSE were determined, but as well all σ-values with a nRMSE up to $\mathrm{nRMSE_{min}} + 0.05$. The optimal σ-values for each method were determined by exponential curve fitting to the histogram of the values determined from the grid search. A generic example can be found in Figure 4 depicting the result for the LET1 method. The maxima of these curves denote the optimal σ-values.

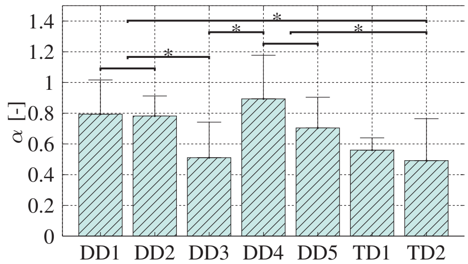

Fig. 2. Means and standard deviations of α-values for the single-α-model across subjects for all combinations

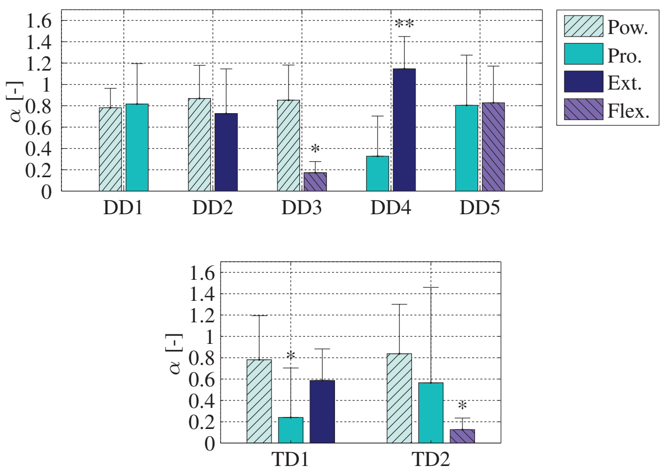

Fig. 3. Means and standard deviations of α-values for the multi-α-model across subjects for all combinations

For the four different training methods we determined the performance by calculating the nRMSE for the seven different multi-DOF combinations in Table I. The means and standard deviations across these combinations and across subjects are $\mathrm{nRMSE^{SD}} = 0.3572 \pm 0.0444$, $\mathrm{nRMSE^{MD}} = 0.0954 \pm 0.0419$, $\mathrm{nRMSE^{LET1}} = 0.1912 \pm 0.0789$ and $\mathrm{nRMSE^{LET}}^{m} = 0.1702 \pm 0.0763$ and can also be found in Figure 5. The brackets with and without asterisks have the same indications as in Figure 2.

As a further measure to compare the two LET methods we determined the variance of each α-parameter across subjects. The means and standard deviations of these variances across all parameters are the following

$$\overline{\mathrm{Var}(\alpha_{\mathcal{F}_1})} = 0.0335 \pm 0.0260 \qquad \overline{\mathrm{Var}(\alpha_{\mathcal{F}_m})} = 0.1648 \pm 0.1820$$

V. Discussion

The performance comparison between SD, MD, LET1 and LETm shows a significant improvement in the performance of both LET methods compared to the SD method; on the other hand, both LET methods perform significantly worse than the MD method. This is to be expected since LET is an approximation of the ideal case MD, and is supposed to work better than the no-information case SD.

Furthermore, the nRMSE values are very similar to the ones obtained in [6] ($\mathrm{nRMSE^{SD}} = 0.3661 \pm 0.0446$,

TABLE II

MEANS AND STANDARD DEVIATIONS OF α-VALUES FOR THE MULTI-α-MODEL ACROSS SUBJECTS FOR ALL COMBINATIONS

Comb.	Pow. Gr.	Wr. Pro.	Wr. Ext.	Wr. Flex.
DD1	0.7812 ± 0.1823	0.8168 ± 0.3784	-	-
DD2	0.8689 ± 0.3101	-	0.7269 ± 0.4190	-
DD3	0.8524 ± 0.3293	-	-	0.1724 ± 0.1052
DD4	-	0.3274 ± 0.3764	1.1465 ± 0.3024	-
DD5	-	0.8044 ± 0.4702	-	0.8280 ± 0.3437
TD1	0.7815 ± 0.4128	0.2403 ± 0.4636	0.5870 ± 0.2956	-
TD2	-	0.8378 ± 0.4628	0.5656 ± 0.8937	0.1266 ± 0.1083

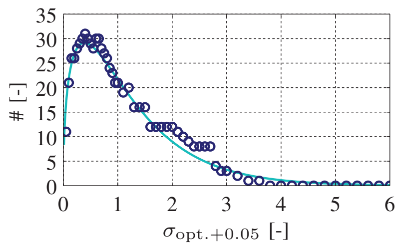

Fig. 4. Histogram of $\sigma_{\mathrm{opt.}+0.05}$-values for the LET1 training method with fitted exponential curve

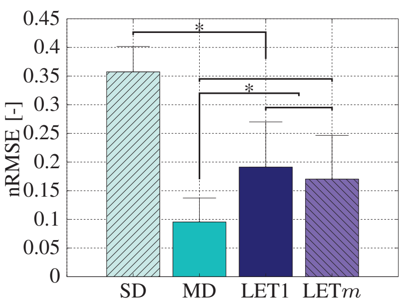

Fig. 5. Means and standard deviations of the nRMSE across all subjects and across all seven multi-DOF combinations for different methods

$\mathrm{nRMSE}^{\mathrm{MD}} = 0.1488 \pm 0.0813$ and $\mathrm{nRMSE}^{\mathrm{LET1}} = 0.1806 \pm 0.0616$) and in [7] ($\mathrm{nRMSE}^{\mathrm{SD}} = 0.3510 \pm 0.0501$, $\mathrm{nRMSE}^{\mathrm{MD}} = 0.1704 \pm 0.1033$, $\mathrm{nRMSE}^{\mathrm{LET1}} = 0.2294 \pm 0.1098$ and $\mathrm{nRMSE}^{\mathrm{LET}m} = 0.2050 \pm 0.1048$). This does not yet prove that the LET procedure allows for s/p control of wrist and hand activations, but can be seen as a strong indication. In terms of uniformity across subject the mean variance of the α-parameters is higher than in the case of the finger motions. In [7] the values were $\overline{\mathrm{Var}(\alpha_{\mathcal{F}_1})} = 0.00841 \pm 0.00513$ and $\overline{\mathrm{Var}(\alpha_{\mathcal{F}_\mathrm{m}})} = 0.0706 \pm 0.0427$ and in [6] only the single-α-model was investigated with the result $\overline{\mathrm{Var}(\alpha_{\mathcal{F}_1})} = 0.0050 \pm 0.0013$. The difference between those two experiments was the fact that in [7] fingertip force values were used to keep the force level coherent during the activations, while in [6] no such modulation was used, same as in this study. This suggests that the absolute variance in α-parameters is higher for wrist/hand activations than for finger activations. Whether this negatively influence s/p control has yet to be determined in an online task.

Due to the relatively lower variance of the single-α-model compared to the multi-α-model and no significant difference between the two LET methods ($p = 0.4185$) we suggest that the simpler single-α-model is better suited for online s/p control. While the results in [7] showed a high regularity in the α-parameters of the single-α-model, which allowed grouping the parameter by the number of DOFs active in a multi-DOF activation, in case of wrist/hand activations less regularity can be found. However, for combinations involving wrist flexion and grasping (DD3 and TD2) the values of α seem coherently low. This could be attributed to the use of similar or the same muscles for those activations, which results in only a small increase in muscle activity, when performing wrist flexion and grasping simultaneously. This agrees with remarks made by the subjects about having difficulty to perform said motions simultaneously.

A further interesting finding concerns the hyperparameter σ of our ML method. The optimal value for σ^{LET1} found both in [6] and [7] was approx. 1.0, while here we find $\sigma^{\mathrm{LET1}} = 0.3875$ to be considerable lower. This suggests that the hyperparameter σ does not depend on the user, but rather on the activations a user intends to perform.

VI. CONCLUSION AND FUTURE WORK

The LET procedure has potential to improve myocontrol of dexterous prostheses. Its main aim is that of providing a basis of single-DOF activations, using which multi-DOF activations can be artificially modelled, leading to the correct prediction of combined movements; one typical example is represented by the act of drinking, in which a mug must be firmly held with a cylindrical grasp while lifting one's arm and pronating the wrist. In the ideal case, a LET-augmented myocontrol system would be able to predict such a combination by having the user only perform wrist flexion and grasping in the training phase without performing the combined activation. This leads to a reduction in the calibration phase since the number of combinations of n DOFs is obviously exponential in n.

This claim must be substantiated by experimental evidence. In [6], [7] we already showed that LET is effective when applied to the problem of predicting s/p activation of several fingers; in this paper we have extended this work, showing that the approach works even in case we target two DOFs of the wrist (namely, flexion/extension and pronation) and the act of grasping. The prediction accuracy obtained during an experiment involving six subjects is comparable to that found in our earlier work, and the invariance of the hyperparameters required to make the approach work is good. This could mean not only that there are anatomical / physiological factors, which imply that combined activations of DOFs result from a linear combination of single-DOF activations; but even that those combinations are similar in all human beings, even from a numerical point of view. Moreover, let us stress once again that LET is not a machine learning method *per se*, but rather a way of building an improved training dataset. This means that any ML method can be then applied to enforce the control itself. In this case we chose Ridge Regression with Random Fourier Features, an approach which has several advantages with respect to its competitors (see, e.g., [10] for more details).

Regarding future work, in [7] forces at the fingertips were used to make activations more comparable and ensure a uniform level of force across subjects. An interesting further experiment would be the parameter determination involving such a force modulation for wrist/hand activations to understand whether such an mechanism is required for adequately determining all the parameters. This would require an online task to compare the two sets of parameters. An immediate extension of this work consists of employing the LET-augmented datasets in an online experiment, engaging the subjects in a real-time grasping task, either in a virtual reality or on a real prosthesis, for instance *Ottobock's Michelangelo* (www.ottobock.com), whose prototypes come equipped with an innovative two-DOF wrist and the ability to grasp in two different ways. And in the end, of course, tests on amputees in real-life conditions will tell us whether LET is effective or not.

Acknowledgments

We acknowledge Mr. Risto Kõiva of the CIT-EC, University of Bielefeld, for designing, and Mr. Miguel Neves of the German Aerospace Centre for printing the housings for the EMG electrodes, which have considerably simplified the setup.

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