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On the Utility of Bioimpedance in the Context of Myoelectric Control

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Abstract - Objective: **Electric hand prostheses are typically controlled using electromyographic (EMG) signals recorded from the residual muscles. However, non-stationarities that are characteristic for EMG interfaces impair the reliability of machine-learning-based approaches during daily life activities-based approaches (e.g., the limb position effect). Including additional EMG-independent information in the classification algorithm may mitigate this problem.**

Methods:

In this study, we systematically investigated an electrical impedance myography (EIM) interface for its possible utility as an additional source of information to EMG. To this goal, six different hand-wrist motions in three arm positions were recorded from ten able-bodied volunteers and three prosthetic hand users. EIM and EMG data were evaluated in terms of information content and classified using linear discriminant analysis (LDA).

Results: **EIM contained less information and was more strongly influenced by changing limb positions than EMG, but a combination of EIM and EMG outperformed EMG alone. Training with pooled data from multiple arm positions was necessary to mitigate the limb position effect.** ***Conclusion:*** **EIM can be valuable for myoelectric control as it contains complementary information to EMG, but it is also strongly influenced by changing arm positions.**

Significance: **This paper provides fundamental insights required for advancing the application of EIM in the context of modern prosthesis control.**

***Index Terms*—myocontrol, hand prostheses, bioimpedance, electromyography, machine-learning**

I. Introduction

ELECTRICALLY powered hand prostheses are typically controlled with electromyographic (EMG) signals generated by the muscles of the residual limb. Conventionally, two pairs of electrodes integrated into the prosthetic sockets acquire and amplify the signals from two antagonistic muscles that are used to control a single degree of freedom (DOF) in two directions (e.g., hand opening and closing) [1]. To control more DOFs, the user can sequentially circle through the active functions (e.g., grip types or active joints) by generating a trigger signal through a co-contraction or a quick wrist motion [1]. This slow and cumbersome process limits the potential benefit of clinically available multifunctional prosthetic hands that have many actuated joints [2]. Recently, machine-learning-based control approaches that use a higher number of EMG signals and allow to directly access all functions without switching became clinically available [3], [4]. The classifier in these systems is typically trained by recording the EMG activity of the residual limb during different phantom limb motions. Various features and classifiers have been proposed in the past decades [5], [6]. It has been demonstrated that in the context of myocontrol, the time-domain feature-set [7], in combination with linear discriminant analysis (LDA), provides reasonable results and is widely used even today, three decades after its introduction [8]–[11].

Under laboratory conditions, machine-learning approaches for myoelectric prosthesis control often yield excellent results; however, in unconstrained, physically demanding, and challenging activities of daily life, non-stationarities can lead to differences between the muscle patterns used to train the algorithm and the patterns generated in the respective prosthesis usage scenario. These differences can cause misclassifications that lead to unwanted motions [12], [13], which deteriorate the prosthesis's usability and performance and consequently reduce the user's satisfaction. A change of the arm position [14]–[16], small shifts of electrodes [17], [18], or changes in skin condition [12] are common reasons for such non-stationarities. Whereas electrode shifts can be mitigated by developing better socket technology and changed skin conditions can be, to some extent, addressed by enhanced signal post-processing, the limb position effect remains a crucial problem for achieving robust machine-learning-based myocontrol. The current state-of-the-art techniques for tackling this issue include acquiring training data in several limb positions [14], [16], [19], and in combination with optimized feature sets [20]. To overcome the challenges associated with machine-learning-based myoelectric control, additional sources of information unrelated to the EMG signal could be used. Other studies explored inertial measurement units [21]–[23], ultrasound [24]–[26] or force resistors [27], [28] as additional modalities.

Electrical impedance myography (EIM) is a promising alternative approach for measuring muscle activity. This technique is based on measuring changes in the tissues' passive electrical characteristics, which occur during the geometrical changes typically induced by muscle contractions [29], [30]. EIM has the advantage that in contrast to other alternative muscle contraction measurement approaches, such as MMG or

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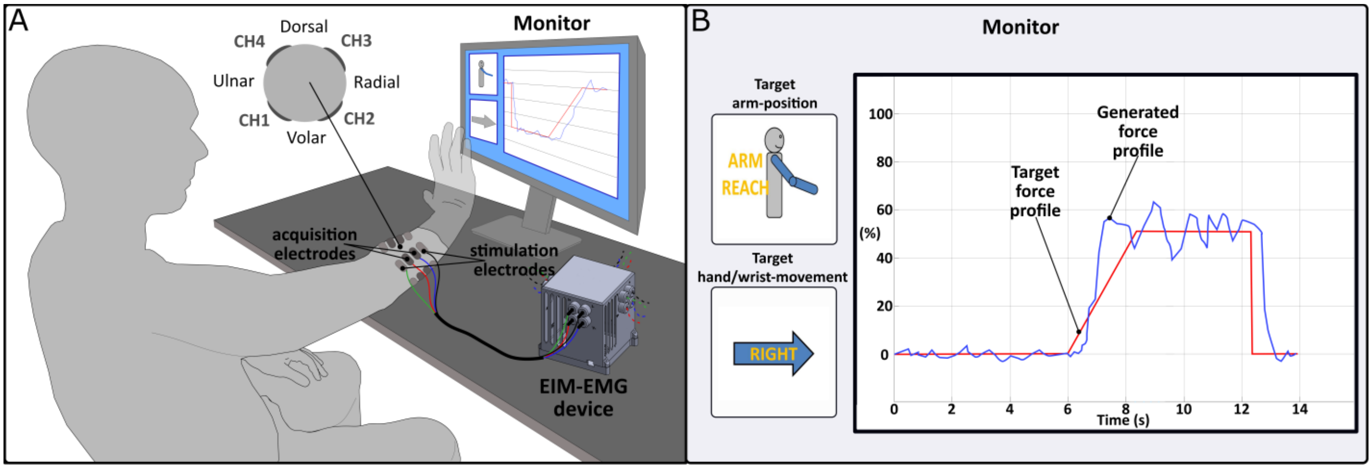

Figure 1. The experimental setup consisted of a device that simultaneously measured EIM and EMG from four recording sites (channels) and a PC for data recording and visual instructions (A). Instructions were provided regarding the arm targeted position, the motion class, and the contraction level. Visual feedback was provided on the contraction level only (B).

optical setups, a common set of electrodes, cables and circuitry can be used. This makes EIM an excellent candidate for a supplementary information source to EMG.

In this study, we systematically investigated the EIM interface for its possible utility in the context of myoelectric control on ten able-bodied participants and three participants with upper limb deficiency. We studied the classification performance while varying the following parameters: arm position, type of muscle contraction, signal features, and training data. We also assessed the overall reproducibility and information content of both EIM and EMG features. These evaluations allowed us to quantify the influence of different factors independently and in combination with each other, thus establishing a sound fundament for further research regarding the application of EIM technology in prosthetics.

II. Methods

To investigate EIM as an alternative or additional control signal for prosthesis control, we recorded both EMG and EIM from the (residual) forearms of able-bodied and upper limb-impaired participants during a series of (phantom) hand and wrist motions. During pilot tests with able-bodied participants, we found that using constrained (isometric muscle contractions) and unconstrained (concentric/eccentric muscle contractions) motions produced substantially different EIM patterns. For able-bodied participants, the motions could be constrained by blocking the motion of the wrist and the hand with an orthopedic splint. After amputation of the hand, most muscles remain intact and can be voluntarily contracted by the user. However, the muscles do not connect to any joint that could be constrained, and the anatomy after an amputation is very individual. Since it was not clear whether the phantom motions executed by participants with limb deficiency would be more similar to the constrained or unconstrained motions of able-bodied participants, we decided to include both conditions for the latter subject group.

A. Experimental Setup

The overall experimental setup is shown in figure 1A. To acquire the time-dependent bioimpedances, a low excitation current is applied to the tissue via electrodes, and the resulting voltage drop is measured. This method, which is also known from electrical impedance tomography (EIT), is non-invasive and hazards free [31]. The EMG-EIM measurement device was custom developed for experimental purposes and systematically evaluated in [32]. It offers four channels of simultaneous EMG and EIM recording using 16 wet electrodes (4 electrodes per channel). The two outer electrodes of each channel were used to induce the current for the EIM measurement (100 µA, 91 - 125 kHz sine-wave; To avoid interference between the channels, each EIM channel operated at a different frequency (91 kHz, 100 kHz, 111 kHz, 125 kHz wave). The inner electrodes were used for measuring both the EMG and the voltage drop caused by the current injection for calculating the bioimpedance. Since the stimulation frequency used for the EIM measurement was outside the surface EMG spectrum, it could be efficiently removed from the EMG by filtering, which was implemented in the hardware [32]. The wet, disposable Ag/AgCl electrodes (Ambu Neuroline 720) were placed in a row aligned with the direction of the muscle fibers on the lower-arm areas marked in

Figure 1A with a center-to-center inter-electrode distance of ~24 mm. Due to the small currents, the tissue can be considered a linear time-invariant system [30]. As it was shown in [33], the human tissue can therefore be approximated with a complex impedance model, which explains the phase shifts between the induced current and the resulting voltage. Therefore, the EIM measurements used for this study were characterized in both magnitude and phase features. The currents applied in this work fulfill the standard for medical electrical safety (IEC 60601-1) and are not perceived by the users, nor lead to any discomfort or skin irritation.

The subjects were sitting comfortably in a chair in front of the PC, facing the monitor that provided real-time experimental instructions such as what motions should be performed and at which arm position and intensity (Fig. 1B). The data for able-bodied subjects were acquired from their dominant arm. In unconstrained condition, both able-bodied and subjects with limb deficiency were able to move their arms freely. In constrained condition, the (able-bodied) subjects' arm was fixed using a commercial orthotic splint adapted to their body size (OttoBock 28P44=R-M, small, medium, and large). This splint was designed to prevent any movement of the hand and wrist. During the pause between trials, participants were allowed to position their arm ad libitum. Before starting each task, the arm was positioned flexed next to the body to achieve a comfortable starting position.

The EIM/EMG acquisition hardware was connected to a standard Desktop PC (Windows 7, core @i7, 8GB RAM) running data acquisition software written in MATLAB (Simulink) real-time development framework [34]. The sampling rate of data acquisition was set to 1000 Hz. The visual feedback loop operated at 30 Hz. Experimental Task and Protocol

All experiments were approved by the local ethics committee of the University Medical Center Göttingen (#22-04-16).

Ten able-bodied participants, two individuals with transradial amputation (A1 & A2) and one person with congenital limb deficiency (C1), were recruited for this study (Table 1).

Before starting the experiment, the experimental protocol was explained, and questions were answered. After the participant signed the experimental consent, the skin of the (residual) forearm was prepared with abrasive electrode gel, and the residues were removed with water. Four regions on the lower arm were selected for data recording by palpating the muscles during the following contractions: wrist flexion, wrist extension, radial deviation, and ulnar deviation. Once the regions had been identified, 16 electrodes were placed (4 per region/input channel) and, after a short five-minute break, the data acquisition could begin.

During the experiment, the able-bodied participants performed six motion classes: hand open, hand close, wrist flexion, wrist extension, radial deviation, ulnar deviation, plus the rest class (no motion). The motion classes for the participants with limb deficiency were individually adjusted to include those (phantom) motions that they were able to execute in a reproducible and distinguishable fashion. We decided to use well-separable motions instead of the most intuitive ones, which is common among prosthetic users using pattern recognition systems. Indeed, all commercial systems allow custom (re)mapping of any muscle contraction into any prosthesis function [3], [4]. For participant A1, these included six motions (wrist flexion/extension, index finger extension, thumb extension, pinky extension, and pronation) and the rest class. Participants A2 and C1 could reproduce only four motions and a rest class (A2: hand open/close, thumb flexion/extension, C1: wrist flexion/extension, radial/ulnar deviation). To differentiate for the factor of a used number of classes within the prostheses' users, we analysed A1 once with all six motion classes and once with a reduced set of four motions. To capture the signal variability in different arm positions, all motions were performed in the following three arm positions: arm elbow flexed at 90°, arm reaching towards the table surface, and arm elevated above head level.

TABLE I
OVERVIEW OF PARTICIPANTS WITH LIMB DEFICIENCY

	Prosthesis user 1 (A1)	Prosthesis user 2 (A2)	Prosthesis user 3 (C1)
Limb deficiency type	Transradial amputation	Transradial amputation	Congenital limb deficiency
Residual limb length	Short	Long	Long
Age	60	62	47
Gender	Male	Male	Male
Prosthesis type	2-DoF, 2-Ch. myocontrol	1 DoF, 2-Ch. myocontrol	1-DoF, 2-Ch. myocontrol
Prosthesis use	Daily	Daily	Occasionally
Number of classes	6 + rest	4 + rest	4 + rest

Abbreviations: DoF – Degree of Freedom; Ch - channel

The experiment consisted of data acquisition in two conditions (constrained, unconstrained) for able-bodied and one condition (unconstrained) for participants with limb deficiency. At the beginning for each participant a maximal prolonged voluntary contraction (MPVC) was measured for 3 seconds for each of the motion classes and conditions (constrained, unconstrained) during flexed arm position. This data was used to automatically calibrate amplitude feedback during the data collection phase to equalize the amount of effort across the subjects. The MPVC was calculated as the maximal average root-mean-square (RMS) value of the EMG across all four acquisition channels (150 ms window, 120 ms overlap).

During the data acquisition, the participants were required to follow the trapezoidal "force" profiles by regulating their muscle activation in real-time. The profiles consisted of a 2.5 s long on-ramp and a plateau that was 4 s long (Fig. 1B). The participants received real-time feedback of their contraction level during the data collection, estimated by the mean RMS value across all EMG channels (150 ms window, 120 ms overlap), and were asked to match the target force profiles as good as possible while contracting the muscles in the requested arm position. No classifier feedback was provided during the data collection in order not to bias the results towards a particular feature selection due to potential adaptations of the user. Five trials were recorded for each motion class. Each condition (constrained, unconstrained) consisted of seven motion classes in three arm positions. This resulted in a total of 5 trials x 3 arm positions x 7 classes = 105 trials per condition. The same number of samples was recorded for all motion classes and the rest class in all conditions and arm positions, making the data-set balanced. The order of motions and arm positions was randomized. To avoid possible bias due to training effects or fatigue, half of the able-bodied participants started in the constrained and a half in the unconstrained condition.

B. Data Processing and Evaluation

The acquired EMG data was post-processed with a second-order band-pass filter (10-450 Hz). No stimulation artifacts coming from the current injected by the EIM interface were observed in the filtered signals.

All data were processed offline with MATLAB in blocks of 200 ms with an increment of 40 ms to keep the delay within the acceptable range for an intended real-time application [35]. For the EMG data, four time-domain features (mean absolute value (MAV), zero-crossings (ZC), slope-sign-change (SSC)), wavelength (WL)) [7] were extracted from the static part of the contraction profiles. For the EIM, the magnitude and the phase were averaged across each block and directly used as features. Depending on the investigated combination of modalities, this resulted in a total number of four (i.e., the condition with EIM-phase or EIM-magnitude only) to 24 features (i.e., the condition where EMG was used with both EIM-phase and magnitude). The EIM and EMG features were used to train and validate an *offline* classifier (see III.C-D). We decided for the multi-class LDA classifier [36] due to its efficiency and wide application in myoelectric control [5], [6]. Importantly, since there is no random component and no parameters to be optimized, the LDA has the advantage of generating reproducible results, in contrast to more complex classifiers, such as support vector machines or deep learning networks. Additionally, this choice of the classifier allows for easy comparison between this and other (similar) studies. To estimate the offline classifier performance, five-fold cross-validation was used, where four trials were used to train the classifier and one trial for testing and estimation of the classification accuracy.

The data evaluation was organized in four sections: the first section addressed the qualitative properties of the EIM signals, while the following three addressed the influence of different factors (feature selection, type of muscle contraction, arm position, and training with combined data-sets) on the LDA classifier performance.

In the first section (results presented in III.A), we characterized the reproducibility of the EIM features in unconstrained condition and quantified the contribution of arm position (AP) as well as the muscles activation (MA) to signal magnitude and phase ($|Z|$ and Z_Φ, respectively) for each subject independently. We used the inverse coefficient of variation (Ic), calculated as a ratio between the absolute difference of the signals means ($|\mu_a - \mu_b|$) and its standard deviation (σ_a). More specifically, the influence of the arm position (Ic_{AP}) was evaluated for the 'rest' class (Ic_{AP}^{r}) by comparing: 1) the acquired data in the arm position 'reach' with the data in the arm position 'flexed' ($Ic_{AP}^{r(r-f)}$) and 2) the acquired data in the arm position 'elevated' with the data in the arm position 'flexed' ($Ic_{AP}^{r(e-f)}$) (see formula 1). Furthermore, the influence of the muscle activation (Ic_{MA}) was evaluated for each of six motion classes (wrist flexion/extension/adduction/abduction and hand open/close; $a_i, i = 1, \ldots, 6$) by subtracting the magnitude of the 'rest' class in each arm positions separately: 1) 'flexed' ($Ic_{MA}^{a_i-r(f)}$), 2) 'reach' ($Ic_{MA}^{a-r(r)}$), 3) 'elevated' ($Ic_{MA}^{a_i-r,(e)}$) and 4) flexed, reached, and elevated pooled together ($Ic_{MA}^{a_i-r(fre)}$) (see formula 2). The final Ic_{MA}^{a-r} value for each arm position was calculated as the average of the *Ic's* across all six motion classes (see formula 3). Therefore, the formulas for calculating different *Ics* can be formalized as follows:

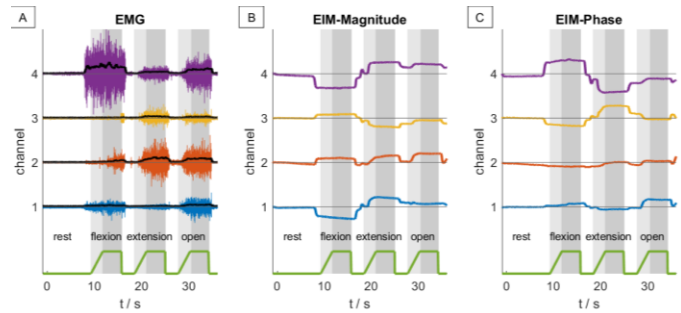

Figure 2. Representative example of EMG and EIM signals for all four channels and three contractions (plus a rest phase) in the arm position 'reach'. The green lines indicate the targeted contraction profiles. Please note that baseline offsets have been removed, and the scaling has been adjusted for improved readability.

(1) $Ic_{AP}^{r(x-f)} = \frac{|\mu^{r(x)} - \mu^{r(f)}|}{\sigma^{r(x)}}$, where '*r*' stands for 'rest' class; '*x*' can be either arm position '*r*' (reach) or '*e*' (elevated); '*f*' is the arm position 'flexed'

(2) $Ic_{MA}^{a_i-r(x)} = \frac{|\mu^{a_i(x)} - \mu^{r(x)}|}{\sigma^{a_i(x)}}$, (3) $Ic_{MA}^{a-r(x)} = \frac{\sum_{i=1}^{N=6} Ic_{MA}^{a_i-r(x)}}{N}$, where $a_i, i = 1, \ldots, 6$ stands for six wrist/hand movements; '*r*' stands for the '*rest*' class; '*x*' can be any of the following arm positions '*f*', '*r*', '*e*' or '*fre*'

Put differently, since Ic compares the magnitude of signal change to its variability, the $Ic_{AP}^{r(r-f)}$ *and* $Ic_{AP}^{r(e-f)}$ effectively describe how much the observed feature is affected by the change of the arm position from 'flexed' to 'reach' and from 'flexed' to 'elevated', respectively. Similarly, the $Ic_{MA}^{a-r(f)}, Ic_{MA}^{a-r(r)}, Ic_{MA}^{a-r(e)}$, *and* $Ic_{MA}^{a-r(fre)}$ capture the contribution of voluntary muscle activation to the signal amplitude for different combinations of arm positions. Also, since each class in the given arm position consists of five trials that were pooled together, the Ic inherently depicts the reproducibility of the investigated features. The lower the variability of the signal across the selected set of trials is, the higher the ratio between its mean and the standard deviation will be. Importantly, although all Ic's were assessed separately for four different acquisition channels, only their total average was used for the statistical analysis. The aforementioned analysis was also performed on EMG signal amplitude (MAV) that served as a baseline for comparison to EIM features.

Additionally, we have computed the correlation matrix for all EMG and EIM features. This analysis involved all able-bodied participants and all four channels. The goal was to further assess how independent EIM amplitude and phase are from each other and from the EMG features.

In the second part (results presented in III.B), we assessed the amount of information contained in the magnitude and phase of the EIM relative to the EMG time-domain features. To this goal, the impact of different feature-sets on the cross-validation classification accuracy was investigated: EMG feature-set only (EMG), EIM magnitude only ($|Z|$), EIM phase only (Z_Φ), EIM magnitude and phase combined (EIM), and finally EMG feature-set complemented with the full EIM features (EMG +

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EIM). For the able-bodied participants, this was done for the constrained and unconstrained conditions separately to identify the influence of constraining the motion and to identify which condition reflects more the situation in the prosthetic users. During this evaluation, the classifier training and testing were always performed in the same arm position. We directly compared the six combinations that are most relevant from a translational point of view: EIM vs. EIM ($|Z|$) and $EIM(Z_{\Phi})$ EIM ($|Z|$) vs. $EIM(Z_{\Phi})$, EMG vs EIM, EMG vs EMG + EIM, EIM vs EMG + EIM.

In the third part (results presented in III.C), we investigated the influence of altering the arm position between classifier training and testing. Here we used the reduced number of combinations between feature sets (EIM, EMG, and EMG + EIM). Similar to section III.A, we specifically assessed the robustness and stability of the EIM signal in the context of changing arm position.

In the last section (results presented in III.D), we employed the conventional approach for addressing the limb position effect [19], [20], [37]. For this, the classifier was trained with a combined assembly of all three arm positions and, likewise, tested in all positions. The goal of these investigations was to assess the effectiveness of the conventional approach in combating the arm position effect when using classifiers based on the EIM only or the combination of EMG + EIM features.

The results for analysis sections III.A-D are presented as a median (interquartile range) and tested for statistical differences. More specifically, the data from able-bodied subjects were tested for significant differences across subjects in each of the experimental conditions separately (constrained, unconstrained). As the Kolmogorov-Smirnov normality test revealed that the results were generally not normally distributed, non-parametric Wilcoxon signed-rank tests were used with a significance level of p = 0.05. To compensate for multiple comparisons, Bonferroni-Holm correction was applied. All statistical analyses were conducted in MATLAB using the statistics and Machine Learning Toolbox.

III. Results

A. Qualitative assessment of the EIM signals

Figure 2A shows a representative example of raw EMG data and MAV features for all four channels, while figures 2B-C show the simultaneously recorded EIM amplitude and phase signals. The correlation between all EMG and EIM features is depicted in figure 3. The correlation between EIM amplitude and phase was relatively low (0.1). Also, the absolute correlation between EMG and EIM features was always lower than 0.17, suggesting that EMG and EIM are not strongly correlated. On the other hand, the correlation between EMG features with each other was often much larger than the correlation between EIM features. For example, MAV and WL had a substantial correlation (0.93), and the ZC and SSC likewise exhibited a similar trend (correlation of 0.65).

The arm position influenced the magnitude and phase of the EIM more than the magnitude of the EMG (Fig. 4A - Ic_{AP}). More specifically, although the Ic_{AP} of all three features significantly increased with the change of arm position from

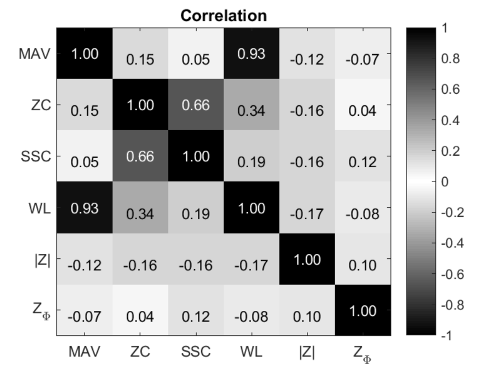

Figure 3. Correlation matrix depicting the correlation between all EMG and EIM features. The absolute correlations between EIM amplitude and phase and between both EIM with the EMG features are consistently lower than 0.17.

'reach' to 'elevated'; this increase was the largest in the case of the EIM-phase. For example, compare the Ic_{AP} in the arm position 'reach-flex' to Ic_{AP} in the AP 'elev-flex' (note that for the sake of simplicity, these will be referred to 'reach' and 'elevated' in the further text). In general, the change of the arm position affected the EIM-phase significantly more than it affected the amplitude of EMG (for both changes of the arm positions) or even the EIM-magnitude (for elevated arm position). On the other hand, the Ic_{AP} of the EIM-magnitude was worse from the EMG only in the case of the elevated arm position (4.2[2.9] vs. 2.2[2.4], for EIM-magnitude and EMG amplitude, respectively).

The influence of the voluntary muscle activation on both EIM-features generally weakened with the change of the arm

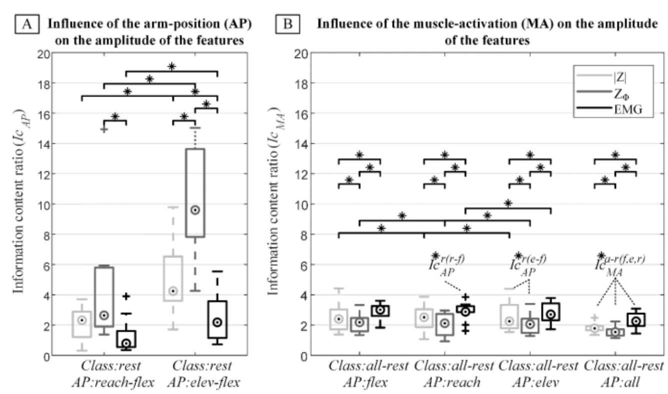

Figure 4. The inverse coefficient of variation (Ic) measures the contribution of arm position (AP, subplot A) or voluntary muscles contraction (MA, subplot B) to the EMG amplitude, EIM-magnitude and phase ($|Z|, Z_{\Phi}$). The "Class:" and "AP:" notations in the x-axis indicate between which two states the Ic was evaluated. In subplot A the class remained at rest while the arm-position was varied and in subplot B the class was changed from rest to any other class. Crosses depict outliers, stars statistically significant differences and the dotted lines connecting a boxplot with an Ic^*-notation depicts statistical differences between the condition of the box and the conditions indicated by the Ic^*-notation for the same feature. The magnitude and phase of the EIM were significantly stronger influenced by a changing arm position than the EMG. The voluntary muscle contractions had a significantly lower influence on the EIM features in comparison to EMG.

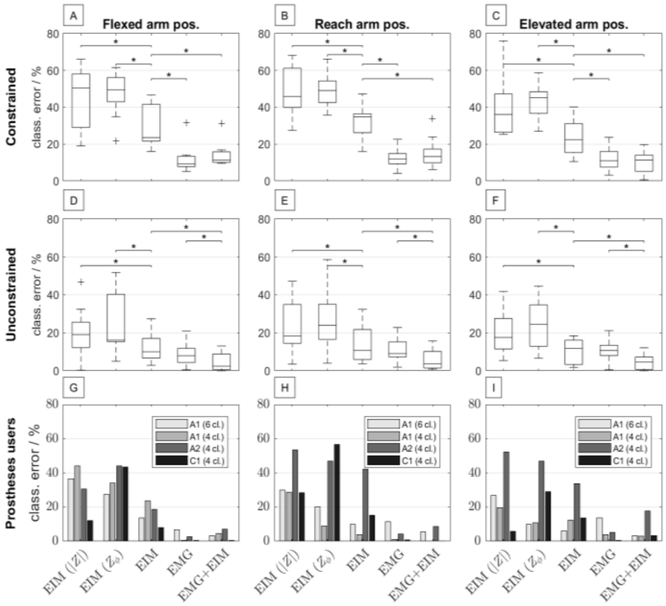

Figure 5. Influence of different combinations of EMG-EIM features, arm positions and muscle contraction types on the classification error when the arm position is not changed between the classifier training and testing. The results are depicted for able-bodied (constrained (A-C), unconstrained (D-F)) and prosthesis users (G-I). A star (*) denotes statistically significant differences. EMG performs better than EIM, but the combination EMG+EIM can further improve the performance.

position for both EMG and EIM. This is reflected in the decreasing trend of Ic_{MA} as the arm position was changed between 'flexed', 'reach', and 'elevated' (Fig. 4B - Ic_{MA}). The Ic_{MA} of the EMG was significantly better from both EIM magnitude and phase for all arm positions. Importantly, in the 'reach' position the Ic_{MA} of the EMG amplitude was higher than the Ic_{AP} of the same arm position, which suggests that the contribution of the muscle activation to the EMG amplitude was consistently higher than that of the arm position itself. Furthermore, in the case of the EMG, in the 'elevated' position, there was no difference between the $Ic_{MA}$and Ic_{AP}, however, the contribution of this arm position to the EIM features amplitude was significantly higher than that of the muscle activation.

Finally, in comparison to the values measured for the individual arm positions, pooling of the arm positions resulted in a significant decrease in the contribution of the voluntary muscle activation for all features (Fig. 4B - $Ic_{MA}, AP{:}\, all$). Even in this case, the EMG amplitude remained the feature that was strongest affected by muscle activation; it is followed by the EIM-magnitude and EIM-phase (2.23[0.8] vs. 1.8[0.1] vs. 1.5[0.2], respectively).

B. Influence of EIM-EMG feature combinations and muscle contraction type on the classification accuracy

LDA classification accuracy without changing the arm position between training and testing is provided in figure 5. Compared to using just the magnitude or the phase, the combination of phase and magnitude in the EIM-classifier leads to significantly better classification accuracy in all cases, independent of the muscle contraction type (constrained/ unconstrained) or arm position (arm flexed/reaching/elevated). The average improvement across all conditions was 12 and 16 percentage points ((EIM($|Z|$) 31% / EIM(Z_Φ) 35% vs. EIM 19%±10%).

The EMG-classifier had moderate error rates for all arm positions and conditions (8-12%, Fig. 5A-F). The three prosthetic users (A1, A2, C1) seem to follow the same trend, although here, no statistical analysis was conducted due to the small sample size (Fig. 5G-I).

The EIM-classifier exhibited a relatively high median classification error in the constrained condition (above 20%; Fig. 5A-C). However, in unconstrained condition (Fig. 5D-F), its classification rate significantly improved for all three arm positions ($p < 0.05$, not depicted in Fig. 5) and achieved similar performance as the EMG-classifier. Interestingly, the EMG-classifier appeared to be less influenced by the constraining of the hand-wrist motion, for here, no significant differences could be detected.

When able-bodied subjects utilized unconstrained motions, the performance of the EMG-classifier improved in all three arm positions when EIM features were added, which was not the case in the constrained condition (Fig. 5D-F). The average error reduction was 5 percentage points in comparison to EMG-classifier alone (EMG 9% vs. EMG + EIM 4%). Amputee A1 with all six classes displayed a similar trend; the error was decreased by 7 percentage points (EMG 11% vs. EMG + EIM 4%; Fig. 5G-I).

Two out of three prosthesis users exhibited consistent trends (Fig. 5G-I). For A2 and C1, the performance appeared better in all arm positions for EMG compared to EIM, as for the able-bodied participants. Especially for A2 the error for the EIM-classifier fell into a relatively high range (19-42%), which was similar to the constrained case of the able-bodied users. For A1 and C2 the performance for EIM features fell into the range of the unconstrained case of the able-bodied participants. A1 was an outlier in the sense that in two arm positions (reach and elevated) he performed slightly worse with EMG than with EIM-classifier. However, this was only the case when all six classes were included. When only four classes were used, as for the other two prosthesis users, he had a better performance with EMG features than with EIM, similar to the able-bodied participants and the other two prosthesis users. Interestingly, when only four classes were used (A1 with reduced motion-set, A2 and C1) the error of the EMG-classifier was already so low that the classification rate could not be further improved by adding EIM features. On the contrary, in several cases, the EMG-EIM classifier performed worse than EMG-classifier.

C. Influence of altering arm positions on classification accuracy for EMG, EIM, and their combination

The classification performance degraded when the arm position between the training and testing was changed (Fig. 6).

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For able-bodied participants, the error of the EMG-classifier increased similarly in both constrained and unconstrained conditions, from approximately 9-12% range to 12-23% range, respectively (Fig. 6A and D). The most considerable degradation was observed when the position was changed between two extremes, that is, between flexed and elevated arm position. The EIM-classifier, which in the unconstrained condition performed in each arm position only marginally worse than EMG, was now substantially more influenced by the change of arm position between training and testing. The classification error increased dramatically to around 34-68% in the unconstrained and around 55-75% in the constrained condition (Fig. 6B and E).

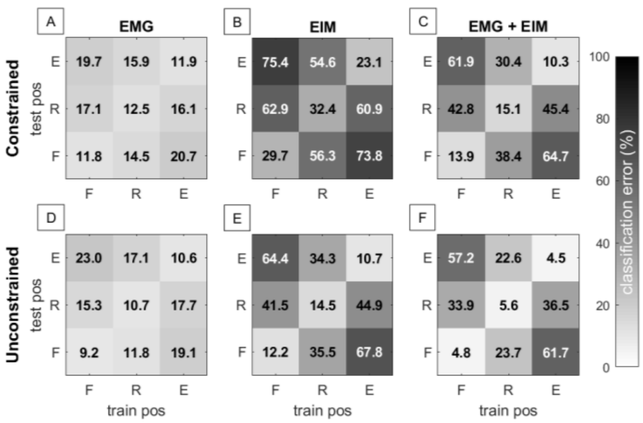

Figure 6. Influence of changing arm position between training and testing on classification error for EMG, EIM and EMG+EIM. The results are depicted for able-bodied subjects in constrained (A-C) and unconstrained (D-F) condition. Annotations F, R, E stand for arm position flexed, reach and elevated, respectively. EIM and EMG+EIM are heavily influenced by changing arm position when trained in one position only.

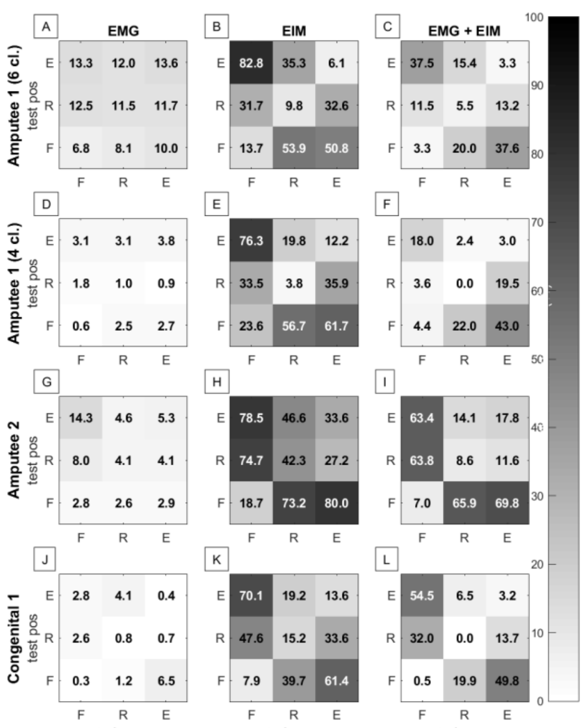

Figure 7. Influence of changing arm position between training and testing on classification error for EMG, EIM, and EMG+EIM classifiers. The depicted classification errors are for individuals with limb deficiency. Annotations F, R, E stand for arm position flexed, reach, and elevated, respectively. Similar to able-bodied, EIM and EMG+EIM are heavily influenced by changing arm position.

When the arm position is changed between training and testing, the performance of the EMG classifier substantially worsened if it was combined with EIM. This contrasts with the results from section III.B, where this was not the case. For example, in the worst combination (alternation between flexed and elevated arm position), the error of the EMG + EIM classifier increased to approximately 57 – 65% (Fig. 6-C and F), which is almost as low as EIM alone.

For participants with amputation or congenital limb deficiency, a similar trend was observed (Fig. 7). Here also, the effect of arm position change was substantially stronger in EIM than in the EMG case. For all three prosthesis users, the negative impact of arm position change was likewise stronger in the combined EMG+EIM case than in the EMG case.

D. *Performance of EMG, EIM and their combination in alternating arm position after pooled training*

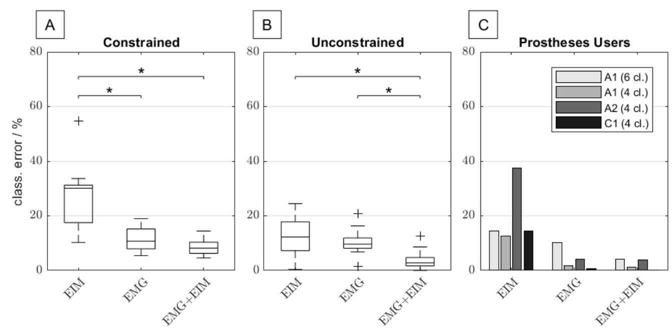

Figure 8. Influence of training with pooled arm position data on the classification error for EMG, EIM and EMG+EIM. The subfigures depict the classification-error of able-bodied participants (constrained (A) and unconstrained (B)) and of prosthesis users (C). A star (*) denotes statistically significant differences. With the pooled training strategy, the combination of EIM+EMG outperforms EIM or EMG alone in most cases.

The performance of the classifier trained with combined arm positions was evaluated across three different feature assemblies: EIM only, EMG only, and EIM + EMG combination (Fig. 8).

As expected, by including all arm positions in the training data, the error rate of the EMG-classifier could be reduced to a similar level as when training and testing in the same arm position.

In the unconstrained condition, the EIM-feature classifier trained with all arm positions improved its classification accuracy compared to training with a single position to a similar range as for unchanged arm position (Fig. 8B). In the constrained condition, the EIM classifier performed significantly worse than the EMG or the EMG + EIM classifier (Fig. 8A). Consistent with previous observations (see section A of the results), for the unconstrained condition, there was no statistically significant difference between EMG and EIM. Finally, in this condition, the combination of EMG and EIM performed significantly better than the EMG alone; that is, the error decreased by 7 percentage points, on average (EMG 9.6%

vs. EIM + EMG 2.7%).

For most prosthesis users the combined arm position training strategy resulted in average errors for EIM features to fall below 15%, which was in the range of errors measured with the able-bodied users in unconstrained condition. Only for A2, EIM-classifier performed substantially worse with an error rate of 37%, which was larger than the most able-bodied users exhibited in constrained condition (Fig. 8C). When the number of classes for prosthesis users was four (A1 (4 cl.), A2, C1), then those users who had classification errors below 5% with EMG alone did not demonstrate any improvement with the inclusion of additional EIM features. However, amputee A1, who was the only prosthesis user who could generate six distinct motion classes, showed significant error-rate reduction when EMG was endowed by EIM features (EMG 10% vs. EMG + EIM 4%; Fig. 8C, A1(6cl)). Therefore, in the case of six motion-classes, his performance with the EMG-EIM classifier was similar to the performance of able-bodied subjects in the unconstrained condition.

IV. Discussion

We have assessed the application of EIM in the context of myocontrol by evaluating how the feature selection, type of muscle contraction, arm position, and training with combined data-sets influence the classification performance. In addition, we have assessed the correlation between all features, the EIM signal reproducibility, and the influence of voluntary muscle activity as well as the arm position on the magnitude of signal change. The evaluation was performed on ten able-bodied and three participants with upper limb deficiency (two amputees and one participant with congenital limb deficiency).

EIM is more influenced by the arm position than by voluntary muscle contractions (Results, Section A). When observing any of the EIM-features and comparing their Ic_{AP} to Ic_{MA} it is evident that the changing arm position contributes to the overall EIM signal amplitude significantly more than the voluntary muscle contraction. A possible reason for this could be the deformation of the body of the muscle due to the change in overall muscle length with changing joint position. The EIM-phase seems to be significantly influenced by the change of muscle morphology since its Ic_{AP} is consistently higher than that of EMG or even of EIM-magnitude. The EIM-magnitude shows somewhat better results than the EIM-phase, as it can be seen when observing the Ic_{AP} in the 'reach' arm position. It seems that in this case, the change of muscle morphology due to the changing arm position was not large enough to render Ic_{AP} of EIM-magnitude significantly different from that of the EMG amplitude; however, this changes once the arm position is switched to 'elevated'. Moreover, the influence of the muscle activation on the EIM features was attenuated with the arm elevation and their Ic_{MA} was never better than that of the EMG. Additionally, as previously indicated, the 'elevated' arm position contributed to the amplitude of the EIM features significantly more than the voluntary muscle activation, which was not observed in the case of the EMG amplitude. Furthermore, in contrast to EIM-features, the contribution of the 'reach' arm position to the EMG-amplitude was significantly weaker than the contribution of the muscle activation. This indicates that, in the context of myocontrol, the EMG in comparison to EIM exhibits overall a better ratio between the useful (Ic_{MA}) and non-useful (Ic_{AP}) information content.

Magnitude and phase of EIM contain complementary information, and unconstrained motions lead to better classification performance than constrained motions (Results, Section B). The results demonstrated magnitude and phase of the EIM are not strongly correlated and that the combination of both increases its classification performance. Additionally, it seems that EIM contains more information for unconstrained than for constrained motions in able-bodied subjects (see also *Results, Section D*). This is a somewhat expected result since bioimpedance measures the tissue composition of the underlying (muscle) tissue. In constrained condition, the muscles cannot change their morphology as much (only isometric contractions), and consequently, the bioimpedance could indeed provide only limited information about executed motions. On the other hand, the unconstrained condition, which allowed for more prominent changes in muscle morphology, exhibited significantly better EIM classification rates. Two out of three prosthesis users (A1 and C1) exhibited EIM-performances similar to the able-bodied subjects in the unconstrained condition, independent of the number of classes used. A2, on the other hand, performed substantially worse with EIM features, similar to the able-bodied in constrained condition. This emphasizes the strong influence of the anatomy of the residual limb on the information content of the EIM signal features.

EMG performs better than EIM, and the EMG+EIM combination outperforms both EMG and EIM when the arm position does not change (Results, Section B). The fact that EIM alone performed worse than EMG but their combination outperformed both indicates that EIM itself contains less reliable information about the conducted motions than EMG, but that at least some part of the information contained in the EIM is complementary to that in the EMG. This is also supported by the low correlation between EIM and EMG features. The EMG features were substantially stronger correlated with each other. For the prosthesis users, this holds only for A1 with all six motion-classes used. In all scenarios with four classes, the performance may have already been saturated with the EMG features only.

EIM is more influenced by the limb position effect than the EMG (Results, Section C and D). In section A it was already observed that the arm position has a significant effect on the magnitude of the EIM signals. This effect was consistently observed also when trying to classify EIM signals in both amputee and able-bodied subjects (Section C). It is most likely a consequence of muscle deformation in combination with changes in body fluids such as blood volume, which in turn changes the bioimpedance of the analyzed tissue. Moreover, the performance of a combination of both EMG and EIM is more influenced by a change of arm position between training and testing than of EMG alone. This indicates that adding the additional EIM information to the EMG is not always beneficial, but due to the strong impact of the EIM features on untrained arm positions, this can even worsen the robustness. When including all arm positions into the training-set as suggested by [19], [37], the negative impact of the additional EIM features is reversed, and combining EIM with EMG performs better than EMG alone as in the case of single-arm positions *(Results, Section D)*. This could be due to complementary information contained in the EIM (as discussed for the unchanged arm positions) and/or a predictive characteristic of the EIM (i.e., reproducibility of its baseline; see Section A) for the arm position that helps to better classify the EMG features. Indeed, we were able to classify the arm position using only the "rest"-class data with an error as low as 20% when using EIM features, which was approximately twice as good as with EMG-features. However, to feed information regarding the arm position into the classifier would be much simpler using IMUs, as suggested by [14], [19], [38], [39].

In summary, including EIM in addition to EMG into the feature set can improve the performance if a proper training strategy is followed, such as including multiple arm positions in the training set. Including all possible arm positions in a prosthetic application may be practically not feasible for the duration of the training protocol, which could lead to degradation for untrained arm positions when using EIM and EMG in comparison with EMG alone. A potential solution could be to use dynamically changing arm positions during the training, as suggested by [23], however, further research would be needed to investigate these approaches.

From a practical point of view, EIM needs more complex hardware and two additional stimulation electrodes per channel, but the measuring electrodes and signal acquisition hardware can be shared with the EMG path. Physiologically, EIM contains a source of delay not present in EMG, as the myoelectric activity precedes muscle contraction. On the other hand, due to the relatively high stimulation frequency of the EIM measurement system, feature extraction can be performed on much shorter time windows than in the case of the EMG signal.

Study outlook. This study recruited ten able-bodied participants and three prosthetic users. Further tests with additional prosthetic users are required to get a better understanding of the practical applicability of the EIM system, specifically because persons with upper limb deficiency present a very heterogenic group, as visible from our study results. Within the relatively short duration of the experiments (around 30 minutes per condition), we did not find substantial drifts in the EIM, which exceeded the impact of the arm position. Longitudinal tests would be required to identify the long-term behavior of the EIM. In the case of slow long-term drifts, e.g., due to metabolic factors, this may be counteracted by a high-pass filter with a very low cut-off frequency (e.g., < 0.01 Hz). Future work could also investigate the potential of using EIM in combination with more complex classifiers, such as deep learning networks. Furthermore, the frequency response of the bioimpedance could be used as additional information [40]. The study was conducted in the laboratory under relatively controlled conditions, and not all results can be transferred into real-world application [41], [42], where additional factors, such as a variation of the contraction level, are present and the user can adapt in a closed-loop on feedback he receives from the system [43]. However, offline investigations are the only way to systematically investigate a larger number of different conditions and factors that influence the reliability of EIM as the additional information source in the context of myocontrol. In this sense, the present work identified advantages but also shortcomings of EIM and evaluated to which extent different factors influence its performance in the context of myocontrol. Therefore, it forms the fundament for further research, including real-time prosthetic applications.

V. Conclusion

In this study, we have assessed the utility of electric impedance myography (EIM) in the context of myocontrol through qualitative (information content) and statistical analysis (classification accuracy). We demonstrate that EIM provides information complementary to EMG since it can increase the classification accuracy although, compared to EMG, EIM is substantially stronger influenced by altered arm positions and is less influenced by muscle activation. Nevertheless, the combination of EMG and EIM successfully mitigates the arm position effects if all positions are included in the training set. Therefore, for the possible application of EIM in future myocontrol interfaces, the great influence of individual anatomy and arm position on the signal features needs to be overcome.

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