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Should Hands Be Restricted When Measuring Able-Bodied Participants To Evaluate Machine Learning Controlled Prosthetic Hands?

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Abstract— **Objective: When evaluating methods for machine-learning controlled prosthetic hands, able-bodied participants are often recruited, for practical reasons, instead of participants with upper limb absence (ULA). However, able-bodied participants have been shown to often perform myoelectric control tasks better than participants with ULA. It has been suggested that this performance difference can be reduced by restricting the wrist and hand movements of able-bodied participants. However, the effect of such restrictions on the consistency and separability of the electromyogram's (EMG) features remains unknown. The present work investigates whether the EMG separability and consistency between unaffected and affected arms differ and whether they change after restricting the unaffected limb in persons with ULA. Methods: Both arms of participants with unilateral ULA were compared in two conditions: with the unaffected hand and wrist restricted or not. Furthermore, it was tested if the effect of arm and restriction is influenced by arm posture (arm down, arm in front, or arm up). Results: Fourteen participants (two women, age=53.4±4.05) with acquired transradial limb loss were recruited. We found that the unaffected limb generated more separated EMG than the affected limb. Furthermore, restricting the unaffected hand and wrist lowered the separability of the EMG when the arm was held down. Conclusion: Limb restriction is a viable method to make the EMG of able-bodied participants more similar to that of participants with ULA. Significance: Future research that evaluates methods for machine learning controlled hands in able-bodied participants should restrict the participants' hand and wrist.**

***Index Terms*—Electromyography, Limb Restriction, Myoelectric Control, Upper Limb Absence, Arm Posture**

I. INTRODUCTION

After enduring a hand loss, individuals experience a reduction in their action capabilities as the degrees of freedom of the hand become unavailable. Many actions that were once easily performed must be relearned during rehabilitation using alternative degrees of freedom. To reduce the strain on the remaining body structures, a prosthetic hand might be provided to regain some of the lost degrees of freedom. Prosthetic hands have until recently only offered one degree of freedom. However, myoelectric multi-articulated hands and machine-learning (ML) control systems have been recently introduced to the market offering multiple degrees of freedom. Such hands are controlled using electromyography (EMG) signals measured from the remnant limb using an array of electrodes. Features of the EMG signals are calculated and constitute a feature space in which a ML classifier is trained. Different regions of the feature space correspond to different movements. Whenever an EMG feature pattern is measured, as during normal use, the ML algorithm maps the pattern in the feature space and sends the corresponding control command to the prosthetic hand. For successful use of a ML-controlled hand, it is required that the EMG feature patterns from the same movement must be consistent and the EMG feature patterns from different movements must be separate in the EMG feature space [1]–[4]. Since people do not intuitively have good control over their EMG generation, these requirements are difficult to satisfy [5], [6]. Furthermore, EMG signals are non-stationary in real-life environments due to various factors such as limb posture and electrode shift during arm movements, and also due to sweat or fatigue, which cause EMG artefacts (see [7] for a review). Additionally, only a few minutes of data from selected fixed limb postures are normally used to train the classifier, which means that the classifier has to account for many other possible situations.

The requirements of the EMG feature patterns for ML control are especially a challenge for those with upper limb absence (ULA) due to the physiological and musculoskeletal effects, which are a consequence of their limb loss. These effects include the deterioration of the neurological link to the muscles in the stump as result of altered cortical areas corresponding to the missing limb [8]–[10]. Additionally, when muscles are not

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being used, fatty degeneration will occur making the muscles weaker, which lowers the magnitude of the EMG [11] and causes less separable EMG feature patterns. Furthermore, if the muscles are sutured to the bone (myodesis), only isometric contractions can be performed, which possibly results into less separable EMG feature patterns as muscle movement is limited. Moreover, altered proprioceptive feedback has been assumed to cause less consistent EMG feature patterns [12]. Finally, stump length, phantom limb sensation and time since amputation all relate to control performance [13].

Despite these differences, the extent to which limb loss in participants with ULA influences the EMG feature patterns is not well understood [2], [3], [14]–[19]. Moreover, able-bodied participants are recruited more often than participants with ULA during research on ML prosthetics to overcome the small number of persons with ULA that can be found or are available. There is however growing evidence indicating that able-bodied participants perform considerably better in various metrics than those with ULA [2], [3], [14]–[17], [20], [21], as well as being grouped into different clusters using hierarchical cluster analysis and principal component analysis than able-bodied participants [21]. Therefore, the validity of recruiting able-bodied participants as substitutes for participants with ULA is questionable. To overcome the above limitations it has been suggested that the effects of limb loss can be reproduced in able-bodied participants by restricting the movements of the hand and wrist using a brace or splint [22]–[25], thus making their EMG features more similar to those of people with ULA. The assumption behind this method is that a constrained hand and wrist would perform only isometric contractions, which should resemble the EMG contractions of a participant with ULA. However, this assumption has never been tested. In summary, the influence of ULA and of wrist-hand restriction on the characteristics of EMG feature patterns represent two unaddressed research assumptions at the basis of many experiments on ML prosthetic control. In this study we address these issues by investigating the influence of ULA on the EMG feature patterns by using the other (intact) limb of people with ULA as a control. We further assess the effects of hand restriction on the quality of EMG feature patterns. Individuals with unilateral ULA were measured while performing bilateral movements in two conditions: one with the unaffected hand-wrist unrestricted and one with the unaffected hand-wrist restricted. Additionally, these movements were measured in different arm postures, since ML classifiers are often trained on EMGs from different arm postures. However, the effect of posture on the EMG's separability and whether it changes between unaffected and affected arms is also not well understood.

To address the issues laid out above, several factors need to be investigated: limb, restriction, postures. Therefore, we performed an experiment with a full factorial design. This allows to investigate the main effects, but also the interactions between these factors. Within this factorial design this research concentrated on two objectives. First, we wanted to understand if the affected and unaffected arm differ in terms of EMG feature patterns consistency and separability. If they differ, this might provide insight to why able-bodied participants achieve better ML control than participants with ULA. Secondly, we investigated if restricting unaffected hands and wrists makes the EMG feature patterns generated by this arm more similar to those generated by affected arms in terms of consistency and separability. If this is the case, it would support the hypothesis that restriction of the able hand makes the generated EMG more similar to the EMG generated by an affected limb.

We expected that the EMG feature pattern consistency and separability are lower in affected arms than in unaffected arms and that restricting the unaffected hand and wrist lowers the consistency and separability of the EMG feature pattern.

II. Materials and Methods

A. Participants

Participants were deemed eligible to take part in the study if they had an acquired unilateral limb-loss at the transradial level. The stump needed to have been properly healed with sufficient reduction of the stump oedema. Participants should have had at least a 2 cm wide region on the forearm without scars. Understanding the Dutch language was required to follow the study protocol. This study was approved by the local ethics committee (ECB/2017.01.30_2). Participants provided written informed consent before entering the study.

B. EMG Measuring

EMG was measured using sixteen active bi-polar electrodes (Otto Bock 13E200=50AC) where eight electrodes were attached to each of two elastic bands. The bands were fastened to the forearms of the participant. On the affected side, the band was fastened at the location where there was muscle activity with no scars present. Muscle activity was determined by palpating the forearm while the participant performed phantom movements. The other band was fastened at the corresponding location on the unaffected side. EMG was sampled at 1000 Hz and transmitted wirelessly to a laptop (Dell XPS 9550).

C. Conditions

The experiment consisted of two conditions during which the unaffected side was compared to the affected side. In the "Unrestricted" condition the unaffected hand and wrist were unrestricted. In the "Unaffected Hand Restricted" (UHR) condition the unaffected hand and wrist were restricted using a medical arm brace (Wrist Lacer, Medical Specialties, USA)) while holding a tennis ball and having the digits taped around the ball, so wrist, thumb and finger movements were restricted as much as possible, see Figure 1.

D. Procedure and Design

The participants sat on a chair with armrests in front of a laptop computer. The electrode bands were fastened to the forearms of the participant. The order of the conditions of the unaffected hand and wrist (restricted or not) were balanced across participants. The participant executed bilateral movements in three different arm postures. The movements were executed in different postures since EMG differs depending on the posture [7]. The three postures were down, front or up, see Figure 2.

Fig 1. Restriction of the unaffected hand and wrist as used in the study. Left: participants wore a wrist brace while holding a tennis ball to restrict wrist movements. Right: The hand was subsequently taped in using skin tape while holding the tennis ball to restrict movement of the thumb and fingers. The band of electrodes is shown at the bottom of both pictures.

In the down posture the arms of the participant would hang down by their sides (shoulder flexion 0º, elbow flexion 0º, Figure 2A). In the front posture the participant would have their arms on the armrest of the chair, with the elbows flexed (shoulder flexion 0º, elbow flexion 90º, Figure 2B). In the up posture the participant would have their upper-arms parallel to the ground while their elbows were flexed so the forearms would be straight upwards (shoulder flexion 90º, elbow flexion 90º, Figure 2C). In the up posture, participants would put their arms down to rest them in the period between movements. The order of these postures was randomised and participants were allowed to rest between postures for as long as they needed.

In each of the three postures, the participant performed seven bilateral (phantom) movements, namely wrist flexion, wrist extension, pronation, supination, open hand, key grip and fine pinch, three times each for three seconds for a total of 63 movement executions for each condition (restricted or not). See Figure 2. To aid in the movement executions, the experimenter said the name of the movement and performed the movement with the participant. Additionally, on the laptop, a picture of the movement was shown together with a progress bar indicating the remaining duration of the movement. Between repetitions the participant relaxed for three seconds. Between movements a six second break took place. All seven movements were executed in the same posture before moving on to the next posture. After a break, the participant followed the same procedure for the other condition. See Figure 2.

E. Outcome Measures

Features of EMG commonly used in machine learning based control were calculated; the mean absolute value, slope sign changes, wavelength and zero crossings. Features were calculated from 200 ms time windows with an overlap of 50 ms.

1) EMG Feature Pattern Consistency

Pattern consistency was calculated as the distance between patterns from different repetitions of the same movement by using the Within-class Distance (WD_{total}) [26] formulated as:

$$WD_{total} = \frac{1}{7}\sum_{j=1}^{7}\left(\sum_{k=1}^{3}\frac{dist_{kj}^{rj} * dist_{rj}^{kj}}{dist_{kj}^{rj} + dist_{rj}^{kj}}\right) \quad (1)$$

Where $dist_{kj}^{rj}$ and $dist_{rj}^{kj}$ are half the Mahalanobis distances in feature space between repetitions r and k of movement j and between repetitions k and r of movement j respectively:

$$dist_{kj}^{rj} = \frac{1}{2}\sqrt{\left(\mu_{Trj} - \mu_{Tkj}\right)^{T} * S_{rj}^{-1} * \left(\mu_{Trj} - \mu_{Tkj}\right)} \quad (2)$$

$$dist_{rj}^{kj} = \frac{1}{2}\sqrt{\left(\mu_{Tkj} - \mu_{Trj}\right)^{T} * S_{kj}^{-1} * \left(\mu_{Tkj} - \mu_{Trj}\right)} \quad (3)$$

Where μ_{Trj} and μ_{Tkj} denote the feature vectors from repetition r and k respectively. S_{rj} and S_{kj} are the covariances of the training data from repetition r and k respectively. Smaller WD corresponds to more consistent EMG feature patterns.

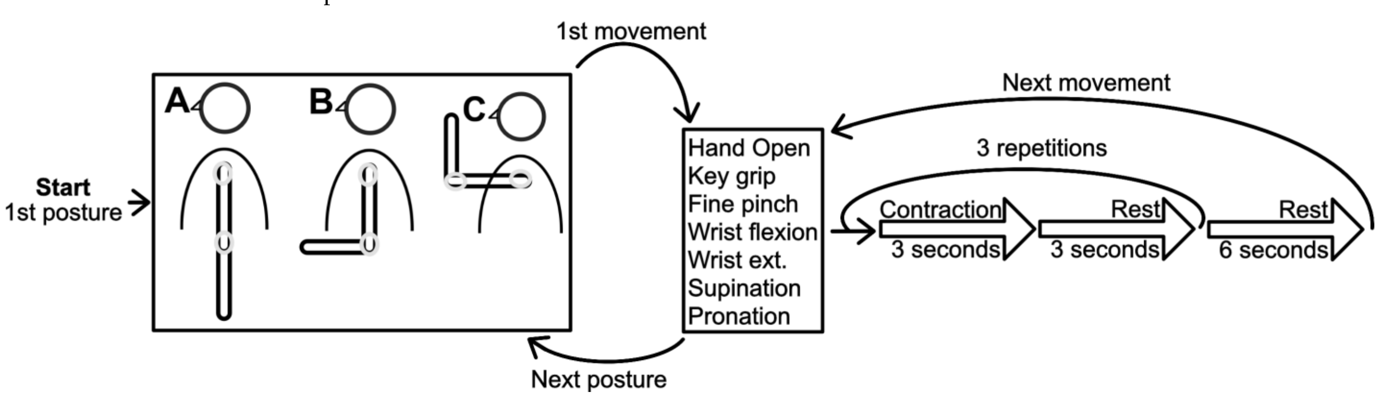

Fig 2. Overview of procedure, postures and movements used per condition. For each of the three postures the seven movements were executed three times for three seconds. Postures were randomized between participants and participants had a six second break between movements.

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2) EMG Feature Pattern Separability

Pattern separability was calculated as the distance in feature space between patterns from different movements by using the Inter-class Distance Nearest Neighbour ($IDNN_{total}$) and Inter-class Distance All Neighbours (IDAN) [26]. The difference between $IDNN_{total}$ and IDAN is that $IDNN_{total}$ measures the distance to the nearest neighbour in feature space, whereas IDAN measures the average distance to all other neighbours in the feature space. The $IDNN_{total}$ and IDAN are formulated as:

$$IDNN_{total} = \frac{1}{7}\sum_{j=1}^{7}\left(\min_{i=1,\dots j-1,j+1,\dots 7}\frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j}\right) \quad (4)$$

$$IDAN = \frac{1}{7}\sum_{j=1}^{7}\left(\frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j}\right) \quad (5)$$

Where $dist_j^i$ and $dist_i^j$ represent half the Mahalanobis distances in feature space between movements i and j and between movements j and i of movement j respectively:

$$dist_j^i = \frac{1}{2}\sqrt{\left(\mu_{Ti} - \mu_{Tj}\right)^T * S_i^{-1} * \left(\mu_{Ti} - \mu_{Tj}\right)} \quad (6)$$

$$dist_i^j = \frac{1}{2}\sqrt{\left(\mu_{Tj} - \mu_{Ti}\right)^T * S_j^{-1} * \left(\mu_{Tj} - \mu_{Ti}\right)} \quad (7)$$

Where μ_{Ti} and μ_{Tj} denote the feature vectors from movement i and j, respectively. S_i and S_j are the covariances of the data from movement i and j, respectively. Larger $IDNN_{total}$ and IDAN corresponds to more separate EMG feature patterns.

F. Data Analysis

For the analyses the metrics described in Outcome Measures were averaged over the seven movements and used as the dependent variables. All the dependent variables were tested for normality using separate Kolmogorov-Smirnov tests with Lilliefors correction. The dependent variables were analysed using a three-way repeated-measures ANOVA with arm (affected and non-affected), restriction (restricted and non-restricted) and arm posture (down, front and up) as within-subject factors. In the case of a 3-way interaction effect being present, the difference between restrictions was calculated and a two-way repeated measures ANOVA was performed with arm and arm posture as within-subject factors. This was done to reduce the number of post-hoc tests required, minimising the risk of making a type-1 error.

Effect sizes were calculated using generalized eta-squared statistics [27]. Post-hoc testing was done using t-test with Bonferroni correction. Results are reported using mean ± standard error of the mean (SEM). The level of significance was set at $\alpha < 0.05$.

III. Results

Fourteen participants joined the study (12/2 M/F, age=53.4±4.05). See Table 1 for characteristics of the participants.

The subject with ID 11 was excluded from the data analysis since he was not able to perform pronation/supination nor wrist flexion/extension.

A. Analysis of EMG Feature Pattern Consistency and Separability

For WD, 6 of the 12 conditions were normal distributed. For the $IDNN_{total}$ 11 of the 12 conditions were normal distributed. For IDAN 4 of the 12 conditions were normal distributed. Since ANOVAs are robust to violations of normality we proceeded with the analyses as planned.

The analysis on WD revealed no significant effects. The analysis on $IDNN_{total}$ revealed a significant main effect of arm on $IDNN_{total}$ ($F(1,12) = 7.613$; $p = .017$, $\eta_G^2 = .047$), showing that the EMG feature patterns were less separated in the affected arm. We found two significant interaction effects: restriction & arm ($F(1,12) = 7.285$; $p = .019$; $\eta_G^2 = .019$), that was mediated by posture, ($F(2,24) = 6.728$; $p = .005$; $\eta_G^2 = .017$), see Figure 3.

ID	Sex	Age	Side of amputation	Loss of dominant hand	Time since loss (years)	Prosthesis type	Prosthesis use	Hours daily prosthesis use
1	F	43	Left	No	2.5	Cosmetic	Daily	5-12
2	M	74	Right	Yes	53	Myo	Daily	12+
3	F	50	Left	No	21	Myo	Daily	12+
4	M	26	Right	Yes	0.5	-	-	-
5	M	59	Right	Yes	25	Myo	Daily	12+
6	M	47	Left	No	3	Myo	Daily	5-12
7	M	30	Right	No	7	Myo	Daily	12+
8	M	45	Right	Yes	11	Myo	Daily	5-12
9	M	80	Left	Yes	29	Myo	Daily	2-5
10	M	67	Right	Yes	47	-	-	-
11	M	54	Right	No	26	Myo	Daily	12+
12	M	52	Left	No	32	-	-	-
13	M	59	Right	Yes	49	Myo	Daily	5-12
14	M	62	Left	No	47	Myo	Daily	12+

Table 1. Participants' characteristics. Abbreviations: M = male, F = female, ID = identification number, Myo = Myoelectric.

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To understand this three-way interaction, we calculated the difference in $IDNN_{total}$ between the unrestricted condition and the UHR condition and performed a new analysis on this difference. This post-hoc analysis revealed a significant main effect of arm ($F(1,12) = 7.182$; $p = .02$; $\eta_G^2 = .06$) and arm & posture ($F(1,24) = 6.654$; $p = .005$; $\eta_G^2 = .06$), see Figure 4. Post-hoc t-tests showed that the UHR condition causes a significant decrease in $IDNN_{total}$ for the unaffected limb compared to the affected limb in the down posture ($t(12) = -3.911$; $p = .002$, $r = .76$) whereas no significant decrease was found for the front ($p = .066$, $r=.50$) and up ($p = .500$, $r=.19$) postures.

The analysis on IDAN revealed no significant effects.

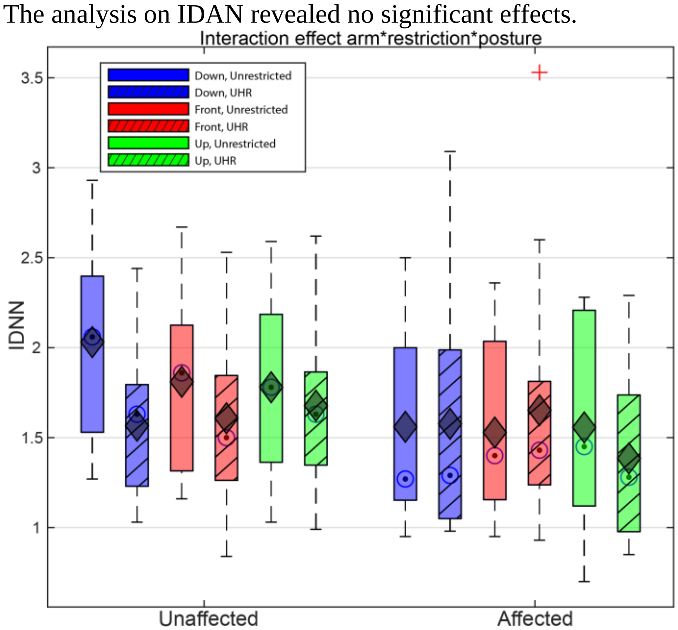

Fig 3. Interaction effect of arm & restriction & posture on the Interclass Distance Nearest Neighbour ($IDNN_{total}$). Each bar denotes the $IDNN_{total}$ for one arm in one condition. The diamonds denotes the mean and the circle with a dot denotes the median. The green, red and blue bars denote the posture. The bottom and top edged denotes the 25th and 75^{th} percentile respectively. + signs denote outliers. Abbreviations: UHR = Unaffected Hand Restricted.

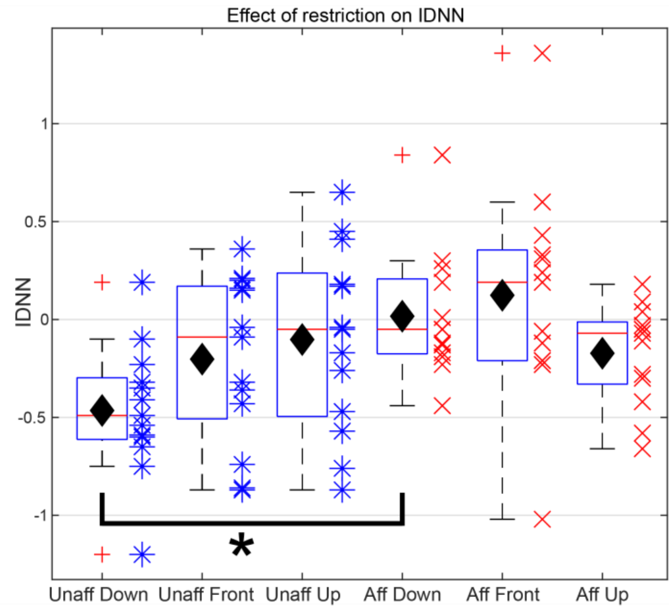

Fig 4. Effect of condition on Interclass Distance Nearest Neighbour (IDNN). The red line denotes the median and the black diamond the mean. The bottom and top edged denotes the 25th and 75th percentile respectively. + signs denote outliers. Data points from individual participants are plotted next to the boxes. The * and the bracket marks the two conditions that are statistically significant. Abbreviations: Unaff = Unaffected, Aff = Affected.

IV. Discussion

In this study the differences in EMG feature pattern consistency and separability were investigated between unaffected and affected arms in individuals with ULA in different arm postures while the unaffected hand and wrist was either restricted or not. The EMG feature pattern separability of the unaffected unrestricted arm appeared to be generally higher than in the other conditions (Figure 3, three leftmost bars). We conclude that the unaffected arm differs from the affected arm in terms of EMG feature patterns consistency and separability. However, the difference was smaller than what we anticipated considering the differences in ML control performance between able-bodied participants and participants with ULA [2], [3], [14]–[17], [20], we discuss this later in the Discussion.

Restriction of the unaffected arm led to a significant decrease of EMG separability in the down posture. Moreover, for the front posture the post-hoc test revealed a p-value (.066) that was close to significance with a medium to large effect size (r=.50). This indicates that there probably is an effect of restriction in the front posture, especially given that with a sample size of 13 it is unlikely that significant effects can be detected with a moderate effect size. Taking the significant decrease of the down posture into account we consider this close to significant effect as a preliminary sign that restricting the unaffected arm could result in a moderate decrease in the separability of the EMG for most of the postures. The relevance of these findings lie in the conditions under which EMG feature patterns of able-bodied and of ULA participants can be made more alike for future EMG studies that employ able-bodied participants in place of participants with ULA. Such studies should now consider restricting the wrist and hand of their participants to make their EMG feature patterns and those of participants with ULA more alike. While able-bodied participants with restricted hand and wrist cannot serve as a substitution for recruiting

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participants with ULA, it will make the data collected more relevant when exploring new methods and during pilot testing.

A. Pattern Consistency

We did not find any effect of arm, restriction or posture on EMG pattern consistency. It should be noted that some studies on user training for ML devices have found that EMG pattern consistency improves with training [2], [3]. This means that EMG pattern consistency might still be an important parameter to consider even though it might not differ between able-bodied participants and participants with ULA. It could be that EMG pattern consistency is not affected by physiological factors.

B. Pattern Separability

Our finding suggests that participants with ULA generate less separable EMG feature patterns than able-bodied participants. This is in line with our expectations given the physiological and musculoskeletal effect of limb loss. That unaffected arms generate more separable EMG feature patterns might explain why able-bodied participants in general achieve better ML based EMG control compared to participants with ULA using their affected [2], [3], [14]–[17], [20] or unaffected arm [28]. However, the difference in EMG separability was smaller than what we anticipated. Literature suggests that training should focus on increasing the separability of the EMG patterns of participants with ULA [2], [26]. Future studies focusing on finding the optimal way of training EMG pattern separability should, based on the current findings, restrict the hand of able-bodied participants when experimentally exploring different training methods that maximally increase separability. However, when aiming for functional improvement with ML based EMG control it should be noted that separability is just one aspect to improve. That is, in other studies we found that the correlation between EMG pattern separability and performance is not linear suggesting that above a certain level of separability, higher separability does not appear to lead to better performance [26], [29]. Furthermore, we only found a decrease in the $IDNN_{total}$ metric and not in the IDAN metric. It is unclear why the IDAN metric did not decrease in a similar fashion as the $IDNN_{total}$ metric. The relation between IDNN, IDAN and performance should be investigated in future research.

C. Effect of Posture

From previous research it is known that arm posture influences the EMG [30]–[32], but it was not clear how it influenced EMG feature pattern consistency and separability. Interestingly, we found that the effects of arm and restriction on separability were not equal over the postures we measured. Most notably, in the postures where the hand is below the head the lowering effect of restriction on separability was most apparent. This specific effect of posture might be due to causes such as gravity compensation (limb stabilisation), skin-electrode interface changes, changes in the force-length relationship of the muscle, changes in musculotendon lever arm or changes in motor execution [32]. To preserve the effect of posture, we suggest, in line with other studies [30]–[32], that in future research different arm postures should be used.

D. Bracing

Bracing of the hand and wrist in this study was done using a medical arm brace designed for comfortable long-term use and by taping the digits around a tennis ball. This method was chosen due to its simplicity and comfort. However, other studies used a glove attached to a board [22], [24] or have the hand grab a cylinder and encase the arm in stiff socket material [23]. The methods used in the other studies might have been more successful at enforcing isometric contractions, but were considered more complex. Furthermore, restricting the hand to a board would mean that the arm would be fixed in one posture. Moreover, our method was comfortable which is important since discomfort or pain can influence the contractions of the participants. The participants in our study did not express discomfort in wearing the brace and the other studies did not report if their participants found the bracing (un)comfortable. Therefore, it is unlikely that pain or discomfort caused the changes between the conditions.

To our surprise, there appears to be some change in the EMG of the affected arm whether the unaffected hand is restricted or not. This might be due to changes in bilateral motor control when the unaffected hand and wrist is restricted.

E. Limitations

A limitation of our study is that the participants did not wear their prosthesis while being measured, which might have led to different results as the weight of the prosthesis affects the EMG [30]. This was unfortunately not possible since the prosthesis socket covered the forearm where we had to place the electrodes. Furthermore, we only measured participants with ULA at the transradial level, meaning that our results might not apply to participants with ULA at the transhumeral level. Additionally, the unaffected arm of an individual with ULA might differ from the arms of an able-bodied individual, which means the effects we observed might not apply to individuals with two intact arms. Lastly, our sample size was limited due to the challenges of recruiting participants with ULA and therefore our results should be confirmed in studies with larger sample sizes.

V. Conclusion

The separability of the EMG feature patterns was found to be lower in the affected arm than in the unaffected arm. Restriction of the able hand and wrist can be used to reduce the separability of the generated EMG patterns, but other parameters should be investigated before the restricted limb can be regarded as a good representative of the affected limb. Looking at separability results, restriction might be useful when testing prosthetic algorithms or hardware on able-bodied individuals. However, restriction of the unaffected hand and wrist does not lower pattern separability when the hand is above the head and restriction has no effect on the consistency of EMG patterns. The consistency of EMG patterns was not found to differ between the affected and unaffected arms meaning that this metric might not differ between individuals with ULA and able-bodied individuals.

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