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RESEARCH ARTICLE

Day-to-Day Stability of Wrist EMG for Wearable-Based Hand Gesture Recognition

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ABSTRACT Wrist electromyography (EMG) signals have been explored for incorporation into subtle wrist-worn wearable devices for decoding hand gestures. Previous studies have now shown that wrist EMG can even outperform the more commonly used forearm EMG, depending on the application. However, the performance and robustness of wrist EMG-based pattern recognition systems in the presence of confounding factors remain relatively unexplored. In this paper, we investigate the day-to-day stability of wrist EMG signals to ascertain their reliability across days. The test-retest reliability of concurrently collected wrist EMG and forearm EMG signals elicited during a variety of finger and wrist gestures was evaluated over a series of days. Several classification approaches, including a novel Maximum independence domain adaptation (MIDA), were investigated to explore and mitigate the effects of natural EMG variations across days. Results showed that wrist EMG signals were reliable and relatively resilient to the negative effects of EMG variations across days. Specifically, wrist EMG-based classifiers consistently outperformed forearm EMG-based classifiers with statistically significant differences ($p < 0.05$) and had average classification accuracies between $93.8\% - 95.7\%$ compared to $91.3\% - 92.6\%$ for the forearm EMG-based classifiers using a novel Inter-Day Feature Set (IDFS) and a novel adaptive-MIDA linear discriminant analysis (LDA) classification technique requiring minimal training. This study builds further evidence for the viability of commercial wrist-worn EMG wearables with minimal training burden for general consumers.

INDEX TERMS Adaptive classification, domain adaptation, gesture recognition, stability, wearables, wrist EMG.

I. INTRODUCTION

For decades, electromyography (EMG) signals recorded from the upper forearm have been used to control prosthetic devices for transradial amputees [1], [2], [3]. With increasingly rapid advancements in wearable technologies, there is a growing demand for reliable yet unobtrusive control interfaces for general consumers as well. Leveraging sensors embedded in wrist-worn wearables has the potential for use in commercial human-computer interaction (HCI) applications and within augmented reality (AR) and virtual reality (VR) environments.

Recently, some studies have shown promising gesture recognition results when collecting EMG signals from the muscles proximal to the wrist joint [4], [5], [6]. Consistent with watches and other wearables, the wrist location is an attractive and convenient location from which to record EMG signals. Other studies have combined wrist and

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forearm EMG together to improve pattern recognition (PR) performance when detecting fine hand grasps [7], [8]. Our recent study [9] showed that wrist EMG yielded high-quality signals that suffered less from additive noise artifacts EMG collected from the forearm. Systems trained and tested on wrist EMG outperformed forearm EMG for gestures involving fine-finger movements and maintained comparable performance for compound hand gestures. Together, these studies have confirmed the potential of wrist EMG and paved the way for more research on the reliability of wrist-based EMG wearables across days.

Within the prostheses literature, the performance of PR systems under different dynamic conditions has garnered substantial attention [10]. Confounding factors that cause changes in EMG signal characteristics over time introduce inaccuracies between the model training phase and practical use. Over the years, many studies have investigated these dynamic factors, which include aspects such as natural variations over time and changes in limb position and forearm orientation, as they relate to the performance of forearm EMG-based PR systems [11]. Natural variations occur due to changes in electrophysiological factors (muscle fatigue, sweating, skin impedance), electrode shift (spatial orientation) and/or changes in muscle contraction effort and behaviours (user intent) [11]. Nevertheless, how these factors may change when EMG signals are recorded from a more distal wrist location has not yet been fully explored.

EMG signal variability has been found to degrade the classification performance of forearm-based PR systems by up to 55% [12], [13], [14]. The corresponding necessity to regularly retrain PR systems has, for a long time, been seen as a roadblock to commercializing myoelectric control systems. Many studies have therefore explored the nature of these forearm EMG changes, including when they occur [15], their impact on classification performance [16], [17], and the amount of training data required to reach a stable gesture recognition accuracy [18]. These studies have shown that EMG classification performance continuously degrades with increasing time between training and testing [18], [19]. Some studies have found that classification accuracy initially decreases exponentially, but then plateaus or even improves as the user becomes familiarized with the PR system and begins performing more repeatable gestures [20], [21].

Many classification techniques have been proposed to overcome the effects of these EMG variations [11], with varying degrees of limited success. Adaptive algorithms have also been explored to maintain or improve the performance of PR systems. These self-enhancing algorithms are able to follow subtle changes in data, and modify or retrain the parameters of the classification models [11]. For instance, adaptive linear discriminant analysis (LDA) classifiers continuously update their class mean vectors, the class covariances, and the pooled covariance [22], [23]. Results have shown that such adaptive algorithms significantly outperform their static counterparts when properly implemented and evaluated over time.

Recently, deep learning algorithms have been explored as a way to maintain the performance of PR systems across days and minimize the need for retraining [24], [25], [26], [27], [28], [29]. Domain adaptation techniques have also been proposed to mitigate drift in data distributions between initial training phases (source domain), and later testing phases and/or when using a different device (target domain) [30]. Such domain adaptation algorithms have been applied to various areas of research including machine olfaction [31], [32], image processing [33], [34] and sentiment analysis [35], [36]. However, the potential of these novel domain adaptation techniques has not been yet fully explored in the EMG field.

Regardless of approach, the vast majority of EMG-related efforts have, nevertheless, focused on forearm EMG signals, and it is currently unknown how the impact of confounding factors may differ at the wrist level. Given the different anatomical structures, muscle bulk, and proximity to the wrist joints, the relative effect is non-trivial. Some previous studies have begun exploring the effect of natural EMG variations at the wrist level. For instance, Jiang et al. [4] used an adaptive LDA classification approach to maintain wrist EMG PR performance across sessions. However, the time span of this study was limited only to one day after the initial classifier training. In another study, wrist EMG signals were recorded across 4 days [6]. However, this study was limited only to 3 gestures and did not take the training burden into consideration. Neither of these studies quantified the stability of wrist EMG PR performance across days nor compared it to the performance of the commonly used forearm EMG in the prosthetics field.

Therefore, for the first time with wrist-based EMG, the goals of this work were (1) to quantify the inter-day stability of wrist EMG in terms of test-retest reliability index, and (2) to quantify any degradation in PR performance across days when using static classification techniques. These results are presented as a head-to-head comparison between wrist EMG and the more commonly used forearm EMG. To combat any degradation, a maximum independence domain adaptation (MIDA) technique and several classification approaches are explored to (3) mitigate the effect of EMG variations and improve PR performance across days while minimizing the user training burden.

II. METHODOLOGY

A. DATA COLLECTION

EMG data were collected from 12 able-bodied participants (27.83 ± 4.90 years, 9 males, 3 females) with no history of muscular or nervous system problems. Informed consent was obtained from all participants before data collection, as approved by the Research Ethics Board (REB #2018-159) at the University of New Brunswick (UNB). EMG signals were collected using a UNB cuff [9], [37] consisting of four wrist electrodes and four forearm electrodes with a 1-kHz sampling frequency (Fig. 1). Data collection and

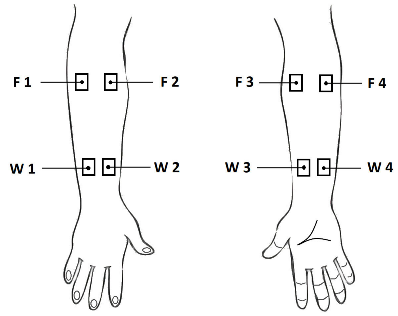


FIGURE 1. Locations of wrist (W1-W4) and forearm (F1-F4) EMG electrodes.

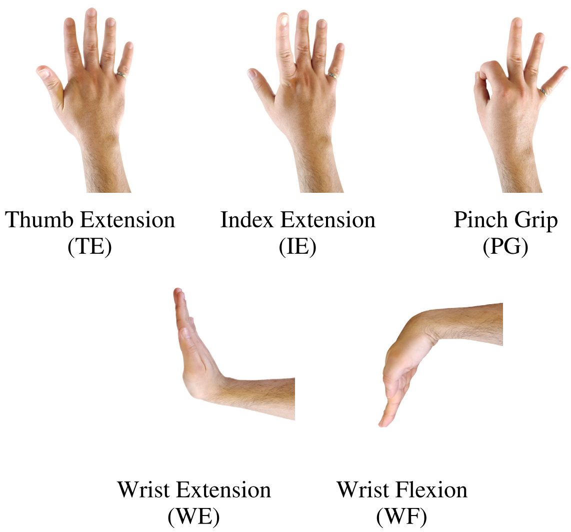


FIGURE 2. Illustration of performed gestures.

subsequent analysis were performed using MATLAB R2022a (The MathWorks, Inc., USA).

Participants performed 5 hand gestures consisting of thumb extension (TE), index extension (IE), pinch grip (PG), wrist extension (WE) and wrist flexion (WF) (Fig 2). PG, WE and WF gestures are commonly used in the prosthesis field to restore lost or missing function while performing activities of daily living [38], [39]. These gestures along with TE and IE gestures can also be used by able-bodied users to control menus and interact with HCI interfaces within smart homes and AR/VR environments [40], [41].

Wrist EMG and forearm EMG signals were concurrently collected from each participant over three different sessions. For all subjects, data of the second session were collected on the following day after the initial data collection session. For the third session: data were collected from 6 subjects on the following day, while the other 6 subjects completed the collection between 3–6 days after the second session. During each session, participants were guided by on-screen instructions to perform 8 repetitions of each gesture. Locations of EMG electrodes—relative to the muscle bellies, elbow joint and ulnar styloid process—were recorded on the first day for consistent placement on the following days. Slight radial and lateral electrode shifts ($\pm$1 cm) were allowed to mimic natural variations in the placement of consumer wearables. Collecting data across different days also incorporates EMG signal variations due to physiological changes, electrode shift, and natural behavioural changes in user intent [11].

The raw EMG signals were filtered using a third-order Butterworth high pass filter with a cut-off frequency of 20 Hz to remove any low-frequency motion artifacts. Additionally, an infinite impulse response (IIR) notch filter with a Q-factor of 50 was applied at 60 Hz and its harmonics to remove electromagnetic interference (EMI) noise [11].

B. FEATURE ENGINEERING

1) FEATURE EXTRACTION

EMG signals were segmented into overlapping windows of length 150 ms with 50% overlap. To improve the information density of the EMG, and evaluate test-retest reliability, 60 different features were extracted from each window including 49 time-domain features and 11 frequency-domain features (Table 1).

2) FEATURE SELECTION

The PR performance of several feature sets was evaluated including the commonly used time-domain (TD) feature set (consisting of MAV, WL, ZC and SSC) [45] as well as TD4 (consisting of LS, MFL, MSR and WAMP) [44] and TD9 (consisting of LS, MFL, MSR, WAMP, ZC, RMS, IAV, DASDV and VAR) [44]. Other feature sets were evaluated including: TDHIST (consisting of TD and HIST features), and TDHISTAR (consisting of TD, HIST and AR features). Additionally, sequential floating feature selection (SFFS) [46] was applied on the features extracted from the wrist and forearm EMG signals independently to identify the feature sets that may be more resilient to EMG variations across days, using the average classification accuracy of the *Across-Days Static Classifier* explained later in the *Classification Algorithms* subsection. Based on the SFFS selected feature sets for the wrist and forearm EMG locations, the performance of a new feature set consisting of the common features between the two selected feature sets was evaluated. This generalizable and stable feature set is referred to here as the Inter-Day Feature Set (IDFS) and the full list of its features is provided in the *Results* section.

3) DOMAIN ADAPTATION

A maximum-independence domain adaptation (MIDA) feature transformation technique was applied on the IDFS selected feature set to mitigate the effect of EMG variations across days. In this technique, a domain feature is defined to represent the different days of data collection as a source of feature variation. The domain feature is represented using one-hot encoding and augmented with the raw features. The combined features are then projected using a linear kernel onto another space that maximizes the independence from the

TABLE 1. List of extracted features [42], [43], [44].

Type	Abbreviation	Feature Name
Time Domain Features	AAC	Average Amplitude Change
	AFB	Amplitude of the First Burst
	AR	Auto-Regressive Coefficients
	ASM	Absolute Value of the Summation of the expth Root and its Mean
	ASS	Absolute Value of the Summation of Square Root
	COV	Coefficient of Variation
	CP	Cepstral Coefficients
	DAMV	Difference Absolute Mean Value
	DASDV	Difference Absolute Standard Deviation Value
	HC	Hjorth Complexity
	HDSM	Hjorth Difference Spectral Moment
	HIST	Histogram of EMG
	HM	Hjorth Mobility
	HNSM	Hjorth Normalized Spectral Moment
	HRSM	Hjorth Root Spectral Moment
	HSM	Hjorth Spectral Moment
	IAV	Integrated Absolute Value
	IQR	Interquartile Range
	KURT	Kurtosis
	LOG	Log Detector
	LS	L-Scale
	MAD	Median Absolute Deviation
	MAV	Mean Absolute Value
	MAV1	Modified Mean Absolute Value Type 1
	MAV2	Modified Mean Absolute Value Type 2
	MAVS	Mean Absolute Value Slope
	MFL	Maximum Fractal Length
	MHW	Multiple Hamming Windows
	MSR	Mean Value of The Square Root
	MTW	Multiple Trapezoidal Windows
	MYOP	Myopulse Percentage Rate
	PK2RMS	Peak-Magnitude-To RMS Ratio
	RMS	Root Mean Square
	RSS	Root-Sum-of-Squares Level
	SampEn	Sample Entropy
	SKEW	Skewness
	SPARSE	Sparseness
	SSC	Slope Sign Change
	SSI	Simple Square Integral
	STKEO	Summation of The Teager-Kaiser Energy Operator
	TM3	Absolute Value of the 3rd Temporal Moment
	TM4	Absolute Value of the 4th Temporal Moment
	TM5	Absolute Value of the 5th Temporal Moment
	VAR	Variance of EMG
	VO	V-Order
	WAMP	Willison Amplitude
	WL	Waveform Length
	WLR	Waveform Length Ratio
	ZC	Zero Crossing
Frequency Domain Features	FR	Frequency Ratio
	MDF	Median Frequency
	MNF	Mean Frequency
	MNP	Mean Power
	PKF	Peak Frequency
	PSR	Power Spectrum Ratio
	SM1	1st Spectral Moment
	SM2	2nd Spectral Moment
	SM3	3rd Spectral Moment
	TTP	Total Power
	VCF	Variance of Central Frequency

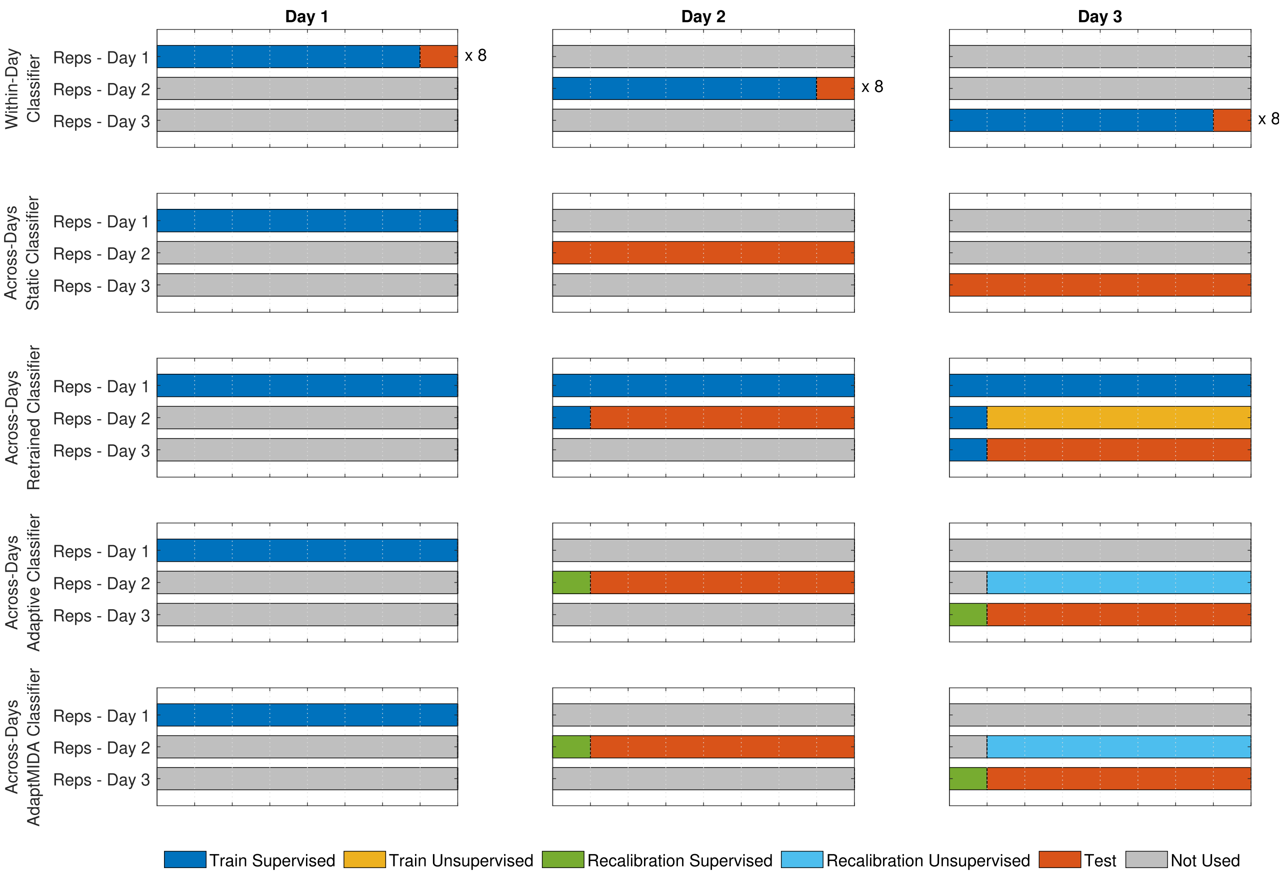


FIGURE 3. Illustration of the different classification techniques and how repetitions of hand gestures are used accordingly for training, calibration, or testing across days. The Within-Day Classifier is denoted with an (x8) to indicate the employed 8-fold leave-one-repetition-out cross-validation technique.

domain feature in the sense of the Hilbert–Schmidt independence criterion to produce features that are more robust to day-to-day EMG variations [47].

C. TEST-RETEST RELIABILITY

To assess the test-retest reliability of the EMG extracted features across days, the intraclass correlation coefficient (ICC) [48] was computed based on the one-way analysis of variance model:

$$\mathrm{ICC} = \frac{\mathrm{MS}_{\mathrm{between}} - \mathrm{MS}_{\mathrm{within}}}{\mathrm{MS}_{\mathrm{between}} - (k-1)\,\mathrm{MS}_{\mathrm{within}}}, \tag{1}$$

where $\mathrm{MS}_{\mathrm{between}}$ is the mean square of feature value between windows, $\mathrm{MS}_{\mathrm{within}}$ is the mean square of feature value within windows (across days), and k is the number of days. ICC takes values in the range: $0 \leq \mathrm{ICC} \leq 1$, where higher values indicate stronger agreement and consistency of feature values across days.

D. CLASSIFICATION ALGORITHMS

Several classification techniques were investigated to evaluate PR performance across days as illustrated in Fig. 3. The goal was to maintain high classification accuracy across days while minimizing the amount of required retraining data, thus, reducing the perceived burden on the user and potentially improving the usability of wearable devices. In all approaches, a comparison between the gesture recognition performance of wrist and forearm EMG signals was conducted using an LDA classifier and the different feature sets.

1) WITHIN-DAY CLASSIFIER (WiDay)

In this approach, the classifier was retrained every day from scratch using the new training repetitions and evaluated using a leave-one-repetition-out cross-validation technique. For instance, 7 repetitions were used for training the classifier, and the 8^{th} repetition was used for testing (Fig. 3). The average classification accuracy was computed across all 8 validation folds and all subjects for each group of gestures. This supervised classification approach represents the maximum training burden on the user while having the best possible PR performance within each day.

2) ACROSS-DAYS STATIC CLASSIFIER (AcDays-STATIC)

Here, the classifier was fully trained using only repetitions collected on the first day. No further retraining was conducted on the following days and the PR performance of the static classifier was evaluated on repetitions of the second and third days (Fig. 3). This classifier is termed *static* since it is trained only on the first day and no changes occur to the classifier parameters across days. This approach represents the least training burden on the user but provides no adjustment to account for variations across days.

3) ACROSS-DAYS RETRAINED CLASSIFIER (AcDays-RETRAINED)

In this classification technique, the classifier was trained from scratch every day using all the repetitions collected on the previous days plus the first collected repetition on the current test day (Fig. 3). The predicted labels of the hand gestures used for testing on the 2nd day were used (unsupervised training) along with the true labels of the new repetition on the 3rd day (supervised training) to retrain the classifier. This technique represents a low training burden on the user since it requires performing each gesture just once before the user uses the wearable device on a given day.

4) ACROSS-DAYS ADAPTIVE CLASSIFIER (AcDays-ADAPTIVE)

This classifier was first trained using repetitions collected on the first day. On subsequent days, the first new repetition of each gesture from the current test day was used to adapt the previously trained classifier (Fig. 3) [49]. Again, the predicted labels of the hand gestures used for testing on the 2nd day were used (unsupervised recalibration) along with the true labels of the new repetition on the 3rd day (supervised recalibration) to recalibrate the classifier. LDA classifier parameters were adapted using:

$$\widetilde{\mu} = (1 - \tau)\,\mu_1 + \tau\,\mu_2, \tag{2}$$

$$\widetilde{\sigma} = (1 - \lambda)\,\sigma_1 + \lambda\,\sigma_2, \tag{3}$$

where μ_1 and σ_1 represent the mean and covariance matrices of the previously trained classifier, μ_2 and σ_2 represent the mean and covariance matrices of the recalibration repetitions of the new day, and $\widetilde{\mu}$, $\widetilde{\sigma}$ are the adapted mean and covariance matrices used to construct the adapted LDA classifier. A Bayesian optimization technique was used to find the optimal values for the τ and λ parameters. This approach has a low perceived training burden on the user similar to the across-days retrained classifier.

5) ACROSS-DAYS ADAPTIVE MIDA CLASSIFIER (AcDays-AdaptMIDA)

In this proposed approach, the MIDA domain adaptation technique was applied in conjunction with the across-days adaptive classification technique to mitigate the effect of EMG changes across days. MIDA is used first to project the features onto another space that maximizes the independence from the domain feature (changes across days) then the classifier is adapted as with the AcDays-Adaptive classifier. This approach has the same perceived training burden on the user as the across-days adaptive and retrained classifiers since it requires only one recalibration repetition on any given new day.

E. STATISTICAL ANALYSIS

Statistical significance between the performance of wrist EMG and forearm EMG-based techniques was assessed against the null hypothesis that their respective means come from populations with equal means. The Lilliefors test was first used to assess the null hypothesis that the wrist and forearm results come from normal distributions or not. If the normality condition was satisfied, then two-sample paired *t*-tests were used to identify statistically significant means ($p < 0.05$). Otherwise, if the distributions were not found to be normal, then a Wilcoxon signed-rank test ($p < 0.05$) was used to assess the significance level.

Box charts were also used to compare between the classification accuracy of different techniques using wrist EMG and forearm EMG. The horizontal line inside each box represents the median classification accuracy across all repetitions of all subjects for each technique. The top and bottom edges of each box are the upper and lower quartiles corresponding to the 0.75 quantile and the 0.25 quantile respectively. Whiskers connect the upper and lower edges of each box to the non-outlier maximum and minimum classification accuracies (values within 1.5 times the interquartile range) respectively. Box charts whose shaded regions do not overlap have different medians at the 5% significance level. The significance level is based on a normal distribution assumption.

III. RESULTS

In this study, EMG signals were recorded from the wrist and forearm levels while subjects performed different hand gestures. A SFFS technique was applied on all features from the wrist and forearm EMG independently to identify the corresponding feature sets that yielded the highest PR robustness across-days without retraining (across-days static classifier), as shown in Table 2. Another feature set (IDFS), comprising of the common features between those two feature sets, was identified and used for further analyses in the rest of the paper (Table 2).

The ICC test-retest reliability index was evaluated on different feature sets extracted from the wrist and forearm EMG signals. The ICC values were plotted against the classification accuracy within the first day for the different feature sets (Fig. 4). Results show that, while forearm EMG had significantly higher ICC values across days using the well-known TD feature set, wrist EMG had significantly higher ICC values than forearm EMG for SFFS and IDFS ($p < 0.05$). Fig. 4 also shows that wrist EMG consistently had higher within-day classification accuracy on the first day compared to forearm EMG using all features sets with the difference being statistically significant ($p < 0.05$) for the TD, TDHIST, TDHISTAR, TD9, SFFS and IDFS feature sets.

To assess the effect of EMG variability across days at both the wrist and forearm locations, the uncorrelated linear discriminant analysis (ULDA) projection technique was applied on each independently to help visualize the variability of EMG feature clusters of different gestures across

TABLE 2. SFFS selected features and the corresponding average static classification accuracy across days extracted from wrist and forearm EMG electrodes.

Wrist EMG			Forearm EMG			Common Inter-Day
Feature	Accuracy %	*p*	Feature	Accuracy %	*p*	Feature Set (IDFS)
MFL	85.05 (5.54)	*	MFL	82.63 (7.60)	*	MFL
AR	90.44 (4.99)	*	AR	85.16 (7.08)	*	AR
SKEW	91.81 (4.37)	*	WAMP	85.33 (6.94)	-	SKEW
SSC	92.19 (4.44)	-	WLR	85.58 (6.94)	-	SSC
SampEn	92.33 (4.35)	-	KURT	85.82 (6.94)	-	SampEn
WLR	92.42 (4.30)	-	HC	85.99 (6.73)	-	WLR
DASDV	92.54 (4.32)	-	SSC	86.17 (6.59)	-	KURT
KURT	92.60 (4.26)	-	HNSM	86.19 (6.59)	-	MNF
MNF	92.67 (4.25)	-	HM	86.20 (6.65)	-	HNSM
FR	92.71 (4.19)	-	SKEW	86.31 (6.85)	-	HC
HNSM	92.72 (4.26)	-	IQR	86.37 (6.87)	-	ASM
HC	92.78 (4.13)	-	ASM	86.38 (6.86)	-	
ASM	92.76 (4.23)	-	PSR	86.39 (6.85)	-	
MAVSLP	92.78 (4.22)	-	SampEn	86.42 (6.85)	-	
			MNF	86.47 (6.82)	-	
			SPARSE	86.48 (6.82)	-	

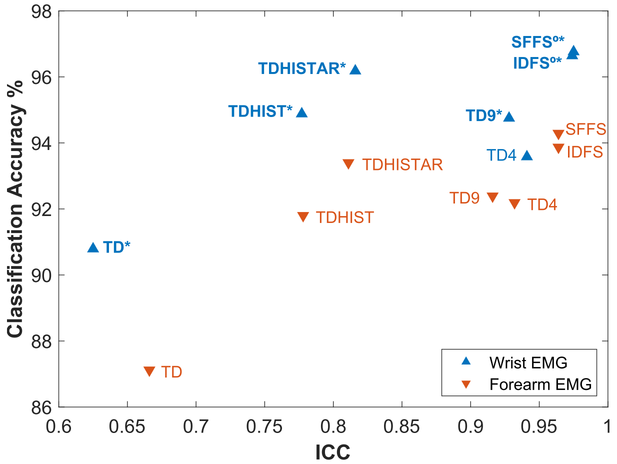


FIGURE 4. Comparison between test-retest reliability of wrist EMG and forearm EMG in terms of intraclass correlation coefficient (ICC) across days, and the corresponding classification accuracy within the first day using different feature sets. Significant differences between the ICC of wrist and forearm EMG are denoted by ° when $p < 0.05$. Significant differences between the classification accuracy of wrist EMG and forearm EMG are denoted by * when $p < 0.05$.

days (Fig. 5). Results show that the wrist EMG clusters were more consistent and separable in the feature space across days compared to their forearm EMG counterparts, especially for finger gestures (Fig. 5a). Also, the PR performance of the across-days static classification approach was evaluated and compared to the within-day classification approach (Fig. 6). Results show that wrist-based EMG PR had consistently higher performance than forearm EMG using the within-day classification approach. Wrist EMG also had higher resilience to EMG variations across days compared to forearm EMG in detecting hand gestures (Fig. 6). Specifically, wrist EMG AcDays static classification accuracy dropped by 3.54% and 8.40% on the second and third days of data collection, respectively, compared to 10.85% and 12.58% drops in performance for forearm EMG.

Multiple domain adaptation and classification approaches were explored to mitigate the effect of EMG variations across days. Fig. 7 shows the average classification accuracies across subjects of separate repetitions using different projection and classification techniques on both wrist EMG (Fig 7a) and forearm EMG (Fig 7b). Fig 8 also shows box plots of the day-to-day classification accuracy of the same techniques using all subjects' repetitions of gesture using wrist EMG (Fig 8a) and forearm EMG (Fig 8b). Results in Fig 7 and Fig 8 show that using the across-days retrained, MIDA, adaptive and adaptive MIDA classifiers improved the PR performance with minimal training burden on the user (one repetition per gesture for recalibration on a new day).

Wrist EMG consistently outperformed forearm EMG using different projection and classification techniques on different days (Fig 9). Particularly, wrist EMG had higher average values and less variability in classification accuracy compared to forearm EMG with the difference being statistically significant ($p < 0.05$) for the AcDays-Static, AcDays-Retrained, AcDays-MIDA and AcDays-Adaptive and AcDays-AdaptMIDA techniques on Day 2 (Fig 9a) and for the AcDays-Static, AcDays-MIDA and AcDays-Adaptive techniques on Day 3 (Fig 9b).

Fig. 10 shows the effect of increasing the number of recalibration repetitions (hence the training burden on the user) on the classification performance of the across-days adaptive MIDA classification technique. Shaded areas represent the standard classification error at different numbers of recalibration repetitions. Results again show that wrist EMG consistently had higher classification accuracy using different numbers of calibration repetitions compared to forearm EMG both on Day 2 (Fig 10a) and Day 3 (Fig 10b).

IV. DISCUSSION

The main aim of this work was to evaluate the day-to-day stability of wrist EMG signals for hand gesture

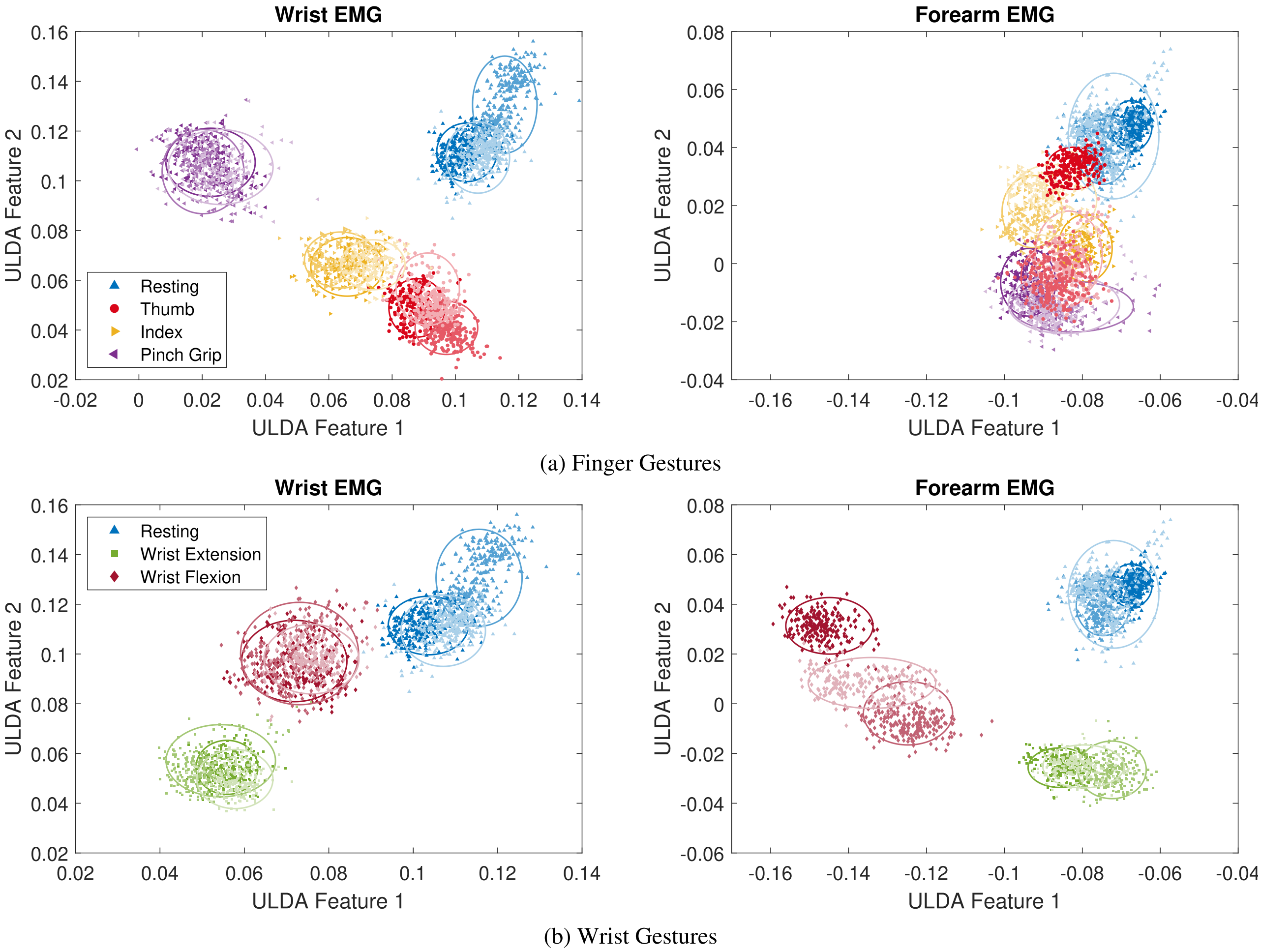


FIGURE 5. Scatter plot showing changes in the feature space of Wrist EMG and Forearm EMG across days for (a) finger gestures and (b) wrist gestures, using uncorrelated linear discriminant analysis (ULDA) projection matrix calculated on the first day. Darker to lighter shades of the same color represent the projection changes across days and the ellipses represent the 95% confidence interval of each cluster.

recognition in potential wrist-worn wearables. Therefore, wrist EMG and forearm EMG signals were concurrently recorded from 12 able-bodied subjects across 3 days while performing 5 different hand gestures. Results confirmed that wrist EMG-based classification models had high long-term stability across days, and suffered less from the negative effects of natural EMG variations over time compared to their forearm EMG-based counterparts using a novel Inter-Day Feature Set (IDFS) and a novel adaptive-MIDA classification technique with minimal retraining.

In this paper, SFFS was applied on 60 different features extracted from wrist EMG and forearm EMG (independently) to find a feature set for each location that is resilient to EMG variations across days. The SFFS technique is a wrapper-based approach that considers correlation between features and dynamically adds or removes features during the selection process to reach the optimal feature set [46]. SFFS-selected feature sets had an average classification accuracy across days of 92.78% and 86.48% for wrist EMG and forearm EMG, respectively, using a static classification technique without any mitigation techniques (Table 2).

Despite different absolute classification accuracies, the SFFS selected feature sets for the wrist and forearm EMG locations were relatively consistent. A feature set consisting of the common features between the two selected feature sets was therefore identified as a reasonable compromise. This new generalizable feature set consists of *MFL, AR, SKEW, SSC, SampEn, WLR, KURT, MNF, HNSM, HC, and ASM* features, and is referred to here as the Inter-Day Feature Set (IDFS). This IDFS feature set had comparable performance to the wrist and forearm-specific SFFS selected feature sets and was therefore adopted for further analyses in this study.

Wrist EMG signals had consistently high within-day classification accuracy for detecting hand gestures using different feature sets (Fig. 4 and Fig. 6). The strong performance of wrist EMG is at least in part attributed anatomically to the presence of the fine-finger movement controlling muscles closer to the wrist joint [50]. These findings are consistent with the outcomes of our previous study [9] which was performed with a different group of subjects. The first goal of this paper was to quantify the inter-day stability of wrist EMG in terms of the test-retest reliability index. Results confirmed that wrist EMG signals were reliable across days and had high values of ICC for detecting performed hand gestures (Fig. 4). This could potentially be due to less electrode shift occurring at the wrist level given its confined anatomical structure with flat posterior and anterior surfaces that improve the contact at the electrode-skin interface and limits electrode movement [50]. Another contributing factor could be the smaller volume and circumference of the muscles at the wrist level compared to the upper forearm muscles which reduce the EMG variability due to the natural differences in contraction intensity across days [11].

Looking at the performance of different feature sets, results showed that the TD4 feature set (consisting of LS, MFL, MSR and WAMP) outperformed the commonly used TD feature set (consisting of MAV, WL, ZC and SSC) in terms of the ICC test-retest reliability index as well as the classification accuracy (Fig. 4). These findings are consistent with the results in [44] and hence we encourage future studies moving forward to consider using the TD4 feature set as a baseline for the performance assessment of EMG-based PR systems. Furthermore, the IDFS feature set showed robust PR performance and stability across days using different classification approaches and had comparable performance to the optimal SFFS selected feature sets for both wrist EMG and forearm EMG. Therefore, we recommend that the IDFS feature set to be employed in the machine learning systems of wearable devices and neural interfaces to achieve high and stable PR performance across days.

The second goal of this study was to quantify the degradation in the PR performance of wrist EMG across days. Results showed that wrist EMG static classification accuracy dropped by 3.54% and 8.40% on the second and third days of data collection (Fig. 6). The consistent patterns of wrist EMG in the feature space across days (Fig. 5) led to strong test-retest reliability (Fig. 4) and hence high classification accuracy using the static classifier. This across-days static classification approach represents the lowest training burden on the user since no recalibration repetitions need to be collected. However, the classifier parameters do not get updated using any new EMG data which leads to having lower classification accuracies. On the other end of the spectrum, the within-day classification approach has potentially the highest classification accuracy within a certain day since the classifier gets trained from scratch using several (7 in this study) repetitions on any given new day. Nevertheless, this technique represents the maximum training burden perceived by the user since they would need to provide multiple repetitions of each gesture every day before they can start using the wearable device.

Therefore, the third goal of this study was to explore different techniques with a low training burden on the user to mitigate the effect of EMG variations and improve the PR performance across days. Maximum independence domain adaptation was applied to potentially minimize the

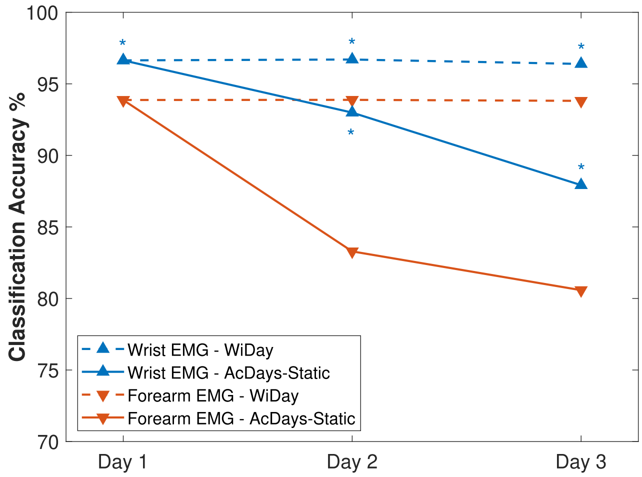
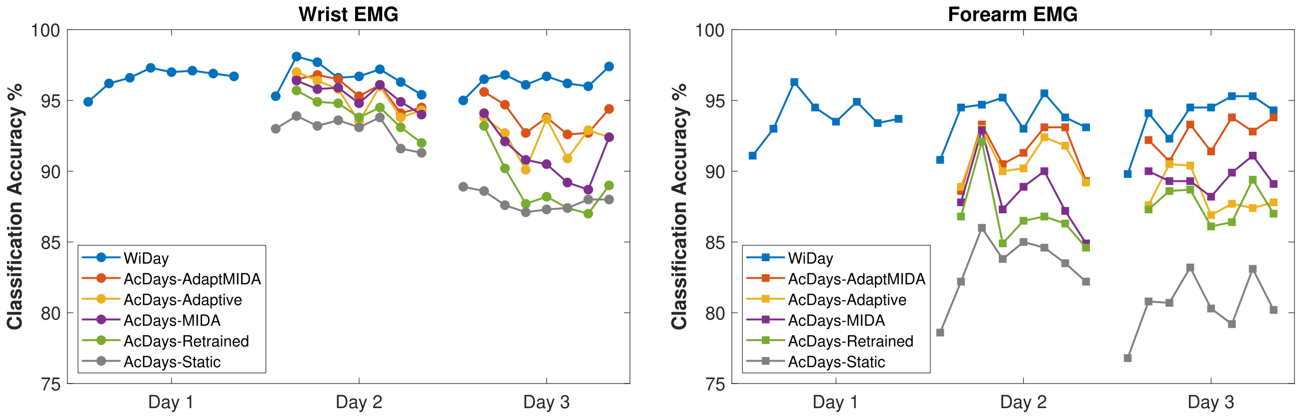


FIGURE 6. Comparison between the classification accuracy of wrist EMG and forearm EMG using the *Within-Day* (dashed lines) and the *Across-Days Static* (solid lines) classifiers for the IDFS feature set. Significant differences between the classification accuracy of wrist EMG and forearm EMG are denoted by * when $p < 0.05$.

variations in the feature space of EMG data collected on different days. Results showed that using only one recalibration repetition on a new day to transform the EMG features significantly improved the PR performance over the performance of the static classifier (Fig. 7 and Fig. 8).

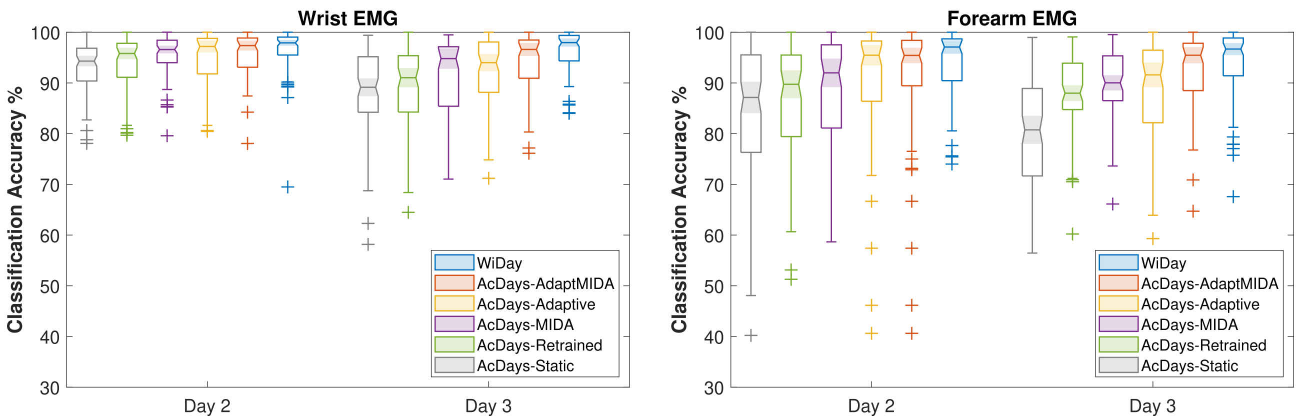
Canonical correlation analysis (CCA) is another feature projection technique that was initially considered in this study. However, CCA performed poorly compared to even the across-days static classifier and the across-days retrained classifier when using one recalibration repetition on a new day. The low performance of CCA, even when optimized for this problem, could be partially attributed to discrepancies in the data distributions across days and the absence of inter-repetition information in the one repetition from a new day. This suggests that a single repetition is not enough to for CCA to infer the extent of the EMG variability leading to less than optimal transformations [51]. It could be also partially attributed to the limitations of the technique itself. Specifically, CCA requires that the data from the previous day (source domain) and data from the new day (target domain) have the same number of observations with the same class labels. Therefore, CCA limits the amount of data from previous days to only one repetition leading to transformation matrices that don't cover the full range of variability from previous days. In a previous study [27], Campbell et al. reported similar limitations of the CCA technique with unsatisfactory performance. In our preliminary work, adding more recalibration repetitions improved the classification accuracy of CCA, corroborating results reported in [52], however, this defeats the intended purposes in this context.

Several other classification approaches were employed to compensate for the EMG variations across days: the across-days retrained classifier, the across-days adaptive classifier and the across-days adaptive MIDA classifier (Fig. 7 and Fig. 8). In the former technique, the classifier



(a) (b)

FIGURE 7. Comparison between the average classification accuracy of separate gesture repetitions across subjects using one recalibration repetition for different classification techniques on (a) wrist EMG and (b) forearm EMG.



(a) (b)

FIGURE 8. Comparison between the day-to-day classification accuracy of different classification techniques using all subjects' gesture repetitions of (a) wrist EMG and (b) forearm EMG.

was retrained from scratch using repetitions from the previous days as well as a new repetition for each gesture on each new day which improved the classification accuracy over the static classification technique. In the adaptive classification technique, the LDA classifier parameters were continuously adapted using a single repetition per gesture on each new day. In the novel adaptive MIDA classifier, the MIDA domain adaptation was applied in conjunction with the adaptive classification techniques to minimize the effect of EMG and features variations across days. This adaptive MIDA classification approach (using 1 repetition) improved PR performance across days to be comparable with the within-day classification approach (using 7 repetitions) and was found to outperform the retraining and adaptive classification approaches (Fig. 7 and Fig. 8) consistent with the forearm EMG literature [22], [23].

In all parts of this study, wrist EMG consistently had lower variability between repetitions and significantly ($p < 0.05$) outperformed forearm EMG in terms of the ICC index and the classification accuracy (Fig. 4 and Fig. 9). In a previous study [4], Jiang et al. hinted at the potential of wrist EMG and its stability across three sessions within one day after the initial classifier training session. This study extends that up to 6 days after initial classifier training and our results confirmed that wrist EMG consistently outperforms forearm EMG in recognizing fine finger gestures and wrist gestures (Fig. 9).

Specifically, results showed that wrist EMG had higher stability and PR robustness than forearm EMG when the analysis was performed on two groups of participants: one with data collection on consecutive days and the other with $3-6$ days between collections. The group with bigger gaps between data collections yielded on average 2.96% and 7.46% lower static classification accuracy on Day 3, for wrist and forearm EMG, respectively, than those with collection on consecutive days. These results further support that patterns of wrist EMG may be more consistent over both sessions and time and explain how the adaptation techniques benefited from the

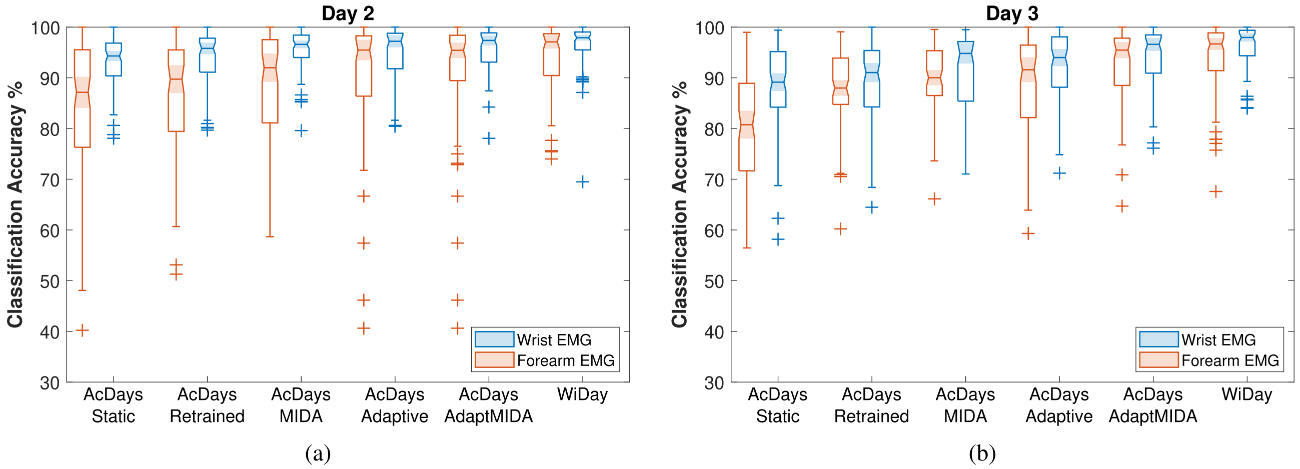


FIGURE 9. Comparison between the classification accuracy of wrist EMG and forearm EMG using different classification techniques on (a) Day 2 and (b) Day 3.

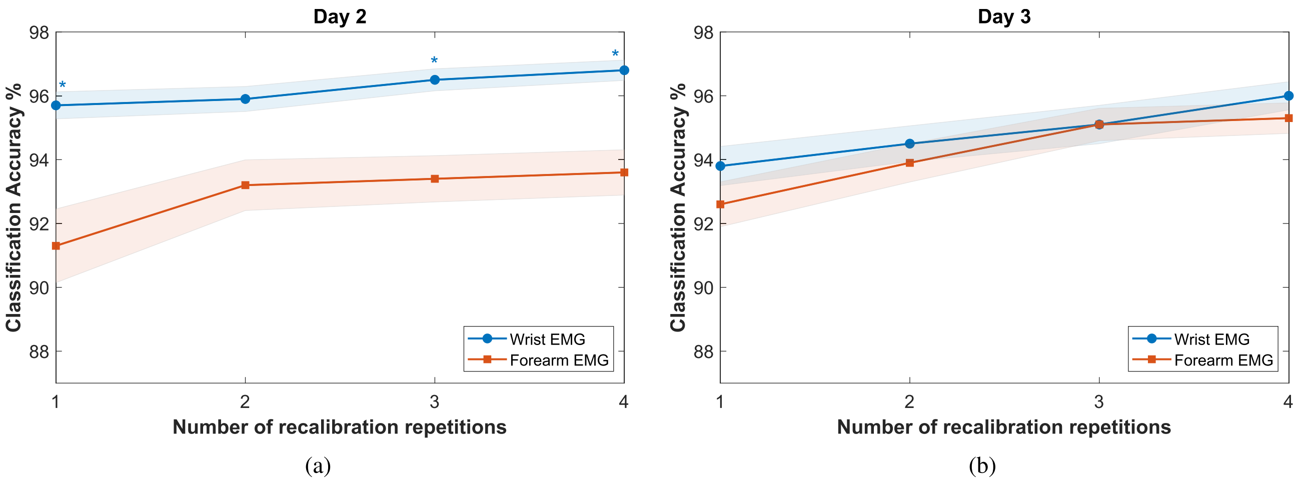


FIGURE 10. Comparison between the effect of adding more repetitions on (a) Day 2 and (b) Day 3 on the classification accuracy of wrist EMG and forearm EMG using the Across-Days Adaptive MIDA Classification technique. Shaded areas represent the standard error of classification accuracy. Significant differences between the accuracy of wrist EMG and forearm EMG are denoted by * when $p < 0.05$.

smaller inter-day differences in wrist EMG, making them better able to translate mapping across days (Fig. 9). With more recalibration repetitions available, wrist EMG continues to have robust PR performance across days (Fig. 10). The newly introduced across-days adaptive MIDA classification approach also helped to improve the performance of forearm EMG while adding more repetitions on Day 3 to be comparable to that of wrist EMG. This suggests that the approach may also be applicable for forearm EMG-focused studies and that it may be employed as a way to preserve performance in myoelectric control of prostheses.

Finally, this study also highlights that wrist EMG had less variability in PR performance across subjects compared to forearm EMG for all classification techniques and gestures (Table 2 and Fig. 9). This result hints at the potential for more robust wrist EMG-based cross-users classification models, enabling a better out-of-the-box wearable experience with minimal user training. Hence, future studies could focus on developing advanced across-users classification models that generalize to many users with minimal user-specific training. Other directions could include and studying the effect of limb position on wrist EMG PR performance.

V. CONCLUSION

In this work, the negative effects of EMG variation across days were explored for both wrist and forearm EMG. Wrist EMG-based PR models consistently outperformed their forearm EMG-based counterparts in finer-finger and hand gesture recognition. Results were repeatable across a series of tests including ICC test-retest reliability testing, feature extraction and selection exercises (leading to a novel Inter-Day Feature Set; IDFS), and an exploration of a novel adaptive MIDA classification technique. This work supports the potential for employing wrist EMG in wrist-worn wearables such as smartwatches to improve human-computer interaction for emerging industrial applications including augmented and virtual reality environments. The demonstration of wrist EMG's day-to-day stability suggests that these systems may provide robust and repeatable long-term performance with minimal retraining requirements for the user leading to potentially more wide adoption of wrist EMG-based wearables.

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