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Comparison of Wrist and Forearm EMG for Multi-day Biometric Authentication

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***Abstract*— Recently, electromyography (EMG) has been established as a promising new biometric trait that provides a unique dual mode security: biometrics and knowledge. For authentication that is used daily and long-term by general consumers, the wrist is a suitable location, which could be easily integrated into the existing form of smartwatches and fitness trackers. However, current EMG-based biometrics still follow the historical path of powered prosthetics research, where EMG signals were usually recorded from forearm positions. Moreover, the robustness of EMG processing algorithms across multiple days is still an open problem that needs to be addressed before for long-term reliable use. This study intends to investigate the difference in authentication performance between wrist and forearm EMG signals, in a within-day and two cross-day analyses. Our open dataset (GRABMyo dataset) was used to examine this difference, which contains forearm and wrist EMG data collected from 43 participants over three different days with long separation (Days 1, 8, and 29). The results showed wrist EMG signals led to at least comparable with forearm EMG signals in within-day Equal-error rate (EER). In cross-day analysis, the EER of the wrist EMG signals was higher than that of forearm signals. In general, the low median EER (<0.1) of wrist EMG in cumulative cross-day analysis demonstrates the promise of using wrist EMG signals for authentication in long-term applications.**

I. Introduction

Biometrics has become an integral part of current authentication systems to verify an individual's identity. Conventional biometrics, such as fingerprints and facial scans in smartphones and laptops, have been widely used in our daily lives. However, with the development of technology, leakage, and artificial regeneration (also termed spoof) of these traits is being easier due to poor hidden and liveness nature, resulting in an increased risk of identity theft. Recently novel biometrics based on bio-signals, such as the electrocardiogram (ECG) and electroencephalogram (EEG) are potentially more resilient to spoofing than the conventional biometric traits [1].

Compared with EEG and ECG, electrocardiogram (EMG), another typical bio-signal, has received relatively little attention for its application in biometrics. EMG has been traditionally used in gesture recognition-based research. In such research, high classification accuracy could be reached when training and test data come from the same individual. However poor cross-user transference performance has been one of the obstacles to commercializing EMG control systems [2]. This suggests that inherent individual difference exists in EMG signals, which is precisely what the biometric trait needs. Hence, EMG has a dual-property: individual difference (biometrics) and gesture recognition (knowledge), providing it a unique advantage as a biometric trait. On the biometrics level, it requires liveness detection and is more covert like EEG and ECG, resulting in less likelihood to be compromised and spoofed than the traditional traits. On the knowledge level, it provides additional security using customized gestures as passcodes, which is not possible with EEG and ECG. Multiple recent studies have shown EMG can be an accurate biometric trait [3-6]. In [6], it has demonstrated the performance of EMG under the same gesture is comparable to EEG and ECG, and is further improved by gesture encoding.

There are generally two common biometric modes: authentication and identification. In the current study, we focus on the authentication mode, where the biometric system grants or rejects the access request of the presenting user (claimant) by comparing the presented biometric data to the template stored in the database. Some of the studies have reported a high biometric authentication performance (>95%) [5-10]. In these studies, EMG signals were majorly collected from forearm muscles. Traditionally, EMG processing has been largely motivated by the application of upper limb prosthesis control, so EMG recording was focused on the forearm muscles. However, in daily life, compared with wearing a band around the forearm, general consumers are more accustomed to wrist-worn devices, which are more comfortable and unobtrusive like a watch. Recently, a study reported that wrist EMG signals have comparable performance with forearm EMG signals for hand gesture recognition [11]. Furthermore, [11] and other studies [12, 13] showed that wrist EMG signals have comparable signal quality metrics with forearm signals at least. However, to the best of our knowledge, the difference in authentication performance between wrist and forearm EMG signals remains to be compared.

For long-term reliable use of EMG-based applications in the real world, the natural variation of EMG over time is a problem that has to be considered. [14] showed that EMG signal temporal variation greatly degrades the classification performance of forearm-based gesture recognition. Within the authentication literature, several recent studies have investigated the multi-day performance based on EMG signals [3, 7, 15]. A multi-day analysis involving training data and testing data from different days was employed to test the robustness of the EMG-based biometrics in practical scenarios.

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Among these studies, [15] utilized a four-day data collection protocol with a small subject pool (5 subjects). [3, 7] had a larger number (20 and 22) of subjects, but the data were from only two days. Hence, a large subject pool and multi-day recording are warranted. Moreover, the vast majority of efforts have focused on forearm EMG signals, and it is currently unknown how cross-day effects may differ for wrist EMG-based authentication.

Therefore, the first purpose of this work is to compare the biometric performance using wrist and forearm EMG signals for authentication based on a large subject pool of up to 43 subjects. The second purpose is to explore the difference in the multi-day biometric authentication performance of wrist and forearm EMG using three different timeline-based analyses involving training and testing data from the same/different days. In this study, a direct comparison between the authentication performance of concurrently collected wrist and forearm signals is presented.

II. Methods

A. GRABMyo Dataset

A previously collected EMG dataset by us, named Gesture Recognition and Biometrics electroMyogram (GRABMyo) Dataset, was used in this study. The data acquisition experiment protocol is briefly introduced as follows, and please refer to [13] for a more detailed description. 43 healthy participants (26.35 ± 2.89 years, 23 M, 20 F) participated in the experiment. EMG data were collected over three different days (Days 1, 8, and 29) from forearm and wrist muscles using monopolar EMG electrodes (AM-N00S/E, Ambu, Denmark). The 8 and 6 electrodes were placed evenly around the forearm and wrist respectively, as shown in Fig.1. For each experimental session, the participants were instructed to perform the same 16 static hand/wrist gestures 7 times. It's worth noting that the dataset is the largest EMG dataset in terms of the total number of recording sessions (43 subjects x 3 days = 129 recording sessions).

B. EMG Signal Processing

For the forearm and wrist rings, initially, the monopolar EMG signals were processed by common averaging. The processed signals were then segmented into 200ms windows with a 150 ms overlap. Then the feature was extracted for each window using the frequency division technique (FDT) [16], which calculates the magnitude of L frequency bands. For the i^{th} band, let $f_{i,1}$, and $f_{i,ni}$ denote the frequency values of the two endpoints. As such, for each window, the i^{th} feature is calculated as

$$FDT_i = F\left[\sum_{j=1}^{n_i}\left|X\left(f_{i,j}\right)\right|\right],\ i=1,2,\ldots L, \quad (1)$$

where $X(\cdot)$ denotes the magnitude of the FFT spectrum, and $F[\cdot]$ denotes a logarithm operator (non-linear transformation). In the current study, the whole EMG frequency band of EMG (20-450 Hz) was subdivided into six equal-width frequency bands: 20-92, 92-163, 163-235, 235-307, 307-378, and 378-450 Hz. Therefore, the feature vector extracted from each window comprises 48 and 36 FDT features from the forearm and wrist ring, respectively.

The matching score was used commonly to assess access granted or denied [6, 9]. For a given feature vector sample p, which is the input from a specific user (the claimant) while performing a specific gesture, its matching score, $S_{i,j}$, with the i^{th} gesture and the j^{th} user, was defined as the Mahalanobis distance between the sample and the class centroid:

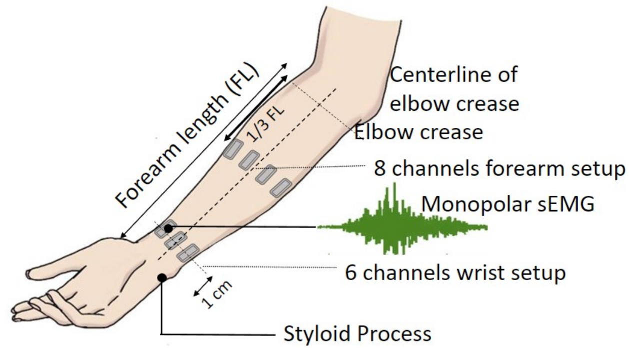

Fig. 1 Positions of the eight surface electrodes on the forearm and six electrodes on the wrist (dorsal view).

$$S_{i,j}(p) = \sqrt{\left(p - \mu_{i,j}\right)^{\mathsf{T}} \Sigma_{i,j}^{-1}\left(p - \mu_{i,j}\right)}, \quad (2)$$

where $\mu_{i,j}$ and $\Sigma_{i,j}$ is the centroid and covariance matrix for the specific gesture and user class, respectively. Both $\mu_{i,j}$ and $\Sigma_{i,j}$ were estimated from the enrollment data.

C. Within-day and cross-day analysis

In the current study, data was collected from each user over three different days comprising seven trials each day and 16 gestures in each trial. The biometric authentication performance evaluation involved a within-day (WD) analysis and two separate cross-day analyses, single cross-day (SCD) and cumulative cross-day (CCD).

For the WD analysis, six trials of the gestures in each day were used as enrollment data (training), and the remaining one trial of that day was used as claimant data (testing). For the SCD analysis, the data from six trials in one day were used as the enrollment data, and one trial data from each of the remaining two days was used as the claimant data. For the CCD analysis, the data from six trials in two of the three days were used as the enrollment data, and one trial data from the remaining day was used as the claimant data. The graphical representation of the WD, SCD, and CCD analysis is provided in Fig 2.

Seven-fold cross-validation was implemented by varying the enrollment and claimant trials from the specific days for both the WD and CCD analysis, and a between-day seven-fold cross-validation was implemented for SCD analysis. Each cross-validation was repeated for each of the three days and the average authentication performance was reported.

D. Performance Evaluation

The equal error rate (EER) is a common-used authentication metric for comparing the performance of different biometric traits. The EER is the point on the detection error tradeoff curve (DEC) where the false acceptance rate (FAR) is equal to the false rejection rate (FRR). The EER value is lower, the performance is better. For an accurate assessment of the biometric authentication capacity of the

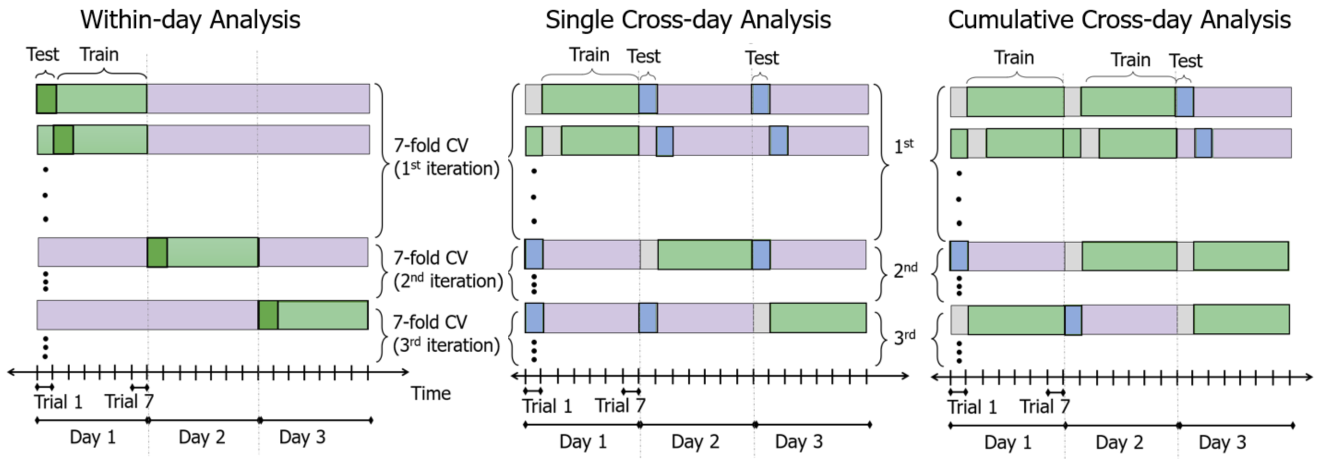

Fig. 2 (From left to right) Within-day, single cross-day and cumulative cross-day analysis. The corresponding training (enrolment) data for each analysis are represented in green; the testing (claimant) data are represented in dark green (for within-day analysis) and blue (for cross-day analysis).

EMG biometrics, two common authentication scenarios were investigated: 1) Normal Test: the correct code was only known to the genuine user, while the impostor had no knowledge of the code and presented a random different from the correct code; 2) Leaked Test: the correct code for the genuine user was compromised, and the impostor presented the correct code by performing the corresponding gestures. Thus, in the leaked test, there is no knowledge-based protection, only the individual difference in bio-signals does work.

E. *Statistical Analysis*

The study aimed to investigate the WD and cross-day authentication performance of the forearm and wrist EMG biometric system. For each of the three analysis scenarios, i.e., WD, SCD, and CCD, a repeated measures ANOVA was performed on the EER of the two test scenarios (normal and leaked) to determine if there was any significant effect of electrode positions (two levels, i.e., forearm-position and wrist-position). And for each electrode position, a repeated measures ANOVA was also performed on the EER to determine if there was any significant effect of the three analysis scenarios. All statistical tests were performed using RStudio 1.0. 136 (RStudio, Boston, MA).

III. Results

Fig.3 shows the EER distribution in normal and leaked test scenarios. In each test scenario, the electrode positions (forearm and wrist) and the three timeline-based analyses (WD, SCD, and CCD) were considered as factors. As expected and evident from Fig.3, the EER for WD analysis was significantly lower ($p<0.01$) than the EER of SCD and CCD analysis, for both the forearm and the wrist position. Further, the EER of the CCD analysis was significantly lower than the SCD analysis ($p<0.01$). The effect of the two electrode positions is presented below for each of the three timeline-based analyses.

For the WD analysis in the normal test scenario, the wrist position had a median EER of 0.028 (Q1=0.018, Q3=0.038) which was similar ($p>0.05$) to the forearm position (median EER=0.026, Q1=0.018, Q3=0.034). For the leaked test scenario, the wrist position had a median EER of 0.04 (Q1=0.026, Q3=0.052) which was significantly lower ($p<0.01$) than the forearm position (median EER=0.046, Q1=0.037, Q3=0.058).

While comparing the cross-day analyses (SCD and CCD), the median EER of the CCD analysis were significantly lower than the median EER for the SCD analysis ($p<0.01$) for all electrode positions and test scenarios. Specifically, for the CCD analysis in a normal test scenario, the median EER for wrist position was 0.09 (Q1=0.069, Q3=0.136), which was significantly higher ($p<0.01$) than the forearm (median EER=0.069, Q1=0.056, Q3=0.113). For the leaked test scenario, the wrist-position resulted in a median EER of 0.145 (Q1=0.101, Q3=0.209) which was not significantly different ($p>0.05$) from the forearm-position (median EER=0.126, Q1=0.103, Q3=0.176). For the SCD analysis, there were similar comparisons between forearm and wrist positions with

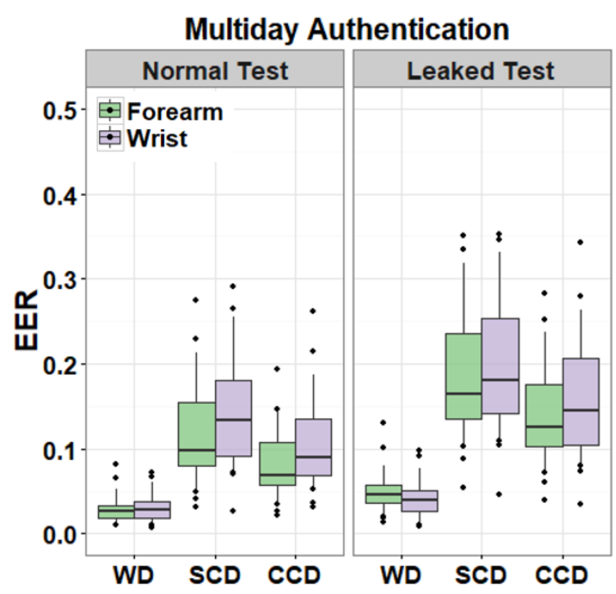

Fig. 3 Biometric authentication performance for the Normal and Leaked Test scenario. Each boxplot represents the interquartile range (IQR, 25th – 75th percentile) and the center horizontal line represents the median *EER* value. The whiskers (solid vertical lines) represent the datapoints within the 1.5*IQR threshold. The outliers (solid black circles) are those with *EER* greater than the 1.5*IQR threshold.

the CCD analysis. It's worth noting that wrist position still kept a high authentication performance for CCD, in which the median EER was less than 0.1.

IV. Discussion

The first purpose of this study was to examine the authentication performance comparison between EMG recorded from the wrist and forearm. The results showed that in the WD analysis, wrist EMG signals had comparable authentication performance with forearm signals in the normal test, and wrist EMG signals even had significantly better in the leaked test. This suggests that wrist EMG signals are as desirable for biometric authentication as forearm EMG signals. Combined with the findings of the study [6], wrist EMG has at least a similar authentication performance to EEG and ECG.

Notably, in the leaked test, wrist EMG signals resulted in a comparable authentication performance with forearm signals even for cross-day analyses. Thus, results from the leaked test could be proof that the wrist EMG signal has good individual differences suitable for biometric traits. In the normal test, forearm EMG signals provided higher biometric performance and this difference is significant, especially for cross-day analysis. However previous article [11] showed that wrist EMG signals provided significantly higher classification performance for all finger gestures and comparable results for wrist gestures. One possible reason for the inconsistency is the difference in gestures that all single-finger extensions were covered in [11]. In the anatomy of the upper limb, the finger-controlling muscles are mostly at the wrist level and EMG signals related to wrist gestures are still likely to be recorded at the wrist level because proximal forearm muscles extend down to the wrist. Furthermore, it is worth noting that all EER results in the normal test scenario were significantly better ($p<0.01$) than the corresponding results in the leaked test scenario. This observation is consistent with the fact that only the inherent EMG signals difference could be exploited for authentication in the leaked test scenario due to the compromise of knowledge level security (password gesture).

The second purpose of this study was to compare the authentication performance between wrist and forearm EMG at multi-day applications. First, compared with the WD analysis, the decrease in wrist EMG signals authentication performance was more than that of forearm signals in both cross-day analyses. This indicates that wrist EMG signals are more sensitive to non-stationary factors due to cross-day than forearm signals. Further effort is necessary to improve the robustness of wrist EMG signals over cross-day. Moreover, a significant increase in EER in each cross-day analysis was observed compared to the WD analysis. This is expected as the EMG signals are affected by non-stationary factors such as electrode shift and changes in skin conditions. While comparing the two cross-day analysis results, the CCD EER was significantly lower than the SCD EER for both two test scenarios. This suggests that EMG data from different days do have enough homogenous information such that training with data from multiple days improves the biometric authentication performance. It's worth noting that the CCD performance for wrist position is median EER = 0.09, which is within the EER range (10-4 - 0.20) of other biometric traits such as bio-signals, fingerprint, keystroke, etc., reviewed by previous studies [1]. In conclusion, wrist EMG signals are promising as reliable biometric traits used in long-term authentication applications.

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