Survey of the stability of uniqueness of muscle synergy patterns in handwritten signature over time

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ABSTRACT:
Biometric characteristics of the human body can play a decisive role in the accuracy of automatic signature verification systems due to their stability over time and resistance to variability in different conditions. In this study, the accuracy of an automatic handwritten signature verification system is checked during nine months. In this system, the electromyography (EMG) signals from the hand muscles of people during signing are recorded at different times up to nine months, and after the pre-processing of the signals, muscle synergy patterns are extracted by the none-negative matrix factorization (NMF) method. Finally, the patterns extracted by the SVM classifier are classified into two classes: genuine and forgery signatures.

KEYWORDS: handwritten signature, EMG, muscle synergy

1. INTRODUCTION

Handwritten signatures have been one of the most important indicators of people's approval in official and unofficial documents since the past. Based on this, automatic verification systems of the genuineity of manuscript signatures were also considered in studies of recent decades [1, 2].In the training phase, these systems first store the features taken from people's genuine signatures and forged signatures in the database. Then, in the ID test phase, the claimed signatures are classified as genuine or forgery signatures by a comparator with genuine and forgery signatures in the database [3, 4].

Automatic signature verification systems are classified into two categories in terms of collecting features extracted from genuine and forgery signatures: offline or static systems that mostly examine the image or geometric features of the signature [5] and the system Online or dynamic ones, other than the image features of the signature, record the motion characteristics of the signer's pen, such as movement speed and pressure of pen, etc., by touch screen [6].

These systems are more accurate than offline systems due to the registration of more and specific features of the signer [7] On the other hand, offline signature verification systems can check all signatures regardless of how they are written, because they only verify the shape of the signature [8]. The use of muscle synergy patterns as a biometric feature in the classification of people has been developed in recent studies [9, 10]

These patterns are better known as higher-order mappings of neural commands from the central nervous system (CNS) to muscles [11]. In block control definition, synergy patterns are defined as functions of smaller commands that the CNS activates with different coefficients simultaneously or asynchronously in complex movements [12]. In this definition, a synergy pattern may activate several muscles, and a muscle may be involved in several synergies [13].

Muscle synergy patterns are usually obtained from dimension reduction methods such as none negative

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matrix factorization (NMF) from the electromyography (EMG) signal recorded from the muscle [14, 15]. In the last decade, many studies have been conducted on the function of the neuromuscular system through the recording of muscle signals in humans and animals [16].

In this study, we investigate the performance of an automatic handwritten signature verification system using hand muscle synergy as a biometric feature over time.

2. MATERIAL AND METHODS

First, before participating in the signature registration sessions, the candidates were asked to send a sample of their signature so that all the candidates have access to the signatures of all the participants in all the sessions. Then, every candidate has to sign his signature five times and forge others' signatures three times. EMG signals from hand and arm muscles are recorded during all signatures performed.

After that, synergy patterns were extracted by NMF method. After that, the muscle synergies obtained from the signal registration in consecutive times of several months were classified into two categories of genuine and forgery signatures by the SVM classifier. At the end, the results of the classification of dams were evaluated by EER, FAR and FRR statistical parameters.

2.1. Participants

14 people (6 women and 8 men) aged 18-65 participated in this study. All participants were healthy and had no history of neuromuscular disease. All signed the consent form before the study. Also, this study was approved by the Department of Physiotherapy, Faculty of Rehabilitation, University of Isfahan.

2.2. Equipment

Recording of EMG signals in this study was done by MEGA Me6000 device. This device has 8 channels to record EMG data in a portable or desktop form. The user interface of the device is the exclusive MegaWin software in Windows™, which can export EMG data for MATLAB software.

2.3. Data sets

According to previous studies[17-22], eight muscles were selected to record EMG data. which include the following muscles: Flexor Digitorum Superficialis, Extensor Carpi Ulnaris, Abductor Pollicis Longus, Extensor Carpi Radialis Brevis, Triceps Brachii, Flexor Carpi Radialis, Extensor Digitorum, Biceps Brachii (Figure 1).

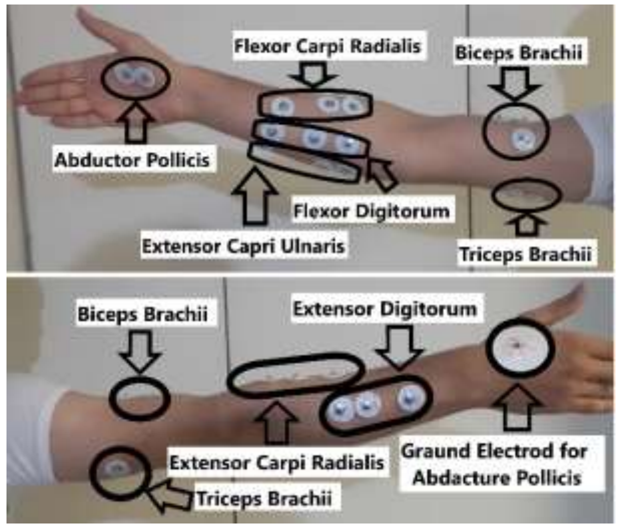

Fig. 1. Electrode arrangement on selected muscles

Before placing the electrode pad, the excess hair was shaved, the placement site was cleaned with alcohol and soft emery paper to remove any disturbance or dead skin. Finally, the electrodes were placed on the selected muscles under SENIAM protocols**.**

2.4. Data processing

First, the recorded signals are rectified, then denoising using a 250-25 Hz low-pass filter. Then windowing the signal was done using the Root Mean Square (RMS) method to find the maximum amplitude of the signal (Figure 2).

Muscle synergy was extracted in this study using the NMF method. NMF is a blind separation method. Its equation is as follows:

$$EMG_{O\,(m\times t)} = W_{(m\times n)} \,.\, C_{(n\times t)} + e = EMG_r + e \qquad (1)$$

Where EMG_O is the muscle EMG matrix after preprocessing. M is the number of muscles and t is the length of the signal per time unit, matrix W or synergy matrix expresses the role of each muscle according to the synergy number (n) and C is the control matrix containing the main components to activate synergy in time [23, 24]. Finally, EMGr is the reconstructed matrix after the NMF method. In order to see how similar the reconstructed matrix after the NMF method is to the genuine EMG_O matrix, we use the VAF method:

$$VAF = \left\{1 - \frac{(EMG_O - EMG_r)^2}{EMG_O{}^2}\right\} \times 100 \qquad (2)$$

Figure 3 shows the VAF diagram for different values of the synergy number (n). It is usually used for a limit for similarity in the NMF method, in this study we consider the similarity limit to be 90%, in this case, the acceptable synergy number in this study is considered 4, because less than that does not have an acceptable VAF [25].

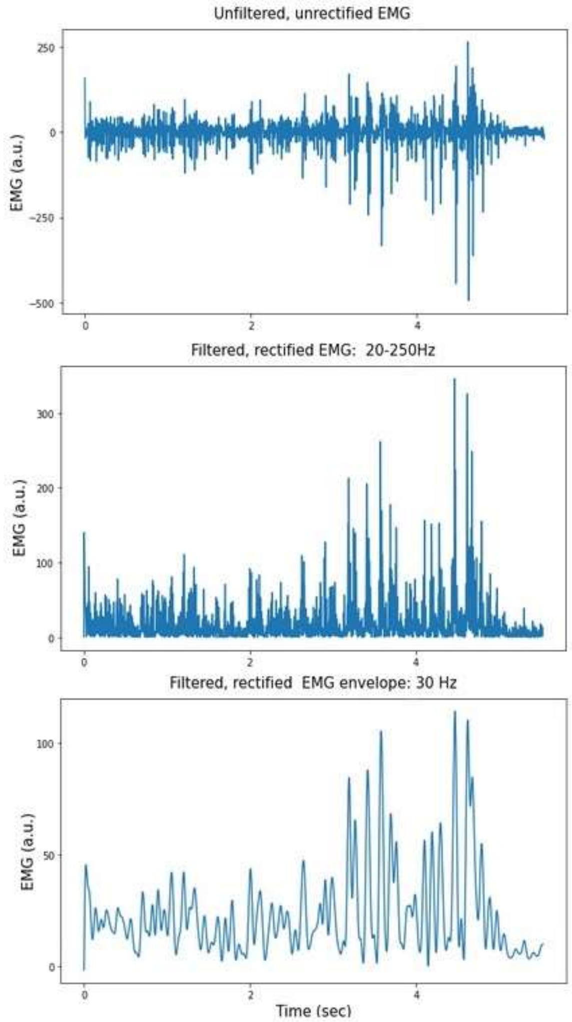

Fig. 2. EMG signal preprocessing steps for a muscle

After that, we classify the synergy matrices (W) by the support vector machine (SVM) classifier, this classification is first taught to the system in the train phase by the genuine and forgery signatures, then in the test phase of the trained system, the claim signatures classified into two categories of genuine and forgery signatures.

3. RESULTS

To determine the performance of signature verification systems, three statistical characteristics are usually used: False Accept Rate (FAR), which shows the system error in wrongly confirming forgery signatures by the system, False Reject Rate (FRR), which shows the system error in wrongly rejecting forgery signatures. shows [26].

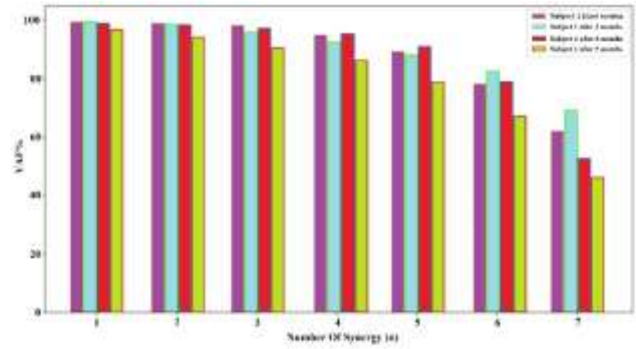

Fig. 3. VAF diagram for different recording times and different synergy numbers

Usually, in a signature verification system, improving the performance to lower one of these errors causes the other to increase. Therefore, to improve the overall performance of the system, the statistical characteristic of Equal Error Rate (EER) is used, which shows the performance of the system when both errors are at their lower limit at the same time [27]**.**

Table 1. Statistical results of the analysis of the output of the classifier for the signature verification system.

Model		First session	After 4 months	After 6 months	After 9 months
Number of signatures	genuine	68	57	61	53
	forgery	532	502	521	490
Total signatures		600	559	582	543
FRR		1.86	2.03	2.53	2.14
FAR		2.56	1.92	1.82	1.42
EER		2.20	2.825	1.47	2.46

Table 1 shows the performance of the system during different times by the mentioned parameters. In all cases, the train phase is the first session, and in the following times, only the signature for the test phase is registered.

4. DISCUSSION

As you can see in Table 1, the FAR in the first session was higher than in the rest of the sessions, which means that in the first session, the system mistakenly accepted more forgery signatures as genuine signatures, but in the rest of the sessions, this trend was almost reversed and as the FRR of the system increased It accepts more genuine signatures as forgery, and this is probably due to the increased sensitivity of the system after several months of training.

Figure 4 shows a comparison between the synergy matrix diagram of different candidates and the synergy matrix diagram of one candidate (the first author of the article) which was recorded sequentially. As you can see, muscle synergy patterns in a person are almost

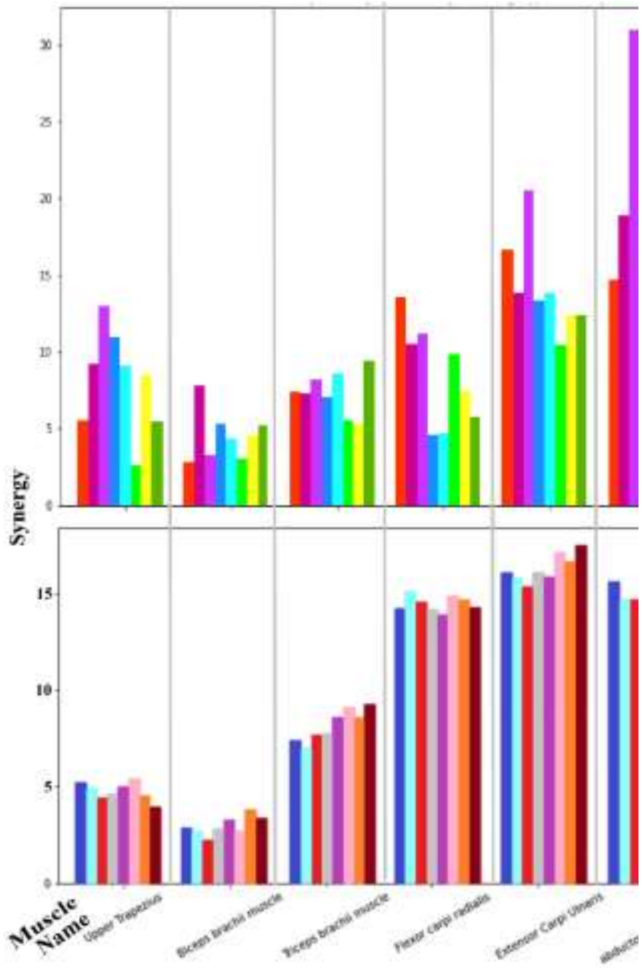

Fig. 4. Comparison of the synergy matrix diagrams of genuine signatures among 8 candidates in one session (top) Comparison of the synergy matrix diagram of a candidate's genuine signature in consecutive times (bottom).

constant and the changes are probably environmental (fatigue, how to sit, the user's concentration, etc.).

5. CONCLUSION

In this article, we tried to investigate the signature verification system based on the synergy of muscles involved during signing over time. This study shows the necessary performance for a database collected from synergistic patterns of people's signatures over time for a signature verification system.

A person may undergo physical changes over time or have a different signature compared to the past depending on environmental conditions. The statistical analysis of the system showed its performance to be relatively acceptable considering the errors, and this performance can be improved by improving the EMG signal recording conditions and modifying the features**.**

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