Biometric Authentication of Individual using SEMG Signals

Samer Chantaf, Amine Naït-Ali, Mohamad Khalil, Mahmoud Abbas

Abstract — In this study, a new biometric method based on surface EMG (SEMG) signals in response to a fixed force is developed. The main goal is to study the possibility of a contactless verification of individuals by using SEMG signals. This method based on estimating the power spectral density (PSD) of the SEMG signals, and then extracting frequency parameters that will be used in radial basis function (RBF) to classify individuals. At fixed intensity of Maximum Voluntary Contraction (MVC), SEMG signals have shown good performance and high specify regardless of fatigue or electrode displacement. This role may have vital impact on the biometric field.

Index Terms — SEMG, Biometrics, PSD, RBF, MVC, Classification.

I. INTRODUCTION

The use of SEMG signals in human recognition is relatively new. Actually no research has been published using SEMG in biometry. Recent researches and experiences proved the utility of SEMG in human authentification. Biometry or biometrics is defined as an automatic recognition of a person using distinguishing traits [4]. View its wide application as a form of identity access management and control in different fields, new unfalsifiable methods and unique characteristics should have been developed. Based on these facts, the idea of using physiological signals like ECG [5]-[11], and SEMG in biometric verification arised. The electromyography (EMG) is the study of muscle electrical similar to nerves; muscle tissues conducts electrical potentials called muscle action potential [2]. These muscle action potentials are recorded through a noninvasive method named surface EMG (SEMG) [1]. The aim of this article is to show the usage of SEMG in favor of individual's verification. A new method in biometric authentification is proposed in this article. This method uses SEMG in response to a fixed force to determine the individuals' ID. First, we calculated the PSD of the SEMG signal in order to extract frequency parameters. Then, these parameters were used to identify individuals. In section 2, materials and methods were described. The protocol was presented in section 3. In section 4, results were provided and discussed. And finally in section 5 the conclusion was given.

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II. MATERIAL AND METHOD

This section, presents the materials and methods used to identify individuals using SEMG signals. SEMG signals in response to a fixed force have been obtained from 10 healthy persons. The equipment used for these measurements is a BIOPAC system that by suitable software converts the information from SEMG signals to the format ".txt" supported by Matlab. After acquisition of SEMG signal, PSD of each SEMG signals were estimated in order to extract frequency parameters that will be used to identify individuals (Fig.1). These different phases are described in the following sub-section.

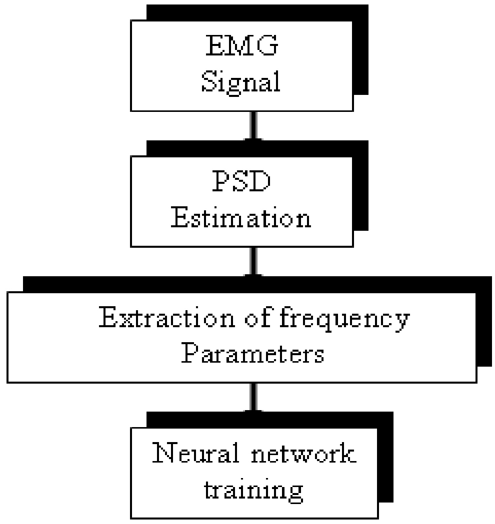

Fig. 1 Block diagram showing the main steps required to identify individuals by their EMG features.

The power spectral density (PSD) describes how the power of a signal or time series is distributed with frequency. The goal of spectral density estimation is to estimate the spectral density of the signal from a sequence of time samples of the same signal. Conventionally, two estimation techniques exist: parametric and non-parametric. In our method, we used the non-parametric approach. Nonparametric methods are those in which the estimated PSD is made directly from the signal itself. The simplest method is the periodogram. It consists of calculating the discrete-time Fourier transform of sampled processes and taking the magnitude squared of the result [6]-[7]. In this paper, the spectral density was estimated by periodogram using Welch's method mainly [9]. Welch's method is used to estimate the power of a signal versus frequency, thus reducing noise. It is based on the concept of using periodograms that convert a signal from the time domain to the frequency domain. This method is carried out by dividing the time signal into successive blocks, then forming the periodogram for each block, and finally taking the average of all the blocks. Each block is divided as follow (1):

$$x_i(n) = x(n+iD) \quad n = 0,1,\ldots, M-1 \quad i = 0,1,\ldots, L-1 \tag{1}$$

Where M is the length of the blocks after division, D the shifting between blocks and L the number of blocks.
The periodogram for each block is given by (2):

$$\hat{S}^{i}(f) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n).w(n).e^{-j2\pi fn}\right|^2 \tag{2}$$

Where U is the normalization factor of the window used to divide the signal into blocks (3).

$$U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n) \tag{3}$$

The Welch PSD estimate is given by (4):

$$\hat{S}_W(f) = \frac{1}{L}\sum_{i=0}^{L-1} \hat{S}^{i}(f) \tag{4}$$

Once the PSD is estimated, we extract the necessary parameters to be used in the classification and the verification of individuals.

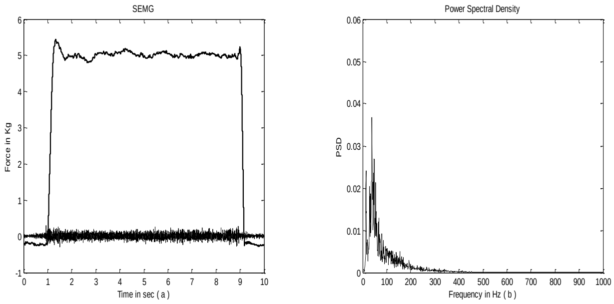

Fig. 2 SEMG with intensity of 40% of MVC (a) Estimated PSD of 40% of MVC (b).

Fig. 2(a) and Fig. 2(b), show respectively the SEMG signal with intensity of 40% of MVC (Maximum Voluntary Contraction), estimated PSD in case of 40% of MVC (Maximum Voluntary Contraction). The extracted parameters are power of the signal, kurtosis, median frequency, deciles, dissymmetry coefficient and frequency peak.

A. Power

The power of a signal represents the distribution of energy M_0 (order 0) on the frequency axis (5).

$$M_r = 2\int_0^{\infty} f^r S_x(f)df \tag{5}$$

With S_x the estimation of the PSD by Welch method.

B. Kurtosis

Kurtosis measures the degree of peakedness of a distribution, defined as a normalized form of the fourth central moment M_4 of a distribution (6).

$$CA = M_4^{*} \big/ M_2^{2*} \tag{6}$$

C. Median frequency

The median divides the spectral density into two parts: 50% of data are less than the median, 50% are greater
The median is calculated by (7):

$$\int_0^{Fmed} S_x(f)df = \int_{Fmed}^{F\max} S_x(f)df \tag{7}$$

D. Deciles

We've seen that the median divides the distribution of the spectral density into two parts. We can generalize the division of this distribution into four, ten, one hundred, or n parts. The obtained values are named quartiles, deciles, percentiles or quantiles (8).

$$\int_{f_{p-1}}^{f_p} S_x(f)df = k\int_0^{F\max} S_x(f)df \quad 0 < k \leq 1 \tag{8}$$

E. Coefficient of dissymmetry

This parameter gives information about the shape of the spectral density from a symmetrical point of view. It is given by (9):

$$CD = \frac{M_3^{*}}{\sqrt{M_2^{3*}}} \qquad Mr^{*} = 2\int_0^{\infty} (f - MPF)^r S_x(f)df \tag{9}$$

MPF is the mean power frequency given by (10):

$$MPF = M_1 / M_0 \tag{10}$$

F. Peak frequency

The peak frequency is the frequency for which the spectral density function is maximum. Once extracted, these parameters were presented to the input of the artificial neural network to be classified. Radial Basis Function (RBF) neural network was used in supervised applications. They were embedded into a two-layer feed forward neural network. This network is characterized by a set of inputs and a set of outputs where a hidden layer lies in between. The neurons in the hidden layer contain Gaussian transfer functions. To train RBF networks we have determine the number of neurons in the hidden layer, the coordinates of the center of each hidden-layer RBF function, and the weights applied to the RBF function outputs [3]-[10]. The training consists of optimizing the network parameters in order to fit the network outputs to the given inputs [8].
The output of the network is thus (11)

$$\varphi(x) = \sum_{i=1}^{N} a_i \rho(\|x - c_i\|) \tag{11}$$

The activation function used for the neurons in the hidden layer is the Gaussian function. It is given by (12):

$$\rho(\|x - c_i\|) = \exp[-\beta\|x - c_i\|^2] \tag{12}$$

Where x is the input feature vector, N is the number of neurons in the hidden layer,

c_i is the center vector for neuron i, and a_i are the weights of the linear output neuron. The weights a_i, c_i and β are determined in a manner that optimizes the fit between φ and the data. In this work, the neural network inputs correspond to the parameters extracted from the PSD (15 parameters) and the outputs correspond to each specific individual. The training set was composed of 30 contractions for each individual and the neural network was learned for 200 epochs. Then it was tested using other contractions from the same individuals. The extracted parameters were presented to the input of the network to be classified. The RBF scheme used in this study is given by (Fig. 3).

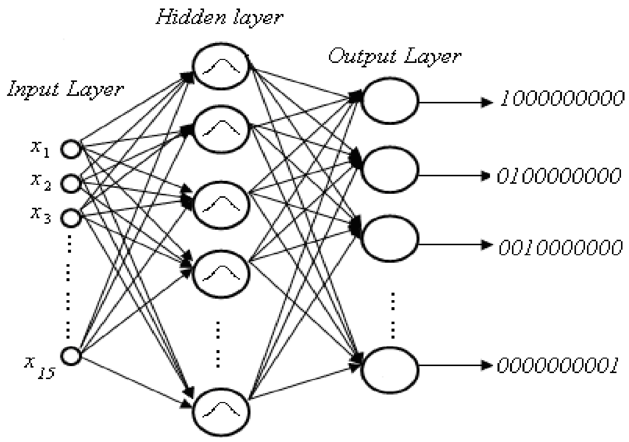

Fig. 3 An RBF Neural Network, presenting the input, hidden and output layers.

III. PROTOCOL

The SEMG signals used were recorded from a BIOPAC system in response to a force of intensity of 40% of MVC. 10 healthy persons, mainly 9 men and 1 woman volunteered in this study their ages ranged between 25 and 40 years old. Our database was 60 responses were recorded for each every response consisted of 3 seconds of acquisition containing one contraction (SEMG signals) in response to a clench force and sampled at 2000 Hz. The measurements were done as follows: Three electrodes were placed on the right hand as shown in Fig. 4. The person exercised a clench force of intensity 40% of MVC (Fig. 4). An SEMG signal in response to this force of duration 3 seconds was recorded.

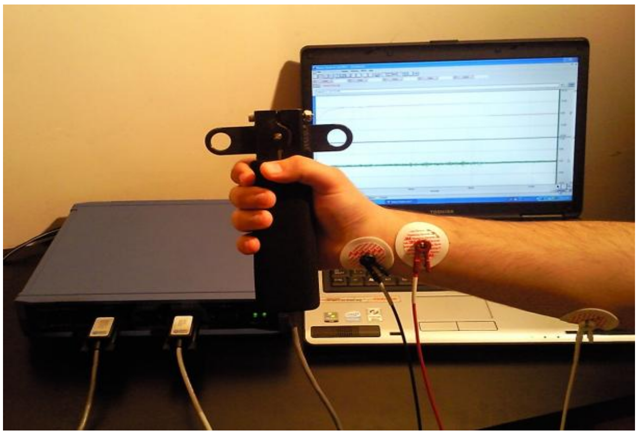

Fig. 4 Measurements of SEMG showing clench force and electrodes position.

IV. RESULTS AND DISCUSSIONS

For each individual, 30 contractions were used for the purpose of training and the other 30 for classification. Table 1 shows the classification of performances corresponding to each individual. The performance was analyzed by using contractions in response to a force of intensity 40% of MVC, and by modifying each time, the number of contractions employed to identify individuals (10, 15, 20, 25, and 30).

Number of contraction	Individual 1	Individual 2	Individual 3	Individual 4	Individual 5
10	60%	50%	50%	50%	50%
15	73%	67%	67%	73%	67%
20	75%	75%	75%	75%	75%
25	76%	76%	76%	76%	76%
30	80%	80%	77%	80%	77%
Number of contraction	**Individual 6**	**Individual 7**	**Individual 8**	**Individual 9**	**Individual 10**
10	60%	50%	50%	50%	60%
15	67%	73%	73%	67%	67%
20	75%	75%	75%	75%	75%
25	76%	76%	76%	76%	76%
30	80%	80%	80%	77%	80%

Table 1 Results of the Identification performance in case of clench force of intensity 40% of MVC.

Results from Table 1 show that the highest identification performance for each individual was obtained when using 30 contractions for the authentication process. The performance increased up to 80% when using 30 contractions [11]. But this performance remained constant (80%) when using more than 30 contractions. Consequently, the best results were achieved at 30 contractions. Next, the effect of fatigue and electrodes displacement was evaluated. In the first case, an individual was asked to execute many push-ups. Fig. 5 shows that fatigue had no signification effect on the authentication performance since the curves were very close.

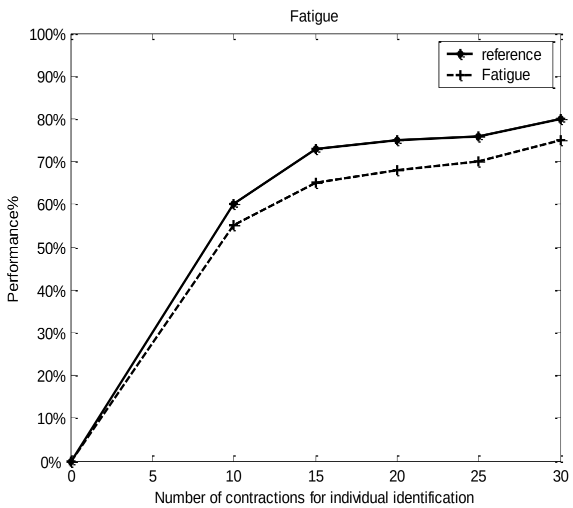

Fig. 5 Fatigue after push-ups in case of 40% of MVC.

In the second case, the electrodes were shifted a little from their position (i.e. 3 cm).

As shown in Fig. 6, we noticed that electrodes displacement had no effect on the performance.

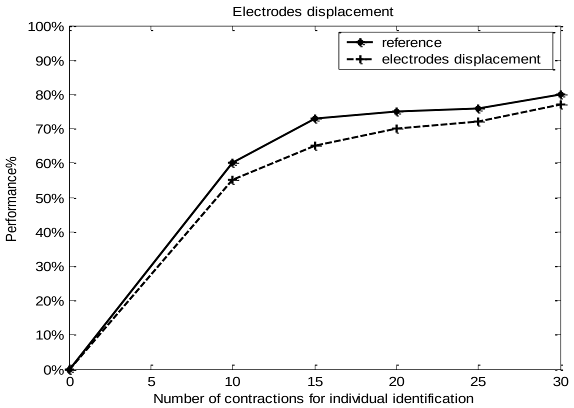

Fig. 6 Electrodes displacement.

V. CONCLUSION

In the literature, no methods using SEMG signals were proposed. In our study, these signals were used in order to identify individuals through estimation of PSD, frequency parameters and classification by RBF in response to a force of intensity of 40% of MVC. This innovation is considered unfalsiable and highly accurate which serves in other than biometrics field, such as security origination, airports.

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