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QRS Complex Based Human Identification

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***Abstract*—In the last years, the electrocardiogram signal has become an important biometric modality due essentially to the physiological or/and behavioral characteristics variation of the heart among different individuals. The aim of this paper is to present a human identification approach using some time and frequency features of the QRS complex of the ECG signal. These features are extracted from a fractional order model of the frequency content of the QRS complex besides of its temporal area. The K-Nearest Neighbors (KNN) classifier is used for the human identification through the proposed clustering features. Series of tests have been performed to evaluate the proposed identification algorithm using 20 subjects from the MIT-BIH arrhythmia database.**

Keywords—ECG signal, Fractional Order System, Human identification, KNN classifier, QRS Complex Modeling.

I. INTRODUCTION

The electrocardiogram (ECG) signal is the electrical variation caused by the contraction and relaxation of the heart muscle. The ECG is generally dissimilar from person to person due to many factors such as the physiological and morphological differences of the heart in different individuals and the nature of different dysfunctions afflicting the heart itself. Then, the ECG signal may contain significant pointers to distinguish and identify persons; so it can be used as a biometric trait.

In the recent years, several biometric recognition methods were presented based on the ECG signals with the aim of building an efficient and reliable human identification system. These presented biometric approaches differ in terms of feature extraction and person identification mechanisms. In [1-3], the authors have analyzed the ECG signal and proved its feasibility and potential to be used as a biometric modality for human identification due to its universality, permanence, uniqueness and stability. In some ECG based biometric techniques, the authors have used beat morphological and pattern features such as the ECG waveform durations, intervals, amplitudes and segments slopes [1-2, 4-7]. Lately, the features used in the ECG based biometric methods are extracted from the processed ECG signal using various signal processing techniques such as correlation, wavelet decomposition, data modeling and statistical analysis [8-12]. For person identification mechanisms, the methodologies generally used in the literature include template matching, neural networks, KNN classifier, wavelet distance measurement technique, principal component analysis and linear discriminant analysis.

Recently, fractional order systems and operators have been found to be useful in many areas of biomedical field [13-17]. In [18], the author has given a historical perspective of the dynamic link between fractal physiology and fractional calculus. Some examples of fractional calculus in biomedical applications from signal processing point of view are given in [19].

In this paper, we propose to investigate the human identification using some time and frequency features of the QRS complex of the ECG signal. These features are extracted from a fractional order model of the frequency content of the QRS complex besides of its temporal area. KNN classifier is used for the human clustering mechanism using only the three extracted features. Series of tests have been performed to evaluate the proposed identification algorithm using 20 subjects from the MIT-BIH arrhythmia database [20].

II. MATERIALS AND METHODS

The schematic description of the proposed ECG based person authentication system is shown in figure (1). This biometric algorithm is a low complexity technique starting with a preprocessing step which consists of filtering of the ECG signal to reduce several kinds of noises and artifacts then extracting the QRS complexes segments using the Blackman window. In the second step the QRS complexes are modeled using fractional order model through an identification technique in the frequency domain. The features used in the identification process are extracted from the obtained model and the QRS itself in the third step. In the final step, the KNN classifier is used for the person identification.

A. MIT/BIH arrhythmia database

In this work, we have used 20 ECG records from the MIT/BIH arrhythmia database of 30 minutes each where their sampling frequency is 360 samples per second [20]. Each ECG record represents a different person. These 20 records contain about 76 % of normal beats and 24 % of abnormal beats.

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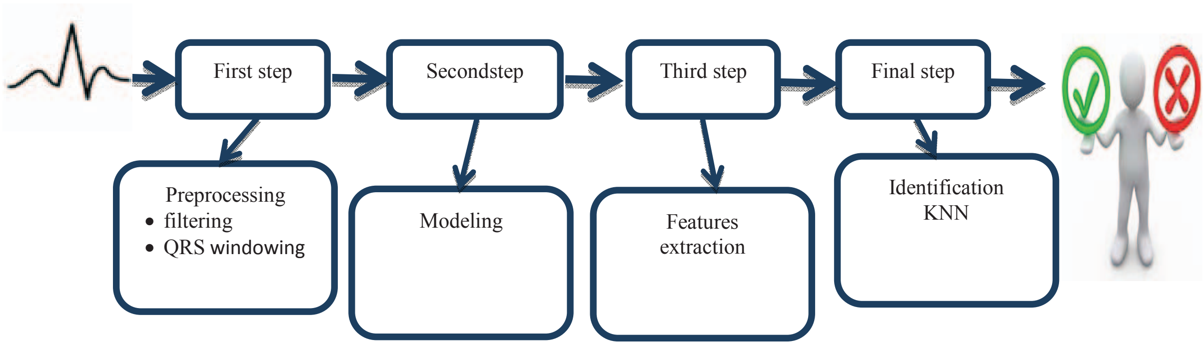

Fig.1.Bloc diagram of the biometric identification process

B. Signal Pre-processing

The ECG signals used have undertaken a band-pass filtering stage to reduce several kinds of noises and artifacts and to enhance the QRS complexes. The band-pass filter used is an integer coefficient digital band-pass filter made of a cascaded digital low-pass filter whose frequency response has a 3-dB point at 20 Hz and a first zero amplitude at 60 Hz with a digital high-pass filter whose frequency response has a cut-off frequency of 1 Hz [21]. Then the QRS complexes segments are extracted using the Blackman window from the ECG signal where each QRS segment is consisting of 30 samples (83.33 ms) before the R-wave and 40 samples (111.11 ms) after the R-wave.

C. Modeling of QRS complexes using fractional order system

A QRS complex is formed by the depolarization of the ventricles of the heart. The QRS complexes are usually the most visually obvious part of the ECG signal. Generally, the morphologies of the QRS complexes in normal and abnormal (presence of arrhythmias) cases can be used to distinguish a person from another as shown in figures (1) and (2).

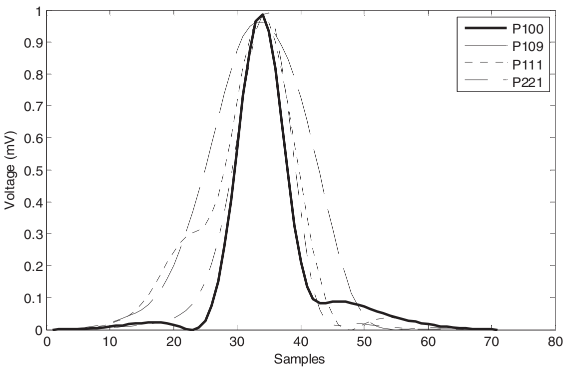

Fig.2.waveform from different persons with normal QRS

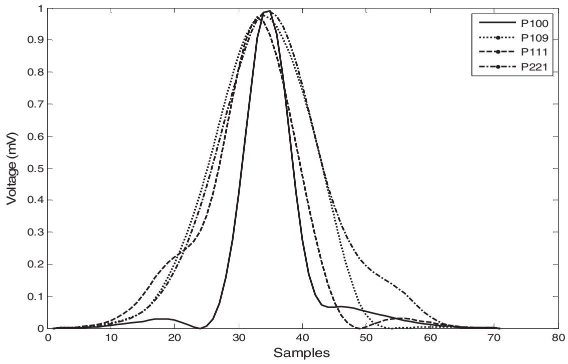

Fig.3.waveform from different persons with abnormal QRS

In the literature, it has been found that the power spectrum density of the QRS complexes of the ECG signal at different frequencies in log-log plot shows a fractional slope behavior. In this context, to exploit this fractional power law property as a potential quantitative quality for characterizing cardiac biometric identification, the modeling of the frequency content of the QRS complex of the ECG signal using a fractional system of commensurate order is considered through an identification technique in the frequency domain. The proposed model is defined as a fractional system of commensurate order represented by the following linear fractional order differential equation [22]:

$$y(t) + \sum_{i=1}^{N} a_i D^{i\alpha} y(t) = \sum_{j=0}^{M} b_j D^{j\alpha} e(t) \qquad (1)$$

whose transfer function is the irrational function [24]:

$$G(s) = \frac{\sum_{j=0}^{M} b_j s^{j\alpha}}{1 + \sum_{i=1}^{N} a_i s^{i\alpha}} \qquad (2)$$

where M and N are integer numbers ($M \le N$), the model parameters a_i ($1 \le i \le N$) and b_j ($0 \le j \le M$) are constant real numbers and the fractional order α is a real number such that $0 < \alpha < 1$. The best combination of the parameters α, M and N are the ones for which the square error between the QRS complex frequency data and the estimated model is the smallest one and the stability of the obtained model of (1) is verified. In [23], the parameter α, M and N are set as: $\alpha = 0.68$, M = 4 and N = 6. Hence the proposed identification model is given by:

$$G(s) = \frac{\sum_{j=0}^{4} b_j s^{0.68j}}{1 + \sum_{i=1}^{6} a_i s^{0.68i}} \tag{3}$$

The QRS modeling procedure is carried out using the algorithm called function Sanko [24]. The function Sanko receives the gain in dB and the phase in degrees of the frequency content of the QRS complex and the frequency in rad/s, the commensurate order $\alpha = 0.68$, M = 4 and N = 6; it then returns the 11 estimated parameters $a_i (1 \le i \le 6)$ and b_j $(0 \le j \le 4)$ of (3) and the estimation quadratic error [23]. Figure (4) shows the log-log plots of the frequency content of a QRS complex of a beat from record 100 (Normal beats) and the frequency response of its corresponding estimated model. Figure (5) shows also the log-log plots of the frequency content of a QRS complex of a beat from record 221 (PVC beats) and the frequency response of its corresponding estimated model.

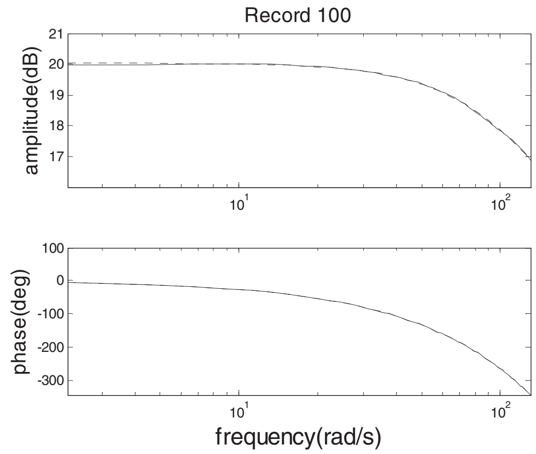

Fig.4. log-log plot of the frequency content of the QRS of normal beat (dotted line) of record 100 and of its corresponding estimated model (solid line).

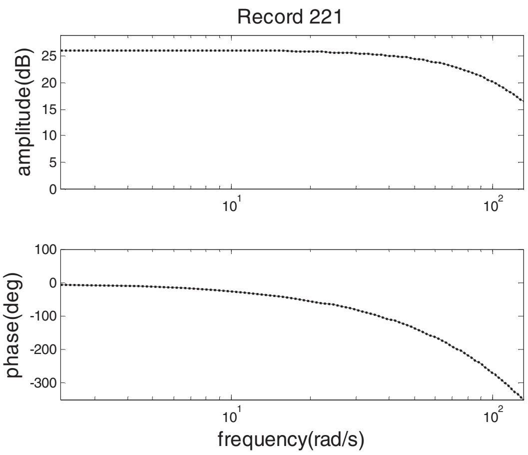

Fig.5. log-log plot of the frequency content of the QRS of normal beat (dotted line) of record 221 and of its corresponding estimated model (solid line).

D. Features database template

The first step in any biometric system is the construction of the features database template. In this context, the pertinent parameters chosen to build the features database template are the coefficients b_0, b_1, b_2, b_3, b_4 of the numerator of the transfer function of the fractional model of the frequency content of the QRS complex of the ECG signal of equation (3) as well as the area of the QRS complex itself noted as the coefficient A. The computational procedure to generate the features database template is described as follows:

- Take 100 beats of the filtered ECG record of a person and extract their 100 corresponding QRS complexes as shown in section II.B.
- Model the frequency content of the 100 QRS complexes using the fractional order model of section II.C, and extract the 100 sets of the coefficients b_0, b_1, b_2, b_3, b_4 of the numerator of the transfer function of equation (3).
- Calculate the area coefficient A of all the 100 QRS complexes.
- Calculate the mean values of the coefficients $\overline{b_0}$, $\overline{b_1}$, $\overline{b_2}$, $\overline{b_3}$, $\overline{b_4}$ and $\overline{A}$ using the 100 sets of the coefficients b_0, b_1, b_2, b_3, b_4 and A.
- Finally, a person is featured by the six coefficients set $\overline{b_0}$, $\overline{b_1}$, $\overline{b_2}$, $\overline{b_3}$, $\overline{b_4}$ and $\overline{A}$.

Hence, the features database template is the ensemble of the above coefficients sets of the persons considered in the biometric system.

E. Person identification

Generally, person recognition is the final step in any biometric identification process. In this work, the KNN classifier is used in person recognition because of its simplicity, success in problem resolution and the high accuracy of the results obtained. The KNN classifier is commonly based on the Euclidean distance between the features of the query sample and each sample of the stored features database template. The normalized Euclidean distance between two points x_1 and x_2 is the length of the line segment connecting them given as:

$$D(x_1, x_2) = \frac{1}{n}\sqrt{(x_1 - x_2)^T (x_1 - x_2)} \tag{4}$$

where n is the dimension of x_1 and x_2.

The computational procedure to generate the person recognition score of an ECG query sample is described as follows:

- Take a segment of only 50 beats (around 45 seconds) of the ECG query sample then filter it and extract the 50 corresponding QRS complexes as shown in section II.B.

- Model the frequency content of the 50 QRS complexes using the fractional order model of section II.C, and extract the 50 sets of the coefficients b_0, b_1, b_2, b_3, b_4 of the numerator of the transfer function of equation (3).
- Calculate the area coefficient A of all the 50 QRS complexes.
- Calculate the mean values of the coefficients $\overline{b_0}$, $\overline{b_1}$, $\overline{b_2}$, $\overline{b_3}$, $\overline{b_4}$ and $\overline{A}$ using the 50 sets of the coefficients b_0, b_1, b_2, b_3, b_4 and A. So, the query sample person is featured by the six coefficients set $\overline{b_0}$, $\overline{b_1}$, $\overline{b_2}$, $\overline{b_3}$, $\overline{b_4}$ and $\overline{A}$.
- Use the KNN classifier for each coefficient of the 5 coefficient $\overline{b_0}$, $\overline{b_1}$, $\overline{b_2}$, $\overline{b_3}$ and $\overline{b_4}$ between the query sample and each sample of the stored features database template to find the best match. So, we will obtain 5 person recognition scores.

If all the 5 person recognition scores are the same stop the person recognition process.

Otherwise, use the KNN classifier for the coefficient $\overline{A}$ between the query sample and each sample of the previously obtained 5 person recognition scores to find the best match among them leading to only 1 person recognition score.

III. Results and Discussions

This section presents the evaluation of the proposed ECG signal based human identification method. In this work, only the QRS complex of the ECG signal has been used. 20 ECG records containing normal and abnormal beats from the MIT/BIH arrhythmia database representing 20 different persons have been used [20]. A series of tests has been conducted in which the features database template and the person recognition process have been done for different sections of each ECG record. For the construction of the features database template 100 beats (around 90 seconds) of each ECG record have been used and for the generation of the person recognition score only 50 beats (around 45seconds) of each ECG record have been used. Besides, only 6 features have been used for both phases of the proposed ECG based biometric. 5 features are from the frequency domain; they are the coefficients of the numerator of the transfer function of the fractional model of the frequency content of the QRS complex and one feature from the time domain; it is the QRS complex area. The KNN classification algorithm has been applied to find the best match of the query sample among all the stored samples of the database template. In order to evaluate the performances of the proposed ECG based person recognition method, we have considered the recognition accuracy expression used in the literature given as follows:

$$\text{ACCURACY (\%)}=\frac{\text{Number of total correctly recognized samples } N_C}{\text{Number of total tested samples } N_T}*100$$

Figure (6) shows the recognition accuracy versus the number of features used in the person recognition process beginning by the feature b_0, then the features b_0 and b_1 and so on up to all the six features b_0, b_1, b_2, b_3, b_4 and A.

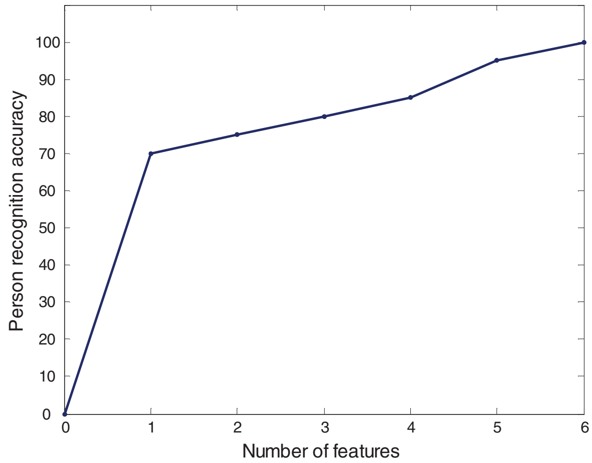

Fig.6. Recognition accuracy versus the number of features

From figure (6), we note that by using only the first feature b0 the person recognition accuracy achieved is 70 %, and by adding more features the accuracy keeps increasing up to 100 % when using all the proposed six features in the recognition process. So, the proposed person recognition method through the fractional order model of the frequency content of the QRS complex and its area has achieved an overall recognition accuracy of 100 %. This is a very satisfactory result considering the low number of features and the simplicity of the classification algorithm used in the person recognition process.

IV. Conclusion

In this work an ECG based biometric system is proposed. Only the QRS complex from a single lead ECG signal has been used in the process of person recognition. The proposed method is a low complexity technique using only six features extracted from a fractional order model of the frequency content of the QRS complex besides of its temporal area. The KNN classifier is used for the person recognition. Series of tests have been performed to evaluate and validate the efficiency of the proposed biometric algorithm using the MIT-BIH arrhythmia database. Although only six features are used to characterize a person, the recognition methodology has achieved an accuracy of 100 % over 20 records of the database. These results are very satisfactory considering the low number of features used and the simplicity of the classification algorithm used in the person recognition process.

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