Human Identification System Based ECG Signal

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***Abstract*—A new human identification system based electrocardiogram (ECG) signal is introduced in this work. The human heart is considered to be a unique system of each person. ECG signal therefore represents as an impulse response of the system. The frequency response of the system (Fourier transform of the ECG signal) is employed to be a tool for feature extraction. In addition, the ECG signals employed in this paper, which may be derived from different heart rates from different subjects at the recording time, are normalized to a standard heart rate. Furthermore, not only the whole sequence of 1 period EC signal, containing P, QRS, and T waves, is processed but also its three subsequences, each respectively representing P, QRS, and T waves, is examined. The results of using neural network have demonstrated that subsequences technique is superior to whole period of ECG signal method.**

***Index Terms*—ECG, Fourier transform, neural network**

I. Introduction

NOWADAYS, human identification has played an important role in many applications, especially in security systems. For example, an authorization for building access, different approaches could be employed. Rather than using a mother key for conventional bolt lock, code lock may be employed. But to gain a higher security level, more complex systems are required. Mostly, many methods involve with the use of a part of human body. A specific feature must be extracted from that selected part to recognize a person. A lot of works have been studied on human face identification [1], [2]. Other techniques include voice recognition [3], [4], palm recognition [5], retina identification [6], and most common method fingerprint identification [7] - [9]. Electrocardiogram (ECG) signal is an alternative method that can be utilized for this objective.

Generally, ECG signal is employed to observe patient's heart function. The shape of ECG signal can indicate whether or not a heart is in normal condition. Based on the consideration a human heart as a system of each person, its ECG signal which represents as an impulse response of the system, thus has its own feature. A few works have been done on this particular purpose [10], [11]. These works collected various features of ECG signals to make a decision of the identification. However; their techniques are quite complicate to implement.

In this paper, a new approach for human identification based ECG signal is proposed. The Fourier transform is employed to be a tool to extract feature from ECG signal. One period of ECG signal, which contains P, QRS, and T waves is taken in the process. Besides, this one period ECG signal is divided into three subsequences corresponding to P, QRS, and T waves, respectively. These subsequences provide an alternative way to be processed in this work. It is noted that each ECG signal may be based on different heart rate at the recording time. Therefore, they are normalized to be signals at a standard heart rate. The detail of the proposed technique will be given in section II. The classification result of using back propagation neural network is then provided in section III. Finally, the section IV devotes to the conclusion.

II. Principle

A. Basic ECG signal

The human heart is one of many important parts of body. Normally, electrocardiogram is a method of observing a heart function. It measures different electrical potentials of a heart resulting in an ECG signal. Based on the consideration of a heart as a system, ECG signal is thus considered to be an impulse response of the system to an impulse somehow created by a body. This system is shown in Fig. 1. ECG signal is generally composed of the following waves: P, QRS and T as shown in Fig. 2.

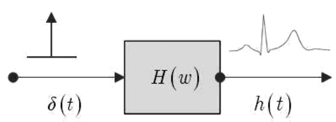

Fig. 1. A system considered as a heart.

Fig. 2. One period of an ECG signal.

Due to the oscillatory in nature of ECG signal, its one period is therefore employed in the process of this proposed method. However, it is interesting to note that the ECG signals may be derived from different heart rates at the recording time. It is thus important to normalize the ECG signals being processed into a standard heart rate. Assuming that normal heart rate of a person is usually 80 times/minute, it is thus selected to be a standard rate employed in this work. The detail of heart rate normalization will be given in the following section.

B. Heart rate normalization

At a normal heart rate 80 times/minute, it implies that it takes 0.75 seconds per one PQRST period. If the ECG signals employed in this work are recorded at the sampling rate f_s = 8000 Hz, therefore an ECG signal of 80 times/minute heart rate must contain 6000 samples in 1 period. However, if at the recording period the heart is functioned at other rates, lower or higher than 80 times/minute, one period of its PQRST wave may be either longer or shorter than that of a standard rate (assuming that the same sampling rate is used).

Let the length of one period PQRST of an interested ECG signal $h(n)$ be N, its discrete Fourier components therefore are

$$H(k)=\sum_{n=0}^{N-1} h(n)\exp(-j2\pi kn/N) \tag{1}$$

where k is frequency index corresponding to digital frequency which is defined to be kf_s/N for $0\le k\le N-1$. As previously described, N may be either larger or less than N_n (N_n = 6000), depending on its heart rate at the recording period. Thus the ratio of signal length must be determined to be a scaled value α for normalization which is obtained by

$$\alpha = N_n/N\,. \tag{2}$$

For $\alpha>1$, it implies that the heart rate of the interested ECG signal is higher than the standard rate. Contrarily, it is lower than the standard rate for $\alpha<1$. To normalize length of this signal to N_n samples in one PQRST period, a new scale of sampling time T_n must be obtained which is

$$T_n = T_s/\alpha \text{ where } T_s = 1/f_s\,. \tag{3}$$

With these scaled parameters, the following signal reconstruction is used to obtain the normalized heart rate of one period ECG signal $h_n(n)$ which is

$$h_n(n)=\sum_{k=0}^{K}|H(k)|\cos(2\pi k\frac{f_s}{N}nT_n+\angle H(k)) \tag{4}$$

for $0\le n\le N_n-1$ where K is the frequency index corresponding to the highest digital frequency which occupies the ECG frequency spectrum (normally 0 – 100Hz [12]).

C. Proposed Technique

Once the ECG signals are normalized to be based on the same heart rate, they are employed in the proposed algorithm. However, information of signal usually is redundant in spatial domain. Instead, other methods that can be extracted information into a concise set of coefficients are thus preferable such as method of signal transformation. In this work, Fourier transform is selected to be a tool for this particular purpose. Moreover, to gain more feature extraction, this normalized one period PQRST signal $h_n(n)$ is divided into three subsequences, ($h_{n1}(n), h_{n2}(n), h_{n3}(n)$) which each corresponds to P, QRS, and T waves, respectively. Then, Fourier transform is also taken on these subsequences. From the resulted Fourier coefficients, only significant elements are selected and employed in neural network for classification. Supervised training by using two groups of dominant coefficients, one represents the person X and another represents other persons, are performed by neural network. The block diagram of the proposed technique is illustrated in Fig. 3. Therewith the described proposed algorithm, the results of computer simulation will be given in the next section.

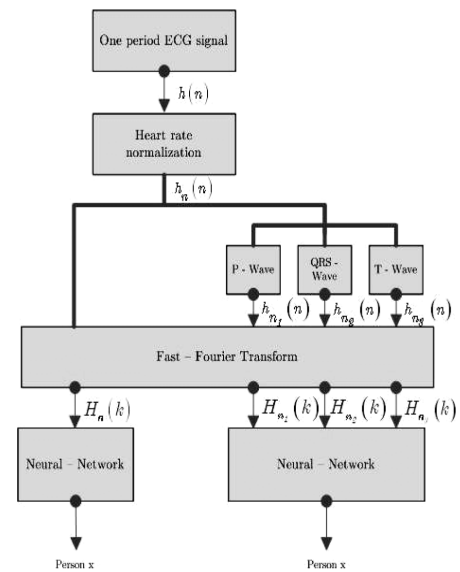

Fig. 3. The proposed technique.

III. Simulation Results

Firstly, the result of normalized ECG signal is demonstrated. As seen in Fig. 4., the upper line represents one period ECG signal of person X. After it is normalized by using the algorithm described in the last section, the normalized result is given as the lower plot of Fig. 4. It is noted that the magnitude of ECG sequence is also normalized so that it is confined in $0 \le |h_n(n)| \le 1$.

Later, the Fourier coefficients of one period normalized (both heart rate and magnitude) ECG signal is obtained as demonstrated in Fig 5. In addition, this one period normalized ECG signal is divided into 3 parts which each part represents P, QRS, and T waves, respectively (see Fig. 6.) These subsequences are also taken the Fourier transform where their Fourier components are given in Fig. 7.

In order to compare the performance of classification, the significant Fourier coefficients obtained from whole sequence and subsequences cases are separately trained by neural network. The results provided by using whole period of PQRST wave case and subsequences case are given in Table I. and II., respectively. The results imply that by using subsequences technique, the classification performance is superior to that of using whole period method.

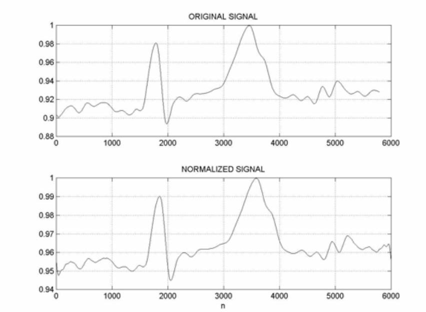

Fig. 4. Normalized heart rate ECG sequence.

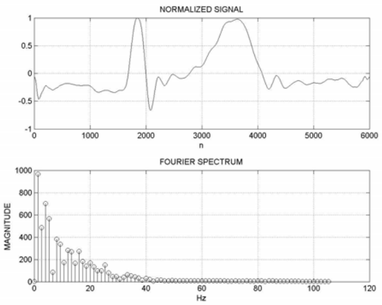

Fig. 5. Normalized heart rate ECG sequence : in spatial domain (upper), in frequency domain (lower).

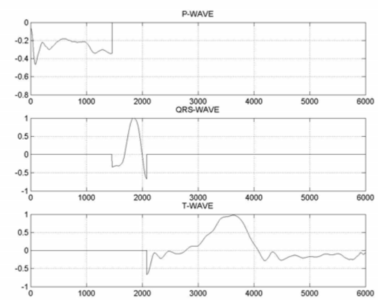

Fig. 6. Subsequences of the normalized heart rate ECG signal : P wave (upper), QRS wave (middle), T wave (lower).

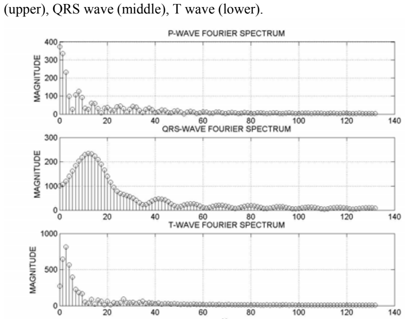

Fig. 7. Fourier components of subsequences normalized heart rate ECG signal : P wave (upper), QRS wave (middle), T wave (lower).

Table I. Neural network classification result using whole period of normalized heart rate ECG signal.

	Case of Classes	Identified Result		
		Owner	**Stranger**	**FR(%)**
Training				
Owner	5	5	0	0
Stranger	15	0	15	0
Total	20	5	15	0
Test				
Owner	5	4	1	20
Stranger	30	5	25	16.67
Total	35	9	25	17.14

Table II. Neural network classification result using subsequences of normalized heart rate ECG signal.

	Case of Classes	Identified Result		
		Owner	**Stranger**	**FR(%)**
Training				
Owner	5	5	0	0
Stranger	15	0	15	0
Total	20	5	15	0
Test				
Owner	5	4	1	20
Stranger	30	0	30	0
Total	35	4	31	2.85

IV. Conclusion

In this work, a system for human identification based on ECG signal is present. The ECG signals employed in this paper are normalized their heart rates to a standard heart rate. Fourier transform technique is chosen as a method to extract ECG features. The significant Fourier components are employed in classification process by using neural network. Furthermore, two cases of one period of normalized heart rate ECG signals : (1) whole period case, (2) subsequences into P, QRS, and T waves are studied to examine their classification performance. The neural network classification results show that the percentage of false rate of using subsequences technique is superior to that of using whole period.

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