HEART SOUND AS A PHYSIOLOGICAL BIOMETRIC SIGNATURE

Saad D. Al-Shamma and Mohammed C. Al-Noaemi

Abstract—this paper presents a system for using heart sound as a physiological biometric signature based on energy percentage in each wavelet coefficients. An electronic stethoscope designed and implemented by the authors is used to record more than 30 heart sound and for each recording a signature is calculated. The signature is calculated during one heart cycle by calculating the total energy for each wavelet coefficient after normalization, filtering and denoising of each recordings. A Euclidean distance is used as an identification tool between the signatures. It was found that the distances for different recordings at different days for the same person are below a threshold value and above the threshold value as compared with the signatures of the other persons. A software based on Matlab is used for recordings, denoising, signature calculations and signature comparison to prove the implemented system.

I. INTRODUCTION

Biometrics is the science of identifying or verifying the identity of a person based on physiological or behavioural characteristics.[1] Physiological characteristics include fingerprints and facial image; behavioural characteristics include signature and voice, see Miller [2]. Physiological biometrics, like fingerprints, are physical characteristics that are not influenced by emotional state. Behavioural biometrics, like signature, on the other hand, are believed to depend more on the state of mind of the subject and are learned or acquired over time. Another way of distinguishing between physiological and behavioural biometrics is that physiological biometrics are rich enough that a snapshot suffices. Behavioural biometrics are weaker and need multiple samples over time to build up uniqueness identifiers, the most used biometrics are shown in Table 1. The issue whether a biometric property is physiological or behavioral is not really that important, this is simply a distinction proposed by Miller [2]. What is important are the necessary attributes of a biometric described by Clarke [3] that characterizes a biometric. These include: 1. Universality, which means that every person should have the characteristic; 2. Uniqueness, which means that no two persons should be the same in terms of the characteristic; 3. Permanence, which means that the characteristic should be invariant over time, 4. Collectability, which means that the characteristic can be measured with some sensing device. The feasibility of applying ECG signal for human recognition and the achieved performance as well as robustness of this biometric has drawn the attentions to the PCG signals as well. Having the same origin with the ECG signal in addition to the medical information that is conveyed through the PCG signal Conjectured that the PCG signal may contain information about an individual’s physiology. Signals having this characteristic usually have the potential to provide a unique identity for each person. Like the ECG signals, the PCG signals are difficult to disguise, forged, or falsified. Moreover, this signal has the advent of being relatively easy to obtain, since it can be collected by placing a stethoscope on the chest. This work is concerned with utilizing the PCG signals as a physiological biometric which is a new concept only lately suggested in the literature [4, 5]. Phua et al. [4] demonstrated the possibility of utilizing PCG signal for human recognition. They proposed an approach for PCG recognition through the frequency analysis of the short-time discrete Fourier transform (STDFT) of the PCG traces. The PCG spectrum was processed by filtering out the frequency band outside the range of 20 to 150Hz and further enhanced by application of a spike removal technique. The extracted cepstral coefficients were used as the biometric features in conjunction with the discrete cosine transform (DCT) for reducing the dimensionality of the data space. However, due to the number of iterations required to train the GMM, the proposed scheme is slow and time consuming; an issue that affects the application of such a scheme in a large scale scenario. Moreover, the designed preprocessing step is incapable of reducing the inter-band noise which degrades the performance of the system for noisy data.[6]

Another approach was proposed by Bertelli et al. [5] for human identification based on the frequency characteristics of the S1 and S2 sounds in digital PCG sequences. A mechanism was proposed to identify the boundary of the S1 and S2 in the PCG traces. Then, the frequency analysis was performed using the Z-chirp (CZT) transform with a frequency band of 20Hz to 100Hz for obtaining an energy trend profile. The obtained signal spectrum was used as the feature vector from the PCG signal and classification was performed using the Euclidean distance measure. However, the localization and delineation of S1 and S2, which is essential for the succeeding stages, is a great challenge in the...
presence of noise. The complexity of this issue is brought to light by considering the fact that there is no universal definition for determining the onset and offset of these components [7]. Fatemian used DWT 5th order Daubechies wavelet for signal denoising and Feature Extraction based on STFT classification using the majority voting rule among the frames using the nearest neighborhood classifier with the Euclidean distance measure.[6]

A. heart sounds

The heart sounds are produced by the mechanical events that occur during the heart cycle, which can be heard normally by using the stethoscope. The first heart sound is produced mainly by the closure of the mitral and tricuspid valves. Its duration is 50-150ms, and with a frequency of 25-45 Hz. The second heart sound is produced by the closure of the aortic and pulmonary valves. Its duration is 25-50ms (shorter), and its frequency is about 100Hz (higher) than the 1st heart sound. [8,9,10].

B. wavelets

In comparison to the Fourier transform, the analyzing function of the wavelet transform can be chosen with more freedom, without the need of using sine-forms. A wavelet function (t) is a small wave, which must be oscillatory in some way to discriminate between different frequencies. The wavelet contains both the analyzing shape and the window. Fig.1 shows an example of a possible wavelet, known as the Morlet wavelet. For the CWT several kind of wavelet functions are developed which all have specific properties[11] The continuous wavelet transform is defined as

\[ X_w(t, s) = \frac{1}{\sqrt{S}} \int_{-\infty}^{\infty} X(t) \phi^*(\frac{t-\tau}{s}) dt \]

The transformed signal \( X_w(t, S) \) is a function of the translation parameter and the scale parameter s. The mother wavelet is denoted by \( \phi \), the * indicates that the complex conjugate is used in case of a complex wavelet. The signal energy is normalized at every scale by dividing the wavelet coefficients by \( \frac{1}{\sqrt{|s|}} \) this ensures that the wavelets have the same energy at every scale. The mother wavelet is contracted and dilated by changing the scale parameter s. The variation in scale s changes not only the central frequency \( f_c \) of the wavelet, but also the window length. Therefore the scale s is used instead of the frequency for representing the results of the wavelet analysis. The translation parameter \( \tau \) specifies the location of the wavelet in time, by changing the wavelet can be shifted over the signal. For constant scale s and varying translation the rows of the time-scale plane are filled, varying the scale s and keeping the translation \( \tau \) constant fills the columns of the time-scale plane. The elements in \( X_w(T, \tau) \) are called wavelet coefficients; each wavelet coefficient is associated to a scale (frequency) and a point in the time domain. The wavelet also has an inverse transformation, as was the case for the FT and the STFT. The inverse continuous wavelet transformation (ICWT) is defined by

\[ x(t) = \frac{1}{c_\phi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} X_w(T, \tau, s) \frac{1}{s^2} \psi(\frac{t-\tau}{s}) d\tau ds \]

Where \( c_\phi \) is known as admissibility constant

\[ c_\phi = \int_{0}^{\infty} \left| \frac{\phi(f)}{f} \right|^2 df \]

A wavelet function has its own central frequency \( f_c \) at each scale; the scale s is inversely proportional to that frequency. A large scale corresponds to a low frequency, giving global information of the signal. Small scales correspond to high frequencies, providing detail signal information. [3] Since the wavelet transform does not lose any information, and the energy is preservative for the transform. So the following equation is tenable:

\[ \text{Energy} = \int \left| x(t) \right|^2 dt = \frac{1}{c_\phi} \int \frac{1}{s^2} ds \int \left| X_w(T, \tau, s) \right|^2 d\tau \]

where

\[ \frac{1}{c_\phi} \int \frac{1}{s^2} ds \int \left| X_w(T, \tau, s) \right|^2 d\tau \]

represents the total energy of a domain centered at \( (\tau, S) \) with scale interval \( \Delta s \) and time interval \( \Delta \tau \) and \( |X_w(T, \tau, s)|^2 \) is defined as the wavelet Scalogram. It shows how the energy of the signal varies with time and frequency. The wavelet Scalogram has been widely used for the analysis of non-stationary signal.

![Fig. 1. morlet wavelet](image-url)
II. METHODOLOGY

A. Selection of one heart cycle wavelets

to choose one heart cycle the heart sound recording undergoes the following processing stages

1-normalization
\[ x(t) = x(t) \ast \frac{x_{\text{max}} - x_{\text{min}}}{2} \]

2-low pass filtering
(Pass frequency = 150 HZ, stop frequency = 200HZ, attenuation = 80dB)

3-denosing using level 5 and db12 wavelet

4-framing and windowing of the signal with Hamming window length = 301 samples Overlapping = 300 samples

5-the energy for each windowed segment is calculated
\[ E = \sum_{0}^{301} x(i)^2 \]

6- after a comparison with a threshold the start and end for one heart cycle could be easily defined (the threshold is selected manually) The result of this stage as shown in Fig.2

Fig. 2. selection of one heart cycle

B. calculating the signature for one heart cycle

1-calculate wavelet coefficients (Wavelet db12, scale = 1: 256)

2-calculate the percentage of energy for each coefficient(Scalogram)

3-calculate the total energy for each coefficient for all samples during one heart cycle as shown in Fig.3 for energy (scalogram) and the signature as shown in Fig.4

Fig. 3. Energy/Coefficient(scalogram)

Fig. 4. signature

III. RESULT

1-The graph for 4 signatures (3 for the same person) shows the matching of the signatures for the same person while there is a clear difference with the other person signature as shown in Fig.5

2-The Euclidean distances (error) are calculated between a person signature and two other signatures for the same person and 19 signatures for different persons It was found that the distance for different signatures of the same person...
are 5.6 and 2.97 (person 1 and person 11) while the distance as compared with other persons are much more greater than 10 as shown in Fig. 6, Table. 2 (matching column).

3-The Euclidean distances (error) are calculated between a person signature not included in the database. It was found that the minimum distance is 9.33 which indicate that there is no matching with any signature stored in the database as shown in fig 7 and table 2 (non matching column).

**Table II**

<table>
<thead>
<tr>
<th>Distance Error</th>
<th>Matching</th>
<th>Non-Matching</th>
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<tbody>
<tr>
<td>P1</td>
<td>5.6</td>
<td>11.54</td>
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<tr>
<td>P2</td>
<td>35.45</td>
<td>36.8</td>
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<tr>
<td>P3</td>
<td>39.11</td>
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<td>P4</td>
<td>44.85</td>
<td>42.53</td>
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<td>P5</td>
<td>36.83</td>
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<td>P6</td>
<td>32.82</td>
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<td>P8</td>
<td>21.07</td>
<td>9.33</td>
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<td>P20</td>
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<td>12.8</td>
</tr>
</tbody>
</table>

**Fig. 6.** signatures comparison (Matching)

**Fig. 7.** signature comparison (no matching)

**REFERENCES**


