A Gaussian Mixture Models Approach to Human Heart Signal Verification Using Different Feature Extraction Algorithms

Rasha Wahid[1,5], Neveen I. Ghali[1,5], Hala S. Own[2,5], Tai-hoon Kim[3], and Aboul Ella Hassanien[4,5]

[1] Al-Azhar University, Faculty of Science, Cairo, Egypt
{rashawahid,neveen.ghali}@egyptscience.net
[2] National Research Institute of Astronomy and Geophysics, Helwan, Cairo, Egypt
[3] School of Information Science, University of Tasmania, Australia
taihoonn@empas.com
[4] Cairo University, Faculty of Computers and Information, Cairo, Egypt
[5] Scientific Research Group in Egypt (SRGE)
http://www.egyptscience.net

Abstract. In this paper the possibility of using the human heart signal feature for human verification is investigated. The presented approach consists of two different robust feature extraction algorithms with a specified configuration in conjunction with Gaussian mixture modeling. The similarity of two samples is estimated by measuring the difference between their negative log-likelihood of the features. To evaluate the performance and the uniqueness of the presented approach tests using a high resolution auscultation digital stethoscope are done for nearly 80 heart sound samples. The experimental results obtained show that the accuracy offered by the employed Gaussian mixture modeling reach up to 100% for 7 samples using the first feature extraction algorithm and 6 samples using the second feature extraction algorithm and varies with average 85%.

Keywords: Heart Sounds, Human verification, Gaussian Mixture Models, Feature Extraction.

1 Introduction

The need to identify persons correctly and irrevocably has existed for a very long time. The authorization to enter a building, to open a cupboard, to cross a border, to get money from a bank etc. is always connected to the identity of a person. It is therefore necessary to prove this identity in one way or the other. We call this procedure Verification. A person claims to be authorized or to have a certain identity, and this must then be verified. The problem is known to the police e.g. persons presenting an ID card which is doubtful. However the police are frequently confronted with another problem: Who is the person who has left a certain trace, e.g. a fingerprint, or who is this dead body? In this case we ask for the identity of an unknown person, we do Identification.

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Knowledge-based and possession-based authentication mechanisms imply that users need to carry or remember the authenticator in order to be granted access to a system, building, or service. For comparing these traditional authenticators with authentication through biometrics, it is often argued that keys could be lost, stolen or easily duplicated and passwords could be forgotten. A serious problem is that the link between the legitimate individual and the authenticator is weak, and the authentication system has no means to distinguish between a designated owner of the authenticator and an impostor or a guesser. On the other hand, the general view is that biometric traits have an advantage in that they cannot be stolen, easily guessed or forgotten [1], [2], [4].

Biometrics are commonly categorized as either physiological or behavioral trait. Physiological traits (sometimes called passive traits) refer to fixed or stable human characteristics, such as fingerprints, shape and geometry of face, hands, fingers or ears, the pattern of veins, irises, teeth, the heart sound as well as samples of DNA. Physiological traits are generally existent on every individual and are distinctive and permanent, unless accidents, illnesses, genetic defects, or aging have altered or destroyed them. Behavioral traits (active traits) measure human characteristics represented by skills or functions performed by an individual. These include gait, voice, key-stroke and signature dynamics [3], [4].

Biometric recognition can be defined as automated methods for accurately recognizing individuals based on distinguishing physiological and/or behavioral traits. The technology of biometrics, in many different forms, is currently being used very widely for identification and authentication of individuals. In a non-automated way and on a smaller scale, parts of the human body and aspects of human behavior have been used for decades as a means of interpersonal recognition and authentication. For example, face recognition has been used for a long time in (non-automated) security and access applications. Safety, quality and technical compatibility of biometric technologies can be promoted through standards and standardization activities. Standards are essential for the deployment of biometric technologies on large-scale national and international applications.

The most salient feature in using the heart sound as a biometric is that it cannot be easily simulated or copied, as compared to other biometrics such as face, fingerprint or voice. Also, if the authorized user is not living, the system will not authorize him even if his fingerprint is still available or his iris is still valid. Furthermore, the proposed framework is relatively economical to install and maintain as it requires only an electronic stethoscope and a simple processor and database server for carrying out the identification task [5]. In this paper Gaussian mixture model is used to investigate the possibility of using the human heart signal feature for human verification, with two different robust feature extraction algorithms with a specified configuration.

The rest of the paper is organized as follows. Section (2) gives a brief introduction to the Gaussian mixture model technique used in the presented approach. Section (3) presents heart signal human verification approach in detail. Experimental results are discussed in Section (4) while Section (5) concludes and presents future work.

2 Gaussian Mixture Model: Preliminaries

Gaussian Mixture Models (GMM) is conventional and successful method for the speaker recognition approach [5]. Here, we will evaluate the suitability of this method for the proposed heart-sound-based identification. A Gaussian mixture density is a weighted sum of M component densities and is given by

$$p(\overrightarrow{x} \mid \lambda) = \sum_{i=1}^{M} P_i b_i(\overrightarrow{x}) \tag{1}$$

where $\overrightarrow{x}$ is a D-dimensional random vector, $b_i(\overrightarrow{x})$ are the component densities and P_i are the mixture weights, where $i = 1, ..., M$. Each component density is a D-variate Gaussian function of the form

$$b_i(\overrightarrow{x}) = \frac{1}{(2\pi)^{\frac{D}{2}} \Sigma_i^{\frac{1}{2}}} exp\{-\frac{1}{2}(\overrightarrow{x} - \overrightarrow{\mu_i})^T \Sigma_i^{-1}(\overrightarrow{x} - \overrightarrow{\mu_i})\} \tag{2}$$

with $\overrightarrow{\mu_i}$ mean vector and covariance matrix Σ_i. The mixture weight satisfies the constraint that

$$\sum_{i=1}^{M} P_i = 1 \tag{3}$$

The complete Gaussian mixture density is parameterized by the mean vector, covariance matrix and mixture weights from all component densities. These parameters are collectively represented by the notation

$$\lambda = P_i, \overrightarrow{\mu_i}, \Sigma_i, i = 1, ..., M \tag{4}$$

3 Heart Signal Human Verification Approach

The proposed heart signal human verification approach is composed of three main phases; Capturing heart signals phase, feature extraction and verification. These three phases are described in detail in the following section along with the steps involved and the characteristics feature for each phase.

3.1 Capturing Heart Signals

Using a Thinklabs Rhythm Digital Electronic Stethoscope (ds32a) [7] different heart sound samples had been collected from 80 different persons (40 Male, 40 Female), with different age range and cases of pregnant women, in addition to cases suffering different heart diseases and healthy people forming a general dataset.

3.2 Feature Extraction Phase

The goal of the heart sound feature extraction is to convert the original wave heart sound sample into a relatively low dimensional feature space matrix. Also, it used to filter the noise caused by the other internal organs (e.g lung) which may overlap the heart sound.This work used two feature extraction algorithms.

In feature extraction algorithm 1(FEal1), the heart sound wave sample is transformed using Fast Fourier transformation (FFt) use hamming window with length 256ms. Next, heart sound is filtered using Mel-spaced filer bank (Melfb). Then the spectral magnitude is calculated. Later the output filtered signal is compressed in the logarithm domain, followed by the discrete cosine transform with 24 coefficients.

In feature extraction algorithm 2(FEal2), the heart sound wave sample is transformed using short time discrete Fourier transformation (STDFT) use non-overlap system, with frame length 256ms and window length 500ms. Then the spectral magnitude is calculated. Then , heart sound spectrum is simply processed by filtering out the frequencies outside the range of 20-100Hz. Later the output filtered signal is compressed in the logarithm domain, followed by the discrete cosine transform with 24 coefficients. After that, hard thresholding with T=6 as a threshold value is applied. Finally, cepstral mean subtraction is applied.

3.3 Heart Sound Verification

For heart sound human verification, each heart signal is represented by a GMM. The expectation maximization (EM) algorithm is usually used due to its simplicity and quick convergence. The GMM model is trained for each person to calculate negative log-likelihood and then in testing by comparing with the Negative log-likelihood of all trained previously samples. The model can have one covariance matrix per Gaussian component *nodal covariance* , one covariance matrix for all Gaussian components in a model *grand covariance*, or a signal covariance matrix shared by all models *global covariance*. The covariance matrix can also be full or diagonal [6]. In this work, nodal diagonal covariance matrices are used for heart sounds models .

4 Experimental Results and Discussion

The heart sounds used in our experiments were recorded using a Thinklabs Rhythm Digital Electronic Stethoscope (ds32a). The digital stethoscope was placed on the chest of the participant seated in a relaxed position. The heart signal was captured using the Thinklabs phonocardialogy [7] software application via the sound card of the computer with a sampling rate of 2KHz and 16 bits. A Pentium IV 2 GHz Intel Core2 Duo personal computer is used. A total of 80 heart sounds were recorded from 80 participants (40 male and 40 female). Each heart sound recording is approximately 30sec. The training phase used the first 10sec while the testing used the next 10sec after a 10sec interval. These heart sounds are analyzed using MATLAB R2008a.

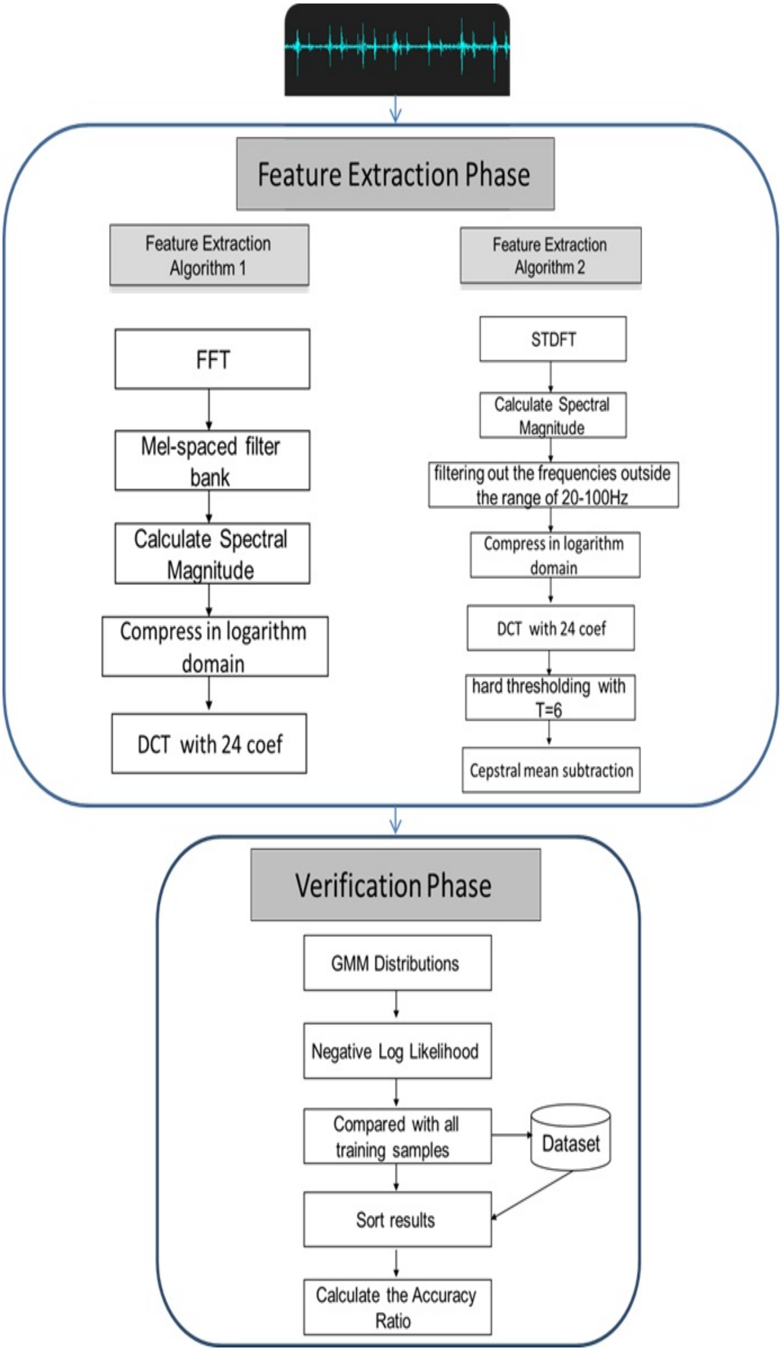

Fig. 1. Gaussian mixture models approach to human heart signal verification using different feature extraction algorithms

Algorithm 1. Classification and Verification

Input Feature extracted matrix $FEMx$

1: Distributed GMM using EM algorithm
2: Compute Negative log-likelihood ($Nlogl$).
Verification stage:
3: Compare with $Nlogl$ of all trained samples and get the difference.
4: Sort the result.
5: Determine the order of the testing sample.
accuracy measure (acc) **using the following form:**

$$Acc = \frac{Tn - (Ort - 1)}{Tn} \times 100\% \tag{5}$$

Where Tn, is the total number of samples while Ort represents the order of tested samples.

Standard EM for mixture learning shows weakness which also affects the EM algorithm it requires knowledge of the number of components for reaching good local optimum. To overcome this difficulty, many deterministic criteria are proposed to estimate the appropriate number of components in GMM. Some examples of such model selection criterion are the Akaike information criterion (AIC), the minimum description length (MDL), the Bayesian inference criterion (BIC), etc [8]. In this study (AIC) is used to determine the best number of component. When samples was trained with 50, 40, 20, 10, 4, 2 components, It found that AIC decreased as number of component decreased. Since the number of components $m \geq 2$,so $m = 2$ is an optimal number of components.

The training sample of each person was compared with all training samples in the dataset. Comparison using $Nlogl$ was established. Then the result was sorted. Table(1) shows deferent accuracy ratios and the number of samples verified using feature extraction algorithm1 FEal1, and feature extraction algorithm FEal2.

Table 1. Comparison results of GMM with FEal1 and FEal2

Ratio	FEal1	FEal2
Recognized 100%	7	6
Over 95%	25	13
Between 95% and 90%	10	14
Between 90% and 80%	18	22
Less than 80%	20	25

Figure (2) shows the accuracy ratio of all samples.

Then samples categorized according to age. Figure (3) shows the accuracy ratio of different heart samples classified according to age.

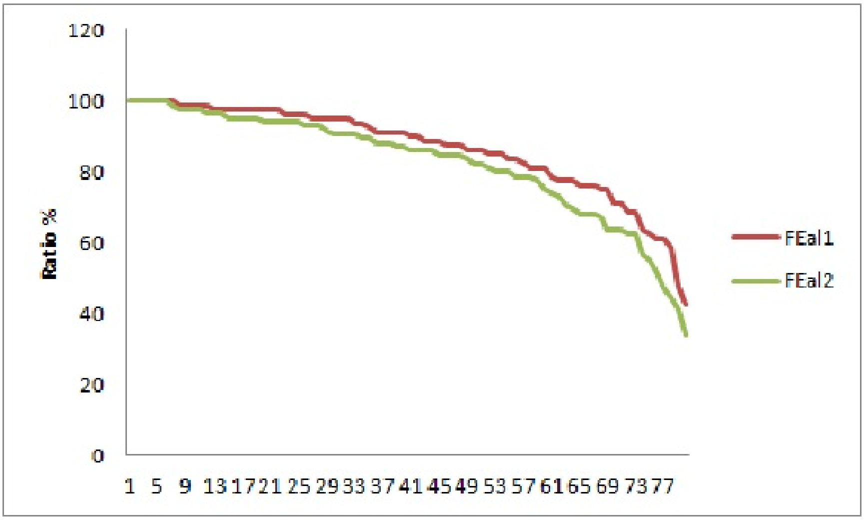

Fig. 2. Accuracy ratio for heart sound taken samples using FEal1 and FEal2

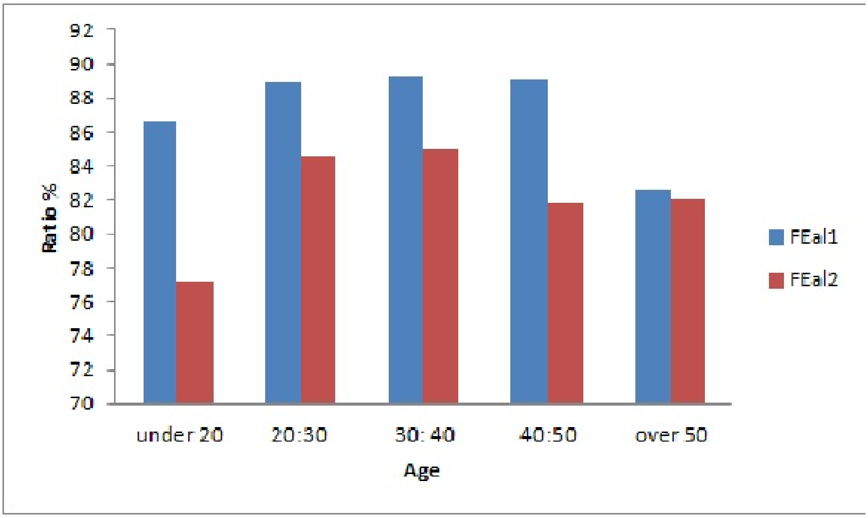

Fig. 3. Accuracy ratio according to the age of the taken samples using FEal1 and FEal2

Further investigation was done to detect the accuracy ratio for the collected heart sound samples according to the gender, figure (4) shows the accuracy ratio for the samples according the gender.

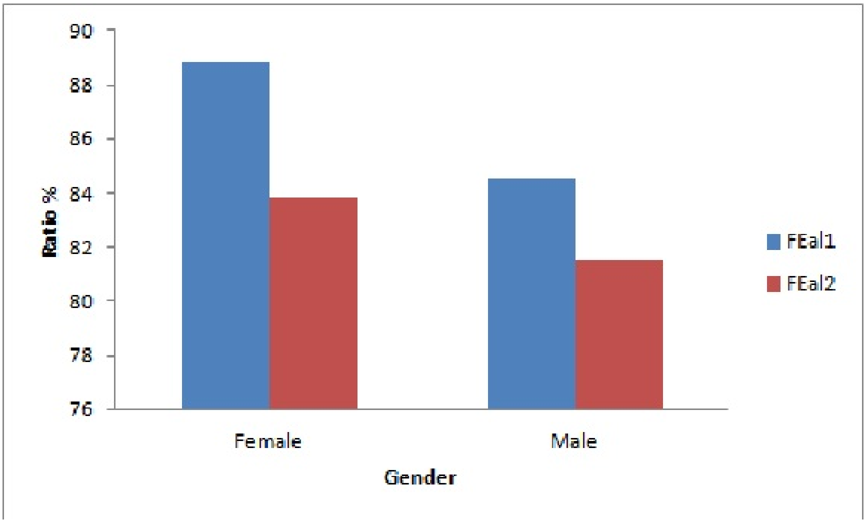

Fig. 4. Accuracy ratio according to the gender of the taken samples using FEal1 and FEal2

5 Conclusion and Further Scope of Research

In this work, the possibility of using human heart sound as a biometric for human identity verification was investigated. After a preliminary study for nearly 80 heart sound samples which were collected from 80 different persons. In our experiments, AIC was used to determine the best number of components. It found that AIC decreased as number of component decreased. So, using two components gave promising results.

Two different feature extraction algorithms were used. For the feature extraction algorithm1 the accuracy ratio was nearly the same for both male and female. But, it appeared to be more accurate in age under 50, specially between 20 and 50. The accuracy ratio reached 100% for 7 samples, over 95% for 25 samples, over 90% for 10 samples, over 80% for 18 and the rest samples accuracy ratio less than 80%. For the feature extraction algorithm2 the accuracy ratio was nearly the same for both male and female. But, it appeared to be more accurate in age over 20, specially between 20 and 40.The accuracy ratio reached 100% for 6 samples, over 95% for 13 samples, over 90% for 14 samples, over 80% for 22 and the rest samples accuracy ratio less than 80%.

Future work will concentrate on combining other biometric to achieve a more reliable authentication and identification, the effect of heart diseases or taking certain drags which effect on heart beats will be also tested. Finally, the change in heart rates caused by sporting or stop sporting after long interval of time.

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