Jurnal
Teknologi

Full Paper

Human Identification Based on Heart Sound Auscultation Point

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Article history
Received
19 April 2016
Received in revised form
20 June 2017
Accepted
10 September 2017

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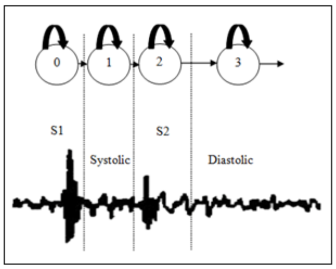
Graphical abstract



Abstract

The application of human identification and verification has widely been used for over the past few decades. Drawbacks of such system however, are inevitable as forgery sophisticatedly developed alongside the technology advancement. Thus, this study proposed a research on the possibility of using heart sound as biometric. The main aim is to find an optimal auscultation point of heart sounds from either aortic, pulmonic, tricuspid or mitral that will most suitable to be used as the sound pattern for personal identification. In this study, the heart sound was recorded from 92 participants using a Welch Allyn Meditron electronic stethoscope whereas Meditron Analyzer software was used to capture the signal of heart sounds and ECG simultaneously for duration of 1 minute. The system is developed by a combination Mel Frequency Cepstrum Coefficients (MFCC) and Hidden Markov Model (HMM). The highest recognition rate is obtained at aortic area with 98.7% when HMM has 1 state and 32 mixtures, the lowest Equal Error Rate (EER) achieved was 0.9% which is also at aortic area. In contrast, the best average performance of HMM for every location is obtained at mitral area with 99.1% accuracy and 17.7% accuracy of EER at tricuspid area.

Keywords: Identification, verification, heart sound, MFCC, HMM

Abstrak

Aplikasi pengenalan dan pengesahan manusia telah digunakan secara meluas sejak beberapa dekad yang lalu. Walaubagaimanapun, pemalsuan biometrik sukar ditangani kerana bergerak siring dengan kemajuan teknologi. Oleh itu, kajian ini dijalankan bagi mengkaji kemungkinan menggunakan bunyi jantung sebagai biometrik. Tujuan utama kajian adalah untuk mencari satu tempat optimum merakam bunyi jantung sama ada daripada aorta, pulmonik, tricuspid atau mitral untuk digunakan sebagai corak bunyi dalam aplikasi pengenalan diri. Dalam kajian ini, bunyi jantung direkodkan daripada 92 peserta menggunakan stetoskop elektronik *Welch Allyn Meditron* manakala perisian *Meditron Analyzer* telah digunakan untuk menangkap isyarat bunyi jantung dan EKG secara serentak untuk tempoh 1 minit. Sistem ini dibangunkan oleh gabungan Mel Frequency Cepstrum Coefficients (MFCC) dan Hidden Markov Model (HMM). Kadar pengiktirafan tertinggi diperolehi di kawasan aortic dengan 98.7% apabila HMM mempunyai 1 *state* dan 32 *mixtures*, Equal Error Rate (EER) yang paling rendah dicapai adalah 0.9% yang juga di kawasan aorta. Sebaliknya, prestasi purata yang terbaik dalam HMM untuk setiap lokasi diperolehi di kawasan mitral dengan ketepatan 99.1% dan 17.7% ketepatan EER di kawasan tricuspid.

Kata kunci: Pengenalan, pengesahan, bunyi jantung, MFCC, HMM

1.0 INTRODUCTION

Recently, many development of biometrics research were discovered, such as iris pattern, face recognition, signature recognition, hand geometry and speech recognition [1, 2, 3]. Most of the common biometric technologies that are used behavioral biometrics. Behavioral biometrics are traits that an individual exhibits, which can determine identity, like handwriting, speech, gait, gesture and typing patterns. Meanwhile, physical biometrics is biological aspects of a person that can determine identity, such as DNA, fingerprint, hand geometry and retina [4]. Heart sound too, can be classified as behavioral biometric, where it can be easily obtained, altered and copied by one unknowingly [5, 6].

For example, the intruder might obtain voice easily from a hidden recorder to access the system. In this research, heart sound is expected to overcome the issue. Heart sound is the result of the mechanical process of the contraction and relaxation of the heart [10]. The sound passes through the thorax and eventually reaches the chest surface, where an electronic stethoscope can be used in to acquire the sound and save it in a digital format. Each sequence of heart sound acquired can be divided into a few cardiac cycles, whereas each cycle represents one complete working cycle (systole and diastole). The two main components of each cycle are called S1 and S2 sounds. S1 is associated with the closure of the mitral and tricuspid valves during the contraction of ventricles and usually lasts about 150 ms, whereas S2 is associated with the closure of the aortic and pulmonary valve during the relaxation phase and lasts about 120 ms. Each acquired signal lasts between 20 and 70 seconds, the average duration is 43.7 seconds [9].

The heart sound cannot easily be obtained, altered and copied as it is based on intrinsic dynamic signal obtained from the body. The study of heart sound as biometric was previously done by a few researchers for human verification and identification [4, 7, 8, 9]. However, no researchers focused on the four areas of auscultation points for biometrics application. The aim of this research is to investigate the optimal auscultation points based on cepstral analysis, combined with Markov modeling.

2.0 METHODOLOGY

The process of heart sound recognition is similar to speech recognition. Like speech recognition, heart sound recognition can be divided into two parts, i.e. heart sound identification (HSI) and heart sound verification (HSV). In pattern recognition, a training phase is required. Valid users' (known as client) data need to be enrolled in the system. The enrollment phase involved the process of creating templates that contained clients' heart sound signals which stored in the database. The template refers to the digital representation of heart sound signal and it is normally consist of long string of alphanumeric characters. It is the output of the biometric algorithm, characteristics or features of the heart sound signal. In the recognition phase, the system will compare the recorded heart sound signal (known as the test data) with the preset template in the system. The desired output needed by the system is the name of one of the clients in the database. Figure 1 shows the work flow of the heart sound recognition system.

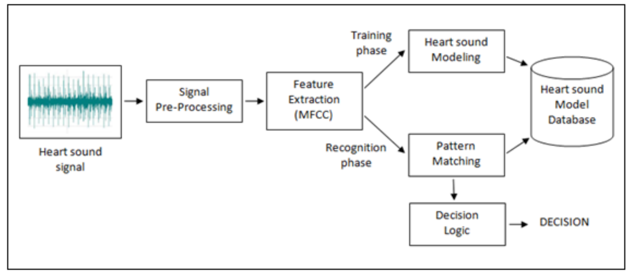


Figure 1 Flow of the heart sound recognition system

The heart sound database is designed based on the data obtained from 92 random participants who were mostly students and staff from Universiti Teknologi Malaysia (UTM) which consist of 57 females and 35 males. These participants consist of 84 Malays, 6 Chinese and 2 foreign students (Pakistan and Iranian). The heart sounds signal is recorded using a Welch Allyn Meditron electronic stethoscope and is captured using the Meditron Analyzer software application with Wave PCM signed 16 bit, 44100hz. A personal computer operated by Microsoft Windows XP was used for this study. In order to get the best heart sounds signal, the stethoscope is placed on the chest of the participant seated in relaxed position. Four locations of heart sounds readings are recorded for each participant (aortic, pulmonic, tricuspid and mitral). The electrocardiogram (ECG) and heart sound are recorded simultaneously within 1 minute for each participant to correlate the heart sounds with the phases of the heart cycle in the time relationship [11].

2.1 Pre-Processing

The preprocessing signals are the pre-analysis process of heart sounds signals in order to gain the finest and useful information of the signals. The signal pre-processing includes segmentation and feature extraction of the heart sounds signal. Iwata A. (1980) has proposed the algorithm to detect the first (S1) and the second (S2) heart sounds by detection of R-wave of electrocardiogram (ECG). The segmentation algorithm was based on the spectral analysis of the heart sounds that separated the heart sound into individual cycles (known as cardiac cycle) where each cycles representing the sound made by heart in one complete working cycle, systole (S1) and diastole (S2). Most of the techniques used previously depend on the reference of ECG signal [12, 13, 14]. The features of heart sound is then, extracted using Mel-Frequency Cepstral Coefficient (MFCC). A set of features extracted from one cardiac cycle is called a feature vector. The feature of vectors provides a more meaningful and compact representation of the heart sound than the raw signal themselves.

2.2 Mel-Frequency Cepstral Coefficient (MFCC)

The second part of the application is highlighting the regions, which have the same HSV value as the centre of the circle. In coding aspect, two thresholds are used for the filtering process. The low threshold is an array which contains the minimum of the HSV value whereas the high threshold holds the maxima of HSV value. Figure 1 shows the color benchmark, which consists of 10 different colours such as black, yellow, orange, green, purple, pink, cyan, blue, grey and red. It also have different shapes according to the color and have different sizes of sphere for red color. The prototype color detection assistive device, for experimental purposes only detects 4 base colours and HSV within its range. Besides the HSV range, the result will display unknown or not detected. MFCC is one of the most popular parameter set used in the recognition system. It is an efficient method used to extract any kind of features [15]. A "mel" is a unit of special measure or scale of perceived pitch of a tone. It does not correspond linearly to the normal frequency, in fact it is approximately linear below 1 kHz and logarithmic at the frequency higher [16]. This approach is based on the psychophysical studies of human perception of the frequency content of sounds [16, 17]. MFCC coefficients were calculated by taking a discrete cosine transform (DCT) of the logarithm spectrum scale after it was warped to the Mel scale, as shown in equation 1:

$$Mel(f) = 2595\log10(1+\frac{f}{700}) \quad (1)$$

This is similar to perceptual linear predictive analysis of sound signals. In other words, the scaling mimics the human perception of distance in frequency. The overview of steps involved in Mel-Cepstral feature extraction is shown in Figure 2.

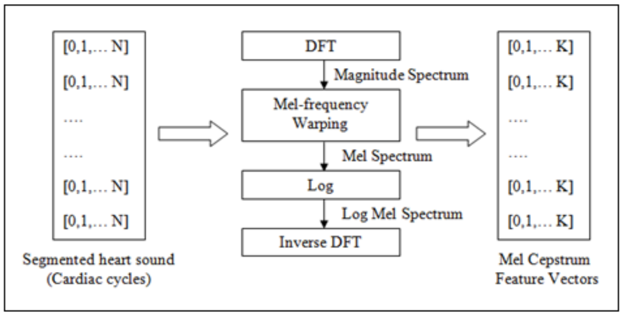


Figure 2 Feature extraction – Mel-Cepstrum

To place greater emphasis on the low frequencies, a special step called mel-scaling is inserted before the calculation of the inverse Discrete Fourier Transform (DFT). One useful way to create mel-spectrum is to use a filter bank with one filter for each desired mel-frequency component. Every filter in this bank has triangular band-pass frequency response. Such filters compute the average spectrum around each centre frequency with increasing bandwidths, as displayed in Figure 3.

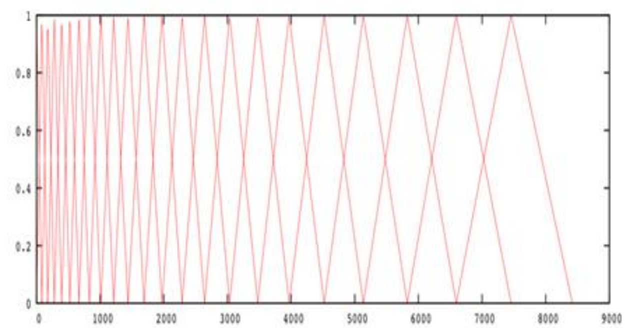


Figure 3 Mel-filters

This filter bank is applied in the frequency domain and therefore, it simply amounts to take these triangular filters on the spectrum. In practice, the last step of taking inverse DFT is replaced by taking discrete cosine transform (DCT) for computational efficiency. The number of resulting MFCC is relatively low, normally in the order of 12 to 20 coefficients. However, in many cases of MFCC analysis, the 0th coefficient of the 7 MFCC cepstrum is ignored because of its unreliability [18]. In this study, 12 coefficients of MFCC per frame are used for classification stage as it has been proven to be a relatively successful method in pattern recognition [16, 17]. The 12 coefficients were selected because the energy of S1 and S2 signals are essentially concentrated around frequencies below 200Hz [9].

2.3 Hidden Markov Model (HMM)

The HMM can be seen as a double stochastic process based on the Markov chains. It is a well-structured mathematical model hence it can easily support different input sources [19]. There are several variants of HMM. It can be ergodic, which any state is reachable from any other state, or it can be left to right, i.e. it cannot transit to a lower state from a higher state. In the speech recognition, the speech signal is usually modeled by the left-right HMM in which the state transitions are only allowed from left to right including self-transitions. This is quite reasonable because the left-right HMM can model the signals whose properties change with time in a sequential manner [20]. In this viewpoint, the heart sound signal may be modeled by the left-right HMM. A four state of left-right HMM for a cycle of the heart sound signal shown in Figure 4, correlates with the four components of heart sound signal, i.e. S1, Systolic, S2 and Diastolic [21, 22], which is denoted by N. Noted that the number of states in the HMM is usually determined based on the nature of how the signal being modeled.

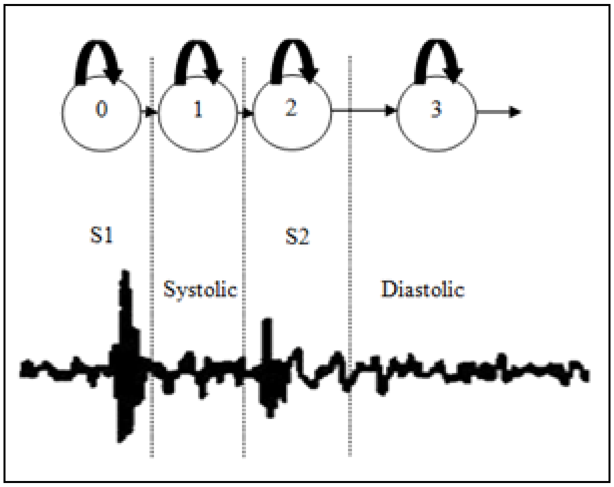


Figure 4 HMM for cycle of the heart sound signal

The 4 state of left-right HMM was sufficient to model a cycle of the heart sound signal [22]. The spectral variability in each state is modeled using multiple mixtures of multivariate Gaussian distributions. Given the observation O(t), the output probability distribution in the state j is given by the equation 2:

$$b_j\left(o(t)\right) = \sum_{m=1}^{M} c_{jm} N(o(t); \mu_{jm}, \Sigma_{jm}) \quad (2)$$

where N(o(t);µjm ,∑jm) is a multivariate Gaussian distribution, with mean vector µjm and covariance matrix ∑jm, each mixture component having an associated weight Cjm. M is the number of Gaussian mixture. The transition from the state i to j is also controlled by the transition probability as follows:

$$a_{ij} = P(j\,|\,i) \quad (3)$$

The left-right HMM assumes that the first component in the heart sound signal is S1, so the continuous heart sound is segmented into isolated cycles, which is used as the input to the left-right HMM.

The procedure of classifying the heart sound signal is shown in Figure 5 and Figure 6, where the HMM parameters µjm, ∑jm, Cjm and aij in equation 2 and 3 are used in training and testing. The HMM model is trained for each person and then in testing, each heart signal is referred to by his/her model as the maximum of the likelihood measures (conditional probability).

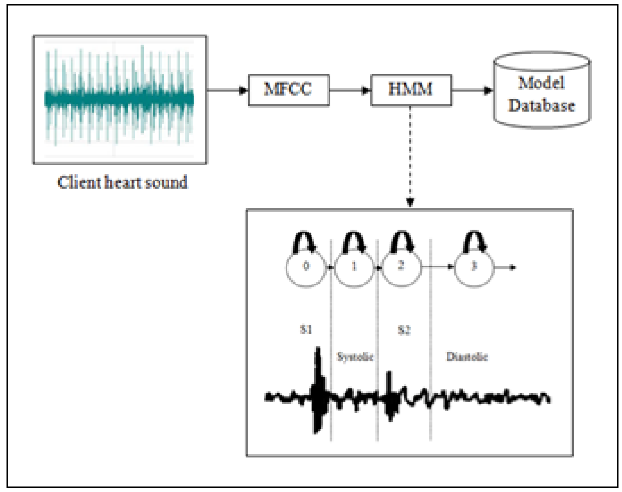


Figure 5 Training of HMM

In the testing stage, the client must first claim his/her identity using identification tag. The system retrieved model λc based on the identity, given the client as c. Then, the system obtained the score from the model as the result of the heart sound x, which is the likelihood of x. After that, the score is compared with the specified threshold θ, as illustrated in Figure 6. The system will only accept the client if the score is greater than threshold.

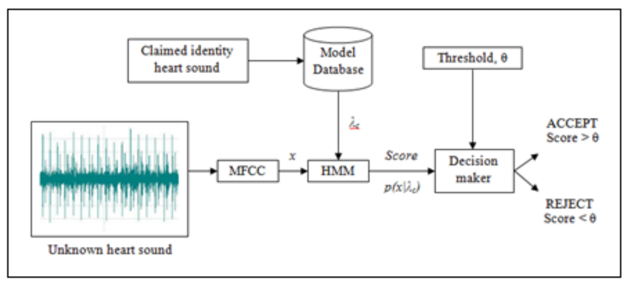


Figure 6 Testing of HMM

2.4 Experiment Set Up

As mentioned earlier in section 2, heart sound recognition can be divided into two parts, i.e. heart sound identification (HSI) and heart sound verification (HSV). There are two types of experiments conducted in this study (see Figure 7). The first experiment is carried out to evaluate the performance of heart sound identification whereas the second experiment designed to test the characteristics of heart sound to verify each person claimed. The performance of heart sound was evaluated under different parameters of HMM which is different number of state and Gaussian mixture. Each participant has 1 minute for heart sound recording which consist of a number of cardiac cycles. The cardiac cycles were separated into two which are 70 percent of them were used for training phase, while the remaining cycles were used for testing phase. The performance of HMM will be evaluated with different parameter setting, i.e. the number of state and the number of Gaussian mixture components.

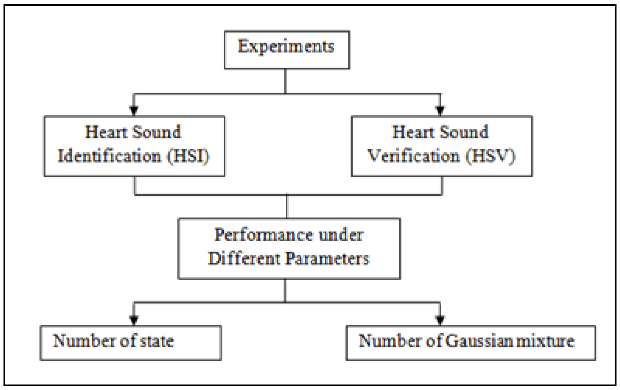


Figure 7 Arrangement of experiments in this work

Noted that the number of states in the HMM is usually determined based on the nature of how the signal being modeled. In this study, the heart sound signal may be modeled by four states of left-right HMM, as it is correlates with the four components of heart sound signal which is S1, Systolic, S2 and Diastolic. Thus, an optimal choice of the state and Gaussian mixture for HMM were tested through experiments. 10 participants were randomly selected out of the 92 participants in the database to represent the client. The experiments were conducted for every auscultation point, i.e. Aortic, Pulmonic, Tricuspid and Mitral area which was assigned as V1, V2, V3 and V4 respectively.

In identification stage, the same data set up is implemented, where 70 percent of cardiac cycles were used for training phase, while the remaining cycles were used for testing phase. Meanwhile, in verification stage the performance is measured based on EER ratio. 20 participants out from 92 participants were selected to be the client of the system. While, remaining data of 72 participants will be known as the impostors in this study.

3.0 RESULT AND DISCUSSION

The performance of HMM-based system is evaluated for four locations of auscultation. The highest accuracy yield at aortic area (V1), pulmonic area (V2) and mitral area (V4) when HMM has 1 state, which is 98.7%, 97.1% and 92.7% respectively. Meanwhile, at tricuspid area (V3), the highest accuracy is 97.1% when HMM has 4 states. In this viewpoint, it can be assumed that the result does not agree on the concept based on four components of heart sound signal described earlier.

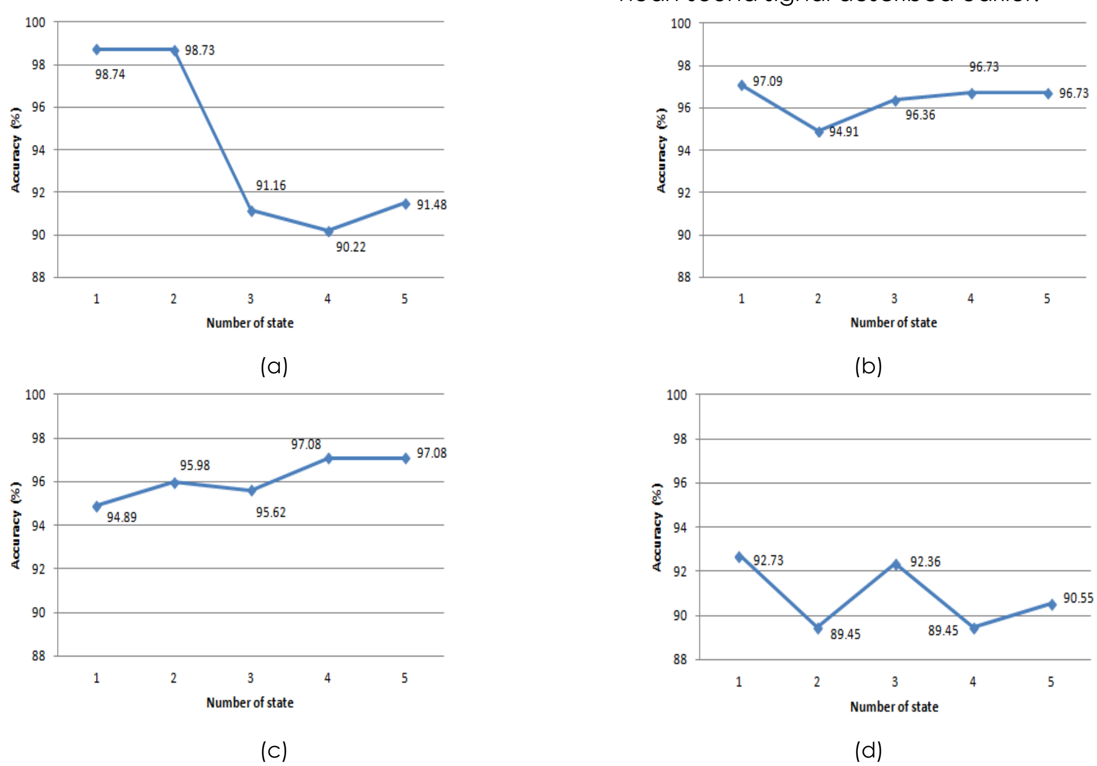
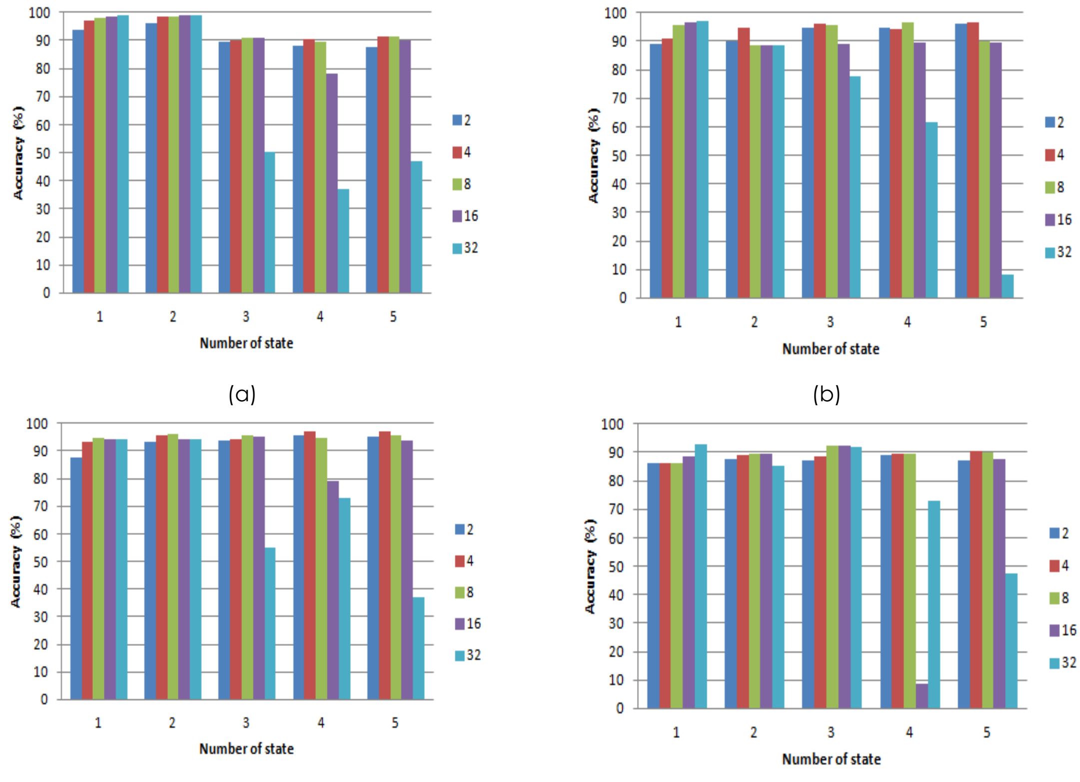


Figure 8 The performance of HMM under different state for four locations of auscultation (a) Aortic area, (b) Pulmonic area, (c) Tricuspid area and (d) Mitral area

According to Figure 8, the overall performance of HMM shown the percentage accuracy of higher than 80%. When a single state was used and Gaussian mixture components increases, the performance of HMM shows satisfactory. Meanwhile, if the number of state was increased, 32 mixture densities provide the worst results (see Figure 9). Average performance of HMM was optimal when the number of state is 1. This is because the overall highest accuracy was when HMM has state 1, even with different Gaussian mixtures. For Gaussian mixture components, the average performance of HMM was optimal when number of Gaussian mixture is 4, 8, 16 and 32. Based on Table 1, the highest accuracy achieved for every state, mostly was at four mixture densities (HMM-4). In this study, only 30% of the test data was evaluated. Further work should evaluate this system with more test data.



(a) (b) (c) (d)

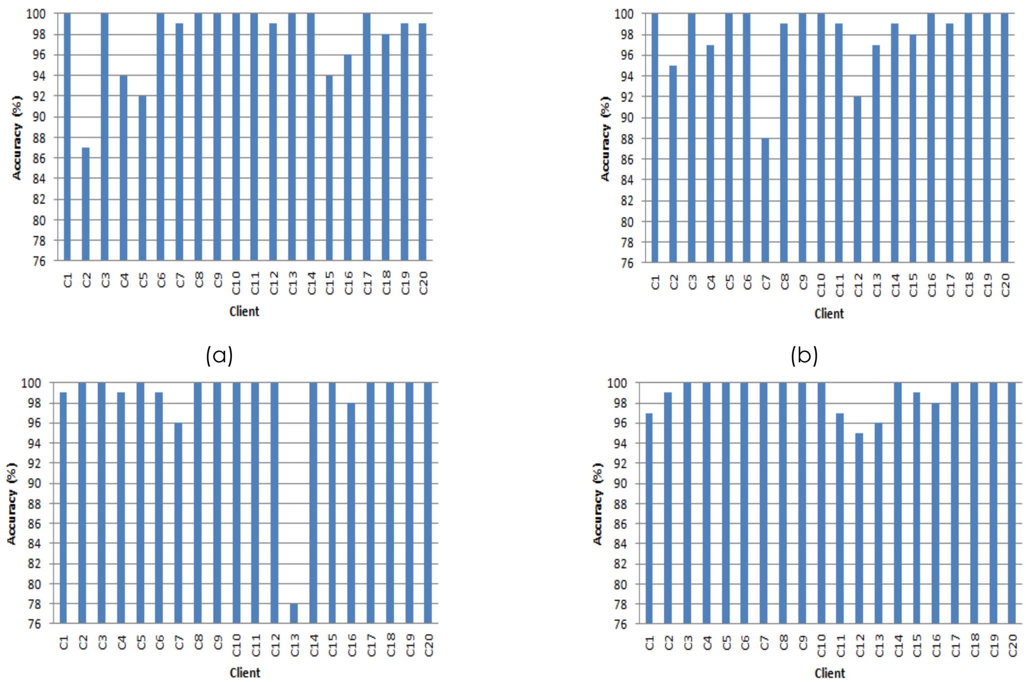
Figure 9 The performance of HMM under different state and mixture for four locations of auscultation (a) Aortic area, (b) Pulmonic area, (c) Tricuspid area and (d) Mitral area

In this research, a single state and 32 mixture densities was decided to be used in the following experiments, because it provides the highest accuracy achieved for four locations of auscultation, i.e. when HMM has 1 state and 32 mixtures.

Table 1 Determination of Gaussian mixture components at every state with the highest accuracy

State	Mixture				Accuracy (%)			
	V1	V2	V3	V4	V1	V2	V3	V4
1	32	32	8	32	98.74	97.1	94.9	92.7
2	16	4	8	8	98.73	94.9	95.9	89.5
3	8	4	8	8	91.2	96.4	95.6	92.4
4	4	8	4	4	90.2	96.7	97.1	89.5
5	4	4	4	4	91.5	96.7	97.1	90.6

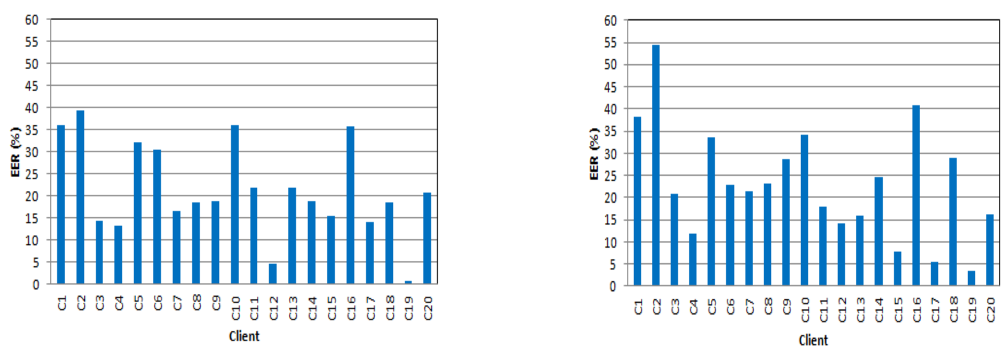
For HSI, the overall accuracy for every locations of auscultation had more than 90% accuracy as shown in Figure 10. The poor performance by certain clients may be due to the interference of noise found in their training and testing samples. In order to overcome the above issue, de-noising method [23, 24, 25] and the computational effort will be used in the future study. Based on Figure 10, there are 4 clients who have an accuracy of less than 95% at V1, while 2 clients at V2 and 1 client at V3. Auscultation point at V4 shows that all of the clients have an accuracy of more than 95%. In fact, 13 of the clients have an accuracy of 100%. The highest average is at location V4 (mitral area) with 99.1%. This might be due to all clients achieved accuracy above 95% and most of them get 100% recognition rate.



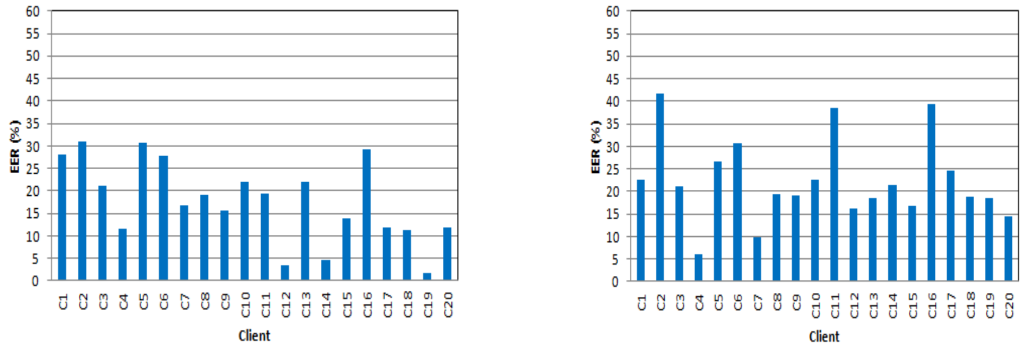
(a) (b) (c) (d)

Figure 10 The result of heart sound identification for 20 clients at four locations of auscultation (a) Aortic area, (b) Pulmonic area, (c) Tricuspid area and (d) Mitral area

The performance of HSV is shown in Figure 11, where there are considerable variations in performance across the clients. It can be seen that 2 clients at location V1 and V2 have an EER accuracy of less than 5%. V3 on the other hand has 3 clients with EER accuracy less than 5% and V4 is the worst as none of its clients has this accuracy. The figure also shows that the minimum EER ratio is obtained from client C19 with EER of 0.9%, which is at location V1 (aortic area) and the maximum is 54.4% obtained from client C2 at location V2 (pulmonic area). This is might be due to the difference of data size, where C19 has a large size of data training compared to the client C2. In this point of view, it can be indicated that the best auscultation point is at location V1 (aortic area).



(a) (b)



(c) (d)

Figure 11 Heart sound verification result at four locations of auscultation (a) Aortic area, (b) Pulmonic area, (c) Tricuspid area and (d) Mitral area

The threshold of each client is different, which can be obtained when plotting the PDF or CDF graph. In this study, the threshold is set at the intersection point of the client and impostor scores. This point also known as EER. For example, Figure 12 shows the PDF and CDF graph for client C19, where the red line is impostor scores, while the blue line is represented client scores.

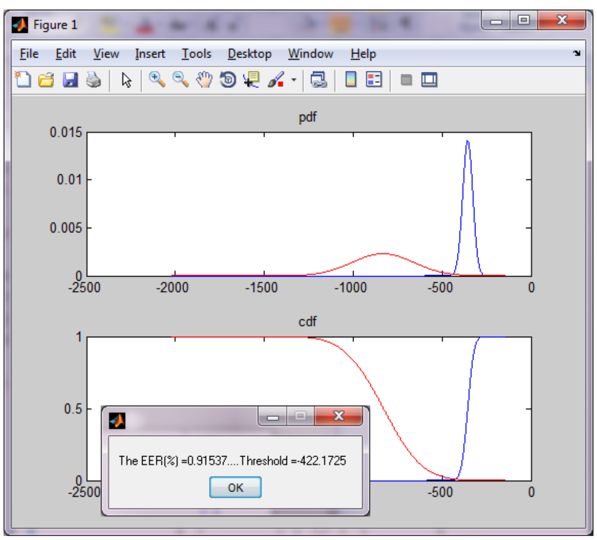


Figure 12 PDF and CDF graph for client C19

4.0 CONCLUSION

Study have shown that none of the biometric research [4, 7, 8, 9, 20, 22, 26] have yet focuses on the four locations of auscultation. This study has therefore covered the idea mentioned previously. Four locations of heart sound are recorded where each location provides different values of sound in term of psychology. The study carried out in this thesis also investigates the optimal auscultation points that can be used in biometric. The combination of MFCC-HMM method was implemented in this study. The performance of this method was evaluated using heart sound data which has been built over a period of 5 months. Several factors are obtained based on the performance of the system. First, the different auscultation point provides different performance of the system. Secondly, HMM with one state provide better performance at location V1, V2 and V4, exception for V3, the highest accuracy is from HMM with 4 states. Third factor that can be seen is that more test data are needed to evaluate the system performance.

Acknowledgement

The authors would like to thank the Centre for Biomedical Engineering, Universiti Teknologi Malaysia and the Ministry of Education Malaysia under FLAGSHIP Research University Grant (Q.J130000.2409.03G01) for providing the research facilities.

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