Malaysian Journal of Industrial Technology, Volume 2, No. 2, 2017
ISSN: 2462-2540

MJIT 2017 Malaysian Journal of Industrial Technology

HMM BASED BIOMETRIC SYSTEM USING CARDIAC SIGNALS

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Abstract

A pattern recognition system which is able to recognize a user is essentially referred to as a biometric system. In this paper, two types of biometric signals were used to build the proposed multimodal biometric system; the Electrocardiogram (ECG) and Heart Sound (HS). The ECG and HS data are not commonly used as biometric due to the signal characteristic complexity which make it very hard to duplicate and more immune to spoof attacks. This work was conducted for Client Identification (CID) with fixed 20 clients, the data were sampled at 44 kHz for the two biometric signal. An adaptive windowed approach of Mel Frequency Cepstral Coefficients (MFCC) was used to extract the features. The extracted features then partitioned into train and test sets, the train set fed to Hidden Markov Model (HMM) to create the independent-client trained model. The purposed biometrics system is based on the performance of two folds of training sets, 30% and 70%. Complexity of states and Gaussians also plays a role on the performance. The best performance for CID with 44 kHz, evaluated with 20 clients is based on HS which provide an accuracy of 93.04% with training data of 70%. The worst performance goes to 87.89% for ECG at 30%.

Keywords: Client identification; Mel Frequency Cepstral Coefficients; Electrocardiogram; Hidden Markov Model

1.0 INTRODUCTION

Biometrics application has risen to become new standard of security. There are wide range of types of biometric signals to choose from. A palm vain recognition [1], [2] is also widely used and it has the ability to operate in challenging environment. The vain recognition has its weaknesses, which are inherently limited accuracy. Another common biometric is Iris recognition that is resistance to false matching. Once enrolled, the stability over the feature of individual characteristic is of a lifetime. Speech recognition lack of negative perception [3], [4], usable friendly but its weakness is ambient noise. Signature biometric is perceived as non-invasive [5], [6] but inconsistence of signature lead to increase in error rates. There are many type of biometric that can be used and each has it advantage and disadvantages. However it also depends on the application and where its implemented. Futhurmore HS and ECG are still new area of research being explore for biometric application compared for example to speech biometric. There is still an extensive work need to be done on this area. The work conducted in the study uses liveliness biometric signals, which mean the data taked from a clients reqires themselves to be aware and permission to retrive. This makes the system secure as it isn't esily stolen and be prone to spoof attacks. Since ECG and HS is a biosignals, the shape and features of the data is uniques and varies from others, duplicating or forging these signal would be difficult for this time point.

This research focused on the development of a single platform that can perform biometric security [7], [8], [9], [10], and [11] which address the problems discussed by other researcher. A biometric evaluation platform is composed of a start/end point, feature extraction and Markov model. In this study, a CID approach to enhance the performance of the biometric system in order to achieve higher accuracy was suggested in comparison to the other standard CID based biometric system [12], [13], [14], [15]. The methodology and the experimental will be discussed in the next session.

2.0 EXPERIMENTAL

Figure 1 show the biometric evaluation platform. Experimental results are evaluated based on the each biometric signals, percentage split of data training (30% and 70%), the increments of client, and complexity of the states and Gaussians classifications. The database consists of 2 biosignals, and the first evaluation of the biometric system is the CID experiments. The performance of HMM varies strongly with the amount of data being trained.

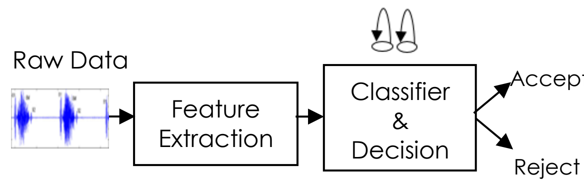

Fig. 1. Block diagram for biometric system

Data based

The database used to evaluate the system is trained with training data of each cycle for the construction of the states and Gaussian model. The model is conducted for 20 clients for ECG and HS. The complexity of stats and Gaussian is conducted for states 1 to 5, and Gaussian 4 to 16.

The data are trained according to the percentages split data training (30% and 70%) for each of the biometric signals which will model the CID system. The frame sizes are 20ms with 15ms overlap. Using standard MFCC analysis [16], [17] feature vector consist of 12 MFCC coefficient were extracted every 20msec from the speech. The same feature extraction technique was carried out also for the other two biosignals.

Feature Extraction

The biometric system is based on MFCC. The MFCC features are robust (especially for speech and heart sound) [18]. The signals will undergo several steps, which are pre-emphasis, Hamming windowing, Fast Fourier Transform FFT, triangular band pass filter, and Discrete cosine transform DCT. 12 MFCC is used to run all the experiments.

Classification

The HMM model is an extended version of the Markov chains, where in each state does not correspond to any of the observable event, but is able to connect to a set of probability distributions of a state. The HMM model is noted to be a very effective model that is popular in the speech processing domains [19], [20], [21], [22]. The HMM model used in this study is a 4-state left-to-right HMM model and can be seen in Figure 2.

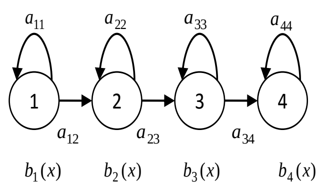

Fig. 2. Representation of the left-to-right HMM

3.0 RESULTS AND DISCUSSION

Table I, shows the CID for 44 kHz for 20 clients. The two biometric signals is conducted for 30% and 70% data training and the rest assigned to testing dataset. The database is split into train and test. Training the data for 30% reqires less time computations compared to training the data for 70%. However what lacks in computation time, could also mean a boost in performance of the system. The experiment was conducted to also explore which would perfroms better.

Figure 3, shows the bar plot of the comparison between the percentage split of data training. Based on the bar plot itself, 70 % outperforms the 30% data training. This seems to suggest that training with more data, increases the accuracy performance for both case of the biometric signals.

Table I. Best CID for 44 KHz.

Best Client Identification for 44 kHz for 20 clients		
	30 %	*70 %*
ECG	87.89	90.72
HS	89.87	93.04

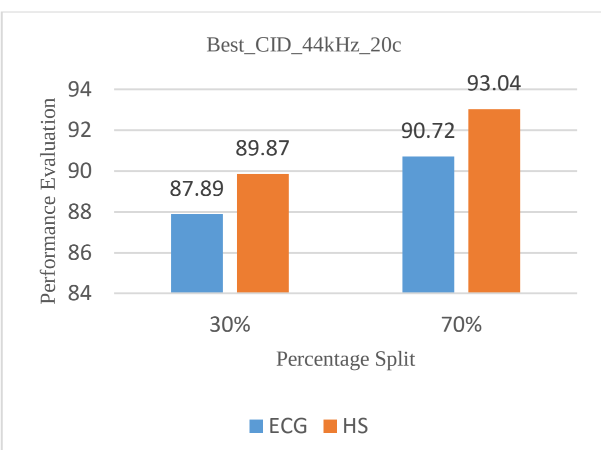

Fig. 3. Best CID for 44 kHz for 20 clients

Figure 4 and Figure 5 shows the performance being evaluated in terms of the complexity of states and Gaussians based on 30% of training data and 70% of training data. Based on the graph both 30% and 70% shows an almost similar pattern. Its shows a gradual increments on performances as the states and Gaussian increments.

The graph also shows HS is more stable and consistence with outcome for both case of training data. Same cannot be said towards ECG performance, though both 30% and 70% gradually increased. The ECG performance started at a lower point compared to HS and increased drastically towards the end. 70% gives the best result outcome for accuracy 90.72% for ECG and 93.04% for HS.

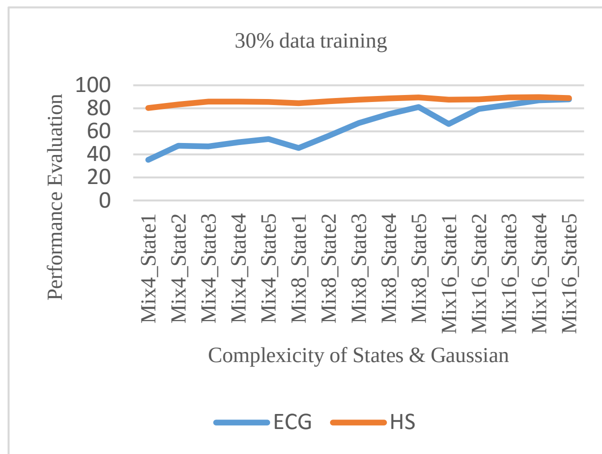

Fig. 4. Performance based on 30% data training

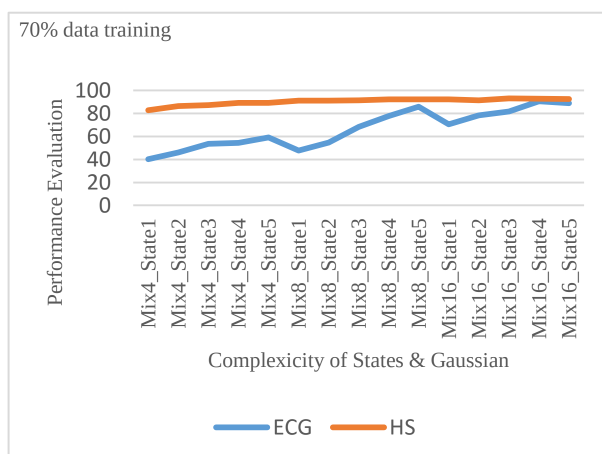

Fig. 5. Performance based on 70% data training

4.0 CONCLUSION

The best overall performance for 44 kHz for 20 clients achieved an accuracy of 93.04% for HS at 70% of data training. The worst overall performance falls at 30% ECG at 87.89%. Overall performance shows that there is a significant improvement of training the data between 30% and 70% at maximum complexity of states and Gaussian of state 5 Gaussian 16.

5.0 FUTURE WORK

Currently, we are working on a switching linear dynamics system of piece wise stationary autoregressive (AR) process for segmentation the heart sound into the fundamental components of first heart sound, systolic, second heart sound and diastolic. The work intend to capture both the continuous state space in the hidden dynamics of the phonocardiogram (PCG) recordings using regime switching [23] and [24] in dynamics using discrete Markov Chain. This is to overcomne limitations of HMMs which is based on a single layer of discrete states. Preliminary results indicate the proposed techniques has the ability to classify each heart beat (segment).

In another area, the key challenge in analysing biological network is the classicle problem of high dimensionality. The brain will consists of huge number of nodes, which involves massive spatio-temporal data and requires estimates of very high dimensional correlation matrics. To overcome this problems, we are developing a milti scale factor analysis (MFSA) model which can handle massive data. Preliminary result is shown in Figure 6.

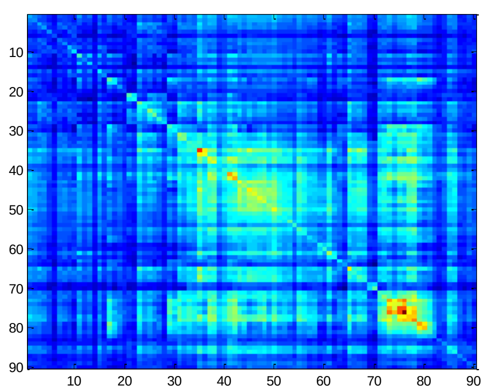

Fig. 6. Covariance matrix y from raw data

The plot represents the clean data without noise. It is driven by Q loding and the factor loding f parameters, using static principle component analysis (PCA). The effects of heart activity on brain function has been research extensively over the past years. Extension to the above work we are studying how the heart activities is correlated with large scale scale patterns of [25] and [26] of the brain functions. Although, there is much to understand, it appears that the above proposed solutions could show the Region of Interest (ROI) are inter-connected within common function and anatomical domains, revealing distinct pattern that can be used in applications such as brain diagnosis for epilepsy, stroke, and even brain signals biometrics.

Acknowledgement

The authors would like to express their appreciation and thanks, Universiti Teknologi Malaysia and the Ministry of Higher Education of Malaysia (MOHE) for the support, Project No (TRGS R.J130000.7845.4L841) and (TRGS R.J130000.7831.4L845) and UTM Zamalah Scholarship.

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