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Analysis of ECG Biosignal Recognition for Client Identifiction

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Abstract— **The most common application for a recognition system of speech signal, finger print, iris, etc. are used for biometric applications. While other biometric signals like electrocardiogram (ECG) and the Heart Sound (HS) are generally used to identify cluster-related diseases. Nonetheless, performance of a traditional biometric system can be easily compromised as it is prone to spoof attack. This paper proposes a unimodal biometric security system that is based on ECG. Physiological biometrics characteristic are based on a human body's, such as the hand geometry, face, palm, ECG and even brain signal. The biosignal data collected by a biometric system would initially be segmented. The Mel- Frequency Cepstral Coefficients (MFCC) method is used for extracting each segmented feature. The Hidden Markov Model (HMM) is used to model the client, and categorize unknown input based on the model. The recognition system involved training and testing of the collected features, known as Client Identification (CID). In this paper, 20 clients were tested with this developed system. The best overall performance for 20 clients at 16 kHz was 71.4% for ECG trained at 50% of the training data, while the worst overall performance was 66.6% for 30% training data.**

Keywords— Electrocardiogram, Hidden Markov Model, Mel-Frequency Cepstral Coeffiecients, Client Identification

I. INTODUCTRION

The ECG involves a universal human characteristic that can be recorded, and has distinct features, which no two individuals would have. There have been debates on how the ECG can comply with the requirements for biometric characteristics. Various health issues may affect the security of a patient's privacy. This may involve the patient's right to determine when, how, and to what extent do they share their health information with other individuals. Such information may not only be confined to the patient's personal data, namely, age, sex, height, and weight, it could also be related to medical information, such as heart murmurs, auditory brain stem responses or even cancer. These types of information need to be protected because a person has the right to their own privacy. Patients should be able to share such information with other individuals, by their own will. Electronic medical information requires appropriate security while being transferred between healthcare managements. In such cases, physicians can make the right decisions with a certain level of access to relevant information from the patient's medical history, while the patient reserves the right to maintain privacy and other confidential health information. Consequently, researches have been conducted to develop a recognition system based on ECG to mitigate problems with biometric human identification. The current development of ECG signals within a biometric system has proved to be a useful diagnostic tool for clinical purposes [1] [2]. Other types of biometrics, such as facial recognition [3] [4] could produce a poor performance when it is affected by the environment (e.g., poor lighting condition), while speech recognition can be seriously affected by ambient noise [5] [6].

Previous findings support the use of ECG as the biometric characteristics in healthcare management. Nonetheless, proper precaution should be taken because there are still issues with whether the ECG is unique enough. Its feasibleness for classifying large numbers of individuals in the general population must be determined. Thus, this has become a different perspective in the field of biometric technologies, with potential application of ECG in this area.

II. METHODOLOGY

The ECG biometric system is a pattern recognition system that extract specific features from the acquired data which is then trained with HMM. The following steps are involved in this developed system:

- The ECG data is recorder by contact electrodes.
- The signal is preprocessed, and segmented.
- The desired features are extracted using MFCC.
- The extracted data is classified accordingly.

A block diagram of the training process is shown in Figure 1.

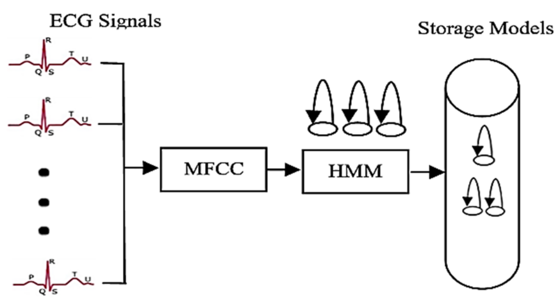

Fig. 1 The process flow of the biometric signals of ECG being trained

This study used the CID and applied them to ECG signals. The numerical score obtained from the probabilistic model was changed into a discrete label for test instances. The class with the highest score was chosen for that test instances as part of a particular class of importance. A Markov Model approach was applied to classify the ECG's bio-signals. The classification model will segment unseen test instances into features, as characterized by the class label.

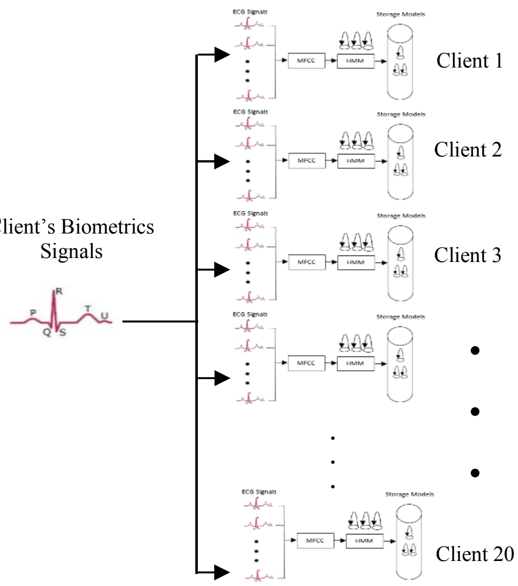

Fig. 2 Testing the ECG biometric signal.

Significant factors include splitting the data into training and testing sets, sampling frequency, and the complexity of Gaussians and the states [9].

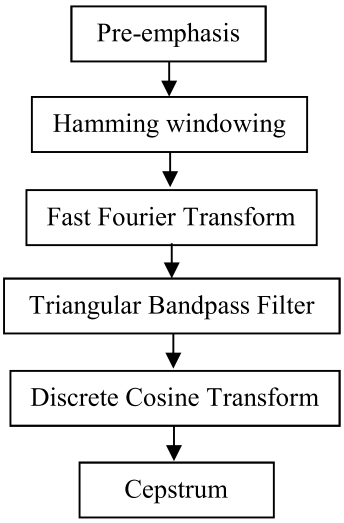

Fig. 3 MFCC flow diagram.

Figure 3 show the flow diagram of the MFCC feature extraction. Pre-emphasis, is where the signal s(n) is sent to a high-pass filter

$$s2(n) = s(n) - a * s(n-1)$$

Where $s2(n)$the output signal and the value of the filter coefficient is a is usually between 0.9 and 1.0.

The goal of pre-emphasis is to amplify the importance of high-frequency formants. Each frame has to be multiplied with a hamming window in order to keep the continuity of the first and the last points in the frame.

Fast Fourier Transform (FFT) is usually performed to obtain the magnitude frequency response of each frame. we assume that the signal within a frame is periodic, and continuous when wrapping around.

With the use of a Hamming window, the harmonics in the frequency response are much sharper. To extract an envelope-like features, we use the triangular bandpass filters, where the signals are multiplied by the magnitude frequency response by a set of 20 triangular bandpass filters to get the log energy of each triangular bandpass filter. The positions of these filters are equally spaced along the Mel frequency, which is related to the common linear frequency f by the following equation:

$$mel(f) = 1125 * ln(1 + f/700)$$

Discrete cosine transform (DCT), is applied on the 20 log energy $E_k, \{k = 1, \ldots, 20\}$ obtained from the triangular bandpass filters to have L mel-scale cepstral coefficients. 12 MFCC is selected. The formula for DCT is,

$$C_m = S_k = 1Ncos[m * (k - 0.5) * p/N] * E_k, m = 1,2, \ldots, L$$

The HMM model used in this study is a 4-state left-to-right HMM model and can be seen in Figure. 4.

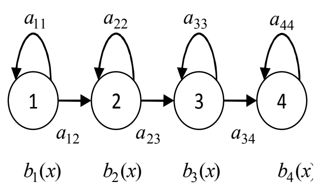

Fig. 4 Representation of the left-to-right HMM.

The following parameters characterizing the HMM

- π_i represents the initial state probability vector,
- $A = |a_{ij}|, 1 \leq i, j \leq N$ is the state transition matrix probability transition
- B represents the observation probability functions

A Gaussian mixture density is the weighted sum of the densities of the M component, given by,

$$p(\vec{x}|\lambda) = \sum_{i=1}^{M} P_i b_i(\vec{x})$$

where x is the D-dimensional random vector, $b_i(x)$ with $i = 1, 2, 3, \ldots M$ are the component's density, and p_i with $i = 1, 2, 3, \ldots M$ are the mixture weight. The Gaussian model must be trained to create each client's specific model. When the models for the clients were ready, they were tested with the allocated training data.

III. Performance Evaluation

The evaluation process used by this study was based on the percentage of accuracy from 20 client's datasets, with a plot of the 20-client score. Depending on the application, the security threshold can be client-specific or client-dependent thresholds. In this study, a client-specific threshold was used during the experiment.

IV. Results and Discussion

According to Table I, the performance of the ECG-based biometrics with 30% of training data had varied from 20% to 64.8%. Additional tests were conducted to improve the system's performance. Thus, the training data was increased from 50% to 70%, which are shown in Table II and Table III, respectively. These tables show the performance differences with different states and different Gaussian distributions. For example, in Table I the first column assume that the one ECG cycle follow a Hidden Markov model with single state with a different sets of Gaussian Mixture model (from 4 Gaussian up to 64 Gaussian). However, the first row in the table represent 4 Gaussian Mixtures model, the 4 Gaussian model here is not strong enough to fit on the testing data, clearly can be seen in Table1, table 2, and table 3 for Gaussian Mixture model of 4, regardless of the training data size. But as the complexity of Gaussians increases the accuracy, the models show a steady increment as we increased the model complexity of states and Gaussian.

Table IV, is the identification table, to which the average accuracy for 20 clients are value at 66.58% for 30% training data. Each one of the box in Table I, has the average value for the same 20 clients as the states and Gaussian increased. Table I, accumulates and simplifies Table IV, and highlight represent the best performance from the batch.

TABLE I. CID PERFORMANCE RESULTS FOR ECG BIOSIGNALS AT FREQUENCY SAMPLING OF 16 KHZ FOR 30% TRAINING DATA.

ECG CID 16 Khz 30% 20 clients					
	State 1	State 2	State 3	State 4	State 5
GM4	20.55	18.66	27.30	26.24	36.64
GM8	20.42	36.63	39.84	41.40	45.33
GM16	39.41	45.57	51.69	53.21	50.18
GM32	49.46	52.76	53.17	59.04	65.95
GM64	50.23	58.35	63.60	66.58	64.82

TABLE II. CID PERFORMANCE RESULTS FOR ECG BIOSIGNALS AT FREQUENCY SAMPLING OF 16 KHZ FOR 50% TRAINING DATA.

ECG CID 16 Khz 50% 20 clients					
	State 1	State 2	State 3	State 4	State 5
GM4	20.31	20.72	23.05	26.14	33.05
GM8	21.27	32.65	41.95	43.25	44.63
GM16	44.11	48.69	55.37	50.32	59.41
GM32	54.05	54.72	59.44	62.77	71.37
GM64	61.08	59.76	65.66	66.99	67

TABLE III. CID PERFORMANCE RESULTS FOR ECG BIOSIGNALS AT FREQUENCY SAMPLING OF 16 KHZ FOR 70% TRAINING DATA.

ECG CID 16 Khz 70% 20 clients					
	State 1	State 2	State 3	State 4	State 5
GM4	21.52	22.45	22.00	23.30	31.43
GM8	21.78	34.67	36.63	42.83	44.27
GM16	45.39	51.23	54.23	57.50	55.47
GM32	52.81	58.59	60.48	57.55	63.47
GM64	63.78	62.95	68.20	68.57	70.11

Tables IV, V, VI show the confusions matrix for Client 1 to Client 20. The best overall performance was obtained with 50% training data, with an average accuracy of 71.4%, for the 20 clients. Client 1 has the worst score, which was only 38.9%, while the best score of 100% came from Client 6 and Client 20.

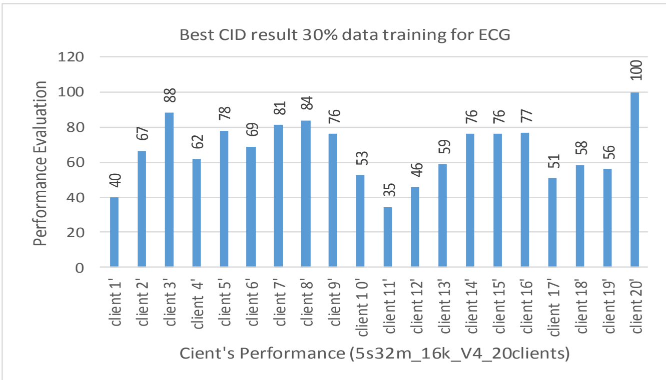

Fig. 5 The bar graph of the identification table for clients' data performance of 20 clients for CID ECG at 30%.

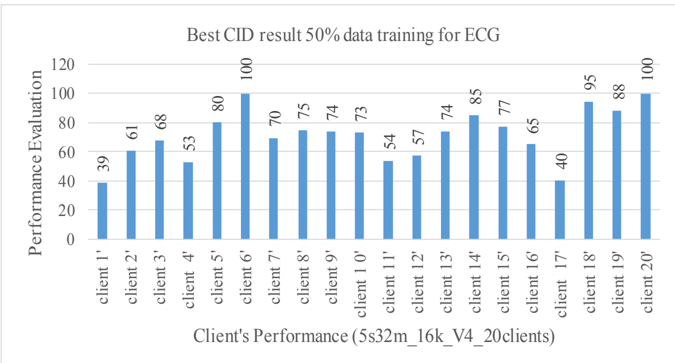

Fig. 6 The bar graph of the identification table for clients' data performance of 20 clients for CID ECG at 50%.

Figure 5, Figure 6, and Figure 7 show the detailed clients' bar graph of biometric data signal performances for 30%, 50%, and 70% training data used for ECG. The performance difference for 30% to 50% of training data was 4.79%, while the performance difference for 50% to 70% was 1.29% (see Figure 8).

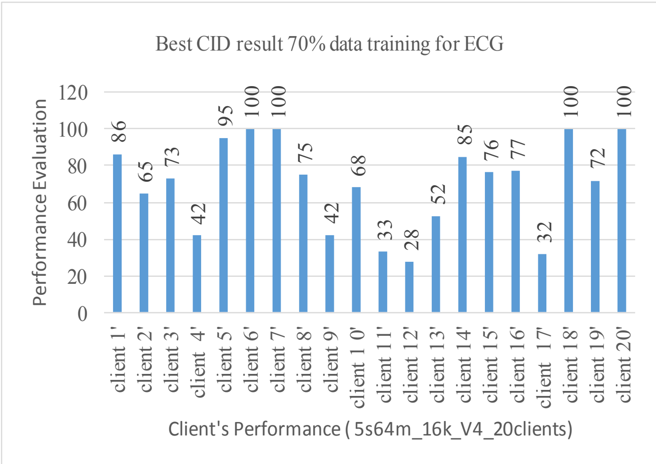

Fig. 7 The bar graph of the identification table for clients' data performance of 20 clients for CID ECG at 70%.

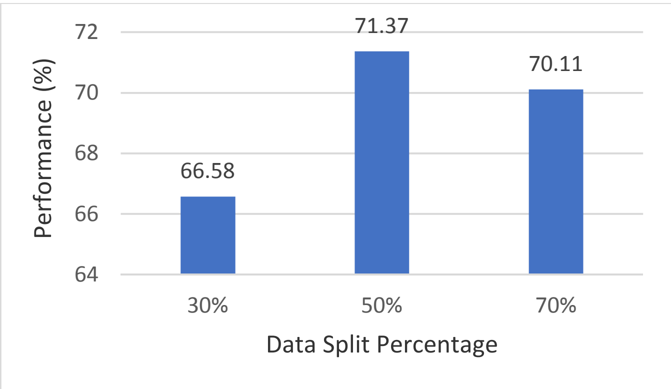

Fig. 8 The bar graph for clients' identification system with different percentage spilt.

The MFCC-HMM approach is often used in speech recognitions. The MFCC features involves an auditory bandwidth (sound). Voice is based on sound, and this feature has been successfully used in this area. It is predicted the ECG would not performed as good as speech because the ECG is based on electrical signals [10], where else speech signals is based on acoustic sound. The MFCC used in this study would be more suitable with signal based on sound rather than based on electrical signals. Thus, applying MFCC for ECG might not have been suitable for this application. Furthermore, sampling at 16 kHz, might still not be significant enough as it is still considered as a low sampling rate.

The validity of using ECG for biometric recognition is supported by the fact that physiological and geometrical differences of the heart for different individual's results in different characteristics of their ECG or heart sound signals [10], [11], and [12]. A study by [10] shows that in order to obtain reliable performance of ECG biometrics, it is not suitable to use lower sampling frequency, thus higher sampling is required to minimize the classification rate.

In other cases, types of database used also play a factor. ECG and HS are considered to be biosignals and unlike speech signal which is commonly applied to HMM. The two biosignals are still quite relatively new and have room for contribution. Furthermore much of the studies are based on medical applications. This paper proposed the HMM model for a healthy person specifically design for a biometrics system for security application. Extensive research has been carried out to study the design of the Markov Model which includes the number of Gaussian parameters, states and the scalability factor of the data in order to obtain achievable accuracy.

Table IV: Client's Confusions Table for Best 30% ECG Biosignals at Frequency Sampling of 16 kHz Percentage Split

Best CID result 30% ECG 4s64m_16k_V4_20clients																					
	client 1'	client 2'	client 3'	client 4'	client 5'	client 6'	client 7'	client 8'	client 9'	client 1 0'	client 11'	client 12'	client 13'	client 14'	client 15'	client 16'	client 17'	client 18'	client 19'	client 20'	accuracy %
client 1'	20	0	1	2	0	0	0	10	0	0	3	2	5	0	4	0	2	1	0	0	40.00
client 2'	6	26	0	1	0	0	0	0	0	0	1	3	0	0	1	1	0	0	0	0	66.67
client 3'	0	0	46	0	1	0	0	0	0	0	1	4	0	0	0	0	0	0	0	0	88.46
client 4'	3	2	1	44	9	0	1	2	0	0	3	0	0	0	1	3	1	1	0	0	61.97
client 5'	0	1	0	6	39	0	0	1	0	0	0	0	0	0	0	3	0	0	0	0	78.00
client 6'	3	0	0	4	2	31	0	0	0	0	0	0	4	0	1	0	0	0	0	0	68.89
client 7'	0	0	0	1	0	0	26	0	3	0	2	0	0	0	0	0	0	0	0	0	81.25
client 8'	1	1	0	2	0	0	0	47	0	2	1	1	1	0	0	0	0	0	0	0	83.93
client 9'	0	0	1	0	0	0	2	4	45	0	3	1	0	0	1	0	0	2	0	0	76.27
client 1 0'	0	0	5	0	0	0	1	21	0	30	0	0	0	0	0	0	0	0	0	0	52.63
client 11'	0	3	3	1	1	0	3	9	0	0	19	9	0	0	1	0	2	4	0	0	34.55
client 12'	2	1	6	3	0	0	0	6	0	1	8	27	0	0	0	0	2	3	0	0	45.76
client 13'	11	0	0	1	2	0	0	5	0	0	0	0	29	0	1	0	0	0	0	0	59.18
client 14'	0	0	6	0	4	0	0	0	0	0	1	0	0	35	0	0	0	0	0	0	76.09
client 15'	2	0	0	3	2	0	0	2	0	0	1	0	2	0	38	0	0	0	0	0	76.00
client 16'	2	0	0	1	5	0	0	0	0	0	1	0	1	0	0	46	0	0	4	0	76.67
client 17'	0	0	4	4	0	0	2	5	4	0	8	1	0	0	0	0	30	1	0	0	50.85
client 18'	0	1	1	8	0	0	1	0	2	0	0	3	1	1	0	1	3	31	0	0	58.49
client 19'	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	22	0	0	33	0	55.93
client 20'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	100.00
Average																					66.58

Table V: Client's Confusions Table for Best 50% ECG Biosignals at Frequency Sampling of 16 kHz Percentage split

Best CID result 50% ECG 5s32m_16k_V4_20clients																					
	client 1'	client 2'	client 3'	client 4'	client 5'	client 6'	client 7'	client 8'	client 9'	client 1 0'	client 11'	client 12'	client 13'	client 14'	client 15'	client 16'	client 17'	client 18'	client 19'	client 20'	accuracy %
client 1'	14	0	0	0	0	0	0	5	2	1	1	2	10	0	0	0	0	1	0	0	38.89
client 2'	4	17	1	0	0	1	0	0	0	0	0	1	1	0	2	0	0	1	0	0	60.71
client 3'	0	0	25	0	0	0	0	0	0	2	0	2	0	4	0	0	0	4	0	0	67.57
client 4'	0	2	1	27	6	1	0	0	0	1	1	2	4	0	2	0	0	1	3	0	52.94
client 5'	0	0	0	1	28	3	0	0	0	0	0	0	3	0	0	0	0	0	0	0	80.00
client 6'	0	0	0	0	0	32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00
client 7'	0	0	0	0	0	0	16	0	4	0	1	0	0	0	1	0	1	0	0	0	69.57
client 8'	1	2	0	0	0	0	0	30	0	5	0	0	2	0	0	0	0	0	0	0	75.00
client 9'	3	0	0	0	0	0	2	0	31	0	0	4	1	0	0	0	0	1	0	0	73.81
client 1 0'	0	0	5	0	0	0	0	5	0	30	0	0	0	1	0	0	0	0	0	0	73.17
client 11'	0	3	1	1	1	0	0	3	0	0	21	8	0	0	0	0	0	1	0	0	53.85
client 12'	0	0	1	4	0	0	0	6	0	1	1	24	0	1	0	0	0	4	0	0	57.14
client 13'	2	0	0	0	1	5	0	0	0	0	0	0	26	0	1	0	0	0	0	0	74.29
client 14'	0	1	2	0	0	0	0	0	0	1	0	0	1	28	0	0	0	0	0	0	84.85
client 15'	0	0	0	0	2	2	0	0	0	0	0	0	4	0	27	0	0	0	0	0	77.14
client 16'	2	1	0	1	2	0	0	0	0	0	0	0	0	0	0	28	0	0	9	0	65.12
client 17'	0	0	1	4	1	0	2	0	2	2	4	3	0	0	0	0	17	6	0	0	40.48
client 18'	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	36	0	0	94.74
client 19'	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	4	0	0	37	0	88.10
client 20'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	36	100.00
Average																					71.37

Table VI: Client's Confusions Table for best 70% ECG Biosignals at Frequency Sampling of 16 kHz Percentage split

Best CID result 70% ECG 5s64m_16k_V4_20clients																					
	client 1'	client 2'	client 3'	client 4'	client 5'	client 6'	client 7'	client 8'	client 9'	client 1 0'	client 11'	client 12'	client 13'	client 14'	client 15'	client 16'	client 17'	client 18'	client 19'	client 20'	accuracy %
client 1'	19	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	86.36
client 2'	4	11	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	64.71
client 3'	0	0	16	0	0	0	0	0	0	1	0	1	0	1	0	0	0	3	0	0	72.73
client 4'	1	0	0	13	6	0	0	2	0	0	1	0	0	0	3	0	1	4	0	0	41.94
client 5'	0	0	0	0	20	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	95.24
client 6'	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00
client 7'	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00
client 8'	0	0	0	0	0	0	0	18	0	5	0	0	1	0	0	0	0	0	0	0	75.00
client 9'	7	1	0	0	0	0	2	0	11	0	2	1	0	0	0	0	0	2	0	0	42.31
client 1 0'	1	0	2	0	0	0	0	5	0	17	0	0	0	0	0	0	0	0	0	0	68.00
client 11'	2	1	0	0	0	0	0	2	1	0	8	4	0	0	0	0	1	5	0	0	33.33
client 12'	0	1	2	0	0	0	0	3	0	1	5	7	0	0	0	0	0	6	0	0	28.00
client 13'	7	0	0	0	0	2	0	0	0	0	0	0	11	0	1	0	0	0	0	0	52.38
client 14'	1	0	2	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	85.00
client 15'	2	0	0	0	1	0	0	0	0	0	0	0	2	0	16	0	0	0	0	0	76.19
client 16'	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	20	0	0	5	0	76.92
client 17'	2	1	0	2	0	0	1	1	0	1	2	1	0	0	0	0	8	6	0	0	32.00
client 18'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23	0	0	100.00
client 19'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	18	0	72.00
client 20'	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	100.00
Average																					70.11

V. CONCLUSION

The best performance for 16 kHz with 20 clients was 71.4% with 50% of training data. The worst performance was 66.6% that was trained with 30% of training data. For 20 clients, the performance difference between at 50% and 70% was only at 1.26%, while a significant improvement of 4.79% was achieved when the training was compared between 30% and 50%.

VI. FUTURE WORK

At 16 kHz, the MFCC features, for use with ECG, was unsuitable for the reasons previously mentioned. Nonetheless, sampling at 16 kHz was insufficient to capture detailed information of the signals. The ECG could have offered better results at a higher sampling rate. Future development to this current study should apply higher sampling rates, and utilizing other feature sets or fiducial markers as features while training the Markov model.

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