Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 12
December 2023

Comparative Study on ECG Based Person Identification System Based on Non Uniform Filter Bank Features Vectors using Vector Quantization and GMM Modeling Techniques

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Abstract

The objective of research work is to experimentally verify the significance of Electrocardiogram (ECG) signal in biometric person authentication. The motivation is based on the earlier work of demonstrating the feasibility of using Electroencephalogram (EEG) signal for person identification [1]. The ECG signals are processed by the cepstral analysis plus Vector Quantization techniques (VQ), Non uniform filter bank plus Vector Quantization and Non uniform filter bank plus Gaussian Mixture Modelling (GMM) to develop person-specific models. The testing of these models indeed found to be person-specific. This experimental work demonstrates that by using simple lead I ECG data recorded through the simple low cost hardware, with the help of traditional feature extraction techniques and widely using modelling techniques like VQ and GMM, it is possible to build the person-specific models for identification of persons. The ECG database of 49 healthy subjects indeed confirms this fact. The studies performed in this work indeed show a promising direction for using ECG as a biometric feature. The best score of person identification using different feature extraction methods along with modelling techniques using 49 persons database can be obtained if the training data include intermixing of three sessions of ECG data The results reveal that the NUFB plus its derivatives with VQ and GMM give highest performances of 93.87%, 97.95% respectively, compared to the cepstral plus its derivatives with VQ, whose highest performance is 91.83%.

Keywords: Electrocardiogram (ECG), Cepstral analysis, on Uniform Filter Bank Features, Vector Quantization (VQ), Gaussian Mixture Modelling (GMM), Person Identification.

1. Introduction

An identification system establishes a given person identity out of a group of N persons, whereas a verification system accepting or denying the identity of person. Methodology depends on biometrics of a person for identification and verification. Anil K. Jain, et al [1] demonstrated that the biometrics truly establishes the identity depending on psychological, physical, behavioural characteristics of person.

A link exits between a person identity and his biometric traits. It cannot be shared, duplicated and lost. Two types of biometrics are used for person identification. Biometrics based on physiology depends on measurements and features human body parts like iris, fingerprints, face, etc. Behavioral biometrics depends on data obtained from an action performed by the person like speech, gait, signature, keystroke, gesture, .etc. To get high security with low error rates, fake detection and liveliness testing is needed for any biometric system [2]. Further, the stability of short or long-term biometric feature and user comfort are the necessary constraints. Hence, there is a need for exploring new biometric features and the improvement of existing techniques along with different modalities independent of each other. These can be combined for further improvement of security level [3].

2. Literature Review

All Biometrics is the science of establishing the identity of a person based on the physical, psychological, chemical or behavioral traits (attributes) of the person. It is only authentication technique that truly identifies an individual, when compared with other traditional methods like photo identity card, tokens, badges and passwords etc., which can be stolen by somebody. Many biometric traits, like hand vascular pattern, voice, gait, face, iris, human tissue, fingerprint, even evoked brain signals, ear canal and knuckle etc., can be used for identification [2]. These methods are not robust because physically spoofing attack may occur. For example, on the doors and glasses finger prints may be present [4].

To make user authentication more transparent than traditional methods with higher security, the biometrics proposes ear canal, brain signals, hand vascular pattern, gait, and human tissue [5, 6].

The shape and size of the mouth and throat, voice, pitch, style of speaking are different among individuals and hence used for speaker identification. High quality speech data collected from microphone under controlled conditions is used for identification. In case of speech signal, environmental and human factors will contribute much to identification errors [7].

The electrical signal produced by the brain is called as electroencephalogram (EEG). High inter subject variability is expected, because brain configurations between persons should be different. The earlier studies have shown that brain waves of each and every person are unique. Therefore EEG can be used for identification of humans and thus become an emerging research topic [8]. Many studies have been proposed using brain waves for person identification. The continuous authentication is possible using EEG, because of its unconscious presentation of biometric features. EEG signal is noisy and hence processing is difficult [9].

In paper [10], to develop practical verification system researchers have suggested spectral features of the EEG. The effectiveness of the proposed new features was evaluated in verification experiments with 23 users and a verification rate of 79% is reported.

As persons have different thought processes, the brainwaves are recorded while the user performs thought activities and a two-stage biometric verification system is proposed [11, 12, 13, 14].

Another new biometric is the electrocardiogram (ECG), which can be used for person identification. Also previous work revealed that an ECG feature unique to an individual, therefore person identification is possible [15-18]. However, it is observed that ECG for identification of persons is difficult due to electrode placement and recording. Many researchers have employed ECG variation and properties of R-R segment as a biological trait for the person verification [19]. Recently, researchers [20-23] have proposed ECG as biometric for identifying a person. EEG can be used as one of the modality from several years to identify the person [24-33, 35-38].

3. Inter individual Variability in ECG

This section will briefly discuss the physiological rationale for the use of ECG in biometric recognition. Overall, healthy ECG signals from different people conform to roughly the same repetitive pulse pattern. However, further investigation of a person's ECG signal can reveal notably unique trends which are not present in recordings from other individuals. The inter-individual variability of ECG has been extensively reported in the literature Draper et al. (1964); Green et al. (1985); Hoekema et al. (2001); Kozmann et al. (1989; 2000); Larkin & Hunyor (1980); Pilkington et al. (2006).More specific, the ECG depicts various electrophysiological properties of the cardiac muscle. Model studies have shown that physiological factors such as the heart mass orientation, the conductivity of various areas and the activation order of the heart, are sources of significant variability among individuals Hoekema et al. (2001); Kozmann et al. (2000). Furthermore, geometrical attributes such as the exact position and orientation of the myocardium, and torso shape designate ECG signals with particularly distinct and personalized characteristics. Other factors affecting the ECG signal are the timing of depolarization and repolarization and lead placement. In addition, except for the anatomic idiosyncrasy of the heart, unique patterns have been associated to physical characteristics such as the body habitus and gender Green et al. (1985); Hoekema et al. (2001); Kozmann et al.(1989; 2000); Simon & Eswaran (1997). The electrical map of the area surrounding the heart may also be affected by variations of other organs in the thorax Hoekema et al. (2001).In fact, various methodologies have been proposed to eliminate the differences among ECG recordings. The idea of clearing off the inter-individual variability is typical when seeking to establish healthy diagnostic standards Draper et al. (1964). Automatic diagnosis Heart Biometrics: Theory, Methods and Applications 2036 Will-be-set-by-IN-TECH of pathologies using the ECG is infeasible if the level of variability among healthy people is high Kozmann et al. (2000).

4. Database

ECG lead I data is recorded for 49 healthy persons (30 male and 19 female) in three different sessions separately with a one day time gap by low cost data acquision system[34] as indicated in table 1.

Table 1. Database in three sessions

Session 1	Session 2 (after 1 day pause)	Session 3 (after 1 day pause)
5 Slots of 10sec duration	5 Slots of 10sec duration	5 Slots of 10sec duration

5.1 F eature Extraction from ECG Signals

Specific information present in ECG signal of the person can be extracted by using feature extraction. Different aspects of ECG signal which are responsible for person identification need to be examined. Feature extraction aims to characterize the information from the Electrical activity of Heart.

The current work presents an experimental evaluation of the different ECG feature extraction techniques to identify the person. The cepstral and NUFB features are used to obtain better person identification performance.

5.1.1 Cepstral Features

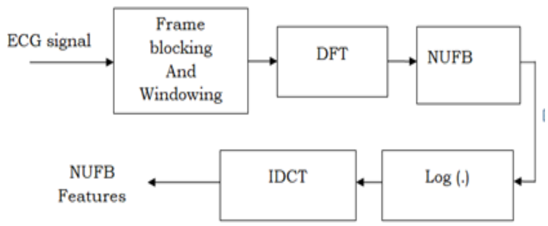
ECG signal segments of 50 ms size (for sampling frequency of 2 kHz, 100 samples) with an overlap of 25 ms (50 samples for sampling frequency of 2 kHz) are considered. The initial values of the cepstral sequence model the slow variations in the spectrum of the windowed signal. The first thirteen cepstral values are dominant as observed in Cepstrals features plots and hence taken as a thirteen dimensional basic feature vector with first order (delta) and second derivatives (delta-delta) of cepstral coefficients, resulting in 39 numbers representing each frame.

5.1.2 Non Uniform Filter-Bank(NUFB) Features

The usage of Non-uniform filter banks is motivated by the fact that, the ECG spectrum is non-uniform and is distributed by a non linear scale in frequency domain

. The ECG spectrum is concentrated within the range of 5Hz – 100Hz. The various steps in NUFB feature extraction are shown in Fig.1

Fig. 1 NUFB features extraction process.



The hamming window is applied to segmented frames to reduce the edge effect of segmentation and the DFT is used to obtain spectral feature. The frequency components of the signal are applied to thirteen narrow band pass filters with centre frequency distributed non-uniformly over the frequency range and the inverse discrete cosine transform (IDCT) is then given to obtain coefficients of NUFB.

6.1 Modeling Using Cepstral And NUFB Methods

The information of a person can be obtained from the features of ECG signal corresponding to the person by proper modeling. The efficiency of the person model depends on the quality and number of feature vectors. Similarity measure like Euclidean distance is used in direct template matching in order to train and test the model. As the feature vectors increases this method is time consuming [83, 84, 85, 86]. Clustering method is used to decrease amount of feature vectors. The code vectors are nothing but centers of the cluster and a codebook is the combination of code vectors. The widely used modeling techniques are VQ and GMM.

6.1.1 Vector Quantization (VQ)

The Soong et al. employed Linde-Buzo-Gray (LBG) algorithm to generate VQ codebooks for speaker identification. Non overlapping clusters are generated by dividing feature vectors set [87].

In this research work VQ has been used as a modeling technique which can be easily implemented and is robust for considering ECG variations. The training of VQ is made using LBG algorithm. The LBG algorithm involves algorithm like binary split and K-means clustering. Clustering with binary splitting is used to generate the codebooks of different sizes. During testing, minimum average distance strategy is used. In this method, each frame accumulates the minimum Euclidean distance of the test feature vector with codebook of all the persons. The codebook of the person which gives the minimum average distance across all frames is considered as the identity of the test ECG data. To apply this procedure the set of feature vectors should be greater that they generate code vectors at least ten times.

6.1.2 Gaussians Mixture Modelings (GMM)

The GMM is the statistical modeling technique used most widely in speaker identification. It is used as state of the art modeling technique, since it captures good statistical variations compared to VQ. Reynolds proposed classifier based on GMM for identification of speaker in 1995 and shown that it outperforms the other modeling techniques [88]. Studies made in[89,90,] also used GMM for speaker modelling in speaker recognition. In [91], speaker recognition under limited data has been considered.

The likelihoods of feature vectors are computed to model the ECG signal. The probability density function of the feature vectors is calculated using Gaussian mixtures. The distribution of feature vectors is represented by weight, mean and covariance in GMM system instead of mean computation in the VQ modelling technique. The GMM requires large data to develop a good model is its limitation. The GMM approach for person modeling is described as follows [88].

7.1 Experimental Results Discussion

First topmost 4 slots of arbitrarily selected any 2 sessions of all the persons ECG data are utilized to generate the codebook using vector quantization. Therefore 1600×2=3200 features for 4 slots of 2 sessions are utilized to train the model. The codebooks of every person are saved in database and this forms procedure of training. Last i.e., 5thslot of all three sessions of 49 person data (400 frames per slot) are used for testing separately. The following arrangements using distinct features tested are;

I. 13 dimensional base cepstra, plus 13 velocity coefficients (first order difference, Δ) and 13 acceleration coefficients (2-order differences, ΔΔ).
II. 13 dimensional Base NUFB, plus 13Δ (1-order differences) and 13ΔΔ second-order difference coefficients.

7.1.1 NUFB with VQ

The experiment is continued with NUFB feature vector for training using vector quantization modeling technique. Any two sessions uppermost four slots are used for training. End most slot of all three sessions are utilized for testing independently. Feature vector contains 13 dimensional basic NUFB coefficients along with its first order and second order coefficients. The combined vectors of 39 dimensions are trained using VQ and the identification performance of person is given in Table 2.

Table 2: The 13 basic NUFB features along with 13 Δ and13 ΔΔ

Sessions for training	**Size of code book**	**session for testing**		
		1	**2**	**3**
1,2	16	67.35	91.84	69.39
	32	77.55	93.87	71.42
	64	81.67	95.91	81.63
2,3	16	67.34	81.63	91.84
	32	81.63	81.63	95.91
	64	77.55	79.59	91.84
1,3	16	79.59	77.55	91.84
	32	81.63	81.63	93.87
	64	81.63	81.63	91.84

During conducting experiment, topmost four slots of session 1 and 2 data are used for training and session 3 slots are not used for training. The endmost session 1 and 2 slot of data and session 3 any of slot are used for testing independently. The 95.91% highest performance is obtained for the endmost test slot selected from trained session 2 compared to the endmost test slot of session 1. The reason is that, the session 2 data is recently learned by the model. For the endmost session 1 and 3 test slot of data model might be not generalized to give better performance. The model is not learned with data of session 3 and 81.63% highest performance obtained for the untrained session 3 endmost slots of test data. It is less than the performance of 95.91% for the trained session 2 endmost slot of test data.

The session 2 and 3 data is further trained to same model in the absence of session 1 data. Maximum performance of 95.91% is obtained during this situation for the trained session 3 endmost slot of test data. The maximum performance of 81.63% is obtained for the untrained session 1 endmost slot of test data and is less than the best performance of 95.91% for recently learned session 3 test data.

The session 1 and session 3 ECG data is again trained to the same model by not using session 2 data for training in order to complete experiment. The maximum performance of 93.87% is obtained from model for trained session 3 endmost slot of test data, because of which is a recently learned session. The maximum performance of 81.63% is again given by model for untrained session 2 endmost ECG test data slot and is less compared to test slot of trained session 3.

It is observed from above experiments that, session generalization problem of the model. The performance is changing from experiment to experiment for test data of untrained sessions. In order to confirm this finding, experiment is conducted further using reversed training sessions and similar observation obtained in Table 3. The large performance of identification is obtained for only recently trained sessions due to session generalization problem as shown in Fig.2.

Table 3. Two sessions in reversal order using NUFB-VQ

Reversed sessions	Size of code book	Sessions for testing		
		1	2	3
2,1	16	91.84	63.26	63.26
	32	93.87	77.55	69.39
	64	93.87	67.35	81.63
3,2	16	63.26	91.84	69.39
	32	77.55	87.75	79.59
	64	81.63	91.84	81.63
3,1	16	87.75	63.26	79.59
	32	91.84	69.39	81.63
	64	93.87	77.55	81.63

Further to explore, ECG data slots are intermixed amongst the sessions chosen for training the VQ model and experiment is again performed with an expectation of enhanced model identification performance.

Following mixing strategy is used for this purpose. Session 1 and session 2 uppermost slots and then second slot of both sessions data and so on are employed in the same way for training the model. After repeating same testing, 93.87% person identification performances are obtained for session 1 and session 2 endmost test slots respectively with enhanced session generalization as indicated in Table 4. The model suffers from session generalization in this case also for untrained session test data as shown in Fig.3.

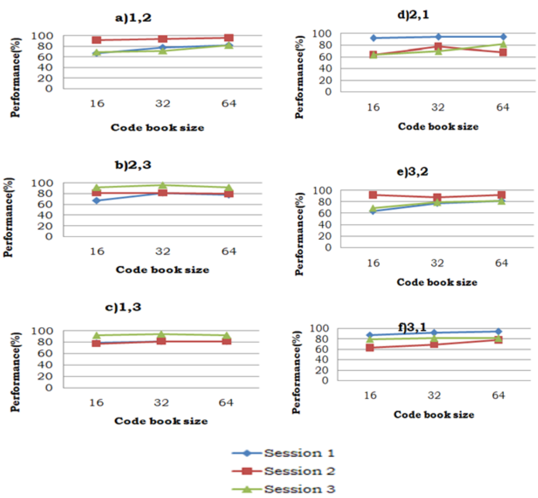


Fig. 2. Forward and reversed sessions using NUFB-VQ

Table 4. Intermixed two sessions using NUFB-VQ

Intermixed data slots	Size of code book	Sessions for testing		
		1	2	3
1,2	16	91.84	93.87	65.31
	32	93.87	93.87	69.39
	64	91.84	93.87	77.55
2,3	16	69.39	89.79	91.84
	32	77.55	93.87	89.79
	64	81.63	91.84	93.87
1,3	16	93.87	83.67	91.84
	32	93.87	81.63	93.87

	64	91.84	85.71	91.84

Intermixing slots of all the three sessions is used for training to solve this problem. The endmost slot from each of the trained session has been used for testing as in a conventional manner. The performance of 93.87% for session 1, 93.87for session 2 and 91.84% for session 3 are obtained by the model as shown in Table 4. The average performance of 93.87% . Consistent performance is observed for interchanged sessions during training with same testing procedure. It is found that, the improvement in session generalization and is indicated in Fig. 3.

This work demonstrates that NUFB features yields better person identification performance compared to cepstral features using vector quantization.

Table 5. Intermixed three sessions using NUFB-VQ

Sessions for training	Size of code book	sessions for testing		
		1	2	3
1,2,3	16	91.84	93.87	81.63
	32	93.87	93.87	91.84
	64	91.84	91.84	91.84
1,3,2	16	91.84	93.87	89.79
	32	93.87	93.87	91.84
	64	91.84	91.84	91.84
2,3,1	16	93.88	91.84	91.84
	32	93.87	91.84	93.87
	64	91.84	91.84	93.87

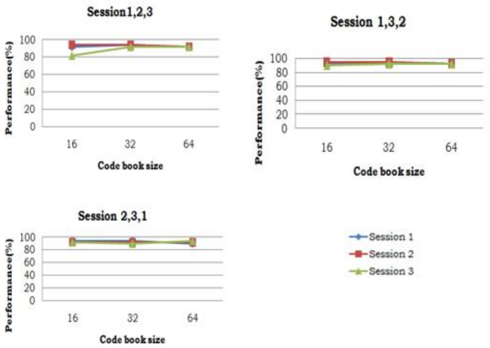


Fig. 3. Performance with intermixed two sessions used for training

Fig. 4. Performance with intermixed three sessions for training

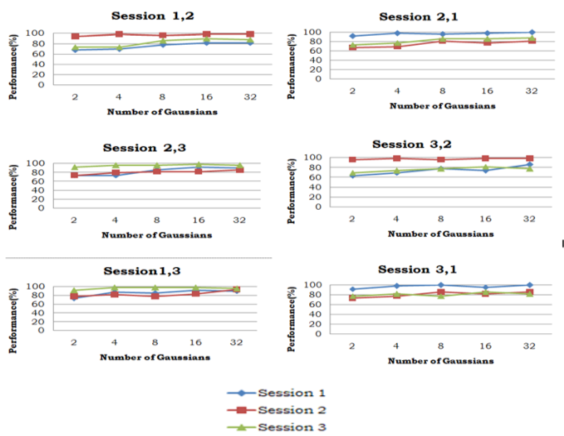
7.1.2 NUFB with GMM

Further to explore, similar experiment is conducted with GMM techniques to enhance performance of ECG based person identification performance. Three sessions ECG data collected with a pause of duration of one day. Each session contains five slots of ten seconds duration. GMM model is trained using starting four slots (4×10 seconds of ECG data) of any two sessions (8×10 seconds ECG data). End most slot of all three sessions are used individually in order to test with Gaussians size of 2, 4, 8, 16, 32 and results of person identification performance are tabulated in the Table 6. Data of session 2 and session 3 is again trained to the same model without using session 1 data. Identification performance of 97.96% is obtained for the trained session 3 end slot of test data.

Table 6. GMM combined with NUFB

sessions for training	Number of Gaussians	Session for testing		
		1	2	3
1,2	2	67.35	93.87	73.47
	4	69.39	97.95	73.47
	8	77.55	95.92	85.71
	16	81.63	97.95	89.79
	32	81.63	97.95	87.75
2,3	2	73.47	73.47	91.84
	4	73.47	79.59	95.92
	8	85.71	81.63	95.92
	16	91.83	81.63	97.96
	32	89.79	85.71	95.92
1,3	2	73.47	77.55	91.84
	4	87.75	81.63	97.96
	8	85.71	77.55	97.96
	16	91.83	83.67	97.96
	32	89.79	93.87	95.92

For the untrained session 1 end slot of test data identification



performance of 91.83% is obtained, which is again less than the performance of 97.96%. This is because model recently trained with data of session 3.

Session 1 and session 3 ECG data is used to train the model without using the session 2 data. In this case, for the trained session 3 endmost slot of test data, GMM model gives performance of 97.96%. This is because the model recently trained with session 3 data. The model produces 93.87% performance for untrained session 2 endmost test data slot.

It can be observed that, best result of 97.96% is obtained using person identification system with NUFB-GMM. Further NUFB features with GMM are more effective compared to NUFB with VQ. It is observed that, best results are obtained for small number of Gaussians compared to large size of code book. Further it is confirmed that, the performance changing from observation to observation and GMM model troubled from session generalization. Experiment is repeated again by reversing the sessions used for training to confirm the fact and similar observation is found in Table 7. Fig.5. shows large identification performance for recently trained sessions. The session generalization problem is again observed from result.

Table 7. Reversed two sessions for training

Reversed training sessions	Number of Gaussians	session for testing		
		1	2	3
2,1	2	91.84	67.35	73.47
	4	97.95	69.39	77.55
	8	95.92	81.63	85.71
	16	97.95	77.55	85.71
	32	100	81.63	87.75
3,2	2	63.27	95.92	69.39
	4	69.39	97.96	73.47
	8	77.55	95.92	77.55
	16	73.47	97.96	81.63
	32	85.71	97.96	77.55
3,1	2	91.84	73.47	77.55
	4	97.96	77.55	81.63
	8	100	85.71	77.55
	16	95.92	81.63	85.71
	32	100	85.71	81.63

Fig.5. Forward and reversed sessions using NUFB-GMM.

The intermixed data slots amongst sessions used for training and same experiment is repeated to enhance the performance. In order to train GMM model, both session 1 and session 2 uppermost slot of ECG data are used in the proposed strategy of mixing and then the second slot of both sessions are used and so on. After similar testing maximum performance of 97.95% and 95.92% are obtained with improved session generalization amongst training session for endmost slot from session 2 and session 1 respectively as shown in Table 8. The average person identification performance of 85.29% using untrained sessions highest score for 16 Gaussians is obtained. The model suffers for untrained session test data, due to generalization of sessions and is as shown in Fig.6.

Table 8 Two intermixed sessions for training

Intermixed data slots for training sessions	Number of Gaussians	Session for testing		
		1	2	3
1,2	2	91.84	91.84	77.55
	4	91.84	95.92	85.71
	8	95.92	91.84	85.71
	16	95.92	97.95	89.79
	32	97.95	97.95	87.75
2,3	2	67.35	91.84	87.75
	4	75.51	95.92	97.95
	8	89.79	95.92	91.84
	16	89.79	95.92	95.92
	32	87.75	97.96	91.84
1,3	2	89.79	77.55	91.84
	4	91.84	87.75	91.84
	8	95.92	85.71	95.92
	16	97.96	87.75	95.92
	32	97.96	89.79	97.96

In this technique, for training the model ECG data of three sessions are used and tested in traditional method as explained earlier. Also, session generalization improvement with enhanced performance is expected from GMM.

In this situation, maximum person identification performance of 97.95% for 32 Gaussians for session 1, 97.95% with 8 and 32Gaussians for session 2 and 97.95% with 16 Gaussians for session 3 is achieved as shown in Table 9.Similar results are obtained when sessions are interchanged and trained with GMM as shown in Fig.7. It is found that, person identification performance is slightly increasing without losing session generalization may be due to the fact that the GMM is a statistical modelling technique requires huge data. Also, the slightly reduced performance may attribute due to the insufficient feature space and training.

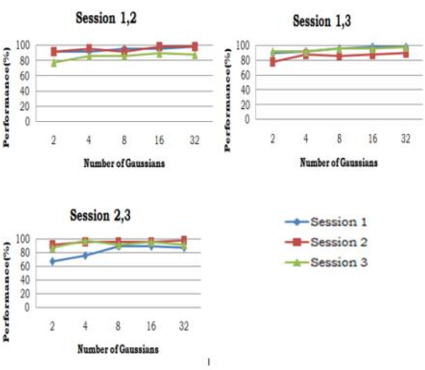


Fig.6. Two intermixed sessions using NUFB-GMM

Table 9 NUFB-GMM with intermixed three sessions for training

Sessions for training	Number of Gaussians	session for testing		
		1	2	3
1,2,3	2	91.84	89.79	91.84
	4	91.84	95.92	95.92
	8	95.92	97.95	95.92
	16	95.92	95.92	97.95
	32	97.95	97.95	95.92
2,3,1	2	91.84	93.88	89.79
	4	91.84	91.84	91.84
	8	95.92	95.92	91.84
	16	97.95	95.92	95.92
	32	97.95	95.92	97.95
3,1,2	2	89.79	91.84	91.84
	4	91.84	95.92	91.84
	8	95.92	97.95	95.92
	16	95.92	97.95	97.95
	32	95.92	100	95.92

Fig. 7. Performance with intermixed three sessions for training

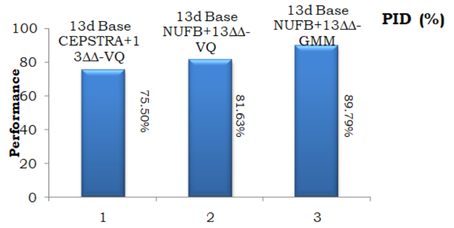
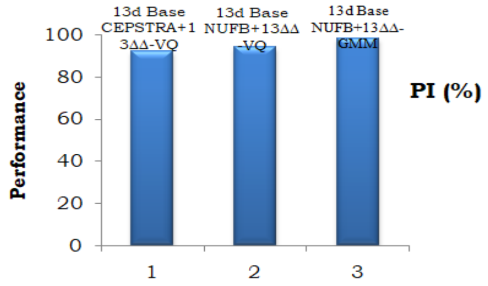


Fig. 8. Average performance with intermixed two sessions



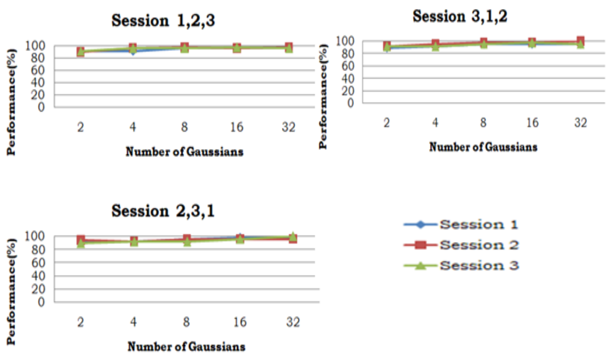


Fig. 9. Average performance with intermixed three sessions

8 Conclusions

In this research paper ,comparative study on NUFB plus Vector Quantization and NUFB plus Gaussian Mixer Modelling Techniques were implemented for ECG signals based person identification systems. Then ECG data of 49 persons has been recorded in three sessions with a pause of one day duration. Each session comprises 2000 data frames of single person in five slots of 10 second duration. Two existing feature extraction algorithms for person identification are used, namely

- Base cepstra of 13 dimensions along with delta and delta-delta coefficients method.
- NUFB basic features of dimension 13 along with delta and delta delta coefficients method.

Features extracted from the SECG signal are used to model persons using the familiar VQ and GMM. These two modeling techniques are rigorously subjected for testing to explore its ability to identify human individuals i.e., person identification. The Euclidean distance based measurement shows that the NUFB cepstral features are better able to represent the person specific information, compared to conventional cepstral features.

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