ECG Significances in Person Authentication and Intra variability and inerter variability analysis by using cepstral and Non uniform filter bank features

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***Abstract*:**

The objective of this 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. The ECG signals are processed by the cepstral analysis and vector quantization techniques (VQ) to develop person-specific models. The testing of these models indeed found to be person-specific. The experimental results demonstrate that by the careful choice and placement of electrodes, it is indeed possible to collect ECG signal that can be person-specific. The ECG database collected using 30 healthy subjects indeed confirm this fact. The studies performed in this work indeed show a promising direction for using ECG as a biometric feature. The Non Uniform Filter Bank cepstral features are proposed for the representation of person specific information present in ECG signal. The variation present in the ECG signals is measured by Euclidian distance measure for the NUFB cepstral features

Keywords: Elecardiogram (ECG), NUFB cepstral features. Biometric feature, Biometric person identification, Vector Quantization.

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1. Introduction

Human beings are highly developed species in the evolution of organisms capable of deriving information about their immediate environment by relying on most efficient mechanisms and capable of demonstrating complex pattern recognition tasks more efficiently. Among complex pattern recognition tasks that human beings are capable to perform, person identification and person authentication task is found most attractive and attracted many researchers worldwide. Human beings demonstrate both person authentication and person identification tasks in their day to day life. An a*uthentication* (or *verification*) system involves confirming or denying the identity claimed by a person (one-to-one matching). On the other hand, an *identification* system attempts to establish the identity of a given person out of a closed pool of N people (one-to-N matching). Naturally, human beings rely on biometric (biological and behavioral) traits for person authentication and person identification tasks, called Biometric recognition. Anil K. Jain, Patrick Flynn, and Arun A. Ross[2] start their Handbook on Biometrics with its definition: “Biometrics is the science of establishing the identity of an individual based on the physical, chemical or behavioural attributes of the person.” Biometric recognition forms a strong *link* between a person and his identity because biometric traits cannot be easily shared, lost, or duplicated. We focus on biometric recognition task of authentication of person based on Electrocardiogram (ECG) signal as a biological trait. Recently, many researchers have attempted to extract task or event specific features from ECG signals for prosthetic and control applications. But person specific information Extraction from ECG signal for biometric person authentication is rarely attempted and is most challenging task. ECG signal find its applications in diagnosis of medical research to identify heart functionality.

1.1 Literature Review

The electroencephalogram (EEG) is suitable for continuous authentication since it enables unconscious presentation of biometric features. However, the conventional authentication methods using the EEG require heavy computational load: AR modeling and/or machine learning. In [3], researcher proposed simple spectral features of the EEG to make the authentication system using the EEG more practical. The effectiveness of the proposed new features was evaluated in verification experiments with 23 users and they obtained the verification rate of 79%. A statistical framework based on Gaussian Mixture Models and Maximum A posteriori model adaptation, successfully applied to speaker and face authentication. Two-stage biometric authentication method using thought activity brain waves that minimizes both false accept error(FAE) and false reject error(FRE) is studied. These brain waves (or electroencephalogram (EEG) signals) are recorded while the user performs either one or several thought activities. As different individuals have different thought processes, this idea would be appropriate for individual authentication [4].

The Electrocardiogram signal is the visualization of electrical activity of the heart muscle fiber and is directly related to the physiology of each individual. Also, past work revealed that the characterization of ECG features, unique to an individual, with clear evidence that accurate ECG based personal identification is possible[5],[6]. Some researchers have employed variation in the use of ECG as a biological trait for the person authentication and they rely on morphological properties of R-R segment in ECG signal. The authenticity of a given R-R segment is decided by comparing it to a matching R-R segment morphologically synthesized from a model characterizing the identity to be authenticated. The morphological synthesis process uses a set of R-R segments (templates), recorded during enrolment at different heart-rates, and a time alignment algorithm. This ensures the authentication to be independent of the, usually variable, heart-rate. The optimum average equal-error-rate obtained in the experiments is 2% [7].

In this work, we present a feasibility study which carries on quantifying the potential of the ECG for biometric person recognition.. The subjects were asked to follow the desired condition for the durations of 10seconds of 3 slots each for the following four case instances

Case1: ECG data recorded at the time of subjects under rest (sitting position) Condition.
Case2: ECG data recorded at the time of Subjects standing position.
Case3: ECG data recorded at the same condition of case-1 but after doing some Simple exercise
Case4: ECG data recorded at the same condition of case-2 but after doing some Simple exercise.
ECG data is collected for all the above three cases in two sessions with a time gap of 1 day. For the data collected above, Cepstral feature extraction, training with Vector Quantization (VQ) and person verification is performed for 30 subjects.

The electrocardiogram (ECG) is one of the most widely used signals in healthcare. Recorded at the surface of the body, with electrodes attached in various configurations, the ECG signal is studied for diagnostics even at the very early stage of a disease. In essence, this signal describes the electrical activity of the heart over time, and pictures the sequential depolarization and repolarisation of the different muscles that form the myocardium. The first recording device was developed by the physiologist Williem Einthoven in the early20th century, and for this discovery he was rewarded with the Nobel Prize in Medicine in 1924 Sornmo & Laguna (2005). Since then, ECG became an indispensable tool in clinical cardiology. The deployment of this signal in biometric recognition and affective computing is relatively young. Figure 1 shows the salient components of an ECG signal i.e., the *P* wave, the *QRS* complex and the *T* wave. The *P* wave describes the depolarization of the right and left atria. The amplitude of this wave is relatively small, because the atrial muscle mass is limited. The absence of a *P* wave typically indicates ventricular ectopic focus. This wave usually has a positive polarity, with duration of approximately 120 ms, while its spectral content is limited to 10-15 Hz, i.e., low frequencies. The *QRS* complex corresponds to the largest wave, since it represents the depolarization of the right and left ventricles, being the heart chambers with substantial mass. The duration of this complex is approximately 70-110 ms in a normal heartbeat. The anatomic characteristics of the *QRS* complex depend on the origin of the pulse. Due to its steep slopes, the spectrum of a *QRS* wave is higher compared to that of other ECG waves, and is mostly concentrated inthe interval of 10-40Hz.Finally, the *T* wave depicts the ventricular repolarisation. It has smaller amplitude, compared to the *QRS* complex, and is usually observed 300 ms after this larger complex. However, its precise position depends on the heart rate, e.g., appearing closer to the *QRS* waves at rapid heart rates.

2. 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).

3. Person authentication system using ECG Biometric

The basic principle of biometric person authentication system using ECG is shown in Fig.1below.

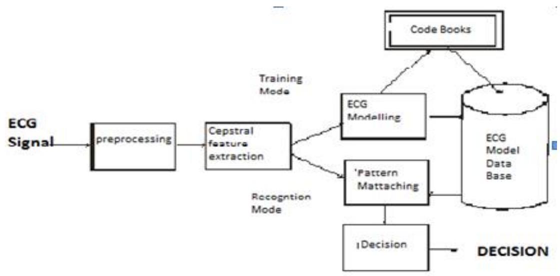

Fig. 1. A ECG Biometric Person Authentication System.

it consists of ECG Pre-processing stage which includes front end high impedance instrumentation amplifier and data acquisition system followed by high pass filter with cut-off frequency f_c =1 Hz, low-pass filter with cut-off frequency f_c = 100 Hz, notch filter with cut-off f_c = 50 Hz.

After the ECG electrodes are attached, the procedure is explained and the subject asked to follow the above mention condition, while data are recorded. ECG data recorded for 30 subjects for the different three cases. In a single session, recording of thirty seconds, consisting of three instances of ten seconds each, is done for each subject.. Two sessions of data is recorded for each subject for all three cases as described earlier. Raw ECG signal has been acquired using line-in port of the sound card with built-in programmable ADC and sample and hold mechanism. The line-in port of the sound card was configured to sample at sampling frequency of f_S = 2000 Hz and at 16 bit resolution. Fig.2 shows waveform obtained from a single burst of ECG signal.

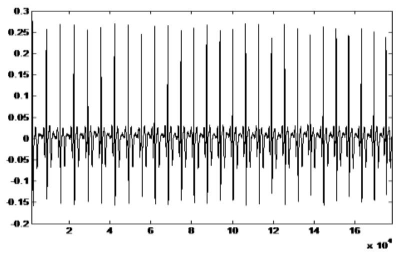

Fig. 2. A typical ECG burst recorded through low cost data acquisition system.

4 Cepstral analysis

Consider a given ECG waveform for a particular person. ECG frames of size 50 ms (100 samples for 2 kHz Signal) with a shift of 25 ms (50 samples for 2 kHz Signal) are taken. The following steps are used for feature extraction from each frame.

1. Compute STFT Magnitude Spectrum by DFT (FFT)
2. Take log on Magnitude Spectrum.
3. Take IDFT to obtain Cepstral Sequence.
4. The initial values of the Cepstral sequence model the slow variations in the spectrogram of the windowed signal. The first thirty nine values are taken as a thirty nine dimensional feature vector for that frame.

The following fig.3a-3d illustrates this process.

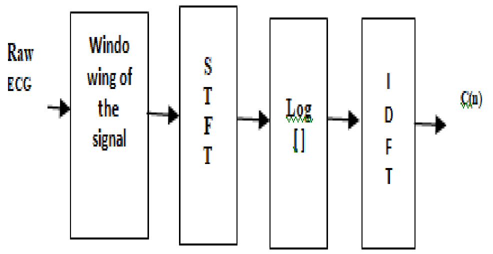

Fig. 3a.Block diagram for Cepstrum Computation

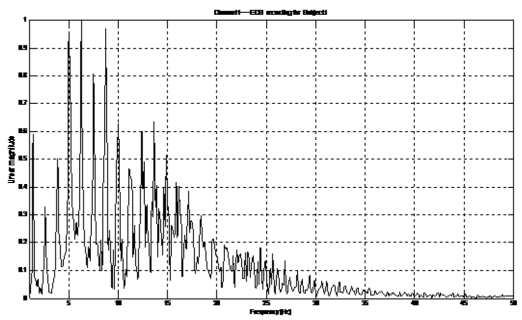

Fig. 3b. Normalized FFT of ECG Data

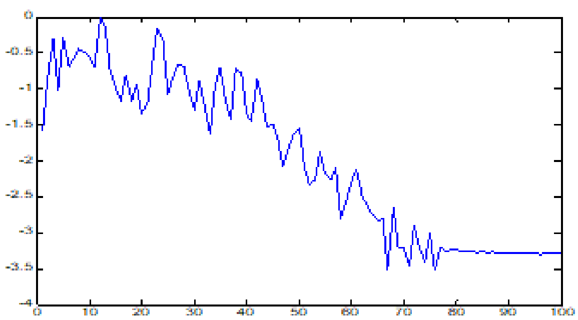

Fig. 3c. Log of magnitude of spectrum.

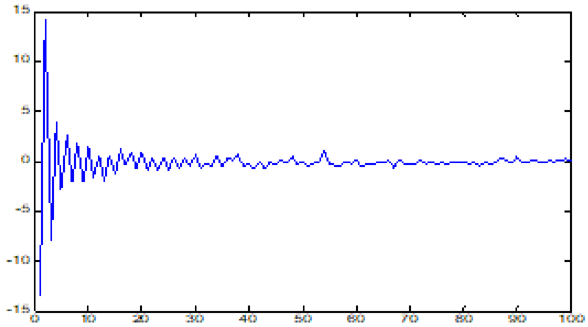

Fig. 3d. Cepstrum

5.1.1. Vector Quantization modeling

After getting cepstral feature vectors, in the modeling stage, second level of compression is done, where a set of nearest feature vectors are clubbed together and assigned with representative vector. As a result one model is formed for each person. At the time of measurement, instead of comparing with all the vectors, the comparison is done with the person model. For this model the vector quantization (VQ) technique is used for modeling. For generating codebook vectors, we use the popular binary split algorithm which in turn uses K-Means clustering for clustering of feature vectors.

5.1.2. Non Uniform Filter-Bank(NUFB) Features

To Analyze the whether ECG Signal can be used for biometric ,in this research work, first The variability computed for the different slots of same person recorded over the session. To verify Session Variability, The variability among the different session data computed for the different sessions data of the subjects. And also computed the variability computed for the different subjects. The slot variability and session variability are used to measure the intra person variability present in the ECG signal, whereas the person variability is used to measure the inter person variability. In order to use ECG for the biometric system the intra person variability should be low compared to inter person variability. The representation of ECG in feature space should possess more inter person variability compared to intra person variability. In the current work Conventional cepstral and Non Uniform Filter Bank (NUFB) Cepstral features are considered for inter and intra person variability analysis. The Euclidean distance computed between feature vectors represents the variability present in the ECG signals

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The real cepstrum [11] of ECG signal is computed by taking the Inverse Discrete Fourier Transform of log magnitude of the ECG signal

$$c[n] = \mathrm{real}\{\mathrm{IDFT}\{\log|X(k)|\}\} \quad (1)$$

Where, X(k) is N point DFT of ECG signal x(n).

The conventional cepstral features are computed by considering entire frequency band of ECG i.e. 0-100 Hz. Since ECG is Quasi-stationary signal and having low bandwidth i.e. maximum spectral information is concentrated with in the low frequency range 0-60Hz high resolution is required in the low frequency band for the effective representation of ECG features. Hence logarithmically scaled filter banks are used to compute the cepstral Features, which are referred as Non Uniform Filter Bank (NUFB) Cepstral features.

The Non Uniform filter banks (NUFB) as shown in the Figure.4. The spectrum of ECG is multiplied with non-uniform filter banks and energy associated with each frequency band is computed. Then the discrete cosine transform of filter bank energies gives the Non Uniform Filter Bank (NUFB) Cepstral representation of ECG signal.

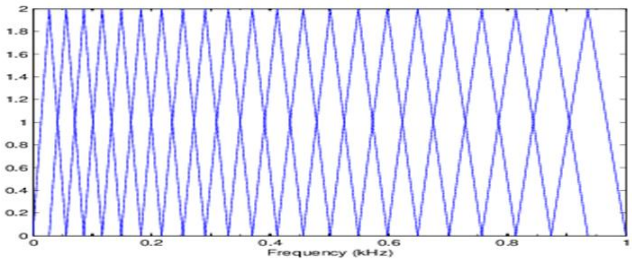

Fig. 4. Non Uniform Filter Banks (NUFB). The EMG spectrum is multiplied with each triangular shaped filter banks shown in the figure and energy associated with the each frequency band is computed

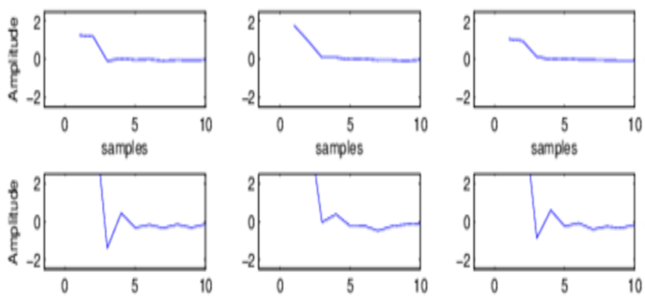

Fig. 5. ECG signal Cepstrum in first row plot and Non Uniform Filter Bank Cepstrum in second row plot shows the different slots of the same person recorded over same session

The Fig. 5 shows the recorded ECG signals conventional cepstrum and NUFB cepstrum representations. The NUFB cepstral features are better able to capture the signal variations more efficiently compared to the conventional cepstral features as indicated by same figure.

Similarly the Fig. 6 shows the ECG signals conventional Cepstrum and NUFB cepstral features of the same person recorded over different sessions. The fig. 7 shows the ECG signals conventional Cepsral and NUFB cepstral features of the different persons.

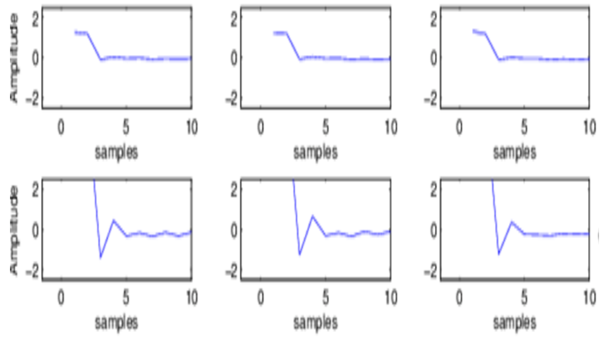

Fig. 6. ECG signal Cepstrum in first row plot and Non Uniform Filter Bank Cepstrum in 2nd row plot shows the same person data recorded over different sessions.

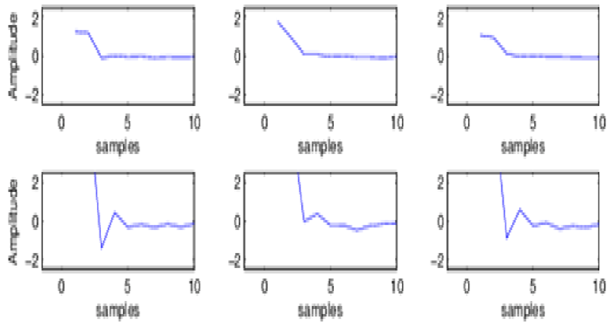

Fig. 7. ECG signal Cepstrum plots in row 1 and Non Uniform Filter Bank Cepstrum plots in row 2 of the different persons.

6.1.1. Euclidian Distance Analysis of Cepstral Features.

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

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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.

The divergence of feature vectors from session to session and person to person is computed using Euclidean distance measurement.

The Euclidean distance D between N dimensional feature vectors X and Y is given by,

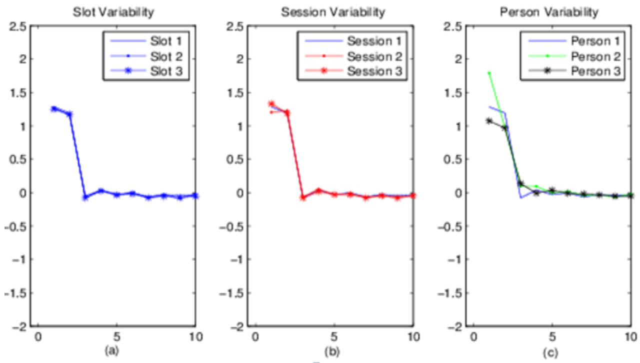
$$D = ||X - Y|| \quad (2)$$

The Euclidian distance is used to study the divergence of cepstral features among the EMG data of same person recorded over same or different sessions and divergence among the different persons. The study is required to ensure that the divergence of ECG among different person is more compare among the same person data. Which helps us to develop the biometric system?

The divergence of the cepstral features computed over different slots and sessions of the same person and different persons which are shown in fig. 5. The slot variability is computed by averaging the Euclidean distances computed for different slots. Similarly session and person variability are computed by averaging the Euclidean distance computed over different sessions and persons. The cepstral Euclidean distance for slot, session and person shows the relationship that, slot variability, session variability and person variability. The slot and session variability are less compared to person variability and which indicates the cepsrtal vector are able to capture the person specific information present in the EMG signal. The enhancement of person variability is carried out by considering Non Uniform Filter Bank (NUFB) Cepstral features. Since the non-uniform filter bank i.e. log scaled filter banks which gives high resolution for low frequency components.

The relationship, slot variability, session variability and person variability is observed for NUFB features similar to that of cepstral features. The person variability computed for NUFB features is 2.9119, whereas 0.6891 for conventional cepstral features. The enhancement of resolution in low frequency components in NUFB features results in large amount of feature diversity from person to person. Since person variability is greater than session and slot variability for NUFB cepstral features are used to develop the ECG based person identification system in the current work. The slot variability i.e. average Euclidean distance of the cepstral vectors of 1ST column plot is 0.1223. The session variability i.e. average Euclidean distance of the cepstral vectors of 2nd column plot is 0.4353. The person variability i.e. average Euclidean distance of the cepstral vectors of column 3rd in the plot is 0.6581 in figure-5

Fig. 5. Variation of the Cepstral Features over the slots,



sessions and persons. The figure shows the slot variability, session variability and person variability.

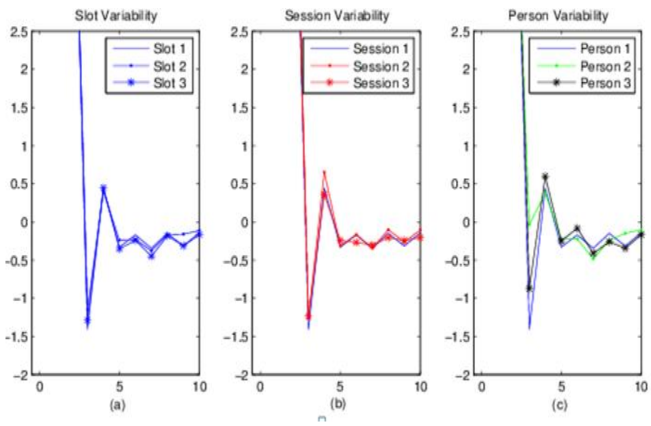


Fig. 6. Variation of the Non Uniform Filter Bank (NUFB) Cepstral Features over the slots, sessions and persons.

The Figure-6 shows the slot variability, session variability and person variability. The slot variability i.e. average Euclidean distance of the NUFB cepstral vectors of column-1 plot is 0.3127. The session variability i.e. average Euclidean distance of the NUFB cepstral vectors of column-2 is 0.6243. The person variability i.e. average Euclidean distance of the NUFB cepstral vectors of column 3rd plot is 3.1541. The feature variation from person to person is better captured by NUFB features compared to cepstral features.

Table 1: The Results of Person Identification Using VQ for Session 1 and Session 2

Size of code book	Session 1			
	Case 1	**Case 2**	**Case 3**	**Case 4**
8	93.33	86.67	86.67	86.67
16	93.33	86.67	86.67	86.67
32	96.67	90.00	90.00	90.00
64	96.67	96.67	93.33	93.33
128	100	90.00	93.33	93.33
256	96.67	96.67	96.67	93.33
512	100	100	96.67	93.33
Avg.	**96.67**	**92.38**	**91.90**	**90.95**
Size of Code book	**Session 2**			
	Case 1	**Case 2**	**Case 3**	**Case 4**
8	86.67	86.67	86.67	80.00
16	90.00	86.67	86.67	80.00
32	90.00	90.00	86.67	80.00
64	93.33	90.00	90.00	86.67
128	93.33	93.33	93.33	86.67
256	93.33	93.33	93.33	93.33
512	93.33	93.33	93.33	93.33
Avg.	**91.47**	**90.47**	**90.00**	**85.55**

7 Experimental Results and Discussion

The ECG data is collected in two sessions with time gap of one day for a population of thirty subjects. In each session, 3 slots of ECG data per subject for three different cases are acquired. That is, total of 15 slots of 10 seconds duration data per session per subject is obtained. For total of 30 subjects, there exists 30 x 15 = 450 slots of data i.e. 4500 seconds of data per session are collected for 30 subjects. We have used first two slots of data in case 1of session 1 of all the subjects to generate the codebook using vector quantization. The codebooks are stored in the ECG database and this constitutes training procedure. The remaining one slot of data in case1of session 1 for 30 subjects are used for testing and we have an average performance of **96.67**%. and case1of session 2 is 91.47%. It is important to note that case 1 data of second session and data in case 2 to case 3 of Results of person identification using VQ for session 1 and session 2 is shown in Table 1.From these studies, we have explored that if the system is properly and adequately trained for all the three cases for good number of sessions over the population of large number of subjects, better performance in identification of persons can be achieved and change in identification performance with adequate training can be accounted for change in properties of the gel between the electrode and the skin surface conditions and change in mental state of the persons and change in electrode characteristics.

8 Conclusions

In this research paper work, experimental study shows that if we properly recorded ECG signal from different subjects, by keeping sensor location or placement of electrode, type of sensor and quality of sensor by maintaining a same sensor type and location of sensor on subject body and if these same across different sessions, then ECG Signal can be used as a biometric feature similar to other biometric such as finger, voice face etc.

And also In this work through a good acquisition of surface ECG signal, we demonstrate the capability of an ECG based person identification system using Cepstrum-VQ approach provides average person identification performance of about **96.67**% for case 1 data of session 1 and 91.47% for case-2 session-2 . And also the slot variability, session variability and person variability can be evaluated for cepstral features and Non Uniform filter bank features, The feature variation from person to person are better captured by NUFB features compared to cepstral features. This experimental research work promised that ECG data can be used for biometric purpose.

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