Development of GMM-UBM based Biometric System using Electromyogram Signals

Suresh M*, Mallikarjun S Holi** and Rudresh M D***
*Professor, SSIT, Tumkur, Karnataka, India
E-mail: sureshm_ap@yahoo.co.in
**Professor, UBDT, Davanagere, India, Karnataka, India
E-mail: msholi@yahoo.com
***Associate Professor, Kalpatharu Institute of Technology, Tiptur, India
E-mail: rudresh_md@rediffmail.com

Abstract: The development of biometric system using Electromyogram signals is discussed in this paper. The EMG signals are the physiological signals generated due to the neuromuscular activity. The EMG signals reflects the strength of muscles of the person, which may vary from person to person. The Non Uniform Filter Bank cepstral features are proposed for the representation of person specific information present in EMG signal. The variation of EMG signals from person to person is measured by using Euclidian distance metric for the NUFB cepstral features and KL Divergence distance metrics for GMM models of NUFB features. The average KL Divergence based inter person variability is 77.19%, whereas intra person variability is 44.19%. The GMM-EM and GMM-UBM systems are developed for 50 persons EMG data using NUFB features. The performances of both systems are analyzed by varying the number of training time slots per person and number of Gaussian Mixtures. The GMM-UBM gives an accuracy of 94.12% for two EMG time slots of 10 seconds duration, whereas GMM-EM requires 6 time slots per person to give the same performance.

Keywords: Electro Myo Gram Signals (EMG), Gaussian Mixture Model(GMM), Kullback-Leibler Divergence (KLD), Vector Quantization(VQ).

Introduction

"Biometrics" means "life measurement" but the term is usually associated with the use of unique physiological characteristics to identify the person. The application which most people associate with biometrics is security. However, biometric identification has eventually a much broader relevance as computer interface becomes more natural. Knowing the person with whom you are conversing is an important part of human interaction and one expects computers of the future to have the same capabilities. A number of biometric traits have been developed and are used to authenticate the person's identity. The idea is to use the special characteristics of a person such as face, iris, fingerprint, signature etc... to identify the person. The signals produced by muscle activity like speech is mainly used for the biometric authentication. The speech is produced by neuro muscular coordination of muscles and nervous system associated with voice production system. The neuro muscular activity of vocal folds and vocal tract are reflected in acoustic characteristics of speech and are unique. Therefore voice based biometric systems are developed [1]. The method of identification based on biometric characteristics is preferred over traditional passwords and PIN based methods for various reasons such as: The person to be identified is required to be physically present at the time of identification. Identification based on biometric techniques obviates the need to remember a password or carry a token. A biometric system is a pattern recognition system, which makes person identification by determining the authenticity of a specific physiological or behavioral characteristic possessed by the user.

The physiological signals like Electro Cardio Gram (ECG), Electro Encephalo Gram (EEG) and Electro Myo Gram(EMG) are mainly used for the clinical diagnosis purpose. The ECG reflects the muscle electric activity of the heart and used to obtain the information about heart rate, strength of cardiac muscles and to diagnose the various arrhythmias like Myo Cardial Infraction, Ventricular arrhythmia, Pre Mature Ventricular (PVC) beats etc. The EEG reflects the electrical activity of the brain. The EEG is used mainly to diagnose the disorders related to nervous system like Epileptic Seizure, Stroke, Brain Tumor. The EMG is the resultant of neuro muscular activity associated with muscle system. The EMG reflects the coordination activity of neural and muscular systems. The EMG is having clinical importance in the measurement of muscle strength, nerve conduction capability and neurological injuries. The physiological signals reflect the various activities of human organ system, which can also use for biometric applications. The ECG is used for biometric applications over a past decade [2]. The features of P wave, QRS and T waves are different for different persons, which reflect the activity of the heart. Similarly the EEG reflects the neural activity of the person which is also varies from person to person. So ECG and EEG are employed in biometric applications due to the presence of person specific information [3], [6], [7].

Like ECG and EEG, EMG also contains person specific information. The ECG is generated by involuntary muscle system and EEG is nervous system. The stimulus and response in EEG and ECG are not controlled by person; hence it is easy to extract person specific information from them. The challenge associated with EMG to use as biometric is that, EMG is generated by voluntary muscle. The EMG based person identification systems are developed for 50 persons using vector quantization(VQ) and Gaussian Mixture Models (GMM) along with Non Uniform Filter bank(NUFB) cepstral coefficients [4], [5]. The motivation behind this work is to emphasize the person specific feature present in the EMG signal. The person specific information is emphasized at feature level by Euclidean distance measurement on conventional and Non Uniform Filter Bank Cepstral coefficients. The modeling capability of GMM for NUFB cepstral features is determined by KL divergence measurement [12], [13].Gaussian Mixture Model-Expectation Maximization (GMM-EM) and Gaussian Mixture Model-Universal Background Model(GMM-UBM) shows good modeling capacity in speaker recognition applications [7], [8], [9], [10]. So GMM-EM and GMM-UBM based person identification systems are developed for NUFB features. The capability of GMM-UBM for limited data condition is also verified.

The paper is organized as follows. Section II explains the EMG database. The Computation of NUFB features and representation of person specific information by NUFB features is discussed in section III. The KLD measurements for inter and intra person variability are explained in section III. The development of biometric system using GMM and GMM-UBM is explained for EMG database in section IV. The experimental results are discussed in section V. The conclusion and future work is explained in section VI.

Database

The Muscles which give the required amount of signal are chosen for EMG data recording. Since hand motions result from contraction of muscles, placed differential electrodes over the forearm flexor Carpi ulnaris muscle involve in hand motion and placed reference electrode over the wrist. After the electrodes are fixed, each person was trained to maintain a static contraction for each motion and to change the motions with a fixed movement velocity. The procedure is explained and the person was asked to practice several times while data are recorded. In the experiment, the EMG data were collected from 50 normal persons for desired upward motion of wrist (30 males + 20 females, average age of 23 years). Four sessions were conducted for every person with a gap of one day duration without changing electrode and position of electrode on the muscle. In a single session, recording of fifty seconds, consisting of five instances of ten seconds each, is done for each person. Each ten seconds recording gives 8-10 bursts of EMG signal. Raw EMG signal has been acquired using line-in port of the sound card with built-in programmable analog to digital converter(ADC) with sample and hold mechanism. The sound card was configured to sample at sampling frequency of fs = 2000 Hz and at 16 bit resolution.

Person Specific Information Present in EMG Signal

A perfect biometric characteristic should be universal and each person possesses this characteristic. It is quite easy technically and convenient for an individual to obtain the unique characteristic, i.e., there are no two persons with same characteristics and permanent (does not change over time). The feature used to represent the EMG signals for biometric application should process diversity from person to person. The features computed for the EMG signals of the same person recorded over the same session i.e. different slots, EMG signals of the same person recorded over different session and EMG signals of the different persons has to be analyzed to ensure the usage of EMG signals for the biometric system.

Slot Variability: The variability computed for the different slots of same person recorded over the session.

Session Variability: The variability computed for the different session of the person.

Person Variability: The variability computed for the different persons.

The slot variability and session variability are used to measure the intra person variability present in the EMG signal, whereas the person variability is used to measure the inter person variability. The intra person variability should be low compared to inter person variability in order to use EMG for the person identification system. The representation of EMG 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 EMG signals.

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

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

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

The conventional cepstral features are computed by considering entire frequency band of EMG i.e. 0-1000 Hz. Since EMG is non-stationary signal and having low bandwidth i.e. maximum spectral information is concentrated with in the low frequency range 0-500Hz, high resolution is required in the low frequency band for the effective representation of EMG 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 Fig. 1. The spectrum of EMG 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 EMG signal. The Fig. 2 shows the recorded EMG signals for the same person over the same session at different slots of 10 seconds duration and its magnitude spectrum, conventional and NUFB cepstrum representations. It is observed that, the NUFB cepstral features are better able to capture the signal variations more efficiently compared to the conventional cepstral features.

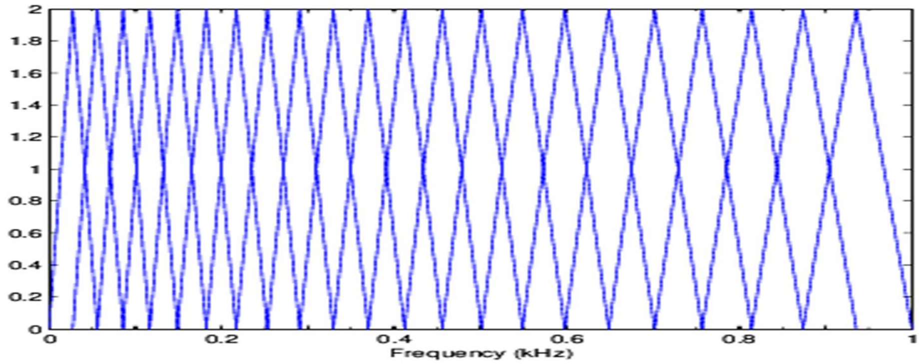

Figure. 1. Non Uniform Filter Banks(NUFB)

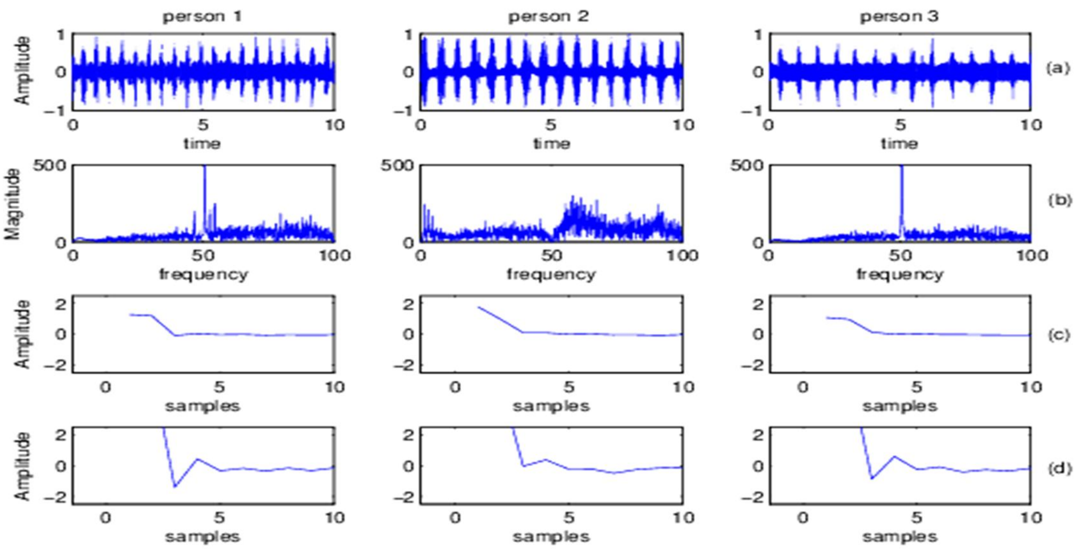

Figure. 2. EMG signal (a), Magnitude Spectrum (b), Cepstrum (c) and NonUniform Filter Bank Cepstrum (d) of the different slots of the same person recorded over same session. The time is in seconds in (a) and frequency is in unit Hz in(b). The spectrum is computed over 2000 Hz, but up to 200 Hz is considered for better visualization

The Fig. 3 shows the EMG signals, spectrum and conventional and NUFB cepstral features of the same person recorded over different sessions. The fig. 4 shows the EMG signals, spectrum and conventional and NUFB cepstral features of the different persons.

Euclidian Distance Analysis of Cepstral Features

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,

$$D = ||X - Y|| \tag{2}$$

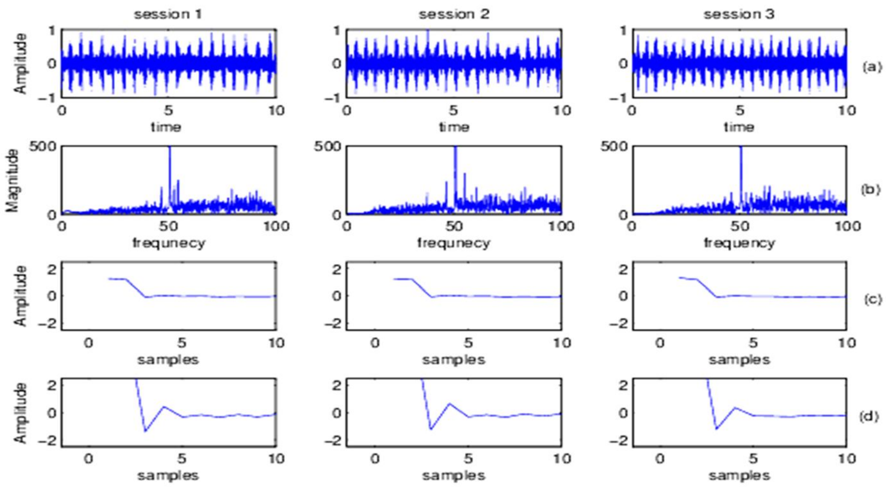

Figure. 3. EMG signal (a), Magnitude Spectrum (b) Cepstrum (c) and Non Uniform Filter Bank Cepstrum (d) of the same person recorded over different sessions. The time is in seconds in (a) and frequency is in unit Hz in (b). The spectrum is computed over 2000 Hz, but up to 200 Hz is considered for better visualization

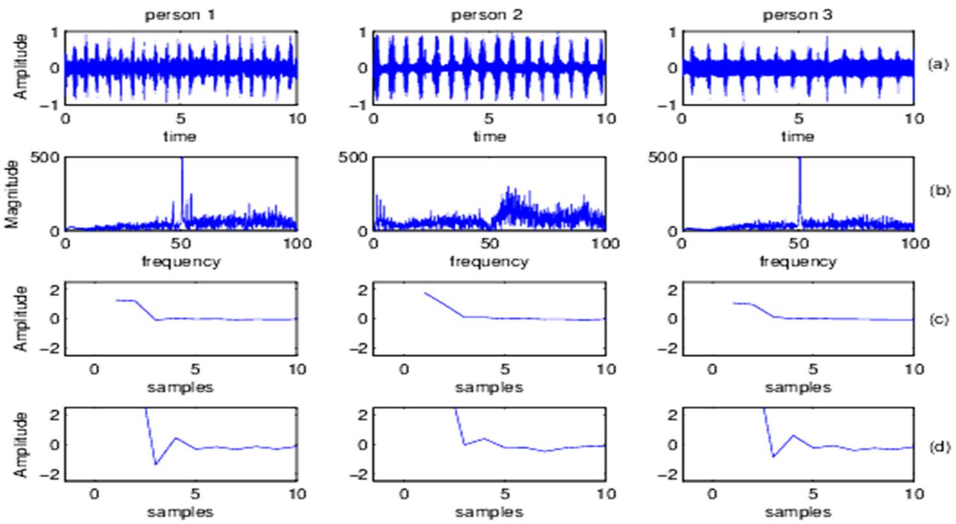

Figure. 4. EMG signal (a), Magnitude Spectrum (b). Cepstrum (c) and Non Uniform Filter Bank Cepstrum (d) of the different persons. The time is in seconds in (a) and frequency is in unit Hz in (b). The spectrum is computed over 2000 Hz, but up to 200 Hz is considered for better visualization

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 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 < person variability. The slot and session variability are less compared to person variability and which indicates the cepstral 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 < 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 of 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 EMG based person identification system in the current work.

KLD Analysis of Features

The NUFB Cepstral features will captures the person specific information present in the EMG signals. The NUFB features resolve the low frequency components of the EMG signals and captures person specific information present in EMG signal. To develop person authentication system using EMG signal a modeling technique is needed and is able to model the person specific information present in NUFB features. The Gaussian mixture model is better able to capture the speaker specific information present in Mel Frequency Cepstral Coefficients (MFCCs) in speaker recognition systems. Similarly GMM are employed in EMG person recognition system in the current work. In order to verify the modeling capability of GMMs, the KL Divergence based distance is computed in between GMMs of NUFB features. Similar to Euclidean distance computed for best feature representation of EMG signals, chosen KL Divergence distance metric to check the modeling capability of GMM for EMG based biometric system [12], [13].The KLD based intra person variability is computed, by considering GMMs of the same persons EMG signal recorded over different sessions. Similarly KLD based inter person variability is computed for the GMMs of EMG of the different persons. The KL Divergence D(f||g), from distribution f(x) to distribution g(x) is given by,

$$D(f||g) = \int f(x) log \frac{f(x)}{g(x)} \qquad (3)$$

The KL Divergence is asymmetric metric, the symmetric KL divergence is given by

$$D(f||g) = 0.5(D(f||g) + D(g||f)) \qquad (4)$$

For two Gaussians f(x) and g(x), the KL divergence has the closed form expression,

$$D(f||g) = \frac{1}{2}[log \frac{\Sigma_g}{\Sigma_f} + Tr\left|\Sigma_g^{-1}\Sigma_f\right| + \left(\mu_f - \mu_g\right)^T \Sigma_g^{-1} \left(\mu_f - \mu_g\right) \qquad (5)$$

Where, $\sum_f$ and μ_f are the covariance and mean parameters of Gaussian f(x) and $\sum_g$ and μ_g are the covariance and mean parameters of Gaussian g(x).

The symmetric KLD is computed between the GMMs of NUFB cepstral features using equations (3) and (4). The KLD computed for the GMMs of same person by taking the EMG signals at different sessions is referred as intra person variability. The GMM models for each person for different sessions are computed. The KLD between GMMs of two randomly chosen sessions of same person gives the intra person variability. The mean of intra person variability is computed gives the average intra person variability. The inter person variability is computed across the different persons and the average value will gives the average inter person variability.

The average intra and inter person variability computed for 50 persons EMG data is given by

Average intra person variability=44.19%

Average inter person variability=70.19%

The lower value of intra person variability as compared to inter person variability shows that, NUFB features with GMM captures person specific information and hence GMM can be used to model NUFB features computed for EMG signals.

The Fig. 5 shows the slot variability < session variability < person variability. The slot variability i.e. average Euclidean distance of the cepstral vectors of (a) is 0.1336. The session variability i.e. average Euclidean distance of the cepstral vectors of (b) is 0.4585.The person variability i.e. average Euclidean distance of the cepstral vectors of (c) is 0.6891. The Fig. 6 shows the slot variability < session variability < person variability. The slot variability i.e. average Euclidean distance of the NUFB cepstral vectors of (a) is 0.3438. The session variability i.e. average Euclidean distance of the NUFB cepstral vectors of (b) is 0.6164. The person variability i.e. average Euclidean distance of the NUFB cepstral vectors of (c) is 2.9119. The feature variations from person to person are better captured by NUFB features compared to cepstral features.

Development of GMM-UBM based person identification system

The MFCC-GMM approach is most successful for the speaker recognition application, since it captures the speaker specific information [14], [15], [16], [17]. The KLD analysis of NUFB features of EMG signals shows the modeling capability of GMM. Hence EMG based person identification system is developed using GMM. The person identification systems using NUFB, Vector Quantization and GMM-EM was proposed in [4], [5]. The Gaussian Mixture Model-Universal Background Model (GMM-UBM) approach is proposed in this paper and performance of GMM-UBM is compared with the system developed for GMM-EM.

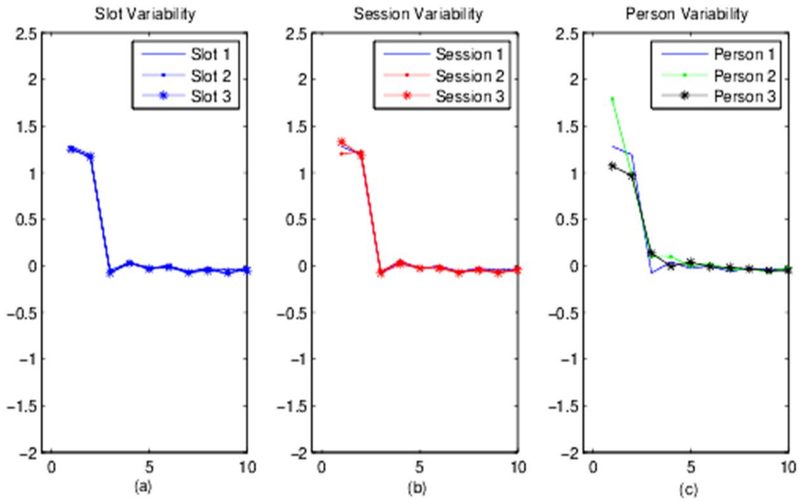

Figure. 5. Variation of the Cepstral features over the slots, sessions and persons

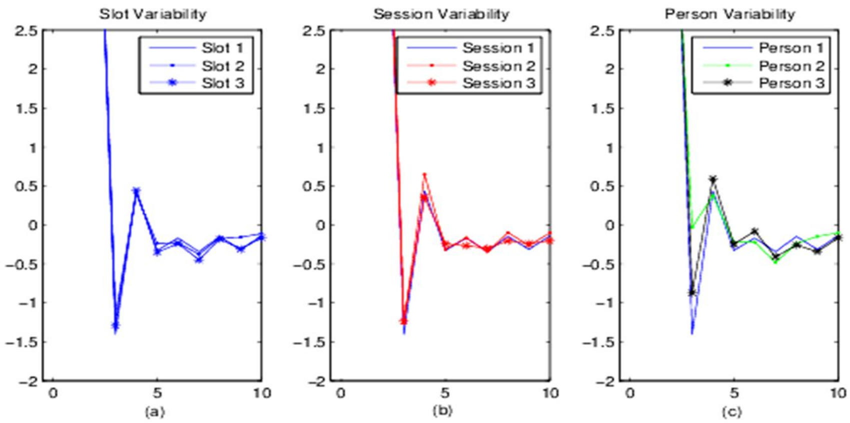

Figure. 6. Variation of the Non Uniform Filter Bank (NUFB) Cepstral features over the slots, sessions and persons

As discussed in database section for each person, data is collected in 4 sessions, in each session 5 slots of 10 seconds EMG signals are collected. Hence 20 EMG time slots per person are collected. The GMM based person identification system is trained from the time slots of session 1, session 2 and session 3and tested by picking time slot from session 4.

The GMM-EM and GMM-UBM systems for person identification using EMG are trained by varying number of time slots per person. The limited data modeling capability of GMM-UBM system is exploited by varying the number of training time slots per person. The testing set is kept common for all different experiments. Table I shows the GMM-EM and GMM-UBM experimental results for the 128 Gaussians. The experiments are conducted by training GMM-EM and GMM-UBM systems by randomly choosing 2 time slots i.e. a slot from session 1 and session 2. The experiment is repeated for randomly 3 time slots i.e. each samples is chosen from session 1, 2 and 3. Finally the experiment is repeated 6 time slots i.e 2 time slots for session 1, session 2 and session 3. Each system is tested by a randomly chosen time slots from session 4.

Table 1. Performance of EMG Based Biometric Systems

No. of training examples	GMM-EM	GMM-UBM
2	82.35%	88.24%
3	86.27%	94.12%
6	88.24%	94.12%

The result shows that the GMM-UBM gives better performance compared to GMM-EM system. The GMM-UBM gives better performance for the less number of training time slots, whereas GMM-EM requires more number of time slots. For example, GMM-UBM gives the accuracy of 88.24%, which is trained for two time slots per person, but GMM-EM requires 6 time slots per person to achieve the same performance.

Conclusion and Future Work

The EMG based biometric system developed in this work, gives better performance i.e. person identification performance of 94.12%.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. The KLD based divergence measurement quantifies the modeling capability of GMM for NUFB features. The average inter person variability is 70.19% and average intra person variability 44.19% computed using KLD shows the presence of person specific features in EMG signal. The GMM-UBM requires less number of time slots compared to GMM-EM to give the same performance, which shows the modeling capability of GMM-UBM for limited person data. The future work includes exploring new features to develop a biometric system using EMG signal and also developing biometric systems for large number of persons.

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