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Processing of Natural Signals like EMG for Person Identification using NUFB-GMM

Suresh M[1], P G Krishnamohan[2], Mallikarjun S Holi[3]

Abstract

Physiological signals like Electrocardiogram(ECG) and Electroencephalogram(EEG), including deoxyribonucleic acid(DNA) are person specific and distinct for different persons. The motor unit firing pattern, motor unit recruitment order and characteristics of muscle changing from person to person, and therefore Electromyogram (EMG) can be used for person identification. EMG records obtained from a single channel data acquisition system are used to develop person identification system. Non-uniform filter bank (NUFB) technique used to extract features from EMG signal. The Gaussian Mixture Model (GMM) is used to generate person models from NUFB features. The EMG data of 100 healthy persons is recorded in different three sessions. So person identification is proposed using EMG signal and gives better result in performance. The performance of this person identification system for change in total number of persons substantially remains stable from Gaussians size of 64 onwards.

Keywords

Biometrics, Electromyography (EMG), Feature extraction, Gaussian mixture model (GMM), Non-uniform filter bank (NUFB).

1. Introduction

Biometrics is the authentication method that identifies actual applicant as a particular person when compared with other traditional methods like photo identity card, tokens, badges and passwords etc., which may be hacked by some body. State-of-the-art person identification system uses finger prints, hand geometry, face, eye, voices, signature and gaits.

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Suresh M, Assistant Professor, Department of E&C, KIT, Tiptur, Karnataka, India.
P G Krishnamohan, Retired Professor, Department of E&C, JNTUH, Hyderabad, India.
Mallikarjun S Holi, Professor & Chairman, Department of E&IE, UBDTCE, VTU, Davangere, Karnataka, India.

Biometric technologies offer a means to make user authentication more transparent with higher security than traditional methods (e.g. text password). Among these kinds of biometric methods, speaker recognition is considered as the simplest, the cheapest, and the most convenient one. The ability of recognizing a person from his voice is known as speaker recognition. Speaker recognition uses the acoustic features of speech that have been found to differ between individuals, and therefore, it can be used as a distinguishing feature for recognizing its owner among other individuals.

Researchers have tried the study of person identification using EEG and ECG from several decades. Neurophysiologists have suspected that direct link between EEG and the genetic information of an individual. Recently, the research work focuses on healthy persons to establish one-to-one correspondence between the genetic information of the person and certain features of EEG. A test for person identification carried out by Poulous et al. (1999). In their work, correct classification scores ranging from 80% to 100% in experiments conducted on real data, show evidence that EEG carries genetic information and this method can be used for person identification based on EEG features [1]. The ECG signal is the electrical activity of the heart muscle fiber and is related to the physiology of each person. Past work revealed that the ECG features also person specific with evidence that ECG based person identification is possible [2, 3].

EMG means to monitor muscle activity. Theado et al. has developed an EMG dynamic model which is person specific in terms of muscle location and size, mass of body, motion of subject, and activities of muscle [4].Many studies have measured the reliability of SEMG measurements, on the basis of stability across many measurements. In 1970 Komi and Buskirk [5] found that the average reliability for surface electrodes was 88%.Motivated from the above, made an attempt to study significance of EMG in biometric person identification in [6]. Characteristic of EMG signals are different even though the appearances of two person gestures might look identical. These works motivated to use EMG signal acquired from flexor carpi ulnaris muscle present in the forearm as a trait to explore the feasibility of person identification.

2. Evidences to Use EMG for Person Identification

Since direct connection between muscle, intact central nervous system, brain and neuromuscular activity unique to an individual, EMG signals changing from individual to individual. The EMG signal is related to the physiology of each individual. The measurements are influenced by muscle fiber pattern, motor unit discharge pattern, changes in blood flow, neural activity, and neurotransmitter activity within the muscle, skin conductivity, position, shape and size of the muscle, development of muscle, motor unit paths, different density of bone, and distribution of heat in the muscle, skin-fat layer, and gesture style. The appearances of two person gestures may look like identical, but the characteristic of EMG signals are not same. Regardless of which factors makes differences in the measurement, the fact that EMG contains physiologic dependant singularities makes its application to person identification.

3. EMG Feature Extraction

The EMG spectrum has special shapes and is distributed by a non-linear scale in frequency domain. Using the filter-banks which are matched to those of the desired signal, the contribution of noise components in the frequency domain can be reduced. EMG spectrum is concentrated within the range of 20Hz-500Hz. In such a band, more resolution is needed to obtain more information of the spectrum. In this work, EMG spectrum is processed by filtering out the frequency band outside the range of 20Hz-500Hz. The NUFB is used due to its consistent person identification performance.

The various steps involved in the NUFB feature extraction are as follows:

(i) Pre-emphasis: This emphasizes the higher frequencies and balance the spectrum of EMG signal that have a steep roll-off in the high frequency region. The transfer function of pre-emphasis filter is given by

$$H(Z)=1+bz^{-1} \quad (3.12)$$

The value of b controls the slope of the filter and is from 0.9 to 1.0.

(ii) Frame blocking and windowing: The EMG is slow varying quasi-stationary signal. Therefore, EMG analysis must always be carried out on small segments across which the EMG signal is assumed to be stationary. Short-term spectral measurements are carried out over the range of 10-250 ms frame size and shift. The frames are hamming windowed. This helps to reduce the edge effect while using the DFT on the signal.

(iii) DFT spectrum: windowed frame is converted into magnitude spectrum by using DFT.

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{\frac{-j2\pi nk}{N}} \qquad 0 \leq K \leq N-1$$

Where N is the number of points.

(iv) NUFB spectrum: This can be computed by passing the Fourier transformed signal through a group of non uniform filters known as NUFB frequency coefficients.

(v) Inverse Discrete Cosine Transform (IDCT): The log operation is performed on the NUFB frequency coefficients. The IDCT is then applied to obtain cepstral coefficients. NUFB cepstral coefficients are computed as:

$$c(n) = \sum_{m=0}^{M-1} \log_{10}(S(m)) \cos\left(\frac{n\pi(m-0.5)}{M}\right)$$

Where n=0, 1, 2,…, C-1

Where c(n) are the cepstral coefficients and C is the number of NUFB cepstral coefficients. To obtain the smoothed representation of slowly changing part of the spectrum NUFB is used. So segmenting the initial 500 Hz spectrum of EMG signal is done in thirteen overlapping rectangular bands to obtain a thirteen dimensional basic feature vector. And then first and second derivatives of basic feature vector are obtained.

4. EMG Modeling Using NUFB Features

The modeling technique is used to capture the distribution of the feature vectors according to the person information. Person models built using the feature vectors from different EMG bursts, but from the same persons. The attributes of person model are better representation of person, must consume less time for processing [7]. The success of each of the modeling techniques depends on the principle used for clustering. Earlier studies for person identification used direct template matching between training and testing data [8, 9, 10, 11, 12, 13, 14]. In the direct template matching, training and testing feature vectors are compared using similarity measure. The limitation of template matching is, time consuming as the feature vector size increases. For this reason, reduce the number of test vectors by clustering approach. Person identification system using EMG employs modeling techniques like GMM, which have some or all of these attributes and used. The Gaussian mixture model (GMM) which is briefly described in this section.

4.1Gaussians Mixture Modeling (GMM)

In GMM, probability density function of the feature vectors of each person is captured using Gaussian mixtures. The complete Gaussian mixture density is parameterized by the mean vector, covariance matrix, and mixture weights for all the components.

The method used to fit a GMM to EMG data is the expectation maximization (EM) algorithm [13], which converges to a maximum likelihood (ML) estimate. Plus several model order selection used to estimate the number of components of a GMM. The GMM needs sufficient data (at least one minute) to model the person.

5. Results and Discussions

Our approach consists of a NUFB feature extraction combined with GMM modeling. Various experiments have been conducted to determine the person identification performance, with collected 3 sessions EMG data in a gap of one day duration for a database consisting of 100 persons. 5 slots of 10 seconds present in each session. There are total of 15 slots of data from all the three sessions. The numbers of EMG frames used for training the VQ per person are obtained as shown in the following Fig.1. For EMG frames of size 50 ms (100 samples at 2 kHz sampling rate) with a shift of 25 ms (50 samples at 2 kHz sampling rate) 2000 frames per session per person are obtained. First four slots of any two arbitrary sessions are used for training. 400 feature vectors obtained for every 10 seconds slot of EMG data. Therefore for four slots of any two sessions data 1600×2=3200 feature vectors are used for training. For testing, last slots (400 frames per slot) of all sessions are used separately.

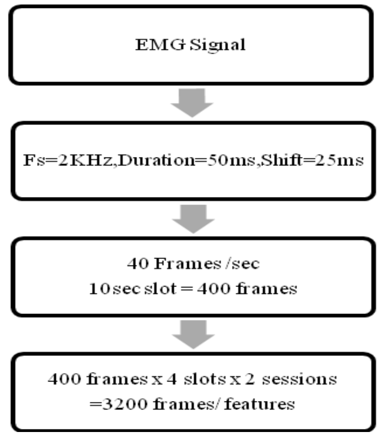

Fig 1: Feature vectors used to generate the codebooks per person

Feature vector consist of 39 dimension coefficients including 13 dimensions of NUFB coefficients combined with its velocity and acceleration coefficients. The 39 dimension augmented feature vectors is trained using GMM modeling technique. First four slots (40 seconds data) of any arbitrarily selected two sessions (80 seconds data) out of three session data collected for training the GMM model. Last slot (10 seconds data) of all three sessions used for testing separately for 2, 4, 8, 16, 32 Gaussians size and results of person identification performance are tabulated in the Table 1.

Table 1: 13 base NUFB plus, 13 ∆ and13 ∆∆ with GMM

Training sessions	Number of Gaussians	Testing session		
		1	2	3
1,2	2	63.27	**97.96 7**	73.47
	4	69.39	**97.96**	73.47
	8	71.43	95.92	**75.51**
	16	69.39	**97.96**	**75.51**
	32	69.39	**97.96**	73.47
2,3	2	57.14	81.63	91.84
	4	63.27	79.59	**97.96**
	8	**65.31**	83.67	**97.96**
	16	**65.31**	83.67	**97.96**
	32	**65.31**	85.71	95.92
1,3	2	57.14	81.63	91.84
	4	65.31	77.55	**97.96**
	8	65.31	83.67	**97.96**
	16	63.27	83.67	**97.96**
	32	65.31	**85.71**	95.92

During the course of experiment, 4 slots of EMG data from session 1 and session 2 are used for training and no slots of data from session 3 is used for training and remaining one slot of data from each of the session 1, session 2 and any of the slot of data of 10 seconds from session 3 are used for testing. Maximum person identification performance of 97.96% is obtained for the last slot of test EMG data chosen from trained session 2 for the 2,4,16,32 Gaussians rather than from session 1 test EMG data. It is obvious for the reason that the model is most recently learned with the session 2 data. It seems model is not yet generalized to yield better performance for the last slot of test EMG data from session 1 and session 3. Further, the model is not trained with session 3 data and hence the maximum identification performance of 75.51% is obtained for the last slot of test EMG data selected from untrained session 3, which is less than the person identification performance of 97.96% for the last slot of test EMG data chosen from trained session 2.

This model is similarly trained with session 2 and session 3 EMG data without using session 1 EMG data for training. In this case, maximum person identification performance of 97.96% is obtained for the last slot of test EMG data selected from trained session 3 with Gaussians of 4, 8 and 16. Since the session 1 EMG data is not used for training the model, the maximum person identification performance of 65.31% is obtained for the last slot of test EMG data selected from untrained session 1 which is less than the maximum person identification performance of 97.96% obtained for the last slot of test EMG data selected from trained session 3 with Gaussians of 8, 16 and 32. In this case also, the model yield better performance 97.96% for the last slot of 10 seconds of EMG data selected from the most recently learned session 3 EMG data.

In order to complete the experiment, the model is again trained with session 1 and session 3 EMG data without using the session 2 EMG data for training. In this case, the model yields the maximum person identification performance of 97.96% with Gaussian of 4,8 and 16 for the last slot of 10 seconds of test EMG data selected from trained session 3 which is also the most recently learned session EMG data by the model. Further, the model yields maximum person identification performance of 85.71% with Gaussian of 32 for last slot of 10 seconds of EMG data selected from untrained session 2. This result is again less than the result obtained from the trained session 3.

It can be seen that the GMM-based system achieved the best result of 97.96% using 13 dimensional base NUFB plus 13 velocity and 13 acceleration coefficients. Further it is evident from these experiments that the model is suffering from session generalization and is varying from experiment to experiment for the test EMG data selected from untrained sessions. In order to confirm this findings, the experiment is again repeated with sessions used for training is reversed and similar observation is found in Table 2.

Table 2: NUFB-GMM with two sessions used for training is reversed

Training sessions reversed	Number of Gaussians	Testing session		
		1	2	3
2,1	2	93.88	57.14	48.98
	4	100	59.18	53.06
	8	100	61.22	48.98
	16	100	63.27	55.10
	32	100	63.27	53.06
3,2	2	63.27	95.92	69.39
	4	69.39	97.96	73.47
	8	73.47	95.92	75.51
	16	71.43	97.96	73.47
	32	71.43	97.96	73.47
3,1	2	91.84	57.14	46.94
	4	100	59.18	51.02
	8	100	61.22	48.98
	16	100	63.27	53.06
	32	100	63.27	53.06

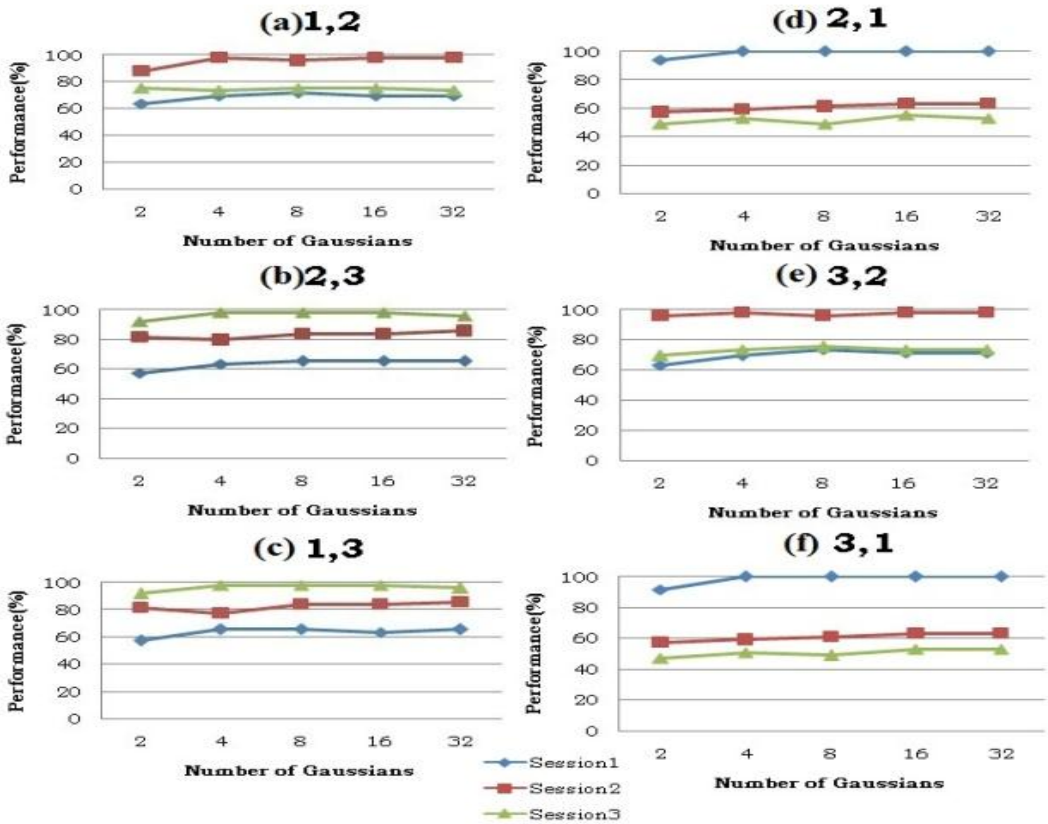

Fig 2: Performance of person identification system based on 13 dimensional base NUFB plus, 13Δ and13ΔΔ with GMM

The Fig.2. Shows the large person identification performance for recently trained sessions. From results, it is well understood that the problem is in session generalization. Further to explore, the EMG data slots are intermixed amongst the sessions selected for training and above experiment are repeated with an expectation of model person identification performance improvements. For this purpose, following mixing strategy is employed. In the proposed mixing strategy, first slot of 10 seconds of EMG data of session 1 and session 2 are first used for training the model and then the second slot of 10 seconds of EMG data of both sessions are similarly used next for training the model and so on. In this case, after similar testing, maximum person identification performance of 93.88% and 95.92% is obtained for last slot of 10 seconds of test EMG data selected from session 2 and session 1 respectively with improved session generalization amongst training session as shown in Table 3.

Table 3: NUFB-GMM with two sessions used for training is intermixed

Training sessions with intermixed data slots	Number of Gaussians	Testing session		
		1	**2**	**3**
1,2	2	89.80	83.67	59.18
	4	87.76	89.80	67.35
	8	91.84	91.84	79.59
	16	95.92	93.88	79.59
	32	95.92	93.88	75.51
2,3	2	67.35	93.88	81.63
	4	75.51	93.88	91.84
	8	91.84	93.88	91.84
	16	77.55	95.92	91.84
	32	77.55	97.96	91.84
1,3	2	79.59	67.35	77.55
	4	85.71	71.43	85.71
	8	91.84	81.63	91.84
	16	93.88	83.67	93.88
	32	93.88	85.71	93.88

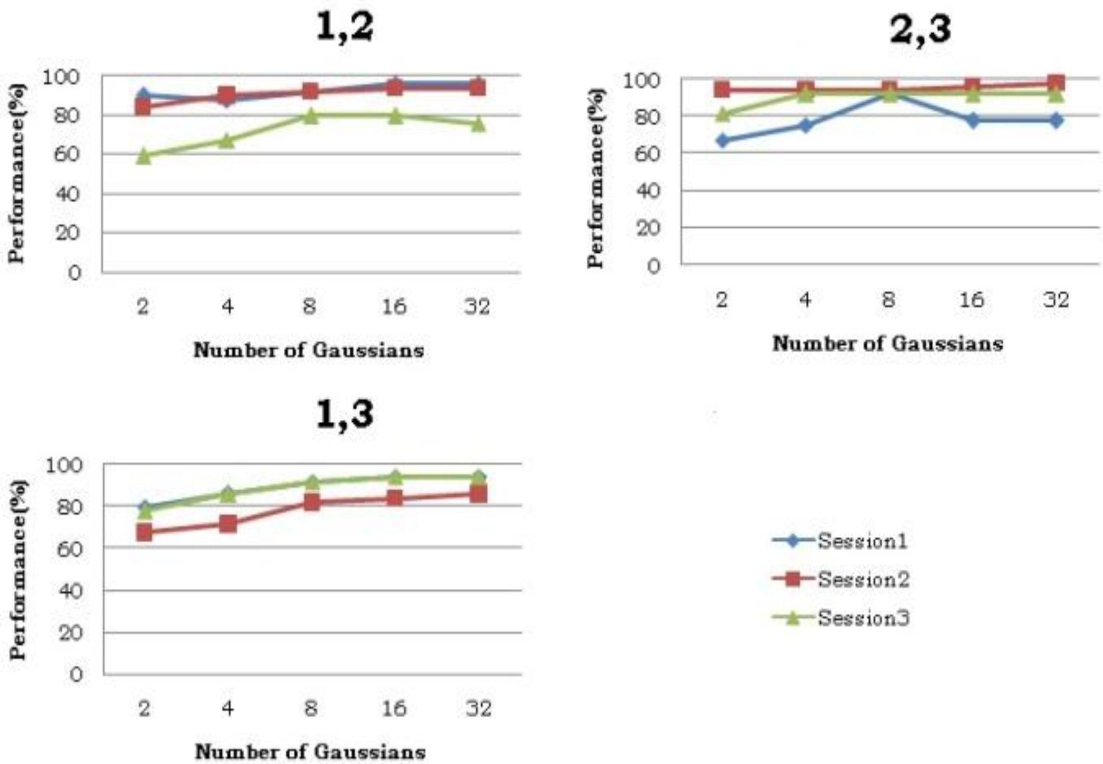

Fig 3: Performance of person identification system with two sessions used for training is intermixed using NUFB-GMM

In this case also, the model suffers from session generalization for test EMG data selected from untrained session as shown in Fig.3.This problem can be overcome by choosing all the three sessions of EMG data for training. In order to explore this fact, intermixing of slots of 10 seconds of data from all the three sessions is employed for training. In a conventional manner the last slot of 10 seconds of test EMG data from each of the trained session is used for testing. Also, session generalization improvement with enhance performance is expected from GMM. In this case, maximum person identification performance of 89.80 for 16 and 32 Gaussians for session 1, 93.88% with only 2 Gaussians for session 2 and 93.88% with 16 Gaussians for session 3 is achieved as shown in Table 4.

Table 4: NUFB-GMM with three sessions for training intermixed

Training sessions	Number of Gaussians	Testing session		
		1	2	3
1,2,3	2	83.68	**93.88**	71.43
	4	81.63	91.84	87.76
	8	83.67	91.84	91.83
	16	**89.80**	91.84	**93.88**
	32	**89.80**	91.84	91.84
2,3,1	2	83.66	**93.88**	71.43
	4	81.66	91.84	87.76
	8	83.66	91.84	91.84
	16	89.66	91.84	**93.88**
	32	**89.80**	91.84	91.84
3,1,2	2	83.68	**93.88**	71.43
	4	81.63	91.84	87.76
	8	83.67	91.84	91.84
	16	**89.80**	91.84	**93.88**
	32	**89.80**	91.84	91.84

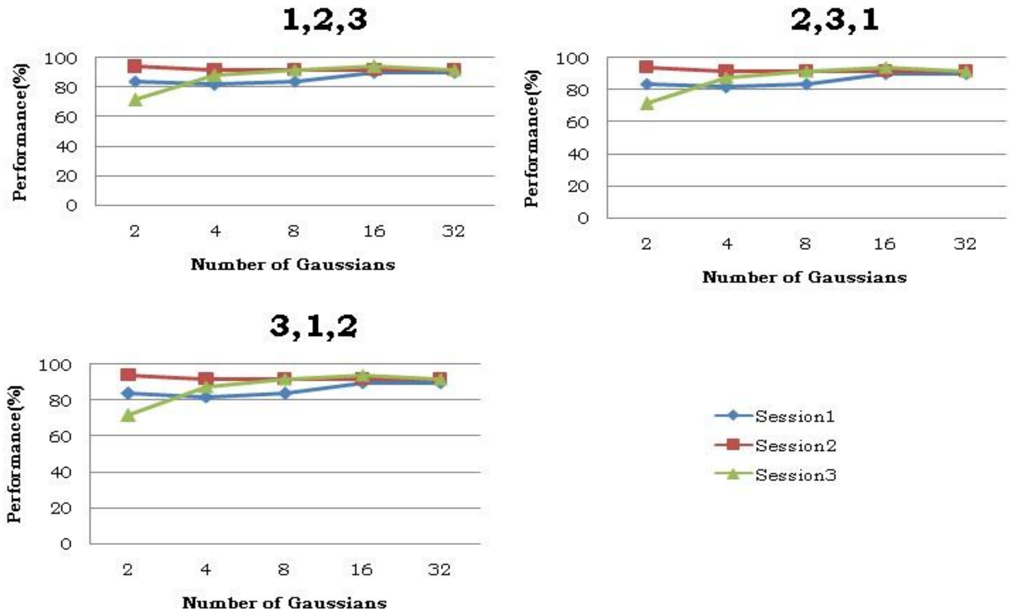

Fig 4: Performance of person identification system with three sessions used for training is intermixed using NUFB-GMM

Similar results are obtained with sessions are interchanged and trained with GMM shown in Fig.4. It is found in this case that, person identification performance is slightly reduced without losing session generalization may be due to the fact that the GMM is a statistical requires huge data.

To customize the EMG based person identification system the experiment is repeated for different groups of persons and tested for up to 1024 sized Gaussians and the results are shown in Table 5.

Table 5: NUFB-GMM with three sessions used for training intermixed for different groups up to 100 people

Total No. Of persons	Number of Gaussians									
	2	**4**	**8**	**16**	**32**	**64**	**128**	**256**	**512**	**1024**
10	90	90	90	100	100	100	100	100	100	100
20	65	60	65	75	75	85	85	85	85	85
30	73	70	73	83	83	83	88	88	80	84
40	80	77	80	87	87	87	92	92	92	90
50	83	81	83	89	89	89	93	93	93	91
60	83	81	83	90	91	90	95	95	95	95
70	85	84	85	91	92	91	95	95	95	95
80	87	83	86	91	92	91	95	95	95	95
90	84	83	86	92	93	92	95	95	94	95
100	86	85	88	93	94	93	96	96	96	96

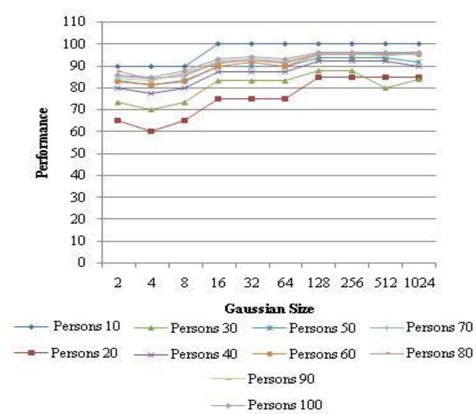

Fig 5: Performance variations versus code book size for intermixed 3 session data using NUFB-GMM

The variation in performance of EMG person identification system for different Gaussians is graphically illustrated in Fig.5. It is evident from the graph that the performance gradually increases from Gaussians size of 2 and become consistent from Gaussians size of 64 onwards. The nature of variation of performance with changing Gaussians size resembles mostly the behavior of over damped system. The performance of EMG based person identification system become substantially stable from Gaussians size of 64 onwards for change in total number of persons. In order to ensure this fact, the performance change against the variation in total number of persons is graphically illustrated in Fig.6. It is clearly revealed the fact that the performance of this EMG based person identification system substantially remains stable from Gaussians size of 64 onwards for change in total number of persons. Thus the stability of EMG based person identification system that is developed in this work demonstrated excellent in its performance from Gaussians size of 64 onwards and is superior at the Gaussians size of 128.

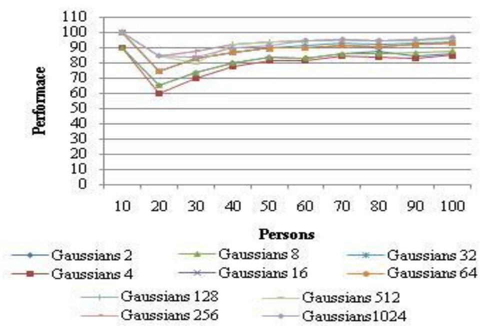

Fig 6: Performance variations versus group of persons for intermixed 3 session data using NUFB-GMM

GMM is the one with the best performance through a highest computational cost and template size. According to our knowledge, this study represents the first effort to use EMG for person identification task.

6. Conclusion and Future work

In this work the capability of an EMG based person identification system using 39 dimensional NUFB-GMM approaches substantially remains stable from Gaussian size of 64 onwards for change in total number of persons. Thus the stability of EMG based person identification system that is developed in this work demonstrated excellent in its performance from Gaussians of 64 onwards and is superior at the Gaussians size of 128.

Bio-physiological signals are non linear, non stationary and stochastic. Recently explored non linear non stationary data analysis tool called hilbert huang transform (HHT) found interesting for the analysis of SEMG. It is empirical mode decomposition (EMD) in time domain combined with hilbert spectral analysis (HSA). EMD may be helpful to derive better person specific features that lead to improved person identification performance.

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M.Suresh was born in India on October 28, 1967.He received the BE degree in instrumentation at Siddaganga Institute of Technology, Tumkur, Karnataka and ME degree in electronics from the BMS College of engineering,, Bangalore, India in 1991 and 1994 respectively. From 1994 to 1999, he was a Lecturer, onwards and currently he is Assistant Professor with electronics and communication department, Kalpataru Institute of Technology, Tiptur, India, pursuing PhD programme at Jawaharlal Nehru Technological University, Kukatpally, Hyderabad, Andhrapradesh. His research interests include biometrics, biomedical and speech signal processing. Prof. Suresh is a member of ISTE and member of IETE.

P.G.Krishnamohan was born in India on June 25, 1952. He received the B. Tech degree in electronics and communication engineering at Regional Engineering College, Warangal in 1975. He received the master degree in Communication Systems at Rookee University, Roorkee, Uttar Pradesh, India in 1977 and research degree in Signal Processing at Indian Institute of Science, Bangalore, India in 1988.

He has 36 years teaching experience, Worked as Head of Department of Electronics and Communication Engineering Department, JNTU, Hyderabad. he guided 30 M.Tech student project and 3 PhD students. Many research projects carried out successfully and published 42 research papers. He was chairman of board of studies of E.C.E department. Currently he is professor in the department of electronics and communication, IARE, Hyderabad. His research interests include signal processing, signal estimation, probability random variables, analog and digital communications.

Dr. Mallikarjun S Holi was Born on 15th August 1970 at Gulbarga, completed BE in Instrumentation Technology from PDA College of Engineering (Gulbarga University) in 1993. He obtained M.Tech. and Ph.D. degree from Indian Institute Technology, Madras in 1997 & 2004 respectively.

He has 20 years of teaching experience and 11 years of Research experience in the area of Instrumentation Technology & Biomedical Engineering. His research interests are: Biomechanics, Rehabilitation Engineering, Biomedical Signal and Image Processing, Biomedical Instrumentation & Process Control. He has published 76 research papers in National & International journals and conferences. Currently he is Professor and Chairman, Department of Electronics and Instrumentation Engineering, University BDT College of Engineering, VTU, Davangere, Karnataka. He is guiding 7 students for Ph.D. Programme. He has carried out three Sponsored Research Projects funded by AICTE and Visvesvaraya Technological University.

Dr. Mallikarjun S Holi is a life member of Indian Society for Technical Education, Indian Society of Biomechanics, Bio medical Engineering Society of India, Ultrasound Society of India, Indian Association of Biomedical Scientists. Dr.Holi has received many awards, among prominent are:

- Institute Merit Award for the Best Academic record in M.Tech (Biomedical Engineering) program for the academic year 1995–1996, from I.I.T, Madras
- Received Travel Grant Award from IEEE-Engineering in Medicine and Biology Society for Best Research Paper in the 28th Annual Northeast Bioengineering Conference, Drexel University, Philadelphia, USA, 2002.
- Received Travel Grant Award from International Bone and Mineral Society & Japanese Society for Bone and Mineral Research for Best Research Paper in the First Joint Meeting of IBMS-JSBMR, Osaka, Japan, 2003.