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Voice recognition system based on intra-modal fusion and accent classification

Srikanth Mangayyagari
University of South Florida

Voice Recognition System Based on Intra-Modal Fusion and Accent Classification

by

Srikanth Mangayyagari

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Major Professor: Ravi Sankar, Ph.D.
Sanjukta Bhanja, Ph.D.
Nagarajan Ranganathan, Ph.D.

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DEDICATION

Dedicated to my parents who sacrificed their today for our better tomorrow.

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ABSTRACT

Speaker or voice recognition is the task of automatically recognizing people from their speech signals. This technique makes it possible to use uttered speech to verify the speaker's identity and control access to secured services. Surveillance, counter-terrorism and homeland security department can collect voice data from telephone conversation without having to access to any other biometric dataset. In this type of scenario it would be beneficial if the confidence level of authentication is high. Other applicable areas include online transactions, database access services, information services, security control for confidential information areas, and remote access to computers.

Speaker recognition systems, even though they have been around for four decades, have not been widely considered as standalone systems for biometric security because of their unacceptably low performance, i.e., high false acceptance and true rejection. This thesis focuses on the enhancement of speaker recognition through a combination of intra-modal fusion and accent modeling. Initial enhancement of speaker recognition was achieved through intra-modal hybrid fusion (HF) of likelihood scores generated by Arithmetic Harmonic Sphericity (AHS) and Hidden Markov Model (HMM) techniques. Due to the

Contrastive nature of AHS and HMM, we have observed a significant performance improvement of 22% , 6% and 23% true acceptance rate (TAR) at 5% false acceptance rate (FAR), when this fusion technique was evaluated on three different datasets – YOHO, USF multi-modal biometric and Speech Accent Archive (SAA), respectively. Performance enhancement has been achieved on both the datasets; however performance on YOHO was comparatively higher than that on USF dataset, owing to the fact that USF dataset is a noisy outdoor dataset whereas YOHO is an indoor dataset.

In order to further increase the speaker recognition rate at lower FARs, we combined accent information from an accent classification (AC) system with our earlier HF system. Also, in homeland security applications, speaker accent will play a critical role in the evaluation of biometric systems since users will be international in nature. So incorporating accent information into the speaker recognition/verification system is a key component that our study focused on. The proposed system achieved further performance improvements of 17% and 15% TAR at an FAR of 3% when evaluated on SAA and USF multi-modal biometric datasets. The accent incorporation method and the hybrid fusion techniques discussed in this work can also be applied to any other speaker recognition systems.

CHAPTER 1

INTRODUCTION

1.1 Background

A number of major developments in several fields have occurred recently: the digital computer, improvements in data-storage technology and software to code computer programs, advanced sensor technology, and the derivation of a mathematical control theory. All these developments have contributed to advancement of technology. But along with advancement of technologies, security threats have increased in various realms such as information, airport, home, international, and national securities. As of July 4th 2007, the threat level from international terrorism is severe [1]. According to MSNBC, identity thefts cost banks $1 billion per year and FBI estimates 500,000 victims in the year 2003 [2]. Identity theft is considered one of the country's fastest growing white-collar crimes. One recent survey reported that there have been more than 28 million new identity theft victims since 2003, but experts say many incidents go undetected or unreported. Due to the increased level of security threats and fraudulent transactions, the need for reliable user authentication has increased and hence biometric security systems have emerged. Biometrics, described as the science of recognizing an individual based on his or her physical or behavioral traits, is beginning to gain acceptance as a legitimate method for determining an individual's identity.

Different biometrics that can be used are fingerprints, voice, iris scan, face, retinal scan, DNA, handwriting typing patterns, gait, color of hair, skin, height, and weight of a person. This research work focuses on voice biometrics or speaker recognition technology.

Speaker or voice recognition is the task of automatically recognizing people from their speech signals. This technique makes it possible to use uttered speech to verify the speaker's identity and control access to secure services, i.e., online transactions, database access services, information services, security control for confidential information areas, remote access to computers, etc.

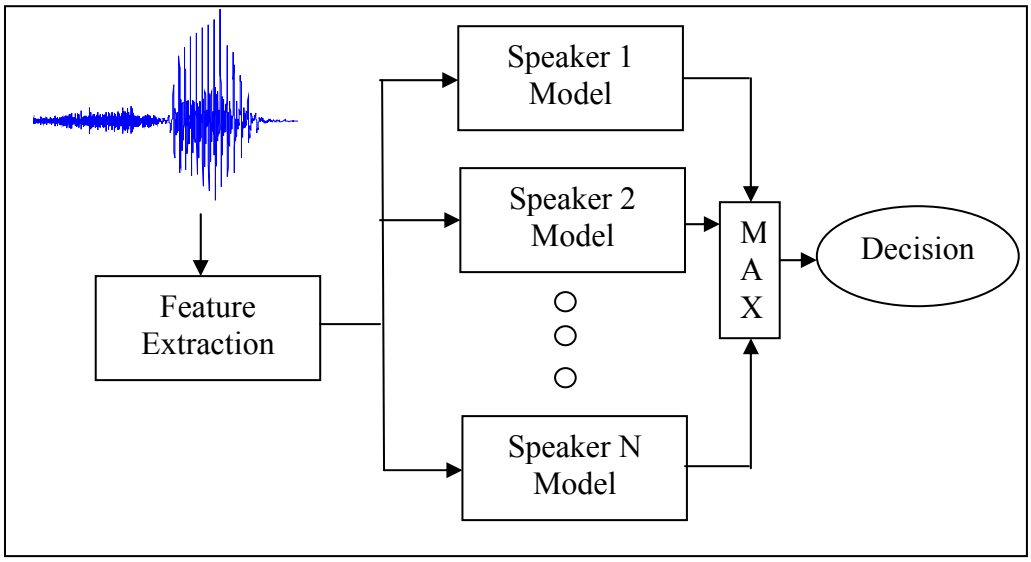


Figure 1. Speaker Identification System

A typical speaker recognition system is made up of two components: feature extraction and classification. Speaker recognition (SR) can be divided into *speaker identification* and *speaker verification*. Speaker identification system determines who amongst a closed set of known speakers is providing the given utterance as depicted by the

block diagram in Figure 1. Speaker specific features are extracted from the speech data, and compared with speaker models created from voice templates previously enrolled. The model with which the features match the most is selected as the legitimate speaker. In most cases, the model generates a likelihood score and the model that generates the maximum likelihood score is selected.

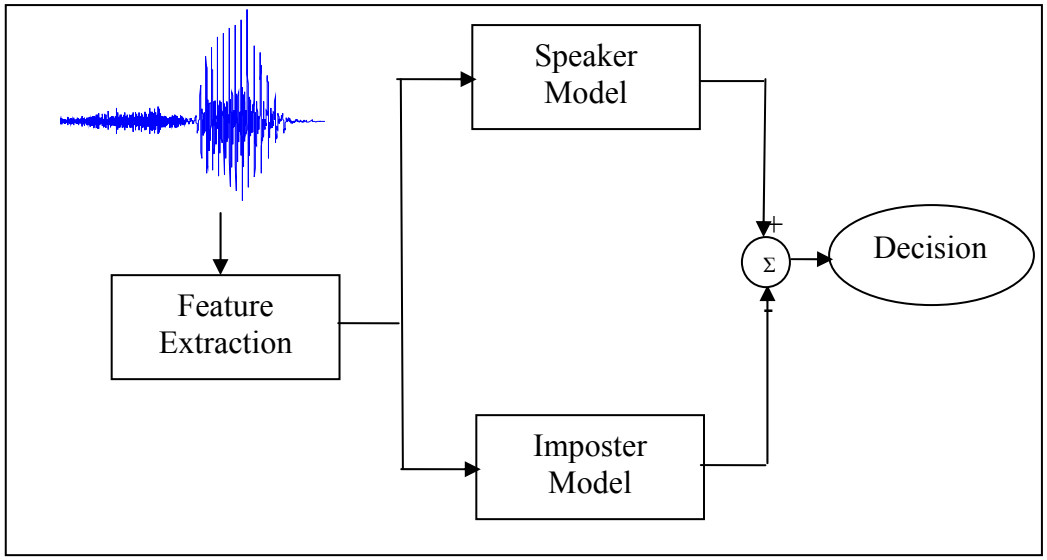


Figure 2. Speaker Verification System

On the other hand, speaker verification system as depicted by the block diagram in Figure 2, accepts or rejects the identity claim of a speaker. Features are extracted from speech data and compared with the legitimate speaker model as well as an imposter speaker model, which are created from previously enrolled data. The likelihood score generated from the speaker model is subtracted from the imposter model. If the resultant score is greater than a threshold value, then the speaker is accepted as a legitimate speaker. In either case, it is expected that the persons using these systems are already enrolled. Besides these systems

can be text-dependent or text-independent. Text-dependent system uses a fixed phrase for training and testing a speaker. On the contrary, text-independent system does not use a fixed phrase for training and testing purposes. In addition to security, speaker recognition has various applications and is rapidly increasing. Some of the areas where speaker recognition can be applied are [3]:

1) Access Control:

Secure physical locations as well as confidential computer databases can be accessed through one's voice. Access can also be given to private and restricted websites.

2) Online Transactions:

In addition to a pass phrase to access bank information or to purchase an item over the phone, one's speech signal can be used as an extra layer of security.

3) Law Enforcement:

Speaker recognition systems can be used to provide additional information for forensic analysis. Inmate roll-call monitoring can be done automatically at prison.

4) Speech Data Management:

Voicemail services, audio mining applications, and annotation of recorded or live meetings can use speaker recognition to label speakers automatically.

5) Multimedia and Personalization:

Soundtracks and music can be automatically labeled with singer and track information. Websites and computers can be customized according to the person using the service.

1.2 The Problem

Even though speaker recognition systems have been researched over several decades and have numerous applications, they still cannot match the performance of a human recognition system [4] as well as not reliable enough to be considered as a standalone security system. Although speaker verification is being used in many commercial applications, speaker identification cannot be applied effectively for the same purpose. The performance of speaker recognition systems degrade especially under different operating conditions. Speaker recognition system performance is measured using various metrics such as recognition or acceptance rate and rejection rate. Recognition rate deals with the number of genuine speakers correctly identified, whereas rejection rate corresponds to the number of imposters (people falsifying genuine identities) being rejected. Along with these performance metrics there are some performance measures and trade-offs one needs to consider while designing speaker recognition systems. Some of the performance measures generally used in the evaluation of these systems include: false acceptance rate (FAR) - the rate at which an imposter is accepted as a legitimate speaker, true acceptance rate (TAR) - the rate at which a legitimate speaker is accepted, and false rejection rate (FRR) - the rate at which a legitimate speaker is rejected (FRR=1-TAR).

There is a trade-off between FARs and TARs, as well as between FARs and FRRs. Intuitively, as the false acceptance rate is increased, more speakers are accepted, and hence true acceptance rate rises as well. But the chances of an imposter accessing the restricted services also increase; hence a good speaker recognition system needs to deliver

performance even when the FAR threshold is lowered. The main problem in speaker recognition is, poor TARs at lower FARs, as well as high FRRs.

The performance of a speaker recognition system [3] for three different datasets is shown in Figure 3. Here, error (%) which is equivalent to FRR (%) has been used to measure performance. The TIMIT dataset consists of clean speech from 630 speakers. As the dataset is clean we can see that the error is almost zero, even though the number of people is increased from 10 to 600. For NTIMIT, speech was acquired through telephone channels and the performance degraded drastically as the speaker size was increased. At about 400 speakers we can see that the error is 35%, which means a recognition rate of 65%. We can see the similar trend for SWBI dataset, where speech was also acquired through telephone

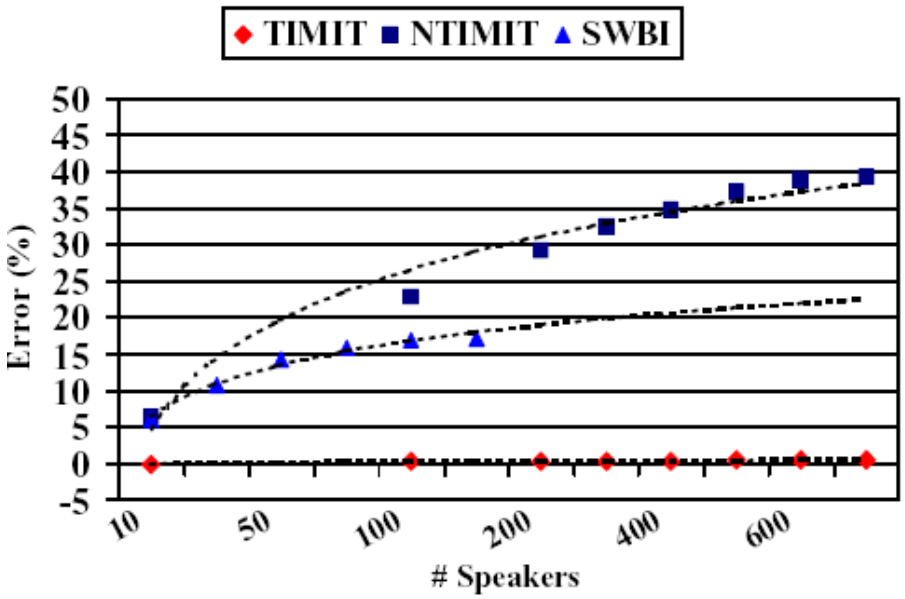


Figure 3. Current Speaker Recognition Performance over Various Datasets [3]

channel. However, the performance for SWBI is not as low as TIMIT, which indicates that various other factors other than the type of acquisition influence the recognition rate. It

depends on the recording quality (environmental noise due to recording conditions and noise introduced by the speakers such as lip smacks) and the channel quality. Hence it is hard to generalize the performance of an SR system on a single dataset. From Figure 3, we can see that the recognition rate degrades as the channel noise increases and also when the number of speakers increases. Another evaluation of current voice recognition systems (Figure 4) conducted by the UK BWG (Biometric Working Group) shows that about 95% recognition can be achieved at an FAR of 1% [5]. The dataset consisted of about 200 speakers and voice was recorded in a quiet office room environment.

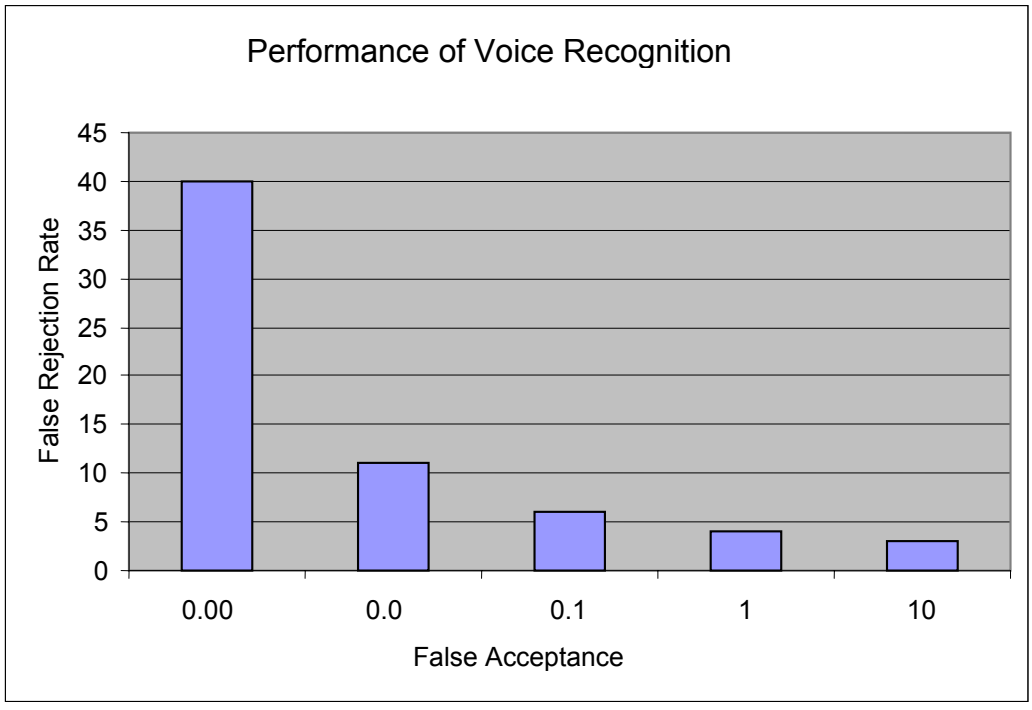


Figure 4. Current Speaker Recognition Performance Reported by UK BWG [5]

On the whole, we can see that speaker recognition performance in a real world noisy scenario cannot provide a high level of confidence. Speaker recognition systems can be

considered reliable for both defense and commercial purposes, only if a promising recognition rate is delivered at low FARs for realistic datasets.

1.3 Motivation

In this thesis, an effort has been made to deal with the problem, i.e. to achieve high TAR at lower FARs even in realistic noisy conditions, by enhancing recognition performance with the help of intra-modal fusion and accent modeling. The motivation behind the thesis can be explained by answering the three questions: why enhance speaker recognition, why intra-modal fusion and why combine accent information? In case of speaker recognition, obtaining a person's voice is non-invasive when compared to other biometrics, for example capture of iris information. With very little additional hardware it is relatively easier to acquire this biometric data. Recognition can be achieved even from long distance via telephones. In addition surveillance, counter-terrorism and homeland security department can collect voice data from telephone conversation without having to access to any other biometric dataset. In this type of scenario it would be beneficial if the confidence level of authentication is high.

Previous research works in biometrics have shown recognition performance improvements by fusing scores from multiple modalities such as face, voice, and fingerprint [6], [7], [8]. However multi-modal systems have some limitations, i.e., cost of implementation, availability of dataset, etc. On the other hand, by fusing two algorithms for the same modality (intra-modal fusion), it has been observed in [8], that performance can be similar to inter-modal systems when realistic noisy datasets are used. Intra-modal fusion reduces complexity and cost of implementation when compared to various other biometrics,

such as fingerprint, face, iris, etc. Various additional hardware and data is required for acquiring different biometrics of the same person.

Finally, speech is the most developed form of communication between humans. Humans rely on several other types of information embedded within a speech signal, other than voice alone. One of the higher levels of information that humans use is accent. Also, incorporation of accent information provides us with a narrower search tool for the legitimate speaker in huge datasets. In an international dataset, we can search within a pool of dataset, where speakers belong to the same accent group as the legitimate speaker. Homeland security, banks, and many other realistic entities, deal with users who are international in nature. Hence incorporation of accent is a key for our speaker recognition model.

1.4 Thesis Goals and Outline

The main goal in this thesis is to enhance speaker recognition system performance at lower FARs with the help of an accent classification system, even when evaluated on a realistic noisy dataset. The following are the secondary goals of this thesis:

1) Study the effect of intra-modal fusion of Arithmetic Harmonic Sphericity (AHS) and Hidden Markov Model (HMM) speaker recognition systems.
2) Formulate a text-independent accent classification system.
3) Investigate accent incorporation into the fused speaker recognition system.
4) Evaluation of the combined speaker recognition system on a noisy dataset.

Figure 5 shows the flow chart of our proposed hybrid fusion – accent (HFA) method. We have used the classification score from our accent classification system to modify the

recognition score obtained from our Hybrid Fusion (HF) speaker recognition system. Thus the final enhanced recognition score is achieved. Our system consists of three parts – HF system, AC system and the score modifier (SM) algorithm. The HF speaker recognition system [9] is made up of score-level fusion of AHS [10] and HMM [11] models, which takes enrolled and test speech data as inputs and generates a score as an output, which is a matrix when a number of test speech inputs are provided. The accent classification system is made up of a fusion of Gaussian mixture model (GMM) [12], and continuous hidden Markov model (CHMM) [13], as well as a reference accent database. It accepts enrolled and test speech inputs and generates an accent score and an accent class as the outputs for each test data. The SM algorithm, a critical part of the proposed system, makes mathematical modifications to the resultant HF score matrix controlled by the outputs of the accent classification system. The final enhanced recognition scores are generated after the modifications are made to the HF scores by the score modifier. Feature extraction is an internal block within both the HF system as well as the accent classification (AC) system. Each building block of the HFA system is studied in detail in the next sections.

The rest of the thesis is organized as follows. In the next sections each segment of the HFA system is described thoroughly in the next chapters. The hybrid fusion speaker recognition is explained in Chapter 2, which consists of background information of speech, feature extraction, speaker model creation and the fusion technique used to fuse the speaker recognition models. In Chapter 3, the accent classification system is described, along with past research work in accent classification, accent feature, and the formulation of accent classifier. In Chapter 4, the combination of speaker and accent models is investigated and its effects are studied. Chapter 5 describes the datasets and shows the results and performances

of hybrid fusion, accent classification and the complete system. Finally, Chapter 6 contains the conclusions and recommendation for future research.

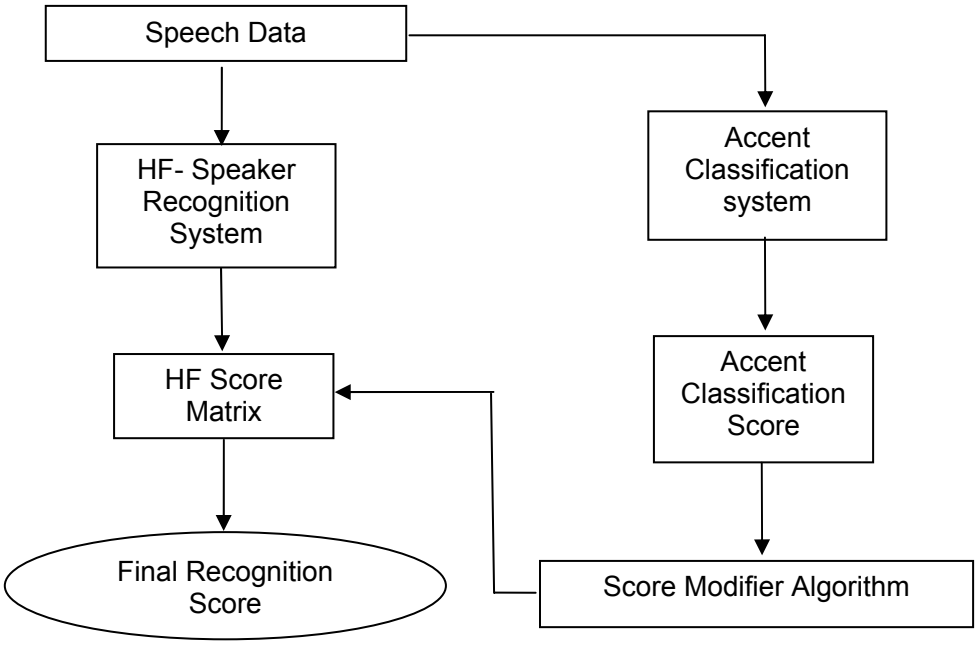


Figure 5. Flow Chart for Hybrid Fusion - Accent (HFA) Method

CHAPTER 2

HYBRID FUSION SPEAKER RECOGNITION SYSTEM

2.1 Overview of Past Research

Pruzansky at Bell labs in 1960 was one of the first ones to research on speaker recognition, where he used filter banks and correlated two digital spectrograms for a similarity measure [14]. P. D. Bricker and his colleagues experimented on text-independent speaker recognition using averaged auto-correlation [15]. B. S. Atal studied the use of time domain methods for text-dependent speaker recognition [16]. Texas Instruments came up with the first fully automatic speaker verification system in the 1970's. J. M. Naik and his colleagues researched the usage of HMM techniques instead of template matching for text-dependent speaker recognition [17]. In [18], text-independent speaker identification was studied based on a segmental approach and mel-frequency cepstral coefficients were used as features. Final decision and outlier rejection were based on a confidence measure. T. Matsui and S. Furui investigated vector quantization (VQ) and HMM techniques to make speaker recognition more robust [19]. Use of Gaussian mixture models (GMM) for text-independent speaker recognition was successfully investigated by D. A. Reynolds and R. Rose [12]. Recent research has focused on adding higher level information to speaker recognition systems to increase the confidence level and to make them more robust. G. R. Doddington used ideolectic features of speech such as word unigrams and bigrams to characterize a certain

speaker [20]. Evaluation was performed on the NIST extended data task which consisted of telephone quality, long duration speech conversation from 400 speakers. An FRR of 40% was observed at an FAR of 1%. In 2003, A. G. Adami used temporal trajectories of fundamental frequencies and short term energies to segment and label speech which were then used to model a speaker with the help of an N-gram model [21]. The same NIST extended dataset was used and similar performance as in [20] was observed. In 2003, D. A. Reynolds and his colleagues used high level information such as pronunciation models, prosodic dynamics, pitch and duration features, phone streams and conversational interactions, which were fused and modeled using an MLP to fuse N-grams, HMMs, and GMMs [22]. The same NIST dataset was used for evaluation and a 98% TAR was observed at 0.2% FAR. Also in 2006, a multi-lingual NIST dataset consisting of 310 speakers was used for cross lingual speaker identification. Several speaker features derived from short time acoustics, pitch, duration, prosodic behavior, phoneme and phone usage were modeled using GMMs, SVMs, and N-grams [23]. The several modeling systems used in this work, were fused using a multi layer perceptron (MLP). A recognition rate of 60% at an FAR of 0.2% has been reported. In [24], mel-frequency cepstral coefficients (MFCC) were modeled using phonetically structured GMMs and speaker adaptive modeling. This method was evaluated on YOHO consisting of clean speech from 138 speakers and Mercury dataset consisting of telephone quality speech from 38 speakers. An error rate of 0.25% on YOHO and 18.3% on Mercury were observed. In [25], MFCCs and their first order derivatives were used as features and an MLP fusion of GMM-UBM system and speaker adaptive automatic speech recognition (ASR) system were used to model these features. When evaluated on the

Mercury and Orion datasets consisting of 44 speakers in total, an FRR of 7.3% has been reported. In [26], a 35 speaker NTT dataset was used for evaluating a fusion of a GMM system and a syllable based HMM adapted by MAP system. MFCCs were used as features and 99% speaker identification has been reported. In [27], SRI prosody database and NIST 2001 extended data task were used for evaluation. Though this paper was not explicitly considering accent classification, it used a smoothed fundamental frequency contour (f0) at different time scales as the features, which were then converted to wavelets by wavelet analysis. The output distribution was then compacted and used to train a bigram for universal background models (UBM) using a first order Markov chain. The log likelihood scores of the different time scales were then fused to obtain the final score. The results indicate an 8% equal error rate (where FAR is equal to FRR) for two utterance test segments and it degrades to 18% when 20 test utterance segments were used. NIST 2001 extended data task consisting of 482 speakers was used for evaluation. In [28], exclusive accent classification was not performed, but formant frequencies were used for speaker recognition. Formant trajectories and gender were used as features and a feed forward neural network was used for classification. An average misclassification rate of 6.6% was observed for the six speakers extracted from the TIMIT database.

In this thesis, we focused on an intra-modal speaker recognition system, to achieve similar performance enhancement observed in [6], [7]. However, we used two complementary voice recognition systems and fused their scores to have a better performing system. Similar approach has been adopted in [24], [25] and [26], where scores from two recognition systems were fused, one of the recognition algorithms was a variant of Gaussian

Mixture Model (GMM) [24] and the other being a speaker adapted HMM [26]. But, there are a number of factors that differentiate this work from those described in [24], [25] and [26]: Database size, data collection method, and the location of the data collected (indoor and outdoor dataset). In [25] and [26], a small dataset, population of 44 and 35 respectively, was used. We, on the other hand, conducted our experiment on two comparatively larger indoor and outdoor datasets.

There has been a great deal of research towards improving speaker recognition rate by adding supra-segmental, higher level information and some accent related features like pronunciation models and prosodic information [21], [22], [27], [28]. But the effect of incorporating the outcome of an accent modeling/classifying system into a speaker recognition system has not been studied so far. Even though performance of the systems reported in [21] and [22] was good, the algorithms were complex due to the utilization of several classifiers with various levels of information fusion. But the system developed in this thesis has relatively simpler algorithms compared to these higher level information fusion systems.

2.2 Hybrid Fusion Speaker Recognition Model

Figure 6 shows the flow chart of our proposed Hybrid Fusion (HF) method. We used same person's voice data from each dataset to extract features. Arithmetic Harmonic Sphericity (AHS) is used to generate a similarity score between the enrolled feature and the test feature. A Hidden Markov Model (HMM) is created from enrolled features and an HMM likelihood score is generated for each test feature. The AHS and HMM likelihood score matrices are of

dimension NxM, where N and M are the number of speakers in testing and training sessions, respectively. These score matrices are then fused using a linear weighted hybrid fusion methodology to generate intra-modal enhanced scores. The features and the speaker models used to generate likelihood scores, as well as the fusion methodology are explained next.

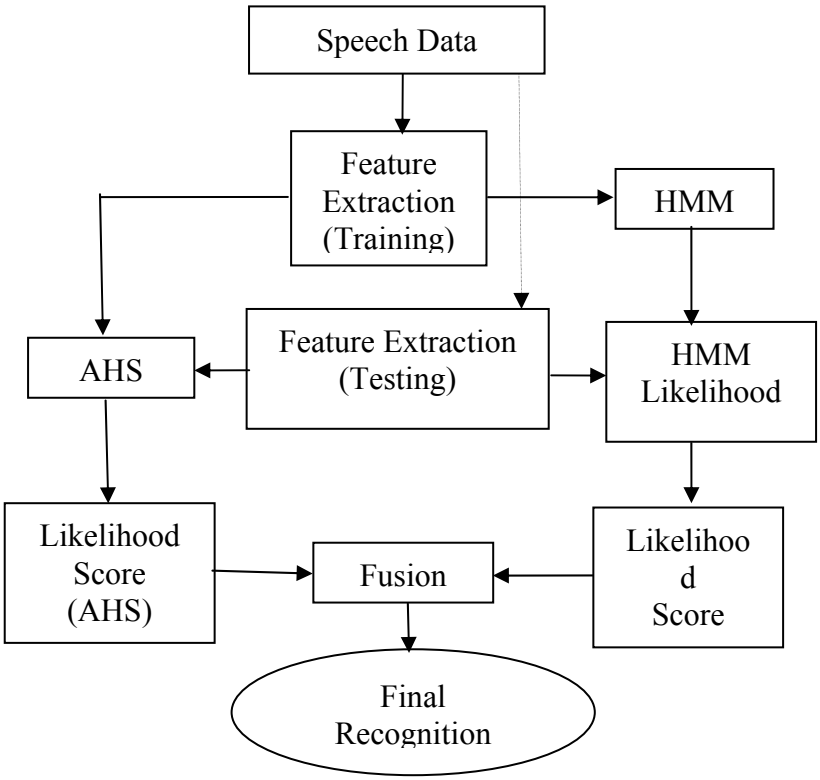


Figure 6. Flow Chart for Hybrid Fusion (HF) System

2.3 Speech Processing

2.3.1 Speech Signal Characteristics and Pre-Processing

Speech is produced when a speaker generates a sound pressure wave that travels from the speaker's mouth to a listener's ears. Speech signals are composed of a sequence of sounds that serve as a symbolic representation of thought that the speaker wishes to convey to the

listener. The arrangement of these sounds is governed by a set of rules defined by the language [29].

A speech signal must be sampled in order to make this data available to a digital system as natural speech is analog in nature. Speech sounds can be classified into voiced, unvoiced, mixed, and silence segments as shown in Figure 7, which is a plot of the sampled speech signal "six". Voiced sounds have higher energy levels and are periodic in nature whereas unvoiced sounds are lower energy sounds and are generally non-periodic in nature. Mixed sounds have both the features, but are mostly dominated by voiced sounds.

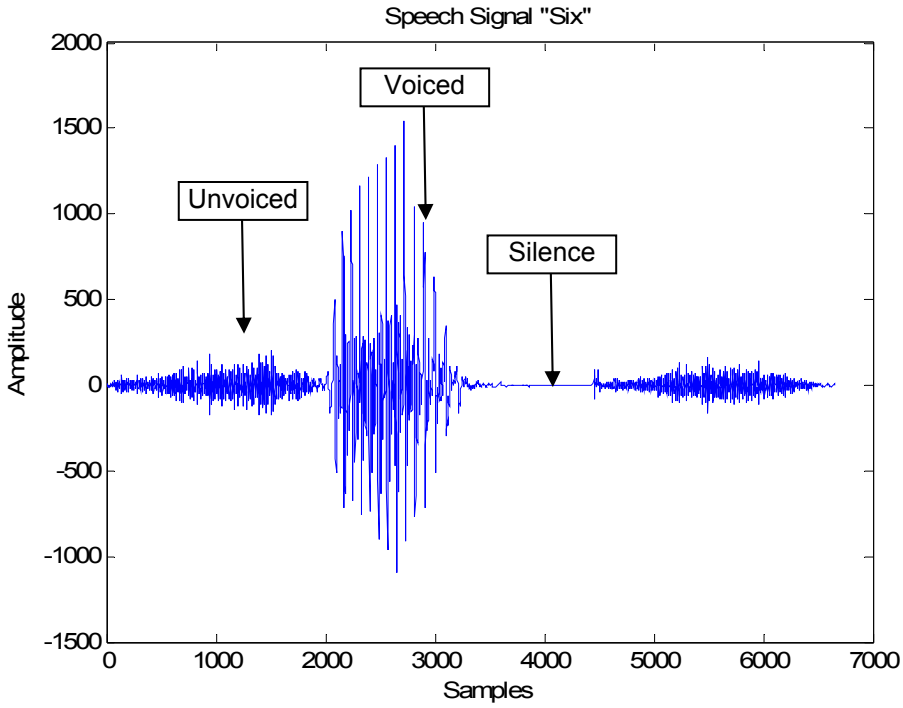


Figure 7. Time Domain Representation of Speech Signal "Six"

In order to distinguish speech of one speaker from the speech of another, we must use features of the speech signal which characterize a particular speaker. In all speaker

recognition systems, several pre-processing steps are required before feature extraction and classification. They are: pre-emphasis, framing, and windowing.

1) Pre-emphasis and Framing

Pre-emphasis is the process of amplifying the high frequency, low energy unvoiced speech signals. This process is usually performed using a simple first order high pass filter before framing. As speech is a time-varying signal, it has to be divided into frames that possess similar acoustic properties over short periods of time before features can be extracted. Typically, a frame is 20-30 ms long where the speech signal can be assumed to be stationary. One frame extracted from the speech data "six" is shown in Figure 8. It can be noted that the signal is periodic in nature, because the extracted frame consists of voiced sound /i/.

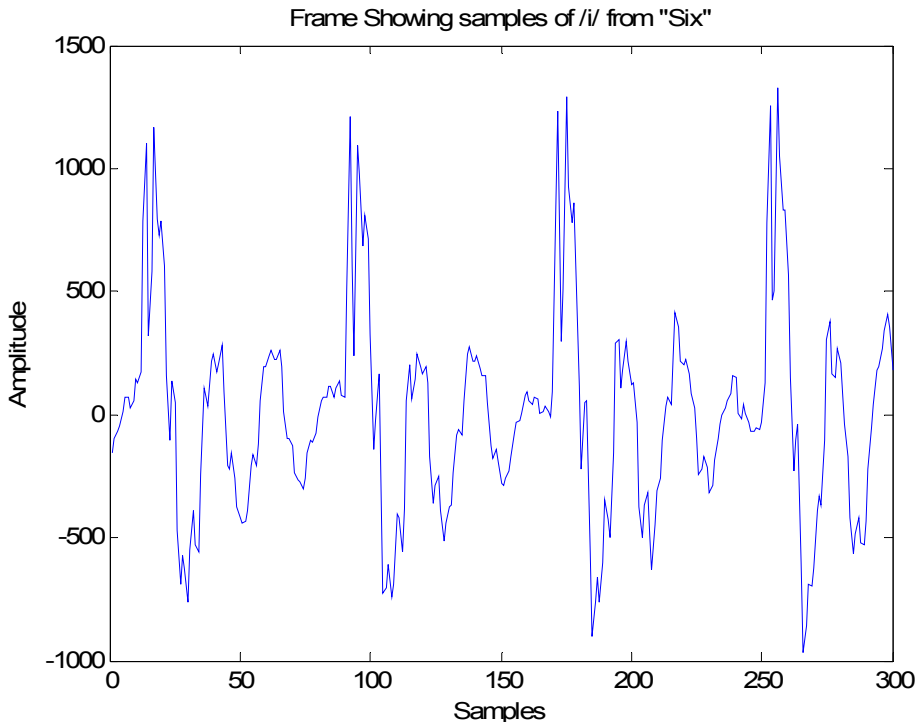


Figure 8. Framing of Speech Signal "Six"

2) Windowing

The data truncation due to framing is equivalent to multiplying the input speech data with a rectangular window function w(n) given by

$$w(n) = \begin{cases} 1, & \text{n=0,1,.....N-1.} \\ 0, & \text{n otherwise.} \end{cases} \quad (1)$$

Windowing leads to spectral spreading or smearing (due to increased main lobe width) and spectral leakage (due to increased side lobe height) of the signal in the frequency domain. To reduce spectral leakage, a smooth function such as Hamming window given by Equation (2) is applied to each frame, at the expense of slight increase in spectral spreading (trade-off).

$$w(n) = \begin{cases} 0.54 - 0.46\cos(2\pi \text{n/N-1}), & \text{n=0,1,.....N-1.} \\ 0, & \text{n otherwise.} \end{cases} \quad (2)$$

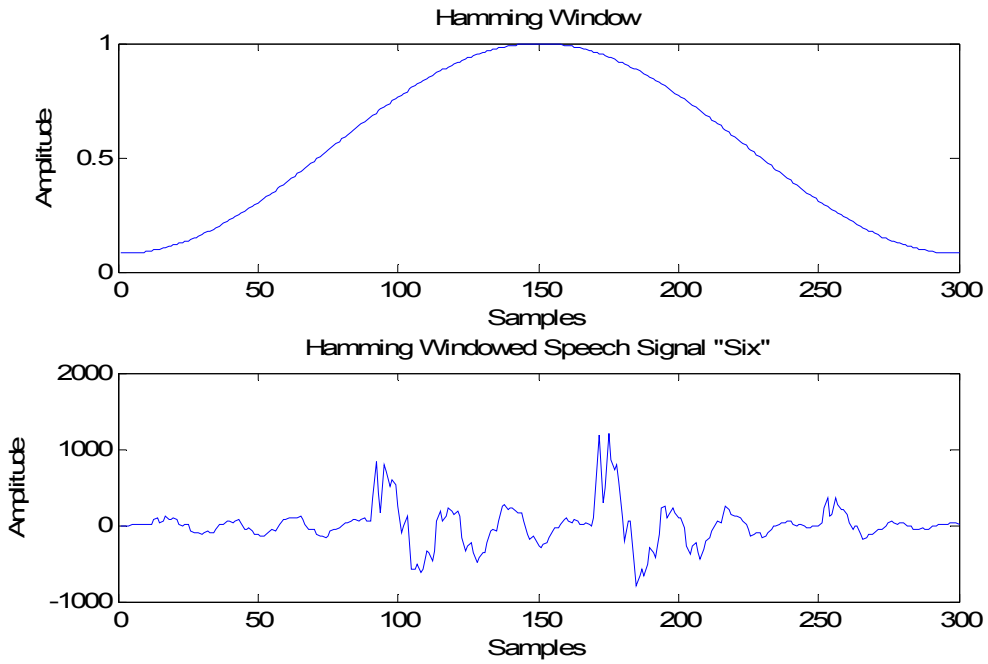


Figure 9. Windowing of Speech Signal “Six”

As seen in the Figure 9, the middle portion of the signal is preserved whereas the beginning and the end samples are attenuated as a result of using a Hamming window. In order to have signal continuity and prevent data loss at the edges of the frames, the frames are overlapped before further processing.

3) Fast Fourier Transform

Fast Fourier Transform (FFT) is a name collectively given to several classes of fast algorithms for computing the Discrete Fourier Transform (DFT). DFT provides a mapping between the sequence, say x (n), n=0, 1, 2……, N-1 and a discrete set of frequency domain samples, given by

$$X(k)=\begin{cases}\sum_{n=0}^{N-1}x(n)e^{-j(2\pi/N)kn}, & \text{k=0,1,.....N-1.}\\ 0, & \text{k otherwise.}\end{cases} \tag{3}$$

The inverse DFT (IDFT) is given by

$$x(n)=\begin{cases}\frac{1}{N}\sum_{n=0}^{N-1}X(k)e^{j(2\pi/N)kn}, & \text{n=0,1,.....N-1.}\\ 0, & \text{n otherwise.}\end{cases} \tag{4}$$

Where, the IDFT is used map the frequency domain samples back to time domain samples. The DFT is always is periodic in nature, where k varies from 1 to N, where N is the size of the DFT. The Figure 10 shows a 512-Point FFT for the speech data “six”.

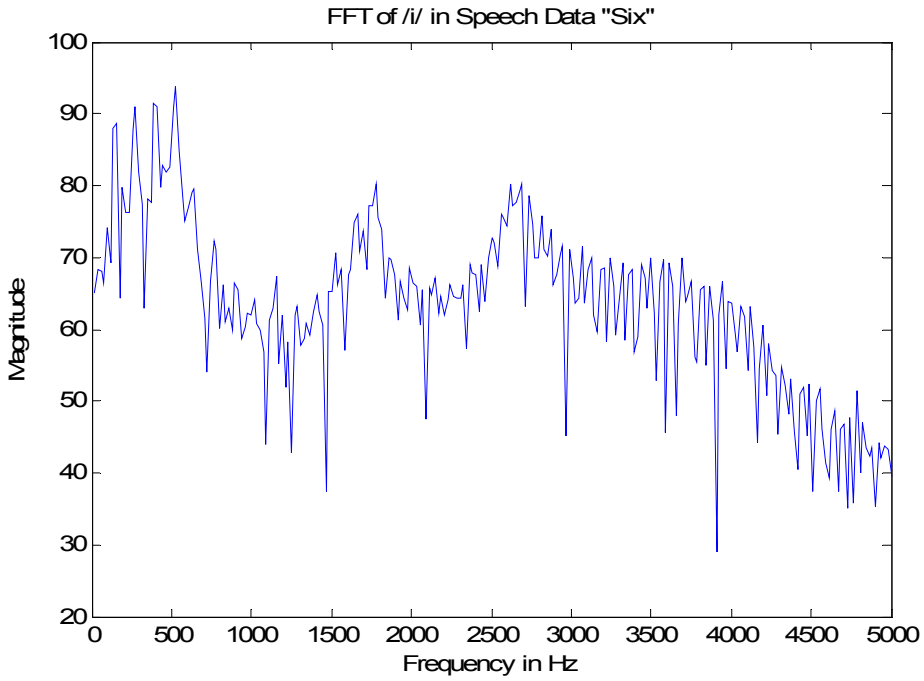


Figure 10. Frequency Domain Representation - FFT of Speech Signal "Six"

4) Cepstrum Domain

Speech is the resultant of an excitation sequence convolved with the impulse response of the vocal system model. Cepstrum is a transform used to separate the excitation signal from the vocal tract transfer function. These two components that are convolved in the time domain becomes multiplication in the frequency domain, which is represented as,

$$X(\omega) = G(\omega)H(\omega) \tag{5}$$

A log of the magnitude on both sides of the transform converts this into additive functions as given by,

$$\log|X(\omega)| = \log|G(\omega)| + \log|H(\omega)| \tag{6}$$

The cepstrum is then obtained by taking IDFT on both sides of the Equation (6),

$$IDFT(\log|X(\omega)|) = IDFT(\log|G(\omega)|) + IDFT(\log|H(\omega)|) \tag{7}$$

This process is better understood with the help of a block diagram (Figure 11). A lifter is used to separate the high quefrency (Excitation) from the low quefrency (Transfer Function). Figure 12 consists of the cepstral representations of sounds ‘eee’ and ‘aah’ uttered by male and female speakers. We can see in the plot that the female speakers have higher peaks than the male speakers, which is due to higher pitch of female speakers. The initial 5 ms consists of the transfer function and the later part is the excitation.

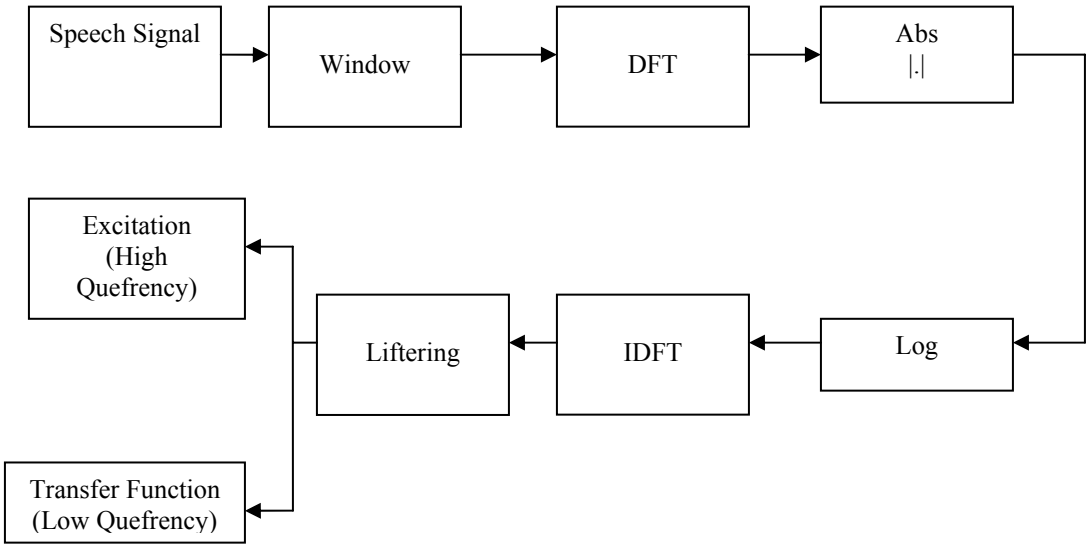


Figure 11. Block Diagram for Computing Cepstrum

2.3.2 Feature Extraction

Many speaker recognition systems use time domain features such as correlation, energy, and zero crossings, frequency domain features such as formants and FFTs, as well as other parametric features such as linear prediction coefficients (LPC) and cepstral coefficients.

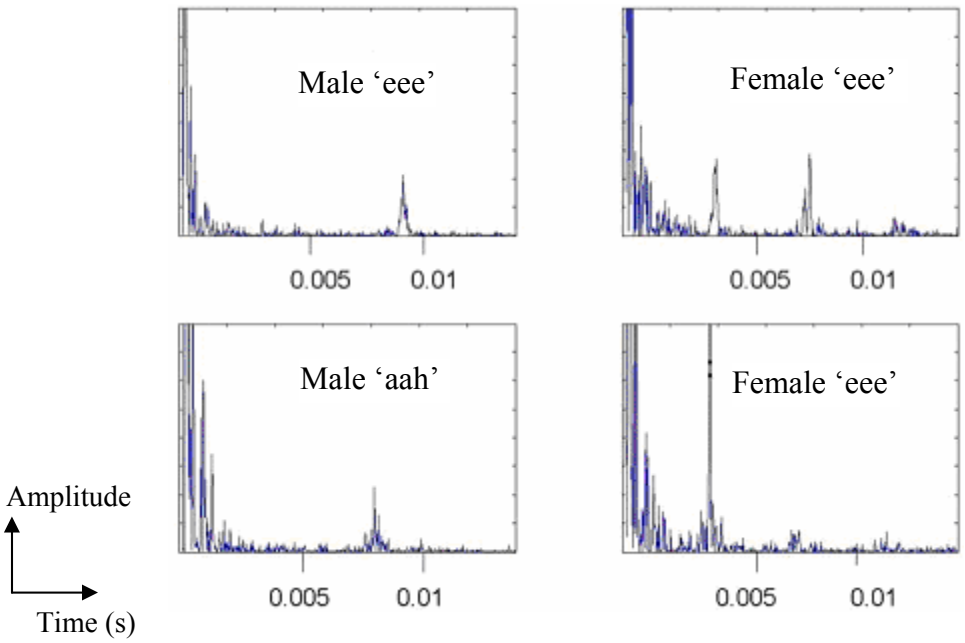


Figure 12. Cepstrum Plots

1) Mel-Frequency Cepstral Coefficients (MFCC)

In the field of psychoacoustics, which studies human auditory perception, it is a known fact that human perception of frequency is not on a linear scale, but on a different scale called *mel*. A mel is a unit of measure of perceived pitch or frequency of the tone. It does not correspond linearly to the frequency of the tone, as the human auditory system apparently does not perceive pitch in this linear manner. The mel scale is approximately linear below 1 kHz and logarithmic above. The mapping from normal frequency scale in Hz to a mel scale is done using,

$$\text{Mel}(f) = 2595 * \log(1 + f / 700) \quad (8)$$

Where f is the frequency in Hz and is shown in Figure 13. An approach to simulate this behavior of our auditory system is to use a band of filters. It has been found that the perception of a particular frequency by the auditory system is influenced by energy in a critical band of frequencies around that frequency. Further the bandwidth of critical band

varies with frequency, beginning at about 100 Hz for frequencies below 1 kHz and then increasing logarithmically above 1 kHz.

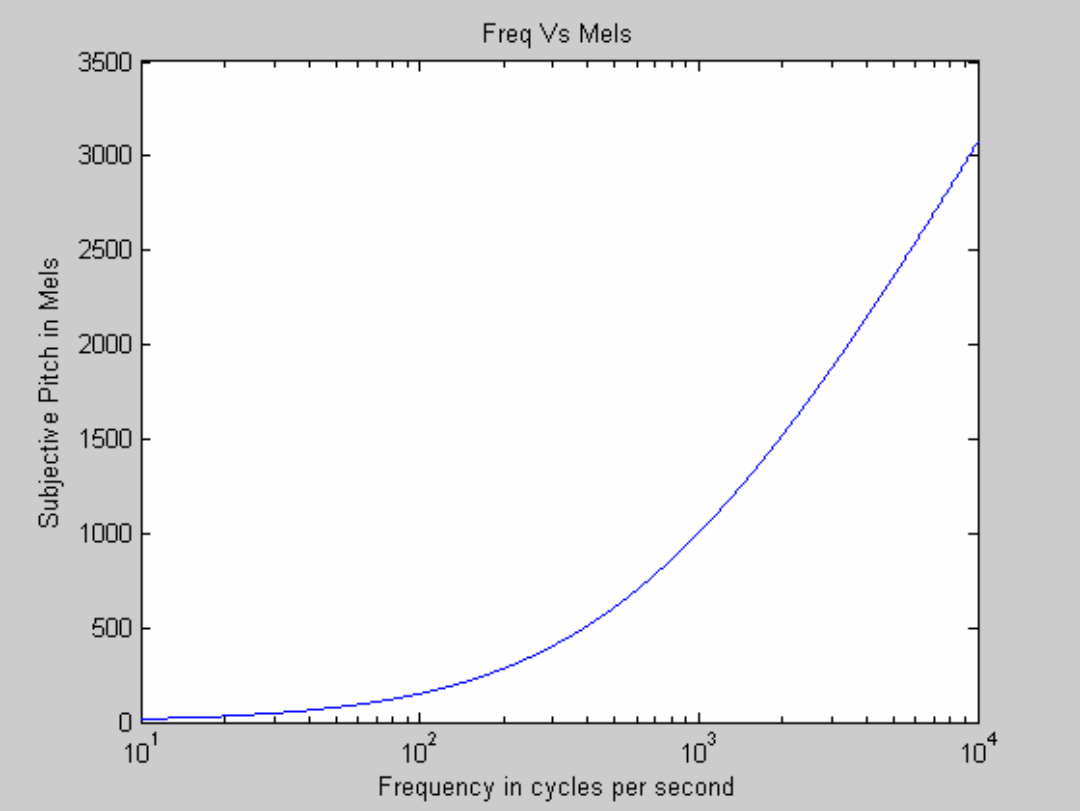


Figure 13. Frequency Mapping Between Hertz and Mels

A pictorial representation of the critical band of filters is shown in Figure 14. The filter function depends on three parameters, the lower frequency f_l, the central frequency f_c and the higher frequency f_h. On a mel scale, the distances f_c-f_l and f_h- f_c are the same for each filter and are equal to the distance between the f_c's of successive filters. The filter function is:

$$H(f) = 0 \, for \, f \le f_l \text{ and } f \ge f_h \quad (9)$$

$$H(f) = (f - f_l)/(f_c - f_l) \, for \, f_l \le f \le f_c \quad (10)$$

$$H(f) = (f_h - f)/(f_h - f_c) \; for \; f_c \le f \le f_h \tag{11}$$

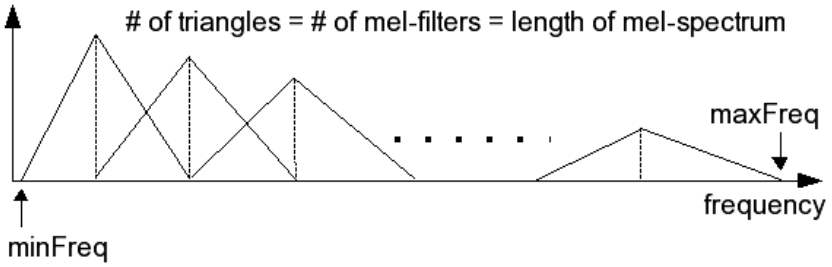


Figure 14. Mel-Spaced Filters

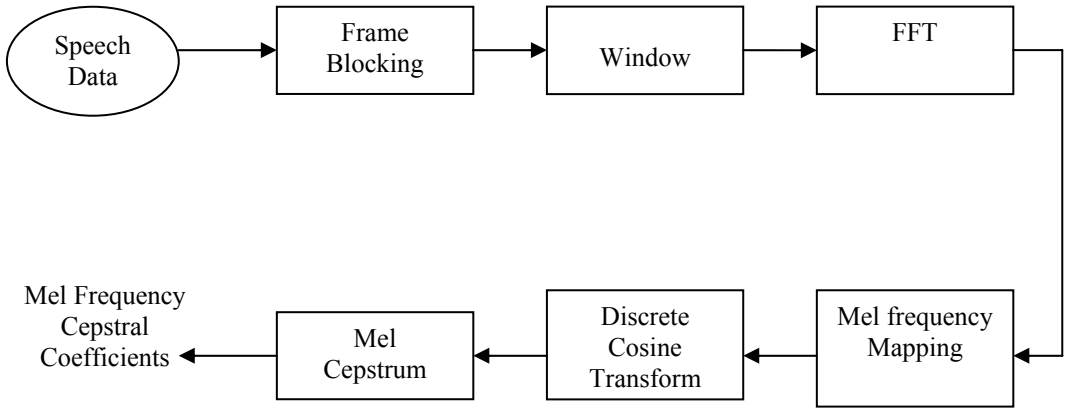


Figure 15. Computation of MFCC

As shown in Figure 15, the speech data is first extracted into 20-30 ms frames, next a window is applied to each frame of data, and then it is mapped to the frequency domain using FFT. Then the critical bands of filters are applied and are mel-frequency warped. In order to convert the mel-frequency warped data to the cepstrum domain, we apply discrete cosine transform since the MFCCs are real numbers. The MFCCs are given by,

$$c_n = \sum_{k=1}^{k} (\log s_k) \cos\left[n\left(k - \frac{1}{2}\right)\frac{\pi}{k} \right], \quad \text{n=1,2,...,k} \tag{12}$$

Where c_n are the MFCCs and s_k is the mel power spectrum coefficients. Typically C_n values are taken from 1 to 20, i.e. about 20 MFCCs for satisfactory results.

2.4 Speaker Models

The models Arithmetic Harmonic Sphericity (AHS) and Hidden Markov Model (HMM) were used to model the MFCC features.

2.4.1 Arithmetic Harmonic Sphericity (AHS)

According to Gaussian Speaker Modeling [10], a speaker X's speech characterized with a feature vector sequence, x_t can be modeled by its mean vector $\bar{x}$ and covariance matrix X i.e.

$$\bar{x} = \frac{1}{M}\sum_{t=1}^{M} x_t \quad \text{and} \quad X = \frac{1}{M}\sum_{t=1}^{M} (x_t - \bar{x}).(x_t - \bar{x})^T \tag{13}$$

Where, M is the length of the vector sequence x_t.

Similarly a speaker Y's speech can be modeled by,

$$\bar{y} = \frac{1}{N}\sum_{t=1}^{N} y_t \quad \text{and} \quad Y = \frac{1}{N}\sum_{t=1}^{N} (y_t - \bar{y}).(y_t - \bar{y})^T \tag{14}$$

Where, N is the length of the vector sequence y_t, $\bar{y}$ the mean vector and Y, the covariance matrix.

Also, vectors $\bar{x}$ and $\bar{y}$ have a dimension of p, whereas the matrices X and Y are $p \times p$ dimensional. We also express λ_i as the eigen values of the matrix τ, where $1 < i < p$, i.e.,

Det[τ - λ I]=0 (15)

Where Det is the determinant, I is the Identity matrix and $\tau = X^{-1/2}YX^{-1/2}$, where X and Y are the covariance matrices.

Matrix τ can be written as,

$$\tau = \Theta\Delta\Theta^{-1} \tag{16}$$

Where Θ, is the $p \times p$ diagonal matrix of eigen values and Δ is the matrix of eigen vectors.

Mean functions of these eigen values are given by,

Arithmetic mean: $a(\lambda_{1,}.....,\lambda_p) = \frac{1}{p}\sum_{i=1}^{p}\lambda_i$ (17)

Geometric mean: $g(\lambda_{1,}.....,\lambda_p) = \left(\prod_{i=1}^{p}\lambda_i\right)^{1/p}$ (18)

Harmonic mean: $h(\lambda_{1,}.....,\lambda_p) = \left(\frac{1}{p}\sum_{i=1}^{p}\frac{1}{\lambda_i}\right)^{-1}$ (19)

These means can also be calculated directly using the covariance matrices, because of the trace and determinant properties of matrices, which states that trace(XY)=trace(YX), Det(XY)=Det(X).Det(Y), we have

$$a(\lambda_{1,}.....,\lambda_p) = \frac{1}{p}tr(\Delta) = \frac{1}{p}tr(\tau) = \frac{1}{p}tr(YX^{-1}) \tag{20}$$

$$g(\lambda_{1,}.....,\lambda_p) = \left(Det(\Delta)\right)^{1/p} = \left(Det(\tau)\right)^{1/p} = \left(\frac{Det(Y)}{Det(X)}\right)^{1/p} \tag{21}$$

$$h(\lambda_{1,}.....,\lambda_p) = \frac{p}{tr(\Delta^{-1})} = \frac{p}{tr(\tau^{-1})} = \frac{p}{tr(XY^{-1})} \tag{22}$$

The Arithmetic Harmonic Sphericity measure is a likelihood measure for verifying the proportionality of covariance matrix Y to a given covariance matrix X, given by

$$S(Y \mid X) = \left[\frac{Det(X^{-1/2} Y X^{-1/2})}{\frac{p}{tr(X^{-1/2} Y X^{-1/2})}} \right]^{N/2} = \left[\frac{Det(\tau)}{\frac{p}{tr(\tau)}} \right]^{N/2} \tag{23}$$

By denoting, $\bar{S}_X$ as the average likelihood function for the sphericity test, we have

$$\bar{S}_X = \frac{1}{N} \log S(Y \mid X) \tag{24}$$

and by defining,

$$\bar{\mu}(\mathrm{X,Y}) = \log \left[\frac{\frac{1}{p} tr(\tau)}{\frac{p}{tr(\tau)}} \right] \tag{25}$$

$$\bar{\mu}(\mathrm{X,Y}) = \log \left[\frac{\frac{1}{p} tr(X^{-1/2} Y X^{-1/2})}{\frac{p}{tr(Y^{-1/2} X Y^{-1/2})}} \right] \tag{26}$$

$$\bar{\mu}(\mathrm{X,Y}) = \log \left[\frac{tr(X^{-1/2} Y X^{-1/2}) * tr(Y^{-1/2} X Y^{-1/2})}{p^2} \right] \tag{27}$$

$$\bar{\mu}(\mathrm{X,Y}) = \log[tr(X^{-1} Y) * tr(Y^{-1} X)] - 2\log[p] \tag{28}$$

Where, $\bar{\mu}(\mathrm{X,Y})$ is the log ratio of arithmetic and harmonic means of the eigen values of the covariance matrices X and Y. $\bar{\mu}(\mathrm{X,Y})$ is the AHS similarity or distance measure which indicates the resemblance between the enrolled and test features.

2.4.2 Hidden Markov Model (HMM)

HMM has been widely used for modeling speech recognition systems and it can also be extended for speaker recognition systems. Let an observation sequence be $O = (o_1 o \ldots o_T)$

and its HMM model be $\lambda = (A, B, \pi)$. Where A denotes state transition probability, B denotes output probability density functions, and π is the initial state probabilities. We can iteratively optimize the model parameters λ, so that it best describes the given observation O**.** Thus the likelihood (Expectation), $P(O|\lambda)$ is maximized. This can be achieved using Baum-Welch method, also known as Expectation Maximization (EM) algorithm [11].

To re-estimate HMM parameters, $\xi_t(i,j)$ is defined as the probability of being in state i at time t, and state j at time t+1, given the model and the observation sequence,

$$\xi_t(i,j) = \frac{P(q_t = i, q_{t+1} = j \mid O, \lambda)}{P(O \mid \lambda)} \tag{29}$$

Using above formula, we can re-estimate HMM parameter

$\lambda = (A, B, \pi)$ by

$$\bar{\pi}_j = \gamma_1(i) \tag{30}$$

$$\bar{a}_{ij} = \sum_{t=1}^{T-1} \xi_t(i,j) \; / \; \sum_{t=1}^{T-1} \gamma_t(i) \tag{31}$$

$$\bar{b}_j(k) = \sum_{\substack{t=1 \\ s.t. o_t = v_k}}^{T} \gamma_t(j) \; / \; \sum_{t=1}^{T} \gamma_t(j) \tag{32}$$

Where $\gamma_t(i) = \sum_{j=1}^{N} \xi_t(i,j)$.

Thus we can iteratively find optimal HMM parameter $\boldsymbol{\lambda}$ [8]. This procedure is also viewed as training since using optimal HMM parameter model we can later compare a testing set of data or observation O by calculating the likelihood $P(O|\lambda)$**.**

Thus AHS and HMM likelihood scores are generated, but in order to fuse these scores we need to bring both scores to the same level, hence we need to normalize them.

2.5 Hybrid Fusion

2.5.1 Score Normalization

The score matrices generated by AHS and HMM are denoted as S_{AHS}^{ij} and S_{HMM}^{ij}; $1 \le i \le m$ and $1 \le j \le n$, respectively, where m is the number of speakers used in training session and n is the number of speakers in testing session. These scores are in different scales and have to be normalized, before they can be fused together, so that both the scores are relatively in the same scale. We have used *Min-Max* normalization, therefore scores of AHS and HMM are scaled between zero and one.

These normalized scores can be represented as follows,

$$S = \frac{S^{ij} - \min(S)}{\max(S) - \min(S)} \tag{33}$$

Where S is the normalized scores obtained from AHS or HMM. Though these scores are between zero and one, their distributions are not similar. A deeper insight into the distributions shows that AHS has wider distribution range when compared to HMM, which has a narrower distribution.

2.5.2 Hybrid Fusion Technique

Figures 16(a) and 16(c) show the genuine score distribution of the AHS and HMM, while Figures 16(b) and 16(d) show the imposter distribution of AHS and HMM algorithm, respectively. It can be seen that distributions among AHS and HMM are clearly different. The imposter and genuine distribution of AHS is well spread out, but the imposter distribution has a Gaussian like shape. On the other hand, the distributions of HMM, are

closely bound. In a good recognition system, the genuine distribution is closely bound and stands separated from that of the imposter which is spread out and similar to a Gaussian in shape.

Thus in order to obtain the best score from both these methods; we have to use the complementary nature of the algorithms. We used a linear weighted fusion method derived as follows,

$$S_{opt} = ((S_{HMM} - S_{AHS}) \times \omega) + S_{AHS} \tag{34}$$

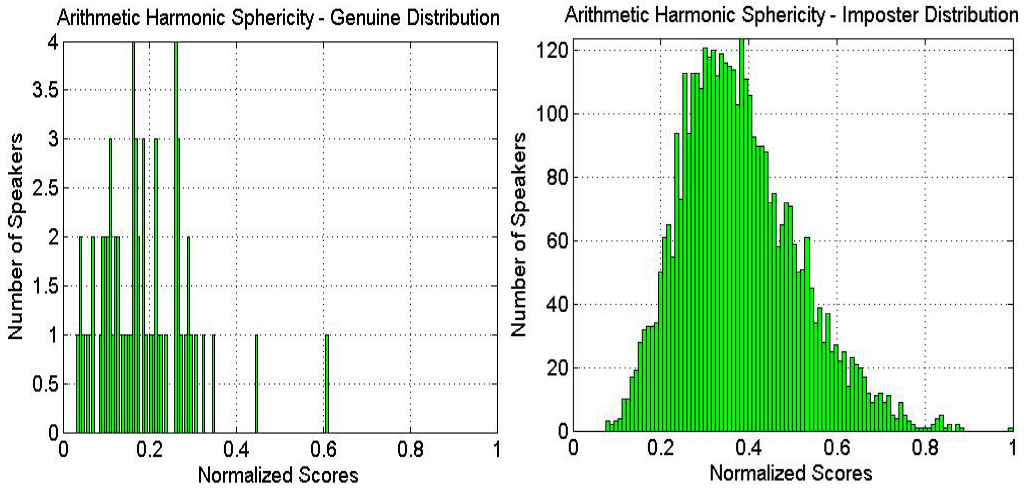
In order to find the weight, we used an enhanced weighting method. The weight ω, is calculated using the mean of the scores,

$$\omega = \frac{M_{AHS}}{M_{AHS} + M_{HMM}} \tag{35}$$

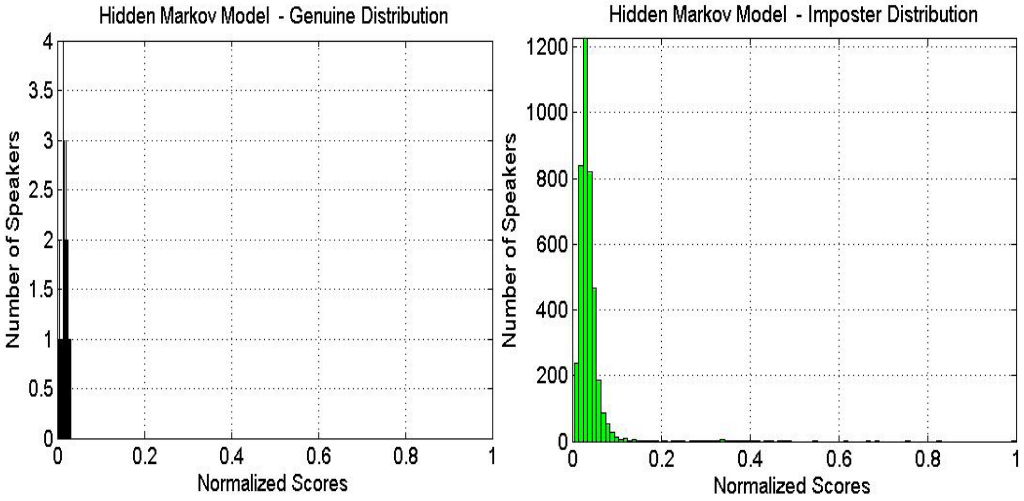
Here, M_{HMM}, M_{AHS} are the means of normalized scores from AHS and HMM, given as,

$$M = \frac{1}{m} \sum_{j=1}^{m} \left[\frac{1}{n} \sum_{i=1}^{n} S^{ij} \right] \qquad \begin{matrix} 1 \le i \le m \\ 1 \le j \le n \end{matrix} \tag{36}$$

Thus the features (MFCCs) are extracted, and these features are modeled using HMM and AHS systems. The scores from these two models are fused to produce the final output score of the HF speaker recognition system.



(a) (b)



(c) (d)

Figure 16. Score Distributions. (a) & (c) Genuine Distribution Generated Using AHS and HMM, Respectively. (b) & (d) Imposter Distribution Generated Using AHS and HMM, Respectively.

CHAPTER 3

ACCENT CLASSIFICATION SYSTEM

Before we proceed towards the accent features and modeling algorithms used in the proposed AC system, a brief background and a research review on accent classification is presented in this chapter.

3.1 Accent Background

Foreign accent has been defined in [30] as the pattern of pronunciation features which characterize an individual's speech as belonging to a particular group. The term accent has been described in [31] as, "The cumulative auditory effect of those features of pronunciation which identify where a person is from regionally and socially." In [32], accent is described as the negative (or rather colorful) influence of the first language (L1) of a speaker to a second language, while dialects of a given language are differences in speaking style of that language (which all belong to L1) because of geographical and ethnic differences.

There are several factors affecting the level of accent, some of the important ones are as follows:

1) Age at which speaker learns the second language.
2) Nationality of speaker's language instructor.

3) Grammatical and phonological differences between the primary and secondary languages.
4) Amount of interaction the speaker has with native language speakers.

Some of the applications of accent information are

1) Accent knowledge can be used for selection of alternative pronunciations or provide information for biasing a language model for speech recognition.
2) Accent can be useful in profiling speakers for call routing in a call center.
3) Document retrieval systems.
4) Speaker recognition systems.

3.2 Review of Past Research on Accent Classification

There has been considerable amount research of research conducted on the problem of accent modeling and classification. The following is a brief review on some of the papers published in the area of accent modeling and classification.

In [30], analysis of voice onset time, pitch slope, formant structure, average word duration, energy and cepstral coefficients was conducted. Continuous Gaussian Mixture HMMs were used to classify accents, using accent sensitive cepstral coefficients (ASCC), energy and their delta features. The frequencies in the range of 1500-2500 Hz were shown to be the most important for accent classification. A 93% classification rate was observed, using isolated words, with about 7-8 words for training. The Duke University dataset was used for evaluations. This dataset consists of neutral American English, German, Spanish, Chinese, Turkish, French, Italian, Hindi, Rumanian, Japanese, Persian and Greek accents. The application was towards speech recognition and an error rate decrease of 67.3%, 73.3%,

and 72.3% from the original was observed for Chinese, Turkish, and German accents, respectively. In [33], fundamental frequency, energy in rms value, first (F1), second (F2), third formant frequencies (F3), and their bandwidths B1, B2 and B3 respectively were selected as accent features. The result shows the features in order of importance to accent classification to be: dd(E), d(E), E, d(F3), dd(F3), F3, B3, d(FO), FO, dd(FO), where E is energy, d() are the first derivatives and dd() are the second derivatives. 3-state HMMs with single Gaussian densities were used for classification. A classification error rate of 14.52% was observed. Finally, they show an average 13.5% error rate reduction in speech recognition for 4 speakers by using accent adapted pronunciation dictionary. The TIMIT and HKTIMIT corpuses were used as the database for evaluation. This paper was focused on Canto-English where their Cantonese is peppered with English words and their English has a particular local Cantonese accent. In [32] three different databases were used for evaluation: CU-Accent corpus – AE: American English, and accents of AE (CH: Chinese, IN: Indian, TU: Turkish), IviE Corpus: British Isles for dialects. CU-Accent Read – AE (CH: Chinese, IN: Indian, TU: Turkish) with same text as IviE corpus. A pitch and formant contour analysis is done for 3 different accent groups – AE, IN and CH (taken from CU-Accent Corpus) with 5 isolated words – 'catch', 'pump', 'target', 'communication', and 'look', uttered by 4 speakers from each accent group. Two phone based models were considered – MP-STM and PC-STM.

The MFCCs were used as features to train and test STMs for each phoneme in case of MP-STM and phone class in case of PC-STM. Results show that better classification rate for MP-STM than PC-STM and also dialect classification was better than accent classification.

The application was towards a spoken document retrieval system. In [34], LPC Delta cepstral features were used as features which were modeled by using 6 Gaussian mixture CHMMs. The classification procedure, employed gender classification followed by accent classification. A 65.48% accent identification rate was observed. The database used for evaluation was developed in the scope of the SUNSTAR European project. It consists of Danish, British, Spanish, Portuguese, and Italian accents. In [35], a mandarin based speech corpus with 4 different accents was used as the native accent. A parallel gender and accent GMM was used to model, with 39 dimensional features of which 12 are MFCCs and 1 is energy along with their first and second derivatives as features, using 4 test utterances and 32 component GMM. Accent identification error rates of 11.7% and 15.5% were achieved for female and male speakers, respectively. In [36], 13 MFCCs were used as features, with a hierarchical classification technique. The database was first classified according to gender, and 64-GMM was used for accent classification. They have used TI digits as the database and results show an average 7.1% error rate reduction relatively when compared to direct accent classification. The application was towards developing an IVR system using VoiceXML. In [37], speech corpus consisting of speakers from 24 different countries was used. The corpus focuses on French isolated words and expressions. Though this was not an application towards accent classification, this paper showed that addition of phonological rules and adaptation of target vowel phonemes to native language vowel phonemes helps speech recognition rates. Also adaptation with respect to the most frequently used phonemes in the native languages resulted in an error rate reduction from 8.88% to 7.5% for foreign languages. An HMM was used to model the MFCCs of the data. In [38], the CU-Accent

corpus, consisting of American English, Mandarin, Thai, and Turkish was used. 12 MFCCs along with energy were used as features and Stochastic Trajectory Model (STM) was used for classification. This classification employs speech recognition in front end, and was used to locate and extract phoneme boundaries. Results show that STM has classification rate of 41.93% when compared to CHMM and GMM which has 41.35% and 40.12% respectively. Also the paper lists the top five phonemes which could be used for accent classification.

In [39], 10 native and 12 non-native speakers were used as a dataset. Demographic data including speaker's age, percentage of time in a day when English used as communication and the number of years English was spoken were used as features, along with speech features: average pitch frequency and averaged first three formant frequencies. Even in this paper F2 and F3 distributions of native and non-native groups show high dissimilarity. Three neural network classification techniques namely competitive learning, counter propagation, and back propagation were compared. Back propagation gave a detection rate of 100% for training data and 90.9% for testing data. In [40], American and Indian accents have been extracted from the speech accent archive (SAA) dataset. Second and third formants were used as features and modeled with a GMM. The authors have manually identified accent markers and have extracted formants for specific sounds such as /r/, /l/ and /a/. They have achieved about 85% accent classification rate.

In [35], [38], [39], the accent classification system was not applied to a speech recognition system even though it was the intended application. All the above accent classification systems were based on the assumption that the input text or phone sequence is known, but in our scenario where accent recognition needs to be applied to text-independent

speaker recognition, a text-independent accent classification should be employed. In [38], text-independent accent classification effort has been made by using speech recognizer as front end followed by stochastic trajectory models (STM). However, this will increase the system complexity as well as introduce additional errors in the accent classification system due to accent variations. Our text-independent accent classification system comprises of a fusion of classification scores from continuous Gaussian hidden Markov models (CHMM) and Gaussian mixture models (GMM). Similar work has been done in the area of speaker recognition in [26], where scores from two recognition systems were fused and one of the recognition algorithm was a Gaussian mixture model (GMM) and the other being a speaker adapted HMM instead of a CHMM.

3.3 Accent Classification Model

The AC model is as shown in Figure 17. Any unknown accent is classified by extracting the accent features from the sampled speech data and measuring the likelihood of the feature belonging to a particular known accent model. Any dataset where speech was manually labeled according to accents can be used as the reference accent database.

In this work, we have used a fusion of mel-frequency cepstral coefficients (MFCC), accent-sensitive cepstral coefficients (ASCC), delta ASCCs, energy, delta energy, and delta-delta energy. Once these accent features have been extracted from the reference accent database (SAA dataset), two accent models are created with the help of GMM and CHMM. Any unknown speech is processed and accent features are extracted, then the log likelihood of those features against the different accent models are computed. The accent model with

the highest likelihood score is selected as the final accent. In order to boost the classification rate the GMM and CHMM accent scores were fused. Due to the compensational effect [26] of the GMM and CHMM we have seen improvement in the performance.

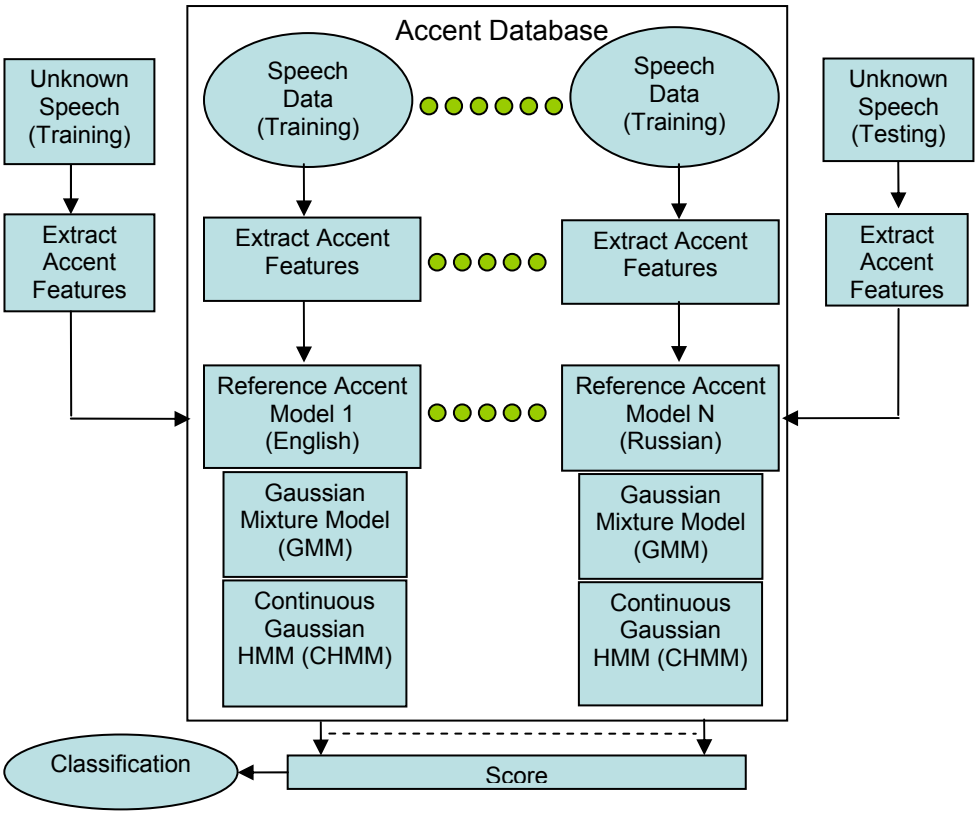


Figure 17. Block Diagram of Accent Classification (AC) System

3.4 Accent Features

Researchers have used various accent features such as pitch, energy, intonation, MFCCs, formants, formant trajectories, etc., and some have fused several features to increase accuracy as well. In this paper, we have used a fusion of mel-frequency cepstral coefficients (MFCC), accent-sensitive cepstral coefficients (ASCC), delta ASCCs, energy, delta energy, and delta-delta energy. MFCCs place critical bands which are linear up to 1000 Hz (Figure

18) and logarithmic for the rest. Hence it allows more selection filters on the lower 1000 Hz, whereas ASCCs [30] concentrate more on the second and third formants. i.e., around 2000 to 3000 Hz (Figure 19) which are more important features for detecting accent. Hence a combination of both MFCCs and ASCCs has been used in this work which provided an increase in the accent classification performance when compared to ASCCs alone. Thus after these features are extracted, they are modeled using GMM and CHMM.

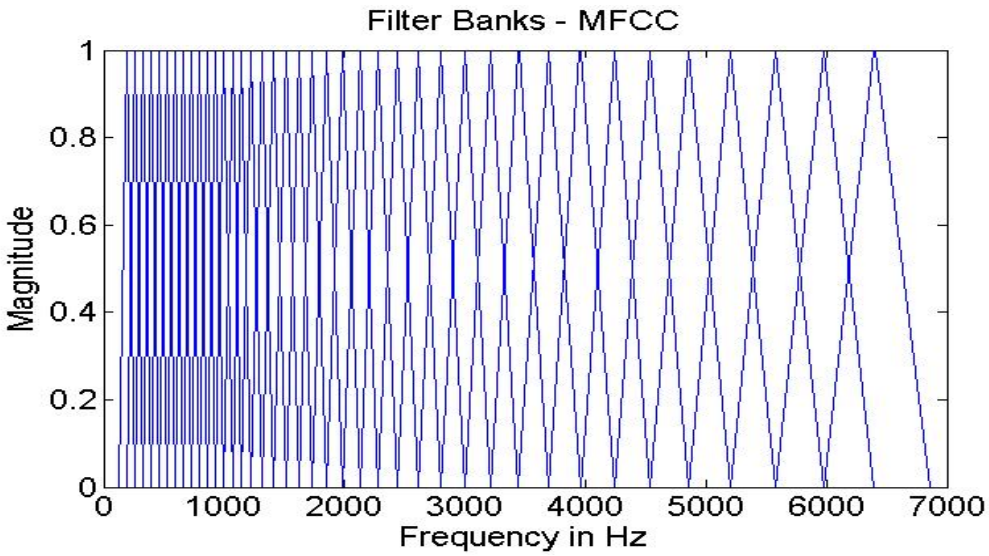


Figure 18. Mel Filter Bank

3.5 Accent Classifier Formulation

Gaussian mixture model (GMM) and continuous hidden Markov model (CHMM) have been fused to achieve enhanced classification performance. GMM is explained next, followed by CHMM.

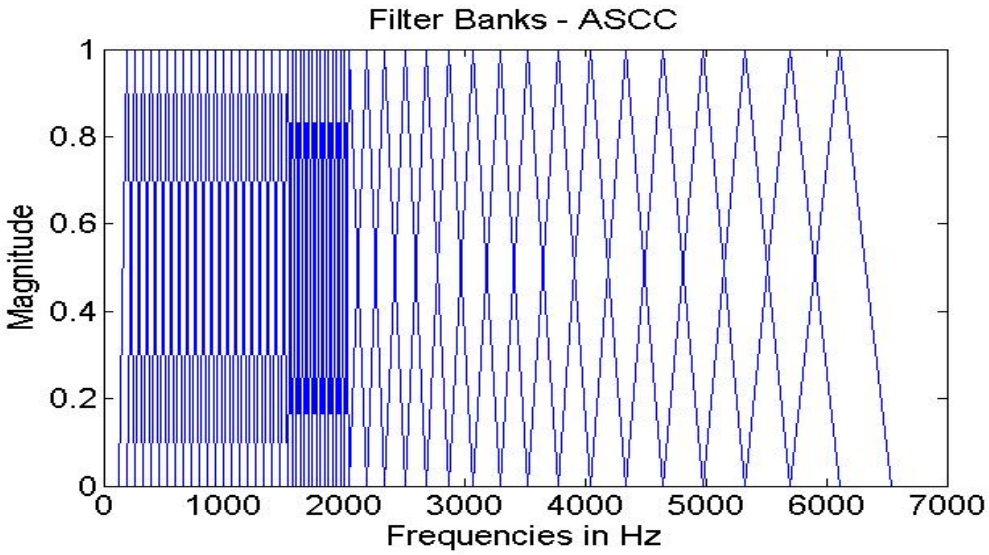


Figure 19. Accent Filter Bank

3.5.1 Gaussian Mixture Model (GMM)

A Gaussian mixture density is a weighted sum of M component densities which is given by, $p(\vec{x} \mid \lambda) = \sum_{i=1}^{M} p_i b_i(\vec{x})$ (37)

Where $\vec{x}$ is a D-dimensional vector, $b_i(\vec{x})$, $i = 1,\ldots,M$, are the component densities and p_i are the mixture weights. Each component density is given by,

$$b_i(\vec{x}) = \frac{1}{(2\pi)^{D/2} \mid \sum_i \mid^{1/2}} \exp\left\{-\frac{1}{2}(\vec{x} - \vec{\mu}_i)^T \sum_i^{-1} (\vec{x} - \vec{\mu}_i)\right\} \quad (38)$$

with mean vector modeling $\vec{\mu}_i$ and covariance matrix $\sum_i$. These parameters are represented by,

$$\lambda = \{p_i, \vec{\mu}_i, \sum_i\} \text{ i} = 1,...,\text{M} \quad (39)$$

These parameters are estimated iteratively using the Expectation-Maximization (EM) algorithm. The EM algorithm estimates a new model $\bar{\lambda}$ from an initial model λ, so that the

likelihood of the new model increases. On each re-estimation, the following formulae are used,

$$\bar{p}_i = \frac{1}{T}\sum_{t=1}^{T} p(i \mid \vec{x}_t, \lambda) \tag{40}$$

$$\bar{\mu}_i = \frac{\sum_{t=1}^{T} p(i \mid \vec{x}_t, \lambda)\vec{x}_t}{\sum_{t=1}^{T} p(i \mid \vec{x}_t, \lambda)} \tag{41}$$

$$\bar{\sigma}_i^2 = \frac{\sum_{t=1}^{T} p(i \mid \vec{x}_t, \lambda)\vec{x}_t^{\,2}}{\sum_{t=1}^{T} p(i \mid \vec{x}_t, \lambda)} - \bar{\mu}_i^{\,2} \tag{42}$$

where $\bar{\sigma}_i^2$, $\bar{\mu}_i$, and $\bar{p}_i$ are the updated covariance, mean and mixture weights. The a posteriori probability for class i is given by,

$$p(i \mid \vec{x}_t, \lambda) = \frac{p_i b_i(\vec{x}_t)}{\sum_{k=1}^{M} p_k b_k(\vec{x}_t)} \tag{43}$$

For accent identification, each accent in a group of S accents, where S={1,2,….S}, is modeled by GMMs $\lambda_1, \lambda_2, ..., \lambda_S$. The final decision is made by computing the a posteriori probability for each test sequence (feature) against the GMM models of all accents, and selecting the accent which has the maximum probability or likelihood.

3.5.2 Continuous Hidden Markov Model (CHMM)

To model accent features, continuous HMM models have been used instead of discrete ones, as in case of CHMMs, each state is modeled as a mixture of Gaussians thereby increasing precision and decreasing degradation. The Equations (29), (30), (31) in Section 2.4.2, used for computing the initial and state transitional probabilities in case of HMM, apply here as

well. But to use a continuous observation density the probability density function (Gaussian in our case) should be formulated as follows,

$$b_j(o) = \sum_{k=1}^{M} c_{jk}\eta(o, \mu_{jk}, U_{jk}), \quad 1 < j < N \tag{44}$$

Where c_{jk} is the mixture coefficient for the kth mixture in the state j and η is a Gaussian with mean vector μ_{jk} and covariance matrix U_{jk}.

The parameter B is re-estimated, by re-estimating the mixture coefficients as follows,

$$\bar{c}_{jk} = \sum_{t=1}^{T} \gamma_t(j,k) \; / \; \sum_{t=1}^{T} \sum_{k=1}^{M} \gamma_t(j,k) \tag{45}$$

$$\bar{\mu}_{jk} = \sum_{t=1}^{T} \gamma_t(j,k).\mathrm{o_t} \; / \; \sum_{t=1}^{T} \gamma_t(j,k) \tag{46}$$

$$\bar{U}_{jk} = \sum_{t=1}^{T} \gamma_t(j,k).(\mathrm{o_t}\text{-}\mu_{\mathrm{jk}})(\mathrm{o_t}\text{-}\mu_{\mathrm{jk}})^{\mathrm{T}} \; / \; \sum_{t=1}^{T} \gamma_t(j,k) \tag{47}$$

Where $\gamma_t(j,k)$ is given by,

$$\gamma_t(j,k) = \left[\frac{\alpha_t(j)\beta_t(j)}{\sum_{j=1}^{N} \alpha_t(j)\beta_t(j)} \right] \left[\frac{c_{jk}\eta(o, \mu_{jk}, U_{jk})}{\sum_{m=1}^{M} c_{jm}\eta(o, \mu_{jm}, U_{jm})} \right] \tag{48}$$

Where $\alpha_t(j), \beta_t(j)$ are the forward and backward variables of HMM, respectively. Thus we can iteratively find optimal HMM parameter **λ** [8]. This procedure is also viewed as training since using optimal HMM parameter model we can later compare a testing set of data or observation *O*.

3.5.3 GMM and CHMM Fusion

In order to enhance the classification rate, the compensational effect of GMM and CHMM has been taken into account [26]. The likelihood scores generated from GMM and CHMM have been fused. A fused model benefits from both the advantages of GMM as well as CHMM. In a nutshell, the following are some of the advantages of GMM and HMM, which combine when they are fused.

1) GMM
    1) Better recognition even in degraded conditions [12].
    2) Good performance even with short utterances.
    3) Captures underlying sounds of a voice, but does not restrict like HMM.
    4) Mostly used for text-independent data.
    5) Fast training and less complex.
2) HMM
    1) Models temporal variation.
    2) Good performance in degraded conditions [19].
    3) Good in modeling phoneme variation within words.
    4) Continuous HMM: models each state as a mixture of Gaussians thereby increasing precision and decreasing degradation.

The following is the fusion formula which has been used to benefit from the properties of both GMM and CHMM,

$$AS_{Comb} = (AS_{CHMM} \times \beta + AS_{GMM} \times (1-\beta)) \tag{49}$$

Where AS_{CHMM} is the accent score of the speech data from CHMM, AS_{GMM} is the accent score from GMM, AS_{Comb} is the accent score of the combination and β is the tunable weight factor.

Thus after assigning a score for each speaker against various accent models, the model which delivers the highest score is decided as the accent class for that particular speaker.

CHAPTER 4

HYBRID FUSION – ACCENT SYSTEM

Until now we have gone through the HF-speaker recognition system as well as the accent classification system. The feature extraction and modeling for both the systems were detailed. The HFA system (Figure 20) is a combination of these two systems; the speaker recognition system and the accent classification system. These systems have been combined using a score modifying algorithm.

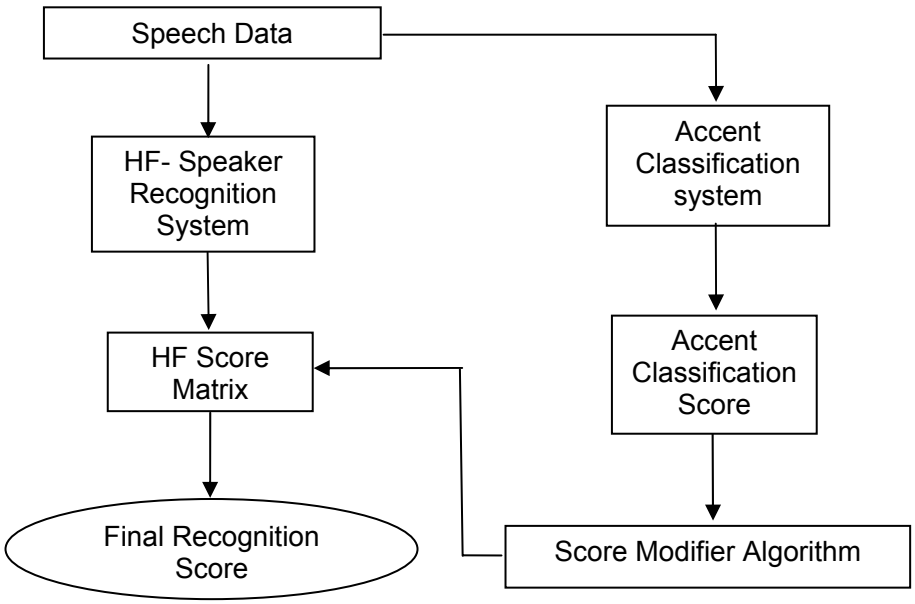


Figure 20. Flow Chart for Hybrid Fusion – Accent (HFA) System

4.1 Score Modifier Algorithm

The main motivation of this research is to improve speaker recognition performance with the help of accent information. After the HF score matrix is obtained from the HF speaker recognition system, the accent score and the accent class outcomes from the accent classification system are applied. This application ensures modification of the HF score matrix so that it improves the existing performance of the HF based speaker recognition system. The pseudo-code of the score modifier (SM) algorithm is as shown in Figure 21.

The matrix *SP* **(***row*, *column***)** represents HF score (enrolled versus test speakers). The variables, accent class and AScore are the class label and accent score assigned by the AC system. The main logic in this algorithm is to modify the HF scores, which do not belong to the same accent class as the target test speaker. The modification should be such that the actual speaker's score is separated from the rest of the scores. As the AC rate increases, the speaker recognition rate should increase and not change when it decreases. The HF scores are changed by subtracting or adding the variable 'M' in the algorithm, which is equivalent to the accent score multiplied by a tunable factor, coefficient of accent modifier (CAM), depending on whether the scores are closely bound towards the minimum score or not. The distance threshold variable *maxvar* is used to specify the range of search for closely bound scores around the minimum score.

HF speaker recognition performance itself plays a significant role because an incorrect accent classification paired with incorrect speaker recognition would cause a degradation of the overall HFA system performance. So, the factor M is multiplied by the variance of the scores of the test speaker versus all the enrolled speakers. Larger variances

```
Set maxvar to maximum of variance of SP (row, column)
Where  SP = HF Score matrix
row → 1:n
column → 1:n
FOR each column
  Set k to accent class (column)
  FOR each row
    IF minimum of SP (row, column)-SP (row, column) < maxvar
        Store row of SP in ro
    END IF
 END FOR
FOR each row where accent class (row) != k
  IF row belongs to ro
   SP (row column)=SP (row, column)-M*Variance of SP (row, column)
        ELSE
   SP (row, column)=SP (row, column)+M*Variance of SP (row, column)
         //Where M=AScore(column)*CAM
        //Where CAM is found empirically
   END IF
  END FOR
END FOR
```

Figure 21. The Score Modifier (SM) Algorithm

indicate large spread of HF scores (good speaker recognition) and vice versa. Hence the SM increases or decreases based on the accent score and the variance of the HF score. The SM algorithm can be applied to any speaker recognition system with some adjustments to distance threshold variable *maxvar* and CAM.

4.2 Effects of Accent Incorporation

The score modifier algorithm bonds the accent classification system and the speaker recognition system, and the entire integrated system is called the hybrid fusion – accent system. This section illustrates the effect of incorporating accent into speaker recognition system through the score modifier. Scores and histograms of the USF biometric dataset (described in Section 5.1) have been used to illustrate the effect. Three specific cases have been used for the illustrations, which are explained below.

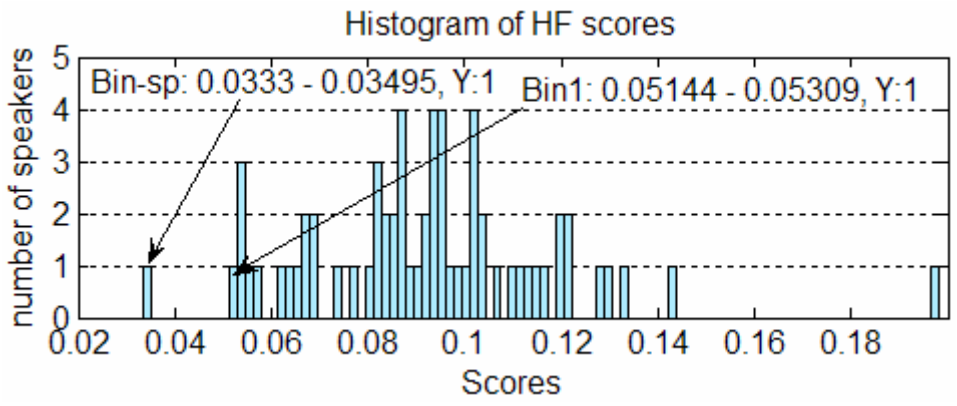


Figure 22(a). Effect of Score Modifier – HF Score Histogram (Good Recognition Case)

1) Case 1: Good Speaker Recognition

This case deals with a scenario when a speaker is recognized correctly, i.e. the score of the legitimate speaker is the minimum and clearly separated from the rest of the scores. The raw

scores and the histograms of HF and HFA are shown in Figures 22(b) & 23(b) and Figures 22(a) & 23(a), respectively. In Figure 22(b), the legitimate speaker is marked by the arrow, where X indicates the speaker number and Y indicates the speaker's score. In Figure 22(a), the legitimate speaker's bin has been indicated by the '*Bin-sp*' marker (arrow) in the histogram, and the neighboring imposter bin is indicated by '*Bin1*'. The same annotations for legitimate and imposter scores and histograms have been used in the rest of the illustrations. The gap between the bins '*Bin-sp*' and '*Bin1*', which is 0.01649, relates to the performance of the system. Greater the gap, better is the performance. For the HFA histograms in Figure 23(a), we can see that the gap difference between the bins '*Bin-sp*' and '*Bin1*' has increased to 0.01914. Since the legitimate speaker's accent has been classified correctly, the score modifier changed the imposter scores which belonged to accents other than that of the true speaker, thereby increasing the performance.

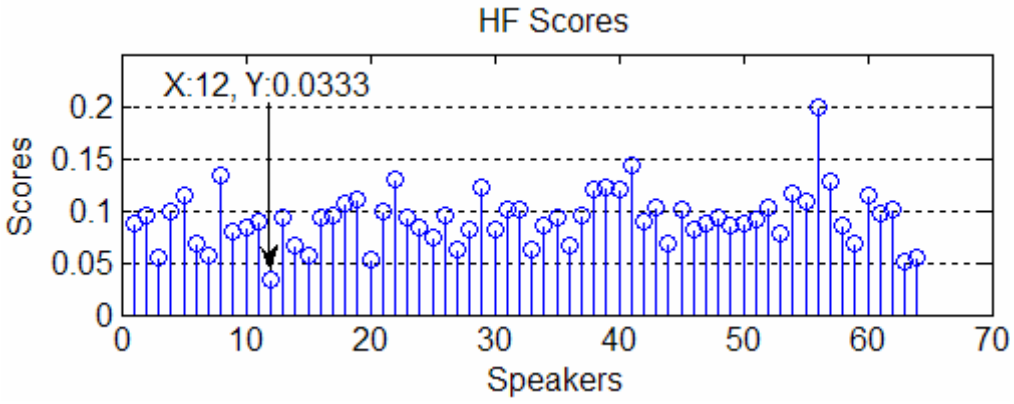


Figure 22(b). Effect of Score Modifier – HF Scores (Good Recognition Case)

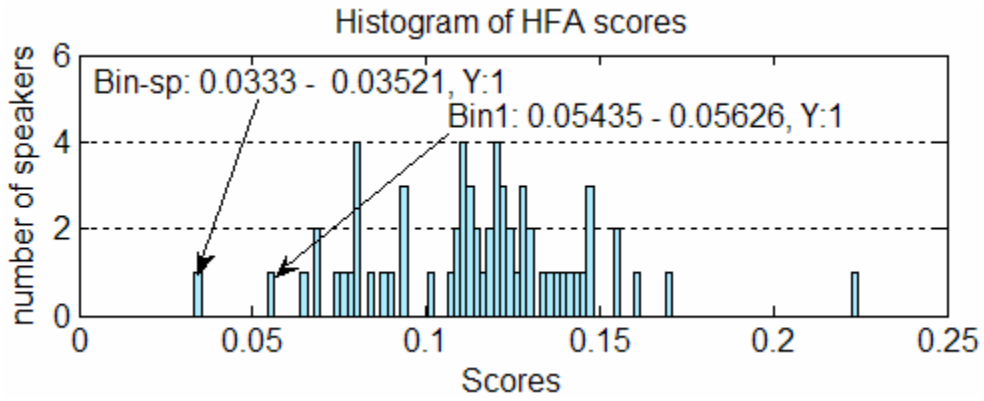


Figure 23(a). Effect of Score Modifier – HFA Score Histogram (Good Recognition Case)

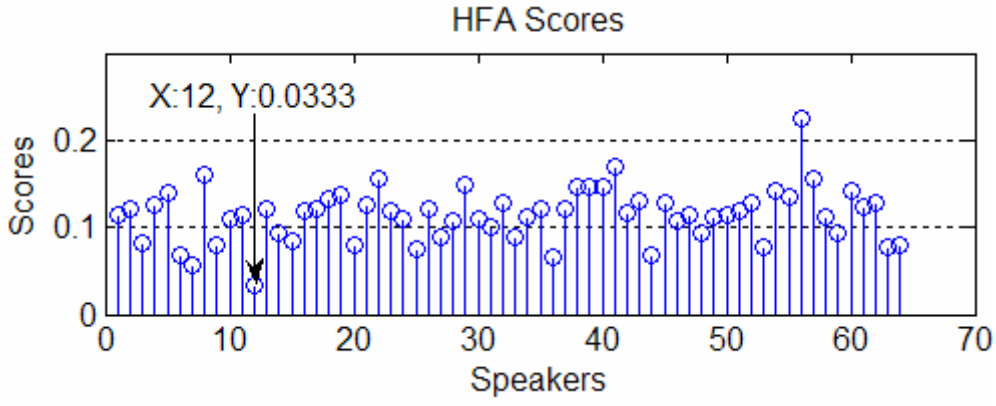


Figure 23(b). Effect of Score Modifier – HFA Scores (Good Recognition Case)

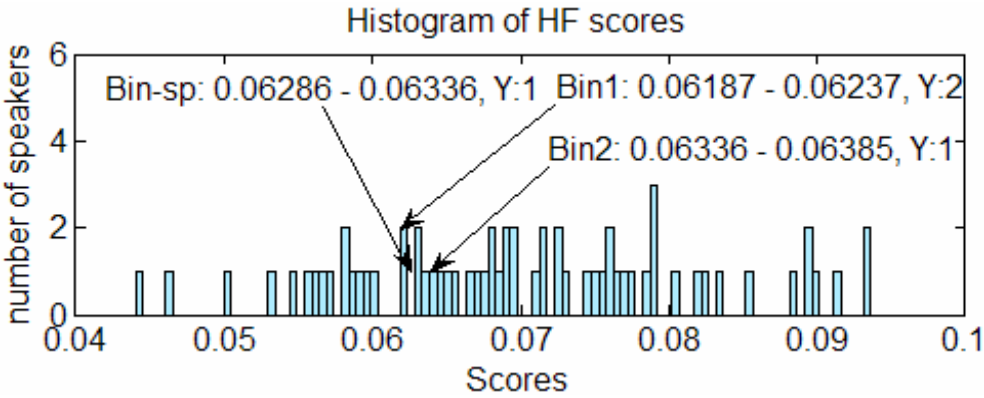


Figure 24(a). Effect of Score Modifier – HF Score Histogram (Poor Recognition Case)

2) Case 2: Poor Speaker Recognition

This case deals with a scenario when a speaker is not recognized correctly, i.e., the score of the legitimate speaker is not distinguishable from the rest of the scores. In Figures 24(a), '*Bin-sp*' is in between the imposter scores. We can see that the imposter bins, '*Bin1*' and '*Bin2*' are very close to the true speaker's bin '*Bin-sp*'. '*Bin1*' is separated from '*Bin-sp*' by a small gap of 0.00099 and there is little or no gap between '*Bin-sp*' and '*Bin2*'. After score modification, we can see that '*Bin1*' is separated by a gap of 0.00112, as shown in Figure 25(a). Also '*Bin2*'has been separated by a gap of 0.00111, whereas before modification, there was no gap. Thus due to the introduction of gaps, though the true speaker's score is not completely separated from the rest, it is more easily separable from the imposters when compared to the HF scores.

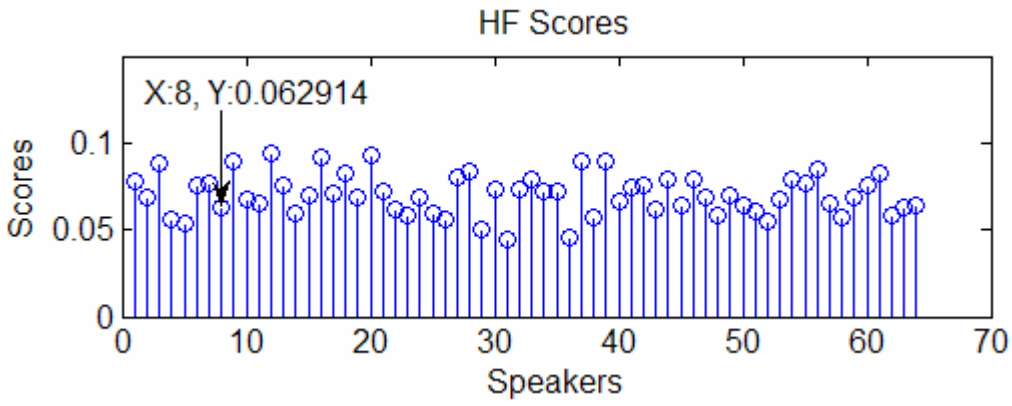


Figure 24(b). Effect of Score Modifier – HF Scores (Poor Recognition Case)

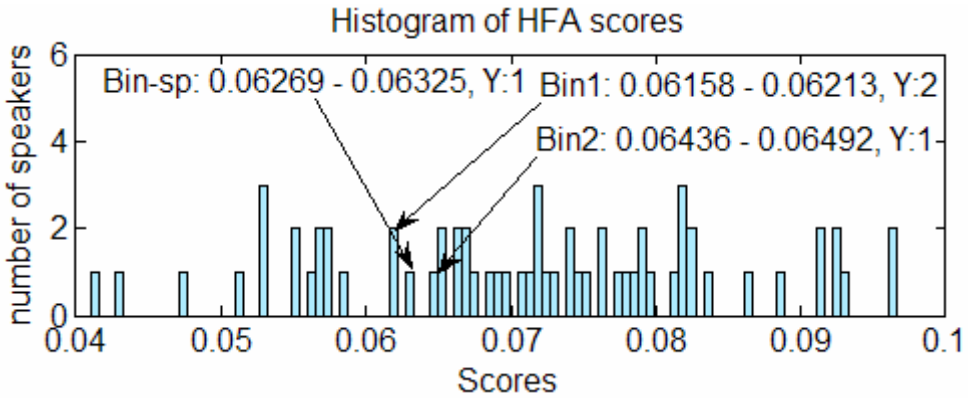


Figure 25(a). Effect of Score Modifier – HFA Score Histogram (Poor Recognition Case)

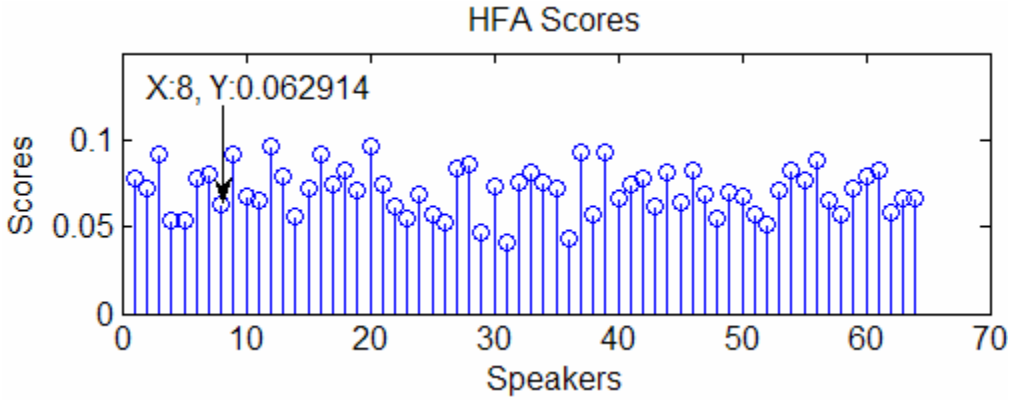


Figure 25(b). Effect of Score Modifier – HFA Scores (Poor Recognition Case)

3) Case 3: Poor Accent Classification

This case deals with a scenario where a speaker was recognized correctly, but the true speaker's accent was not identified correctly. In Figure 26(a), '*Bin-sp*' is clearly separated from the imposter bins. We can see that the imposter bin '*Bin2*' is separated from '*Bin-sp*' by a gap of 0.00319. After score modification, we can see that the score of the true speaker has been modified from 0.028761 to -0.056982, as shown in Figure 27(a). This indicates an accent classification error because the score modifier modifies any score which does not belong to the trained accent as that of the true speaker. Because of this subtraction, even

when there is an error in accent classification, the speaker's score that was truly recognized is further improved but not degraded. Degradation might occur only with a completely inseparable true speaker score and an error in accent classification.

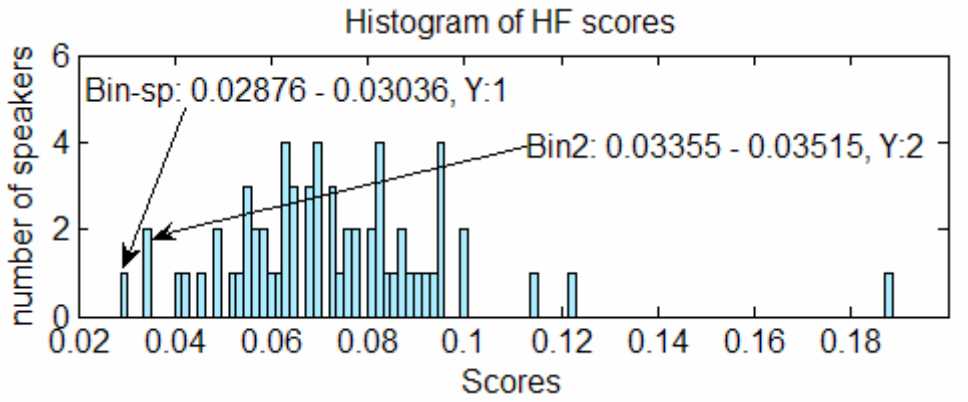


Figure 26(a). Effect of Score Modifier – HF Score Histogram (Poor Accent Classification Case)

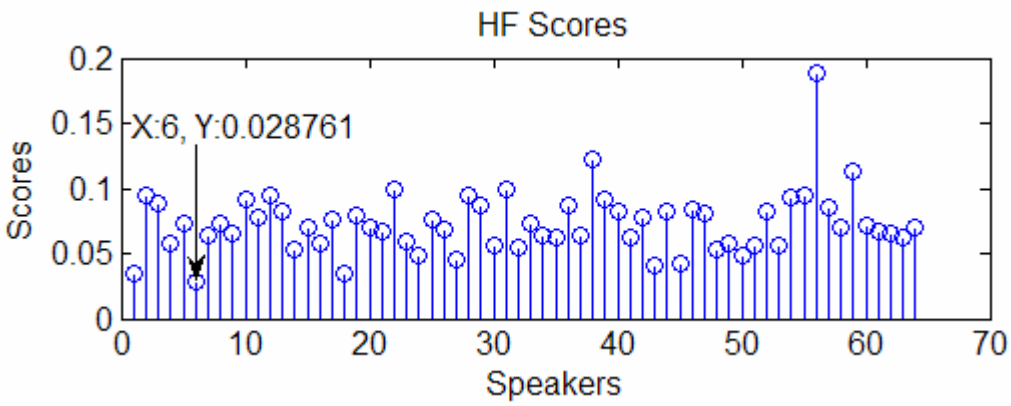


Figure 26(b). Effect of Score Modifier – HF Scores (Poor Accent Classification Case)

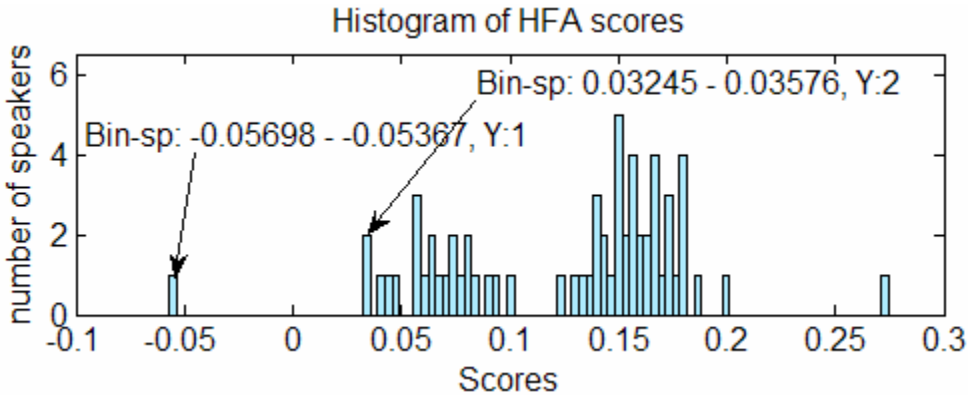


Figure 27(a). Effect of Score Modifier – HFA Score Histogram (Poor Accent Classification Case)

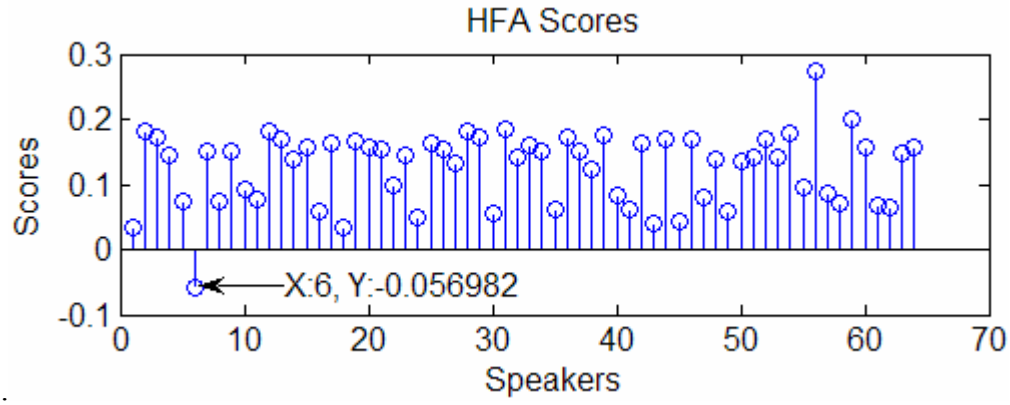


Figure 27(b). Effect of Score Modifier – HFA Scores (Poor Accent Classification Case)

CHAPTER 5

EXPERIMENTAL RESULTS

The HF system, accent classification system and the HFA system have been evaluated on various datasets; the results of these experiments are provided in this Chapter. The HF speaker recognition system has been evaluated on YOHO [41] and the USF multi-modal biometric dataset [8]. For evaluating accent incorporation, i.e. accent classification system and HFA system, SAA system and the USF multi-modal biometric dataset were used. The YOHO dataset was not used for evaluating accent incorporation, as the dataset comprised of only North American accents.

5.1 Datasets

1) YOHO Dataset

YOHO dataset, which can be obtained from Linguistic Data Consortium (LDC), was created in a low noise office environment and has a population of 138 persons (106 males and 32 females). Data structure contains two different types of data-training and testing. Each speaker reads a portion of a six digit combination lock phrases. There are 4 enrollment sessions of 24 utterances. For verification, there are 10 verification session with 4 utterances.

Speaker's voice was recorded using a telephone handset (Shure XTH-383). Data sampling rate is 8000 Hz. Data set was collected over a three month period [11]. YOHO dataset was designed to ascertain system accuracy up to 0.1% false rejection and 0.01% false acceptance rate with 75% confidence.

2) USF Multi-Modal Biometric Dataset

A multi-modal biometric dataset was collected at USF over a time period of nine months. In this dataset 78 persons provided three sessions of indoor and outdoor data for face, voice and fingerprint. As we have used only the voice dataset in this work, we will describe only that portion of the dataset. Each person's voice samples were acquired using Sennheiser E850 microphone in collecting both indoor and outdoor datasets. There are three sets of phrases in the voice dataset: Fixed:-one fixed sentence was uttered by every person; Semi-fixed:-sentence was varied by a small amount for each speaker, i.e., date and time of recording; Random:-completely random utterance. Each person uttered three types of phrases and each phrase was repeated three times, for both indoor and outdoor locations. This gives 9 voice samples for indoor and outdoor per person per session. Sampling rate was 11,025 Hz. There are three different sessions of data available in this dataset. Not all volunteers showed up for all the sessions. Therefore, we used two sessions of data, with population of 65 people. We used indoor data as training and outdoor data for testing.

3) SAA Dataset

The SAA dataset [42], is an online speech database, available to people who wish to compare and analyze different accents of the English language. The archive provides a large set of speech samples from a variety of language backgrounds. All data has been sampled at

22,050 Hz. All the speakers read the following paragraph. "*Please call Stella. Ask her to bring these things with her from the store: Six spoons of fresh snow peas, five thick slabs of blue cheese, and maybe a snack for her brother Bob. We also need a small plastic snake and a big toy frog for the kids. She can scoop these things into three red bags, and we will go meet her Wednesday at the train station."*

For our purpose, we have selected six accents in order to classify the speakers which are Arabic, American, Indian, Chinese, Russian, and Spanish. Though all subjects were recorded in a quiet room environment, the pool used for this purpose had background noise in some cases and an echo in some other cases. In order to test the SAA dataset itself, the phrase "*Please call Stella*" was used for training the accent model and "*Six spoons of fresh snow peas*" was used for testing purposes. 10 speakers per accent were used to train each accent model. For testing the USF dataset, these training models were used as a reference accent database. The performance results of the systems are shown next, starting with hybrid fusion system performance.

5.2 Hybrid Fusion Performance

A frame size of 256 samples per window was used for YOHO and USF datasets. A Hamming window was applied and the FFT size used was 256 points. From each speech signal, 13 MFCCs (mel- frequency cepstral coefficients) for both datasets was extracted at every 256 samples of window (approximately 32 ms for YOHO and 25 ms for USF dataset) with overlap of 128 samples (approximately 16 ms for YOHO and 10 ms for USF dataset). Each HMM was represented using 30 hidden states with 200 iterations for each enrolled or

training speech data sample. Once HMM models were created as described in Section 2.4.2, they were compared with the testing data to find the likelihood score. AHS distance measure (score matrix) from training and testing speech data was found as described in Section 2.4.1.

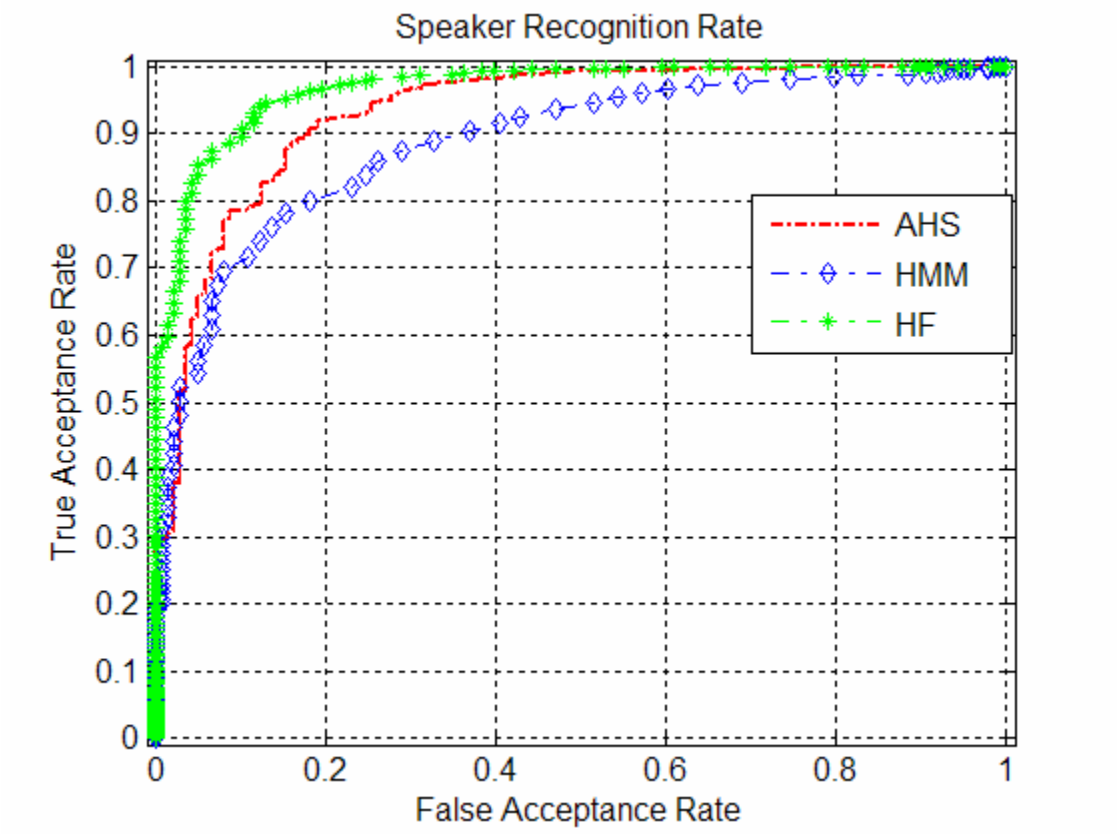


Figure 28(a). ROC Comparisons of AHS, HMM, and HF systems for YOHO Dataset

These scores were normalized using *Min-Max* normalization technique as described in Section 2.5.1 so that the scores are between [0, 1]. Lower score represents closer likelihood between training and testing subjects. The fusion method described in Section 2.5.2 was used to determine the mean of AHS and HMM distributions M_{HMM} and M_{AHS}, respectively. Once the enhanced weight ω was found algorithmically using Equation (34), we fuse both the score metrics to obtain an enhanced score metric.

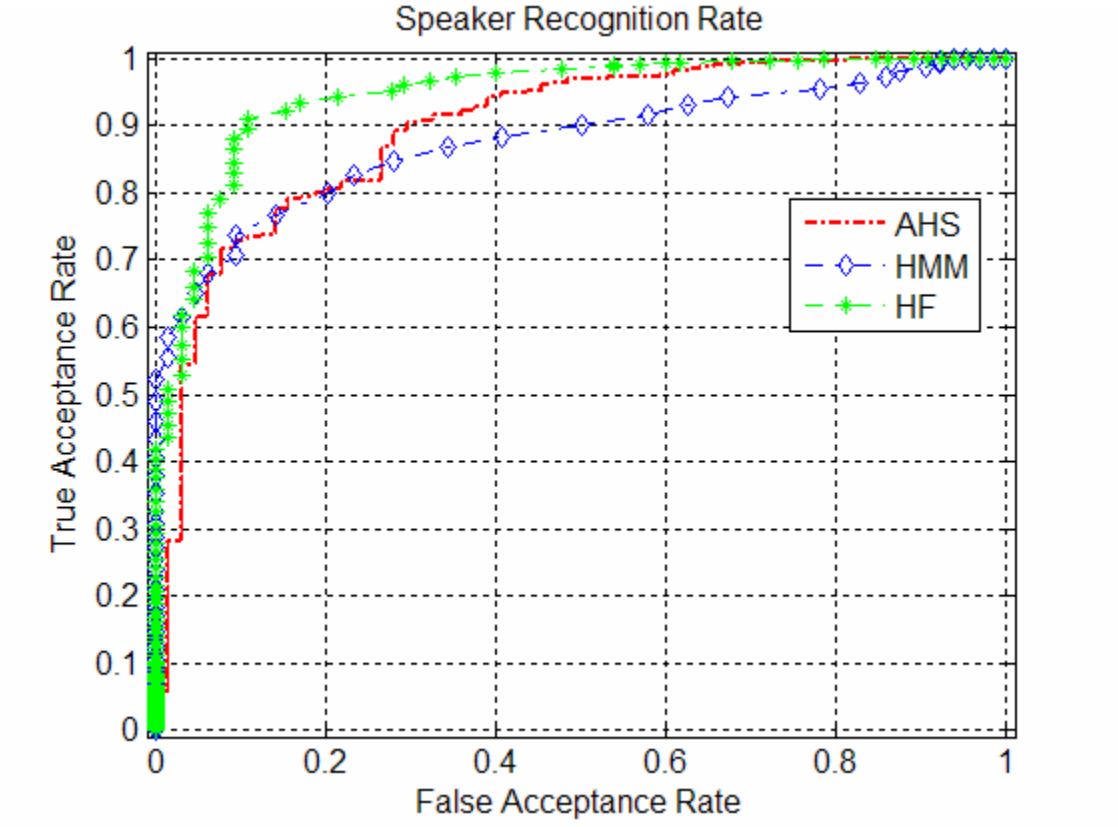


Figure 28(b). ROC Comparisons of AHS, HMM, and HF Systems for USF Dataset

In order to represent the score matrices, the Receiver Operating Characteristic (ROC) curve, which is a plot of the False Acceptance Rate (FAR) versus the True Acceptance Rate (TAR) of the system, was used. Figures 28(a), (b) and (c), show the ROC curve for each of the recognition methods, i.e., AHS, HMM and HF conducted on YOHO, USF, and SAA datasets, respectively. It can be seen that on all the datasets our HF method shows an improvement. However, the improvement was better for fusion on YOHO and SAA dataset (Figures 28(a), 28(c)) compared to USF dataset (Figure 28(b)).

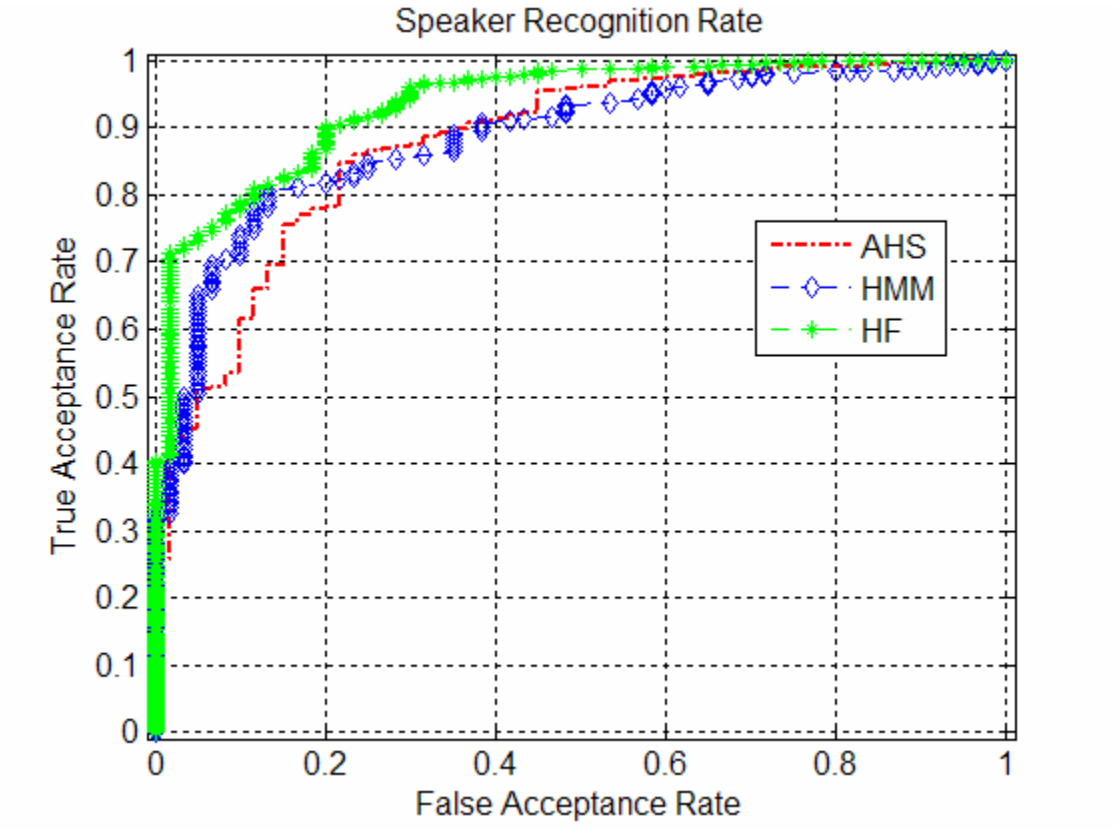


Figure 28(c). ROC Comparisons of AHS, HMM, and HF Systems for SAA Dataset

For better appreciation of the performance gains from hybrid fusion method, Figures 28(a), (b) and (c) are expressed in a bar graph in Figures 29, 30 and 31, respectively. It can be seen that the proposed HF method works better when the dataset (YOHO) was noise free. For YOHO dataset, the TAR performances were 84% and 62% at 5% FAR for HF and AHS methods, respectively. A 22% performance increase, when compared to AHS, which performed better than HMM at 5% FAR (55% TAR). Therefore it would be prudent to compare the performance gain with the better performing algorithm. The HMM method was not speaker adapted, thus the accuracy is lower than HMM in conjunction with *maximum a posteriori probability* (MAP) algorithm's performance [26]. YOHO dataset can provide

enough training samples for MAP algorithm to be effective, however USF dataset does not have enough training samples (per session) to create speaker adaptation.

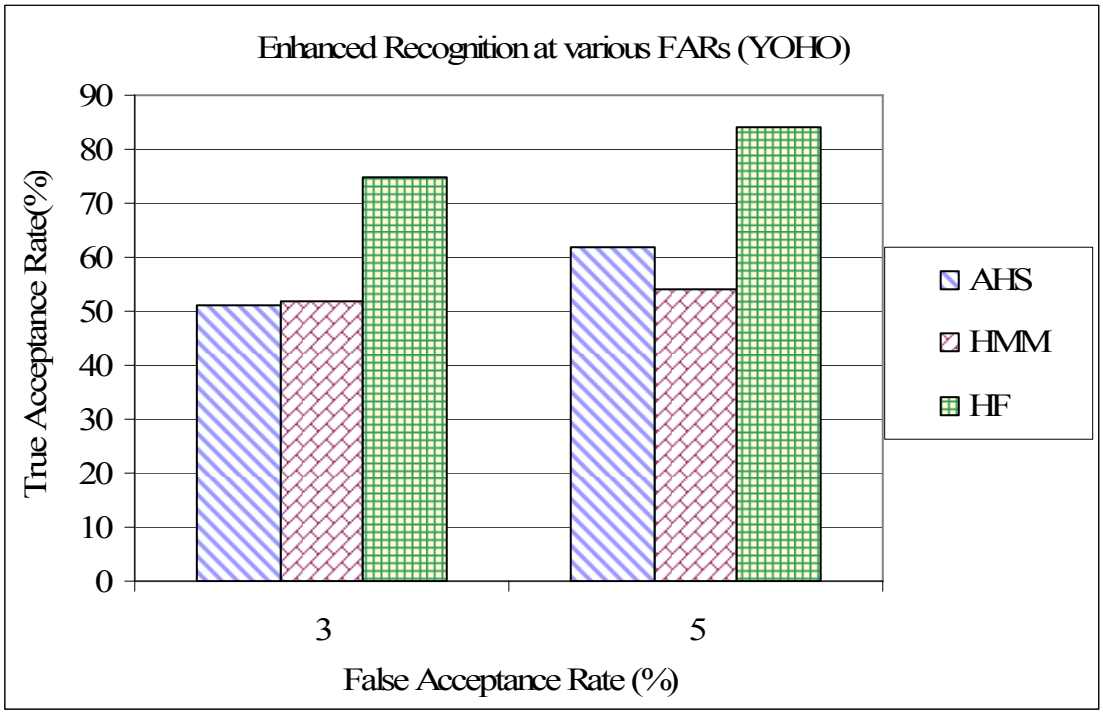


Figure 29. Comparison of AHS, HMM, and HF Recognition Rate at Various False Acceptance Rates for YOHO Dataset

For USF outdoor dataset, the TAR performances were 71% and 65% at 5% FAR for HF and AHS/HMM methods, respectively. A 6% increase in performance at 5% FAR. For this noisy dataset, performance increase was not as drastic as the cleaner YOHO dataset. From Figures 29, it can be seen that HF method shows about 22% increase in YOHO dataset at 3% FAR. However from Figure 30, it can be seen that HF method does not show such improvement when used with USF dataset. TARs were 63% and 59% at 3% FAR for HF and HMM (4% performance gain for HF over HMM). For SAA dataset (Figure 31), the TAR performances were 71% and 50% at 3% FAR for HF and HMM, respectively (21% performance gain). But

at 5%, a TAR of 74% and 65% for HF and HMM systems can be observed, resulting in a 9% performance increase.

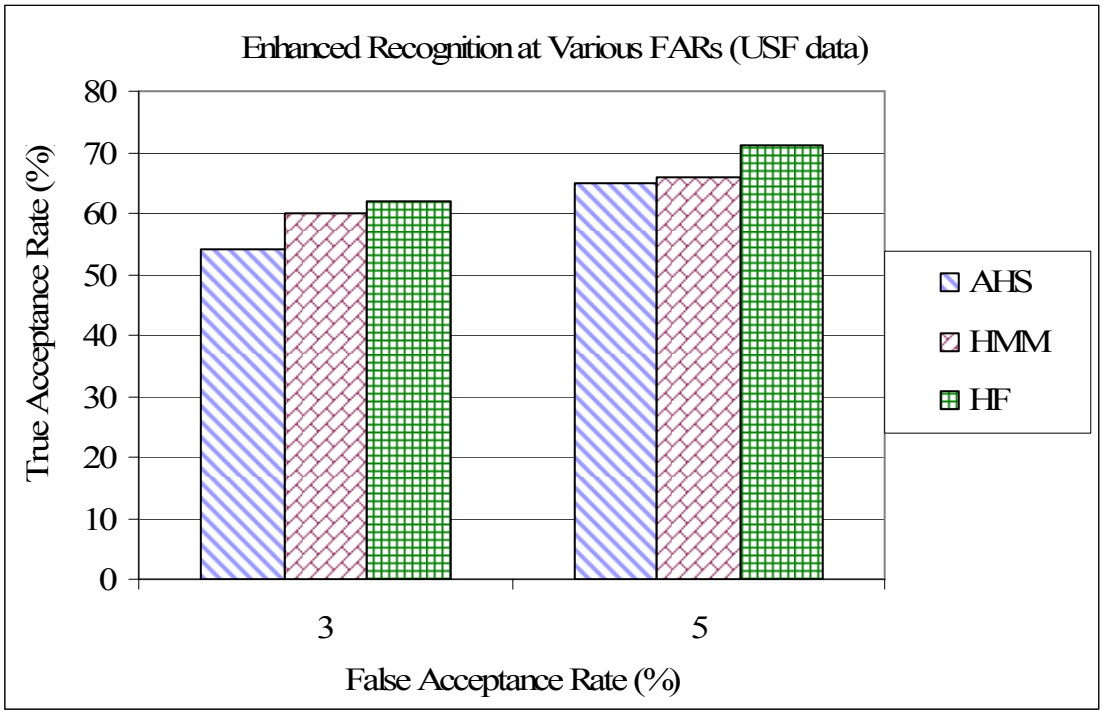


Figure 30. Comparison of AHS, HMM, and HF Recognition Rate at Various False Acceptance Rates for USF Dataset

It is always difficult for any recognition system to perform well when an outdoor dataset is used. USF location being in a large metropolitan city of Tampa combined with a typical busy campus environment resulted in our outdoor speech dataset to be noisy and unpredictable. This explains the lower performance for both AHS and HMM systems when compared to noise free YOHO dataset and the SAA dataset. Thus after fusion, we do not see much performance gain (6% at 5% FAR and 4% at 3% FAR).

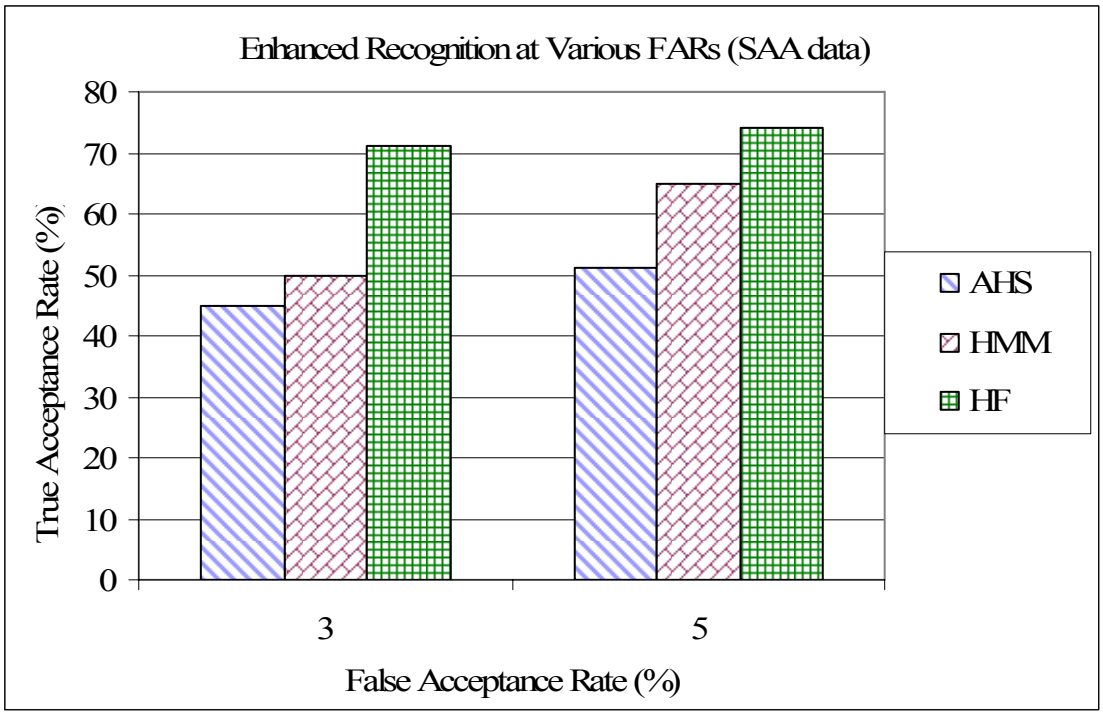


Figure 31. Comparison of AHS, HMM, and HF Recognition Rate at Various False Acceptance Rates for SAA Dataset

We could not compare our results, with FAR less than 2 to 3% for the USF dataset reliably, because the population size was only 65. In other words one erroneous result could swing the performance, by ±1.5%. For the same reason, having a smaller number of speakers in a dataset, with a performance increase (1% or less), as reported in [26], would not be statistically viable.

From Figures 29-31, we can see that AHS and HMM show similar performance varying around 50-65% for all the datasets at 3 to 5% FAR. Yet we see HF method resulted in enhanced performances. In our case HF assigns a larger weight to HMM and a relatively much smaller weight to AHS. Even though AHS and HMM are analogous in performance, mean enhanced weight method makes HF outperform individual algorithm's TAR. The

reason behind the success of such weight assignment is the utilization of the means of the score distribution, rather than the score distribution itself.

5.3 Accent Classification Performance

The sampling rate of SAA and USF dataset being different, we used fixed window period of 25.6 ms with 50% overlap for both datasets. A Hamming window was applied and the FFT size used was 256 points. We extracted 13 MFCCs, 13 ASCCs, 13 delta ASCCs, delta-delta Energy, delta Energy and Energy from each speech signal as described in Section 3.4 from both datasets.

For each enrolled or training SAA speech data sample we used 6 hidden states and 8 Gaussians each with a diagonal covariance and 100 iterations to represent a CHMM as explained in Section 3.5.2. GMMs were created using 7 components with diagonal covariances as explained in Section 3.5.1. The SAA testing data was modeled using 6 states and 15 Gaussians for CHMM and 15 components for GMM. On the other hand the USF dataset was modeled by using 6 states and 18 Gaussians for CHMM and 16-component GMM. Once CHMMs and GMMs were created they were fused according to Equation (49). Then, the accent scores and accent classes for each enrolled and test speakers are stored. After which the SM algorithm of Section 4.1 is used to enhance the HF score matrix. In the case of testing the SAA dataset, the enrolled speakers were already labeled; hence the accent classification system was applied only to the test speakers. In case of USF dataset, both the enrolled and test speakers were classified using the accent classification system with the SAA dataset as a reference.

The weight factor β in Equation (52) was used to tune the fusion of CHMM and GMM accent scores. As Figure 32 shows, best results were obtained for $\beta = 0.95, 0.75$ for SAA and USF datasets respectively. The graph indicates that as the weight factor is changed from 0 to 1, i.e., GMM alone is used when β is 0, whereas CHMM is used when it is 1. There was an improvement of 7% for SAA and 5% for USF datasets, due to fusion of GMM and CHMM, instead of using GMM alone. Hence the final accent classification rate is 90% and 57% for SAA and USF datasets, respectively.

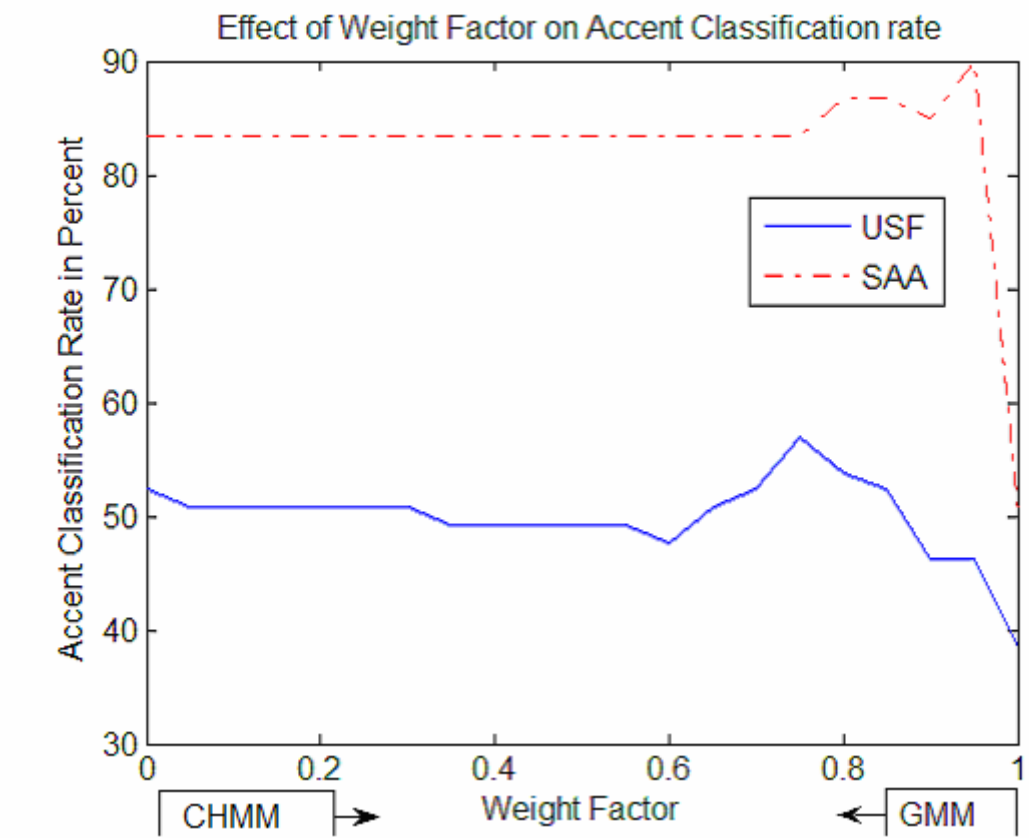


Figure 32. Accent Classification Rate Using Different Weight Factors for SAA and USF Datasets

5.4 Hybrid Fusion - Accent Performance

It can be seen from Figures 33(a) and 33(b) that for both datasets our HF method shows an improvement. However, the improvement was better for fusion on SAA dataset (Figure 33(a)) compared to USF dataset (Figure 33(b)), because of high accent classification rate. Intuitively, accent classification rate in SAA should be better because the reference accent models were created from the same SAA dataset. These final results were obtained by selecting a CAM value of 30 and 52 for USF and SAA datasets respectively. Also, the accent classification rate of SAA was 1.6 times greater than that of USF dataset, interestingly the same rule applies for the CAM variable as well.

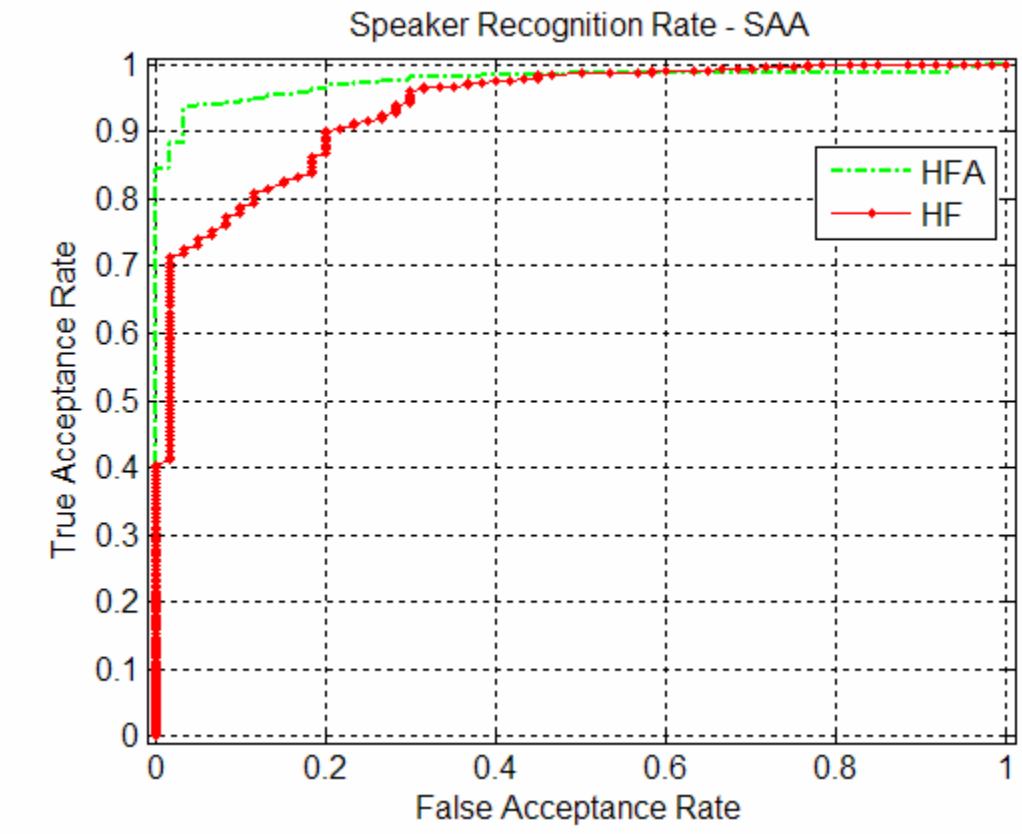


Figure 33(a). ROC Comparisons for HF and HFA Methods Evaluated on SAA

For better appreciation of the performance gains from Hybrid Fusion – Accent (HFA) method, Figures 33(a) and (b) are expressed in a bar graph in Figures 34 and 35, respectively. For SAA dataset, the TAR performances were 88% and 71% at 3% FAR for HFA and HF methods, respectively, i.e., a 17% performance gain for HFA method over HF method.

For USF outdoor dataset, the TAR performances were 78% and 63% at 3% FAR for HFA and HF methods, respectively. A 15% increase in performance has been achieved for HFA method compared to HF method. From Figures 34 and 35, it can be seen that HFA method shows about 20% increase in SAA dataset at 5% FAR. Also, it can be seen that HFA method shows significant improvement when used with the noisy outdoor USF dataset. At 5% FAR, a 13% performance increase was observed for HFA method compared to HF method. We can see from Figure 33(b), that at very high FARs, HFA method does not perform better than HF method. When speaker recognition performs poorly, a higher score is assigned to the true speaker, due to which the true speaker's score lies within the false speaker cluster. But when SM algorithm is applied to the HF-score matrix, it modifies the imposter scores making those false scores come closer towards the true speaker's score, thereby decreasing the TAR at higher FARs. Since FARs as high as 10% are never useful in evaluating a real world speaker recognition system, this specific issue is not a concern.

It is always difficult for any recognition system to perform well when an outdoor dataset like USF dataset is used. But, incorporation of accent modeling brought a significant performance gain at low FARs. A speaker recognition system cannot be considered as a better performing system, even though it performs well at high FARs. A good system is

always expected to deliver performance at low FARs. We can see from Figures 34 and 35 that by adding accent information using SM algorithm, significant enhancement has been achieved at low FARs. The accent incorporation method can be applied to any general speaker recognition system with some adjustments to the weight factor β in the accent classification system, distance threshold variable *maxvar* and CAM in the SM algorithm.

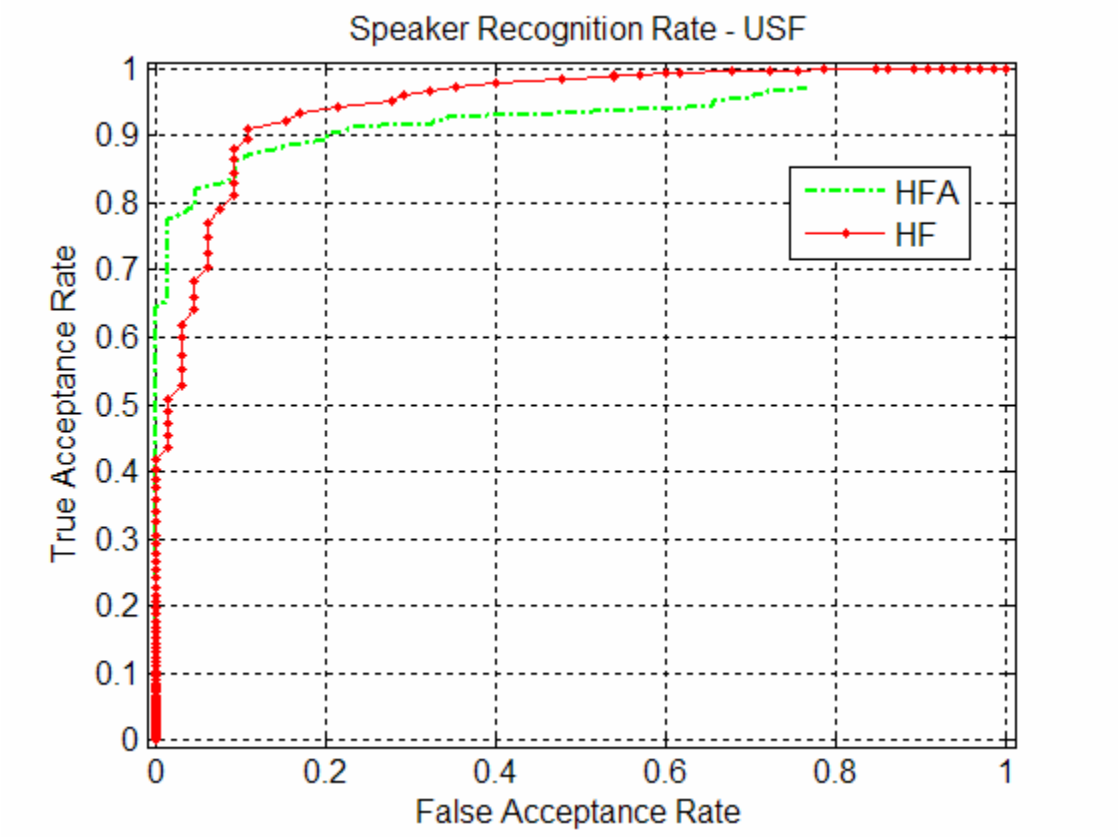


Figure 33(b). ROC Comparisons for HF and HFA Methods Evaluated on USF Dataset

Typically in any well performing speaker recognition system, the true speaker's score would be separated from most of the imposter scores, but still poorly separated from some of them. Incorporation of accent modeling through the SM algorithm would especially achieve significant performance gains in such scenarios. The SM algorithm increases the distance

between the true speaker and the some of the closely lying false speakers as well as the distant imposters, resulting in two separate clusters where one cluster represents imposters and the other cluster representing the rest, while the true speaker score stands separate from either of them.

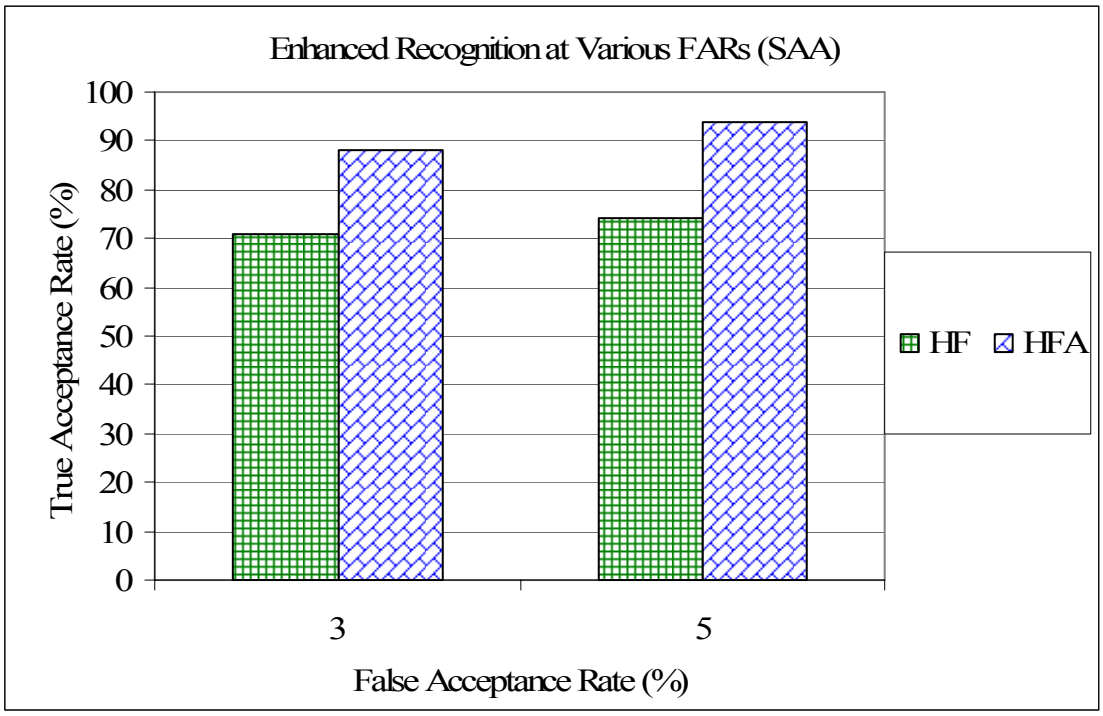


Figure 34**.** Comparison of HFA and HF Recognition Rate at Various False Acceptance Rates for SAA Dataset

On the whole, by implementing the HFA system, for SAA dataset, at 3% FAR, a total recognition rate enhancement of 45% had been obtained through HFA. For USF outdoor dataset, at 3% FAR, a 19% increase through HFA has been achieved.

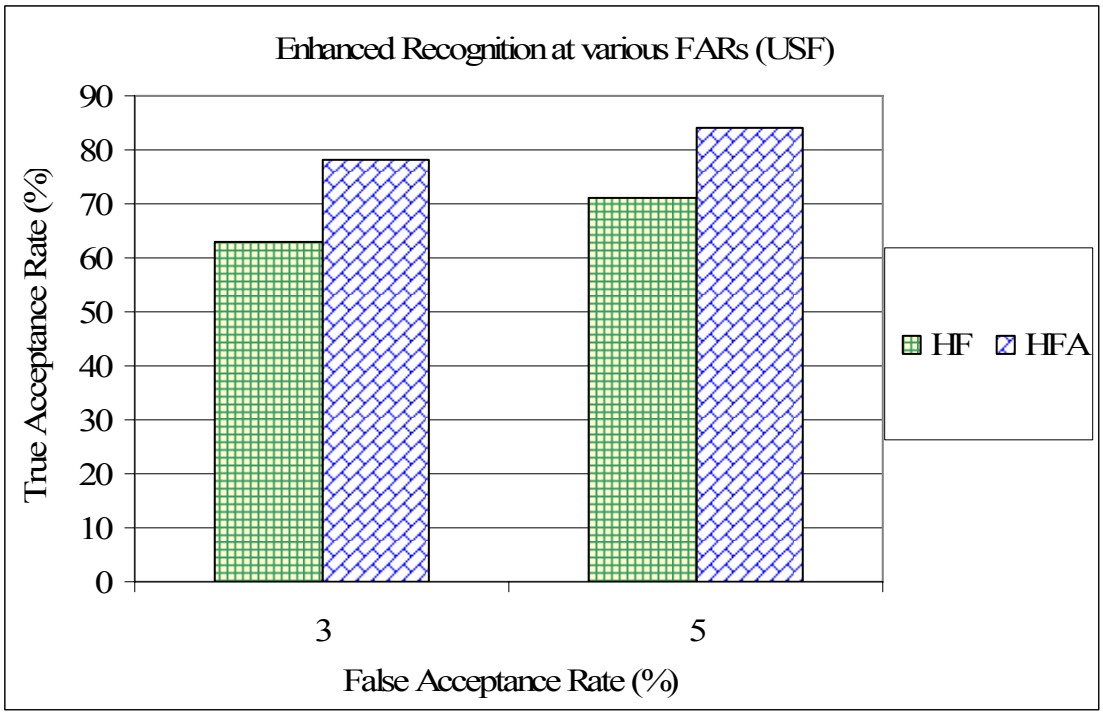


Figure 35. Comparison of HFA and HF Recognition Rate at Various False Acceptance Rates for USF Dataset

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

A good biometric system needs to deliver a high performance at low FARs. By using a text-independent accent classification system with our HF system and a score modifier algorithm, a significant enhancement has been achieved at low FARs. In this thesis, speaker recognition using Arithmetic Harmonic Sphericity (AHS) and Hidden Markov Model (HMM) has been studied. Mel-frequency cepstral coefficients (MFCC) have been used as speaker features. A linear weighted fusion method (hybrid fusion), has been implemented effectively such that the contrastive nature of AHS and HMM is used to benefit the speaker recognition performance.

For the first time a text-independent accent classification (AC) system has been developed without the usage of an automatic speech recognizer. MFCCs, accent sensitive cepstral coefficients (ASCCs) and energy have been used as accent features. MFCCs emphasize the first formant frequency, whereas ASCCs emphasize second and third formants. By combining MFCCs and ASCCs along with energy increases accent classification rate. Gaussian mixture model (GMM) and continuous hidden Markov model (CHMM) have been used to model these features. Continuous HMM was used instead of discrete HMM, as each state in CHMM is modeled as a mixture of Gaussians thereby

increasing precision and decreasing degradation. As GMM and CHMM were fused to benefit from the advantages of both the modeling algorithms, an increase in accent classification performance was observed. Then, the HF-speaker recognition system was combined with accent classification system to enhance the true acceptance rate (TAR) at lower false acceptance rates (FAR). The AC system produces accent class information and the accent score assigned to each speaker. A score modifier algorithm was introduced, to incorporate the outputs of the AC system into the HF-speaker recognition system. The score modifier enhances the speaker recognition, even for low accent classification rates, as it modifies the HF-speaker recognition score as a factor of the confidence measure of the accent score and the HF score. But SM algorithm might fail, when a very poor speaker system is paired with a poor accent classification system. Although there have been previous efforts in using accent to improve speaker recognition, utilizing an accent classification system to enhance a speaker recognition has not been reported so far.

The HF system was evaluated on the YOHO clean speech dataset and the realistic outdoor USF dataset. But the enhancement achieved with HF for the USF dataset was not sufficient, due to which an accent incorporation method was developed to achieve substantial performance levels at lower FARs. The final accent incorporated HF model called the hybrid fusion - accent (HFA) system was evaluated on SAA dataset and USF dataset. Significant improvement was observed by using the HFA system. For SAA dataset, at 3% FAR, a total recognition rate enhancement of 45% had been obtained through HFA. For USF outdoor dataset, at 3% FAR, a 19% increase through HFA has been achieved. Finally, accent incorporation and hybrid fusion technique can be applied to any general speaker recognition

system with some adjustments to the weight factor in the accent classification system, distance threshold variable *maxvar* and CAM in the SM algorithm. Even though performance gains has been achieved at lower FARs using the HFA system, further improvements are necessary before the proposed speaker recognition system can be considered as a stand alone security system.

6.2 Recommendations for Future Research

The HFA system still needs to be tuned for different datasets, i.e. the weight factor in the accent classification system and the distance threshold variable *maxvar*, CAM in the score modifier algorithm. Complete automation of the accent classification system and the score modifier, would be useful, so that no tuning needs to be done for different datasets. Higher level features other than mel-frequency cepstral coefficients (MFCC), accent-sensitive cepstral coefficients (ASCC), delta ASCCs, energy, delta energy and delta delta energy needs to be integrated into the system, so that an accent classification rate can be improved, which would enhance the HFA system performance inturn. The HFA system needs to be evaluated on a variety of larger datasets, so that more inferences can be drawn from the results and enhancements to the HFA can be made. Also different fusion techniques at the modeling level such as SVM versus GMM, HMM versus SVM needs to be studied, and evaluated on a variety of datasets to better understand the effect of different fusions, so that a common frame work can be formulated to find the optimal fusion. Finally, as we know from the results that accent incorporation enhances speaker recognition, studies have to be conducted on several other factors such as gender classification systems.

The process of identifying human through speech is a complex one and our own human recognition system is an excellent instrument to understand this process. The human recognition system extracts several other features from a single speech signal, due to which it achieves high accuracy. The goal of a speech researcher should be to identify such missing pieces of information, in a hope to match the human recognition system some day.

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APPENDICES

Appendix A: YOHO, USF, AND SAA DATASETS

TABLE 1. YOHO Dataset

Sampling Frequency	8 KHz
# of speakers	138 (106 M/32 F)
# of sessions/speaker	4 enrollments, 10 verifications
Intersession Interval	Days-Month (3 days)
Type of speech	Prompted digit phrases
Microphones	Fixed, high quality, in handset
channels	3.8 KHz/clean
Acoustic Environment	Office
Evaluation Procedure	Yes [11]
Language	American English

TABLE 2. USF Dataset

Sampling Frequency	11.025 kHz
# of speakers	78
# of sessions/speaker /utterance/Location	3 sessions
Period of time	9 months
Type of speech	Fixed , Semi-Fixed and Random Phrases
Microphone	Sennheiser E850
Acoustic Environment	Indoor Office and Outdoor Campus
Language	English

Appendix A: (Continued)

TABLE 3. SAA (subset) Dataset

Sampling Frequency	22.050 kHz
# of speakers	60
# of accents	6
accents	Arabic, American, Indian, Chinese, Russian and Spanish
Type of speech	Paragraph split into two phrases
Microphone	Sony ECM-MS907
Acoustic Environment	Indoor Office (but has non stationary noise)
Language	English

Appendix B: WORLD'S MAJOR LANGUAGES

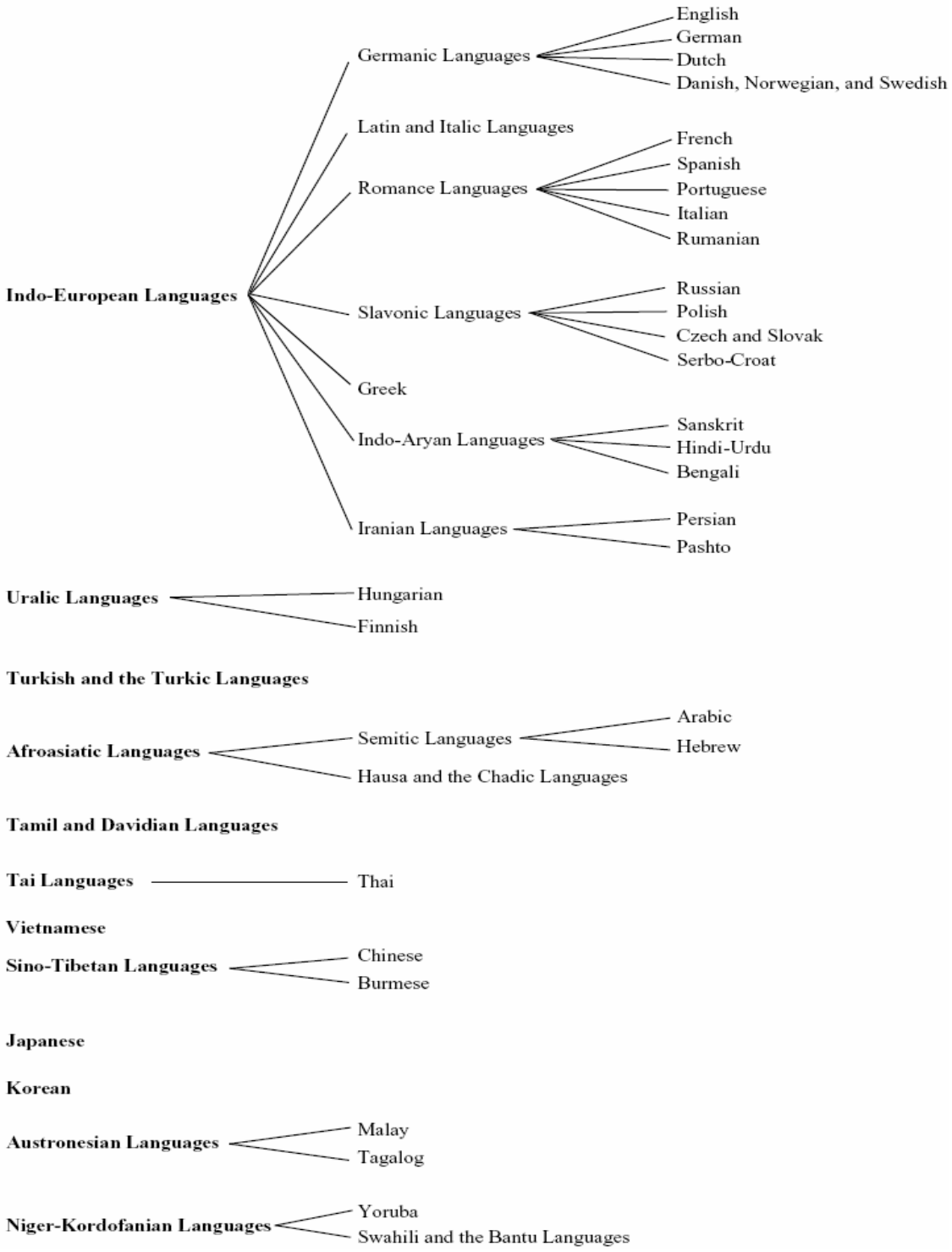

Figure 36. World's Major Languages [30]