Arabic Speaker Identification System Using Multi Features

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A B S T R A C T

The performance regarding the Speaker Identification Systems (SIS) has enhanced because of the current developments in speech processing methods, however, an improvement is still required with regard to text-independent speaker identification in the Arabic language. In spite of tremendous progress in applied technology for SIS, it is limited to English and some other languages. This paper aims to design an efficient SIS (text-independent) for the Arabic language. The proposed system uses speech signal features for speaker identification purposes, and it includes two phases: The first phase is training, in this phase a corpus of reference database is built which will serve as a reference for comparing and identifying the speaker for the second phase. The second phase is testing, which searches the identification of the speaker. In this system, the features will be extracted according to: Mel Frequency Cepstrum Coefficient (MFCC), mathematical calculations of voice frequency and voice fundamental frequency. Machine learning classification techniques: K-nearest neighbors, Sequential Minimum Optimization and Logistic Model Tree are used in the classification process. The best classification technique is a K-nearest neighbors, where it gives higher precision 94.8%.

1. Introduction

There are various types of information in the Human voice (speech signal), as a result, it became an effective choice for authentication, and therefore a speech signal uttered via an individual has the ability to recognize the individual. There are 3 types of recognition in speech signals: speech recognition, speaker recognition, and language identification. Speaker recognition can be defined as the verification and identification of a speaker [1]. Speaker identification is considered as the procedure that recognizes an unidentified speaker through the process of comparing his/her voice with voices of registered speakers in the database, it can be considered as one to- many comparisons

(1: N match in which the voice will be put in comparison against N templates) [2]. Speaker identification can be divided into text-independent and text-dependent. The Text-independent system does not necessitate offering the same text/utterance for testing and training [1].

In the presented study, the MFCC feature is utilized to design text-independent SIS, in which it mimics human ear's behavior and performs adequately in SIS. The extracted speech features (MFCC's) related to the speaker are quantized to a number of centroids through the use of a vector quantization algorithm, then the output is mixed with four selected voiced frequency features and voice fundamental frequency. Sequential Minimum Optimization (SMO), Logistic Model Tree (LMT), and K-nearest neighbor (KNN) algorithms are used for the classification process.

2. Literature Review

Many research has been done related to Speaker Recognition, the following are the most important research in recent: Roma and Priyanka [3], represented solid mathematical algorithm for Automatic Speaker Recognition System based on MFCC for feature extraction, Vector Quantization (VQ) and LBG (Linde, Buzo, and Gray) algorithm for clustering a set of L acoustic vectors into a set of M codebook vectors in speaker recognition. Their system provided 91% accuracy in normal environmental conditions. Hyan-Soo et al. [4], this research proposed an improved voice recognition approach through the use of MFCC, Adaptive MFCC, and Deep Learning. The results are a 96% recognition rate of MFCC and around 96~98% of Adaptive MFCC. Nagwa et al. [5] in 2016, developed the text-independent speaker identification model via taking in MFCCs with VQ for the purpose of obtaining feature vectors without dropping considerable information. The results showed that the model reached a great recognition rate of 91% and about a 50% decrease in processing time. Zimeng [6] a real-time speaker gender identification system has been developed, the system used mathematical calculations of voice frequency and voice fundamental frequency for features extracted. Naive Bayesian Classifier is used for classification, the system is providing the good performance of 92.75% for gender recognition. Mie [7], used labeling audio sample in the indoor or outdoor condition that is referred to as Acoustic Scene Classification (ASC), the study compared the features of various classifiers, and they are k-NN, SVM, Decision Tree, and Linear Discriminant Analysis via applying MFCC feature over 10-fold cross-validation, where the results were as follows: 55.3%, 62.5%, 72.2%, and 43.7% respectively. Ankur et.al [8], implemented speaker recognition for Hindi speech samples through the use of Mel frequency Cepstrum Coefficient–vector quantization (MFCC-VQ) and Mel Frequency Cepstrum coefficient-Gaussian mixture model (MFCC-GMM) for text-dependent and text-independent phrases. The accuracy of text-independent recognition is 77.64% and 86.27%, respectively, while the accuracy of text-dependent recognition is 85.49% and 94.12% respectively.

3. Voice Features

There are three types of features related to voice: Voice Frequency Relevant Features (Standard Deviation and Mean frequency), Voice Fundamental Frequency Relevant Features (Amplitude and Zero-crossing rate) and Mel-frequency Cepstrum Coefficient (such as MFCC) [6].

I. Mean frequency

Mean Frequency of a speech, referred to as $fmean$, can be considered as an average value related to speech frequency in a certain frequency spectrum range. It is estimated as a sum of frequency related to the spectrum divided by the total number of frequency frames in the spectrum. The equation for calculating mean frequency is [6]

$$f_{mean} = \frac{\sum_{i=0}^{n} f_i}{n} \tag{1}$$

Where $fmean$ is voice's mean frequency, n is the number of frequency frames in the spectrum, fi is the frequency of the spectrum at frame i of n.

II. Standard deviation (STD)

Standard Deviation these measures shows how much variation exists from the average (mean). Equation 2 shows the STD of the sample in each frame [9].

$$STD = \frac{1}{m} \sum_{i=1}^{m} (Xi - N)^2 \tag{2}$$

Where *m* is the number of samples in every frame, *Xi* is the value of the signal, and Ṉ is the mean.

III. Zero-crossing rate (ZC)

Zero-Crossing Rate measures how many times in a certain frame/time interval the amplitude of speech signals pass via a value of 0. It is demonstrated in the following equations:

$$ZC = \sum_{m=1}^{N-1} x(m) - x(m-1) \tag{3}$$

Where, *m* is the sample value, and *N* is the total number of samples in every frame.

$$x(m) = \begin{cases} 1, for\ x(m) \geq 0 \\ -1, otherwise \end{cases} \tag{4}$$

IV. Amplitude (Amp)

Amplitude measures the amount of energy transported through the wave, where acoustic energy or intensity of a sound is associated directly through amplitude. The amplitude and intensity are related to the sound's power [10].

$$S(t) \times coswct = G(t)coswct \tag{5}$$

Where: S (t): Is the carrier of the information. G (t): Is a carrier wave and a sine wave (cos*wct*).

V. Mel frequency cepstrum coefficients (MFCCs)

MFCC can be considered as a popular approach for voice feature extraction, In MFCC: Input signal will be passed via a filter that emphasizes higher frequencies and suppresses low-frequency components, the time slot is decided for which input sample is taken. Then windowing integrates all closest frequency lines after windowing FFT converts the vocal tract impulse response in the time domain. Mel spectrum is transformed **t** time domain by DCT, the final converted result is called MFCC [11]. The first 12 values of the Cepstrum contain meaningful information to provide unique characteristics of the waveform [12].

4. Types of Classification Methods

Classification can be defined as a type of machine learning that means an algorithm developed to 'learn' classification of new observations from the examples acquired from labeling data. This algorithm is a general method for extracting features from input speech that makes it likely to predict a label or class. There are many methods to classify. The following are the most effective methods in this research:

I. Logistic model tree

There are two complementary classifiers combined in Logistic Model Trees (LMTs), tree induction and linear logistic regression. The structure regarding decision tree consist of the functions of logistic regression of the leaves, depending on a threshold value, a leaf node will be divided into 2 child nodes in which the right branch will consist of the value of the attribute that is greater than the threshold, and the left branch will consist of the value of attribute lesser than threshold [13].

II. K-Nearest neighbor (KNN)

KNN classifier is considered as a simple classifier that produces a decent classification performance. The class label related to most KNNs is assigned to the new test sample. Parameter K limits the neighborhood, but changing the number of neighbors could impact the performance of the classification system [14].

III. Sequential minimal optimization (SMO)

It is utilized for training support vector classifier through the use of polynomial or RBF kernels. It does replace all the missing values and transforms nominal attributes to binary ones. The amount of memory needed for SMO is linear in the training set size that allows SMO to handle huge training sets [15].

5. Classification Performance Measures

The success rate of the classification is measured by calculating the following measures:

Precision: the proportion of predicted positives which are actual positive TP / (TP + FP).

Recall: the proportion of actual positives which are predicted positive TP / (TP + FN).

F-measure harmonic mean between precision and recall 2 (precision. recall) / (Precision + recall) where [16]:

TP = true positives: number of examples predicted positive that is actually positive.

FP = false positives: number of examples predicted positive that are actually negative.

TN = true negatives: number of examples predicted negative that are actually negative.

FN = false negatives: number of examples predicted negative that are actually positive.

6. Information Gain

The information gained can be defined as a general feature selection approach used sentiment analysis, that measures the content of information acquired after knowing the feature's value. The higher the information gained is utilized for discriminating between various classes. The distribution for the given classes.

$$H(C) = -\sum_{l=1}^{m} p(c_i) \log_2 p(c_i) \qquad (6)$$

Given m number of classes: $C = \{c1, c2,..., cm\}$, where $P(ci)$ is the probability of how many documents in class ci [17].
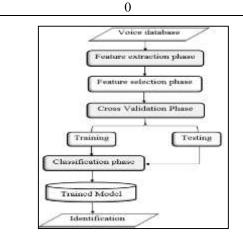
7. Dataset

The experiment of this work is performed using clean speech corpus ARABIC_DB ("Al-Diri & Sharieh, 2000")[1]. The ARABIC_DB is considered as a speech data set specifically developed to help in characterizing speakers as individuals. The dataset consists of 4740 utterances from six speakers (3 females and 3 males). There 171 statements for testing and 620 training. There are 3622 words, with 27725 tri-phones. The digitized speech data were sampled at 16 KH, with 16-bit resolution. Table 1 shows some statements and their phones, vowel, and space.

8. The Proposed System

The proposed system is used for speaker identification purposes, the input of the system is a voice dataset of six speakers: three male and three female with 4404 audio files as the total number. This system includes three phases as shown in Figure 1.

Table 1: Statements of Arabic Speakers [18]

Statements in Arabic			
أبي أمِّي أخَتي وَأخي أجِبُكُمْ مِنَ الأعْماقْ	6	يَمْشي الحِصانُ عَلى أرْبَعَةِ أرْجُلْ	1
عُطْلَةُ السَّبْتِ وَالأحَدِ عالَميَّةٌ	7	عَمِلْنا عَلى قَدَمٍ وَساقْ	2
صِيامُ الإثْنَيْن مُسْتَحَبٌّ وَكَذلِكَ صِيامُ الخَميسْ	8	الكَوعُ وَالرُّكْبَةُ مَفاصِلٌ مُهِمَّةٌ في الأطْرافْ	3
سَأزورُكَ يَوْمَ الثَّلاثاءِ أوِ الأرْبِعاءْ	9	نَسْحَبُ الدَّمَ مِنَ الكَعْبِ عِنْدَ الأطْفال الرُّضَّعْ	4
نَهَى الإسْلامُ عَنْ تَخْصيصِ يَوْمِ الجُمُعَةِ بِصِيامْ	10	أبٌ أمَّ أناديكُمْ فَهَلْ نُصْغونَ لَوْ مَرَّةْ	5

Figure 1: Flowchart of the proposed speaker identification system

Three phases of the proposed system are:

I. Feature Extraction Phase which consists of two extraction steps:
1) MFCC and VQ
2) Voice frequency and Voice Fundamental Frequency
II.Feature Selection Phase
III. Classification phase

I. Feature extraction phase

The most significant procedure in SIS is the Feature Extraction steps, which are used to get the best speaker distinguishing and provide good accuracy rates. This phase was divided into two stages as shown in Fig. (2):

Stage One: Voice Frequency and Voice Fundamental Frequency Features
Implementing feature extraction in this stage could be considered as a mathematical calculation of voice fundamental frequency and voice frequency. There are totally four features to be calculated (Mean frequency, Standard Deviation, Zero Crossing, and Amplitude) as introduced in Section 3.2, 3.3, 3.4, and 3.5. These features have been used for the following reasons:

• *Mean Frequency of a speech* can be considered as an average value related to speech frequency, where each person has a mean frequency different from another.

• *Standard Deviation (STD)* measures the amount of change in the mean frequency of the speech signal. For example, in the training stage, the mean frequency was calculated in ideal conditions of the application stage, the environment and conditions can change such as noise or the person can be sick.

• *Zero-Crossing Rate (ZC)* is pre-processing of the speech signal in this system being used as feature extraction, this is simply because each speaker has a certain pattern, i.e., a pattern of speech. For example, a person that speaks quickly, the gaps between the words will be small and consequently, Zero-Crossing Rate will be relatively high. Either the person that speaks slowly leads to gaps between words is large, consequently, Zero-Crossing Rate will be relatively low.

• *Amplitude of sound* of a sound wave is the measure of the height of the wave, where each person has an amplitude differs from the other.

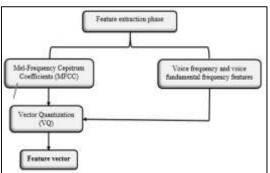**Stage Two:** consisting of two steps are Mel-Frequency Cepstrum Coefficients and Vector quantization (VQ).

Figure 2: Block diagram of the proposed feature extraction

Mel-Frequency Cepstrum Coefficients
MFCC is widely used in the speaker identification task because they are easy to implement, robust to noise and its represent frequencies which could be captured by the ear of human. MFCC consist of Thirty-nine features, in this proposed system only first twelve features are used. Because the first twelve values of the Cepstrum contain meaningful information to provide unique characteristics of the waveform, these features are extracted as follows:

• Pre-emphasis Filtering, it's applied to increase high-frequency energy increase the energy of the signal at a higher frequency.

• The frame duration time is 32ms, which implies that the length of the frame length 16 kHz signal is $0.032*16000 = 512$ samples. The frame step is 16ms (256 samples), that allow certain overlap to the frames. The first 512 sample frame starts at sample 0, the next 512 sample frame start at sample 256 and so on, until the end of the speech file is attained (overlapping 50%). The next steps are utilized to all the frames and one set of 12 MFCC coefficients features is extracted for each frame.

• Hamming windowing is applied to each frame for eliminating edge discontinuities.

- Fast Fourier Transform (FFT) is utilized for all the frames for the purpose of converting from the time domain to the frequency domain, this conversion is needed to acquire the magnitude frequency response.
- Triangular bandpass filters: magnitude, frequency response is multiplied by a set of 23 triangular bandpass filters, for the purpose of getting a smooth magnitude spectrum. It also decreases the size of the involved features.
- Discrete Cosine Transform (DCT): DCT is utilized in the 23 log energy acquired from triangular bandpass filters for obtaining 12 Mel-scale Cepstrum coefficients.

The extracted speech features (MFCC's) of a speaker are quantized to a number of centroids (12 features for each audio file in the dataset) using a vector quantization algorithm, to convert it to a one-dimensional array. Thus, the extracted features (12 MFCC) are merged with Voice Frequency and Voice Fundamental Frequency Features to obtain vector contains on sixteen features.

Vector quantization (VQ)

Vector quantization is the process of mapping acoustic vectors from a large vector space into a finite number of regions in that space. Each region is called a *cluster* and can be represented by its center called a code-word. The collection of all code-words is called a codebook. K-means is a popular technique to design codebooks in VQ as illustrated in the algorithm (1).

The data are thus significantly compressed, yet still accurately represented. Without quantizing feature vectors, the system would be too large and computationally complex. In a speaker recognition system, the vector space contains a speaker's characteristic vectors, which are obtained from the feature extraction described in the section voice feature extraction. After the completion of vector quantization, only a few representative vectors remain, and these are collectively known as the speaker's *codebook*. The codebook then serves as delineation for the speaker, and is used when training a speaker in the system.

This means to extract speech features (MFCC's) of a speaker are converted from the two-dimensional array to a one-dimensional array. Thus, the extracted features are merged with Voice Frequency and Voice Fundamental Frequency Features to obtain vector contains on sixteen features.

Algorithm 1:   K-mean Algorithm
Input: Feature vectors.
Output: Codebooks.
Begin **Step1:** Select K points as the initial centroids. **Step2:** Repeat ●   From K clusters by assigning all points to the closest centroid. ●   Recomputed the centroid of each cluster. **Step3:** Until the centroid don't change. **End.**

II. Feature selection phase

Feature selection is a mechanism of choosing the most significant features and employed them to build the proposed system, where the performance of the classification algorithm depends on the size of the features extracted. In this phase Information Gain (IG) is used for measures the content of information acquired after knowing the values of features, thus the features that have lower information gained will be discarded.

III. Classification Phase

In this phase, 10-Fold cross-validation is applied, which divides the dataset obtained after the feature selection phase into two parts, training and testing, the advantages of this partition are that every training data has become testing data and vice versa. The training data part includes both features extracted and the corresponding class label. The data are trained using three methods of classification, the results of the three methods are comprised to obtain the best precision for the

speaker identify in the Arabic language, and these methods are; KNN, LMT, and SMO. Either testing data part includes only features extracted to the audio file, not the corresponding class label. The testing data is used to assess classification accuracy.

9. Experimental Results of Speaker Identification System

SIS experimental results have tested the ability of classification using three classifiers: K-Nearest Neighbor (KNN), Sequential Minimal Optimization (SMO) and Logistic Model Tree (LMT). Best results are achieved using the KNN classifier compared to SMO and LMT classifier.
Experimental results of the SI System were divided into three-part as follow:

I. First experiment

Three machine learning algorithms were used with Mel-Frequency Cepstrum Coefficient feature extraction, these algorithms are; LMT, KNN, and SMO classifier. The precision of the algorithms is shown in Table 2 and Figure 3, which shows there were six classes with a 4404 audio file after classified using 12 MFCC.

II. Second experiment

Four features (mean frequency, standard deviation, Zero-crossing, and amplitude) were fusion with 12MFCC features that are used to improve feature extraction. Three machine learning algorithms were used for classification are; LMT, KNN, and SMO classifier. The precision of the algorithms is shown in Tables 3 and Figure 4, which shows there were six classes with the 4404 audio file after classified using 12 MFCC.

Table 2: Evaluation metrics for six classes and 12MFCC

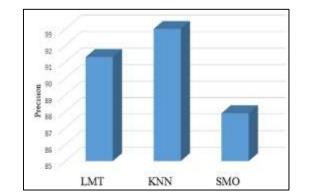| Methods	TP Rate	FP Rate	Precision	Recall	F-Measure
LMT	91.3%	1.7%	91.3%	91.35%	91.35%
KNN	92.9%	1.4%	93.0%	92.9%	92.9%
SMO	87.8%	2.4%	87.9%	87.8%	87.8%

Figure 3: Bar representation precision of the three classifiers +12MFCC
Table 3: Evaluation metrics for six classes and 16 attributes

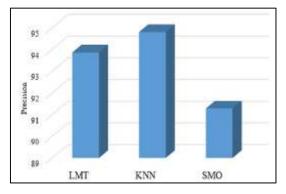| Methods	TP Rate	FP Rate	Precision	Recall	F-Measure
LMT	93.87%	1.2%	93.86%	93.87%	93.86%
KNN	94.78%	1.0%	94.8%	94.8%	94.7%
SMO	91.93%	1.6%	91.28%	91.21%	91.20%

Figure 4: Precision of the three classifiers +16 attributes

III. Third experiment

For the purpose of testing the correlation of features, Information Gain (IG) has been used with the MFCC algorithm and four selected features. Extracted features entered into machine learning algorithms (LMT, KNN, and SMO) and the results measured using some measurements as shown in Table 4 and Figure 5.

Table 5 shows a comparison between the previous three experiments. While Figure 6 shows a comparison between the previous one and two experiments.

Table 4. Evaluation metrics for six classifiers after using Information Gain

Methods	TP Rate	FP Rate	Precision	Recall	F-Measure
LMT	94.3%	1.1%	94.3%	94.3%	94.27%
KNN	94.4%	1.1%	94.4%	94.4%	94.3%
SMO	91.2%	1.8%	91.3%	91.2%	91.2%

Figure 5: Precision after using IG

Table 5: Comparison of the above experiments

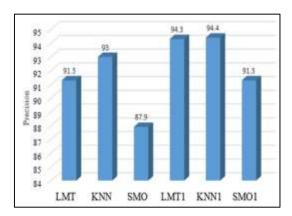| Methods	Precision for six classes				
	MFCC	MFCC+ Four features		MFCC+ Four features+ IG	
	Precision	Precision	Time in msec	Precision	Time in msec
LMT	91.3%	93.9%	295.911	94.3%	185.544
KNN	93.2%	94.8%	2.263	94.4%	1.521
SMO	87.9%	91.96%	4.099	91.3%	2.394

Figure 6: Comparison between precision before and after fusion

10. Conclusions

The speaker identification in the Arabic language intended to extract speaker information from sets of Arabic voices. The main part of this proposed system focused on mixing MFCC with four features, then making feature selection by using IG to choose the most significant features, and employed them for building an Arabic speaker identification system. By studying the experimental results of the first and second experiments, it's observed that the precision of the three classification algorithms has increased after the fusion process four features (Mean Frequency, Standard Deviation, Zero-Crossing, and Amplitude) with 12MFCC coefficients as illustrated in Table (5) and Figure (6). In Figure (6) LMT, KNN and SMO have represented the precision with 12MFCC. While LMT1, KNN1, and SMO1 are represented the precision with 12MFCC plus four features, which means precision with 16 features.

From the above Tables and Figure, it's noticed that the precision of the KNN has increased from (93.2) to (94.8) after fused four features and also the precision of the SMO has increased from (87.9) to (92.28) and also the precision of the LMT is increased from (91.3) to (93.3). By studying the experimental results of the second and third experiments, it's observed that the precision of the LMT has been increased after using IG from (93.9) to (94.3), while KNN has been decreased by (0.4) and SMO has been decreased by (0.5).

The classification performance of three different classifiers KNN, LMT, and SMO were investigated for speaker identification. Some conclusions were drawn from the gotten test results: First, the results after using IG with LMT methods increase the precision of person identification. Second, working with the precise number of features that satisfy the dimensionality reduction has caused to decrease computation complexity and consumed time. Third, MFCC cannot be used with other feature extraction methods without quantization since it produces two-dimensional features array.

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