

THE CLASSIFICATION OF ACTUAL PRONUNCIATION OF QURANIC ALPHABETS FOR NON-ARAB SPEAKER

Sulbalqiah Idris¹, Salmiah Ahmad^{2*}, Abdul Halim Embong¹ and Tareq M.K. Altalmas¹

¹Department of Mechatronics Engineering, Kulliyyah of Engineering, International Islamic University Malaysia, Jalan Gombak 53100, Kuala Lumpur, Malaysia.

²Department of Mechanical Engineering, Kulliyyah of Engineering, International Islamic University Malaysia, Jalan Gombak 53100, Kuala Lumpur, Malaysia.

* Corresponding Author: salmiah@iium.edu.my

ABSTRACT

Each Quranic alphabet has its unique sounds produced by uttering the Arabic language at their point of articulation (*Makharij*) and their characteristics (*Sifaat*), which is called *Tajweed*. Much research has been done related to the *Tajweed*, but there are limited sources associated with the analysis of Quranic pronunciation of non-Arab speakers from signal processing perspective with respect to both *Makharaj* and *Sifaat*. Therefore, this research focus on the identification and classification of the actual pronunciation of the Quranic alphabets on the audio signal obtained from non-Arab speakers. In this research, the features were best identified by the combinations of four formant frequencies (f1, f2, f3, f4), and three power spectral density (psd1, psd2, psd3) extracted from the *sukoon* pronunciation of the alphabets' audio data. All features were combined and classified using both Linear and Quadratic Discriminant Analysis (LDA and QDA) to represent the actual pronunciation of each alphabet for both Arab and Non-Arab speaker categories. The findings indicate that there are 25 alphabets were correctly classified more than 83% threshold value thus indicates the correct pronunciation, where the other three alphabets which are اَضْ, اُغْ and اَفْ are falling under misclassified vector. Later, the Graphical User Interface (GUI) was developed using the training data of 25 alphabets to evaluate the percentage of accuracy (%) with the new audio dataset. The results show that the developed GUI has managed to record, analyze, and evaluate the pronunciation interactively.

Keywords: Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Formant Frequency, Power Spectral Density (PSD), Tajweed, Makharaj, Sifaat

1.0 INTRODUCTION

Quran is the holy book for Muslims, and it has been sent and written in the Arabic language as it is narrated in Surah Yusuf "Indeed, We have sent it down as an Arabic Qur'an that you might understand". The virtues of reading Quran are ten rewards for every recited letter. The people who used to recite Quran are the best and finally Muslim position and rank in Jannah are determined based on the amount of Quran memorized in his life. In fact, when someone makes reading and understanding Quran as daily activities, it will significantly help Muslims who have passed away resting in the graves. Recitation of the Holy Quran with correct rules of recitation or *Tajweed* is compulsory upon each Muslim. Holy Quran has 28 alphabets that each of alphabets produce unique sound originate from its articulation points (*Makharaj*) and

characteristic (*Sifaat*) [1]. The pronunciation of Quranic letters from its correct articulations points and its characteristics is not easy for people from the non-Arab background, where they need much effort to learn the right way of pronouncing the Quranic letters and therefore should be helped. Interestingly, most Muslims are non-Arab speakers and live in societies where Arabic is not the official language, as only 20 % of Muslims are those with Arabic language as their mother tongue. Asian Muslims are distributed around Malaysia, Indonesia, and the Philippines, where they represent 14 % of the total Muslim population worldwide [2]. Such statistics show another problem in addition to the required time to the learning process, where there exists unavailability of teachers in non-Arab societies to teach Quran. Extensive time are needed for pronunciation training that makes it difficult for teachers to address every student's problems accordingly.

Consequently, some Muslim may encounter difficulties in Quranic recitation. Although most Muslim know how to recite the Holy Quran as in daily prayer but not every Muslim can recite with the proper and correct pronunciation [3]. Also, the Arabic language is sensitive, as slight changes in pronunciation will change the meaning of the word [4]. Therefore it can be seen that the knowledge of Quranic recitation according to its *Tajweed* is very important.

As Muslim are located all over the world who are from different nationalities and ethnics, who speak using different languages. The spoken language and accents are among the factor that causes incorrect pronunciation in Quranic recitation. To date, there is not much published study on the identification of *Makhrāj* in the pronunciation of all 28 Quranic letters for non-Arab speaker. Thus a study related to the correct pronunciation of non-native Arab speakers is significant. Generally, learning the Quran starts at early age, with knowing the pronunciation of the alphabet by its *Makhrāj*. At this instant, it is very vital such that each alphabet is pronounced correctly before longer Quranic verses are recited. As today there a lot of learning sources available, however, there is none of the existing techniques that can correct the wrong pronunciation instantly and the traditional method of learning the Quran is still necessary. The *Ustaz* can verify the correct pronunciation by observation, and then the mistakes will be corrected immediately. This way of learning is time-consuming and need to have a specific time and face-to-face.

The rule of thumb says that when the students can read the Quran well, automatically the Quranic alphabet is pronounced correctly. However, there is still no proof that the student pronounces the alphabet correctly except by listening or looking at the way he pronounces the alphabet as expected by the *Ustaz* [4]. It is so challenging to see what happened to the speech organs during the recitation. Thus, speech recognition has been implemented and recently used in various other applications such as criminal investigations, wireless communication, and speech therapy, [5]. The speech assessment on *Makhrāj* recognition and Arabic phonemes was previously done by [5] and [6]. At present, there are limited researches that analyze the correct pronunciation produced by a different Non-Arab speakers [7][8]. In addition to that, the previous study by [9] who focused on developing a system using the combination of Quranic letter as the input data to obtain the correct *Makhrāj* at some point shared the similar goal with us. However, they only analyzed 7 combination of letters while we used 28 combination of letters. Another difference is that we have performed the comparison of the pronunciation between the adult and children expert while they have different scope. The aim is to produce unique models that will represent the correct pronunciation of the Quranic alphabets of an adult and children experts respectively, which can be used as a reference model in the Quran teaching and learning.

A novel application has presented by [10] to verify Quranic recitation based on the right **Makhraj**. The system can reduce the time of learning Quran as compared to the traditional way. This system combines 3 steps starting with data acquisition, followed by signal processing, and end with a matching. Firstly, the input speech is collected and verified by **Makhraj** experts and inside a special room to minimize the noise. Mono microphone has been used to collect the letters from the people who recite it. Sample data have been collected from the experts to be used as a reference. The second step is speech processing, where it is aimed to guarantee the desired signal is processed. This step consists of silent detection, pre-emphasis, windowing, FFT, Mel-frequency filter and DCT cepstrum. The last step is the matching where the mean square error has been used for pattern matching. The aim of using the mean square error is to calculate the mean square error between the coefficient value of the database and the tested sound. The system has been tested under the two modes, one-to-one and one-to-many. From the results, it can be seen that the system performance is good with high accuracy for one-to-one mode. But for the one-to-many mode, the percentage of the accuracy is high except for two letters (أب) and (أت). Automatic speech recognition approach was proposed to help the Algerian learners who have problems with pronunciation of Arabic language to improve their pronunciation skills [11]. The proposed method was to evaluate the proficiency of the pronunciation not to point out the error source, the score that used was global average log likelihood (GLL) score. The system ability to identify the correct and wrong pronunciation was good and the correct acceptance with the correct rejection was above 76 %. False rejection and false acceptance rate were just about 23 %. The system was tested only on 3 words. The multilayer perceptron (MLP) has been used to investigate the process of detecting the correct recitation of Qalqalah Kubra of a reader. The database is built of 50 correct recitations of Qalqalah Kubra and another 50 wrong recitations. Mel-frequency cepstrum coefficients (MFCC) has been implemented as a feature extraction to get the essential characteristics of the pronunciation signals. Then the MLP was trained to distinguish between the correct and the incorrect pronunciation. It is clear from the results that the classification accuracy was high, and the MLP was claimed to be successful in differentiating between the correct and the incorrect pronunciation [12]. Some Quranic letters can be identified using the formant frequencies, more over the power spectral density (PSD) can improve the accuracy of the system as compared to the formants [13]. Many studies have utilized the PSD as features extraction technique for automatic speech recognition [14].

In this paper, Quranic alphabets pronunciation pronounced by the non-Arab speakers was analysed to find the most suitable features that can represent the correct pronunciation of each Quranic alphabet by each category. Since the different native has different vocal tract and accent, it will cause different pronunciation. A Quranic alphabet is recognized by **Makhraj** (articulation point) and **Sifaat** (characteristics). **Makhraj** is the actual position of the speech organs to produce a particular sound so that the alphabet can be differentiated from others by its unique features [2]. The **Sifaat** is vital to differentiate the alphabets that are from the same **Makhraj**. **Sifaat** refers to the attributes or characteristic(s) of the Quranic alphabets in which can be technically said as the way each alphabet articulated. The audio signals (sound) were recorded from the non-Arab speakers consist of Malay, Indian and Chinese to compare if there is any similarity or difference among those categories in producing the actual pronunciation of Quranic alphabets. Then, the Graphical User Interface (GUI) was developed as an interactive tool to classify the selected features in the testing stage; and validate a new signal based on the selected features (test-set classification). Euclidean Distance Algorithm, which is a pairwise distance method, was used to the similarity between the test data and train data, where the

train-set classification performed using Linear and Quadratic Discriminant Analysis (LDA and QDA) techniques.

2.0 DATA COLLECTION

2.1 Experimental Setup

The recorded audio signals were obtained from 18 non-Arab speakers where among them, 6 are Malay and 6 are Indian mix with Bangladesh (considered as Indian) and 6 of them are Chinese. The subjects were selected based on their proficiency in reading the Quran. The reciters are necessary to have a certificate of recognition in the field Al-Quran, and it is preferable if they are experienced in formal Quranic teaching. The portable high-quality field recorder TASCAM DR-05 was used to capture the audio data of Quranic with a frequency response of 40 Hz to 20 kHz. Also, the standard room environment, such as the classroom and offices that represent the common learning room, was chosen. The subject needs to hold the audio recorder close to the mouth for a more precise recording. They were need to recite the 28 combinations of Quranic alphabets the best as they can. The audio signals were sampled with 44.1 kHz sampling rate and processed using Audacity and PRAAT. Table 1 is the *sukoon* (°) combinations of Quranic alphabets and its transliteration used for the recording session. *Makhrāj* and *Sifaat* of each alphabet described by this *sukoon* (°) combinations dataset.

2.2 Audio Pre-Processing

The pre-processing stage was done to remove noise and the audio signals were normalized between -1 and 1 using open software Audacity. A digital audio editor known as PRAAT was used to perform the noise removal for all recorded audio data. Spectral Subtraction method was used for noise reduction. All the recordings were made on the mono channel for the sake of simplicity. Next, the spectral subtraction was applied for noise removal using default settings in PRAAT. Figure 1 and Figure 2 illustrates the waveform graph for ‘أَصْ’ alphabet pronunciation in the time domain before and after enhanced using PRAAT.

Table 1 The *sukun* (°) combinations of Quranic alphabets and its transliteration used for the recording session

Combination of Quranic alphabets	Transliteration	Combination of Quranic alphabets	Transliteration
أَءْ	a	أَصْ	adh
أَبْ	ab	أَطْ	athd
أَتْ	at	أَظْ	azd
أَثْ	ath	أُءْ	a'
أَجْ	aj	أُغْ	agh
أَحْ	ah	أُفْ	af
أَخْ	akh	أُقْ	akk
أَدْ	ad	أُلْ	al
أَذْ	az	أُكْ	ak
أَرْ	ar	أُمْ	am
أَزْ	azz	أُنْ	an
أَسْ	as	أُوْ	aww
أَشْ	ash	أُةْ	ahh
أَصْ	asd	أُيْ	aui

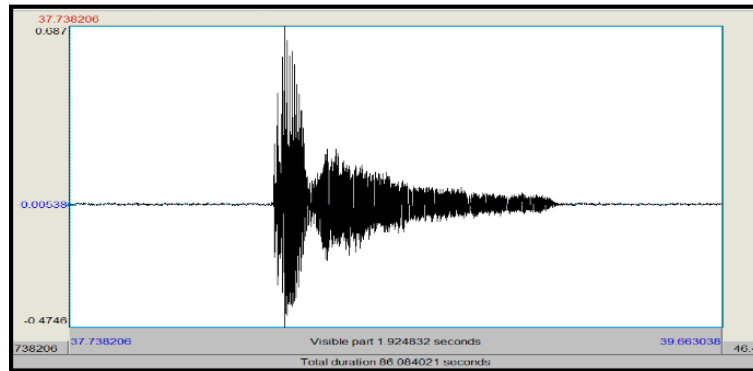


Figure 1 The waveform of ‘أص’ before noise reduction with spectral subtraction method using Praat software

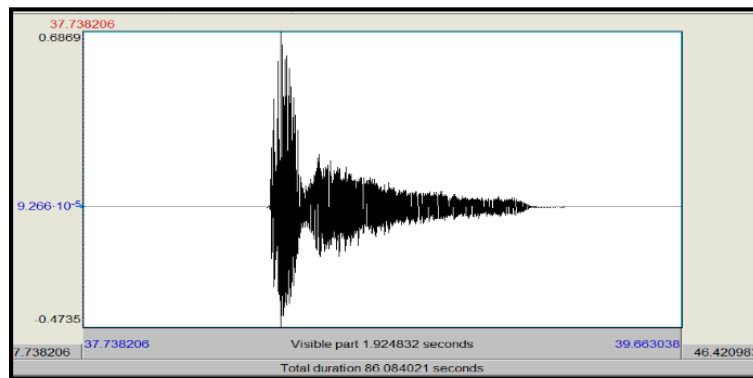


Figure 2 The waveform of ‘أص’ after noise reduction with spectral subtraction method using Praat software

2.3 Features Extraction

Feature extraction has affected directly towards the performance of speech recognition. The correct features are used to distinguish the element in the audio signal that is suitable for the acoustic content representation. As a result, it becomes the most critical stage of the speech recognition process to prepare for data classification. There are two types of audio features, time domain, and frequency domain. For all 28 Quranic alphabets, two types of features were extracted from the audio data for each category.

2.3.1 Formant Frequencies

The different native speakers have different vocal phonemes, and the formant frequency was chosen because this method was frequently used to describe vocal tracts successfully. Formant is related to the resonance of the vocal tract where it is an acoustic energy concentration around a frequency in the speech wave [14]. Formant first can be extracted from the PRAAT software as it has been used by the previous scholars like [4], and [6] used PRAAT for Arabic phonemes analysis while [15] studied this method to find formant used in the Arabic language.

Usually, the first two formants are sufficient to differentiate the vowels [6]. The formant frequency of the audio signal of Quranic alphabets recitation can be found, where in this study, there are four types of formats which are f1, f2, f3 and f4 that have been extracted from 24 samples which contains six people in each category of Malay, Indian and Chinese, where the Spectrogram in was used to obtain the formants frequencies. Figure 3 indicates the formant frequency f1, f2, f3, and f4 in red points on the spectrogram graph.

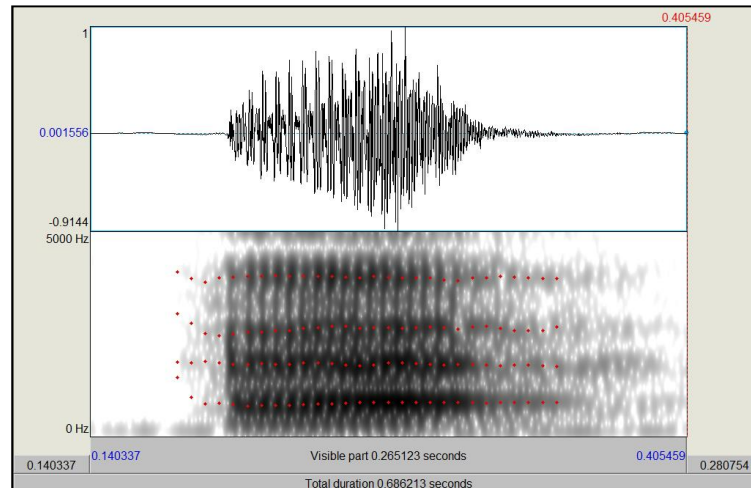


Figure 3 The audio signal with spectrogram and formants represented by red dots.

2.3.2 Power Spectral Density

There are three bands of Power Spectral Density (PSD) used in this study. PSD is the power distribution over a frequency in signals and was obtained using the periodogram method with a frequency range from 0 Hz to 2000 Hz. Table 2 lists the range of PSD, where the selected range provides sufficient acoustic information required.

Table 1 PSD frequency range

PSD Band	Frequency Range (Hz)
PSD1	0-500
PSD2	501-1000
PSD3	1001-1500
PSD4 (ignored)	1501-2000
PSD total	0-2000

2.3.3 Classification and Feature Analysis

Based on Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA), different classes generate data based on different Gaussian distribution. Both classifiers were derived from the probabilistic models. For each class, i was obtained by using Naïve Bayes' rule. LDA techniques were derived from a multivariate Gaussian density function given by,

$$p(X|y = i) = \frac{1}{(2\pi)^{-\frac{p}{2}} |\Sigma_i|^{1/2}} e^{\left[-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i)\right]} \quad (1)$$

$P(y = i)$ is the class prior, the, and the covariance matrices Σ_i . These parameters were estimated from the training data. In QDA, the assumption is the covariance matrices and means vectors are not identical for each class. And the QDA function can be formulated by,

$$g_i(x) = \ln(p(X|y = i)p(y_i)) \quad (2)$$

In the Gaussian distribution case, the discriminant function becomes,

$$g_i(x) = -\frac{1}{2}(X^T \Sigma_i^{-1} X - 2\mu_i^T \Sigma_i^{-1} X + \mu_i^T \Sigma_i^{-1} \mu_i) + \ln(p(y = i)) + c_i \quad (3)$$

where, $c_i = -\frac{1}{2}\ln(2\pi) - \frac{1}{2}\ln(|\Sigma_i|)$

LDA depends on the sample covariance matrix of the training data, where the class covariance matrices are assumed to be identical and same but have different mean values for every class. Thus, for this case, $\Sigma_i = \Sigma$ and c_i becomes a constant. For small data sets, LDA can give a better performance result most of the time due to the pooled covariance matrix assumptions. Meanwhile, QDA may have more flexibility in fitting the data if the estimation covariance matrix for each class increases the variance of parameter estimation and causes instability.

2.3.4 Resampling method

In this research, Jack-knife method was applied, where this method can avoid duplication of resampling training data during classification. A complete set consists of 12 data for each 28 Quranic alphabets pronunciation from non-native Arab was prepared. This data subsequently classified according to their classes, and a different number of row vectors separated by each Quranic alphabets' pronunciation.

2.3.5 Euclidean distance

Euclidean distance is one of the famous and effective methods to compare and compute the percentage of the accuracy and similarity of two data sets with the similar dimension and phase. The similarity percentage of testing data and training data were obtained using this distance formula. For any dimension of i , Euclidean distance definition is

$$D = \sqrt{\sum_{i=1}^{i=n} (x_i - y_i)^2} \quad (4)$$

The Euclidean distance was performed where the minimum distance was calculated to evaluate the testing and training data matching percentage. The smaller the distance, the higher the matching percentage of two data set.

3.0 RESULTS AND FINDINGS

3.1 Formant and PSD Features

Figure 4 shows the mean values of formant frequencies for all Quranic alphabets of Arab and non-Arab speakers. It can be seen that letter 13 which is 'اشن' has the highest value of F1, the highest value of F2 is letter 12 which is 'اسن' while the highest value of F3 is letter 10 and letter 8 which is 'ن' and 'ث' respectively.

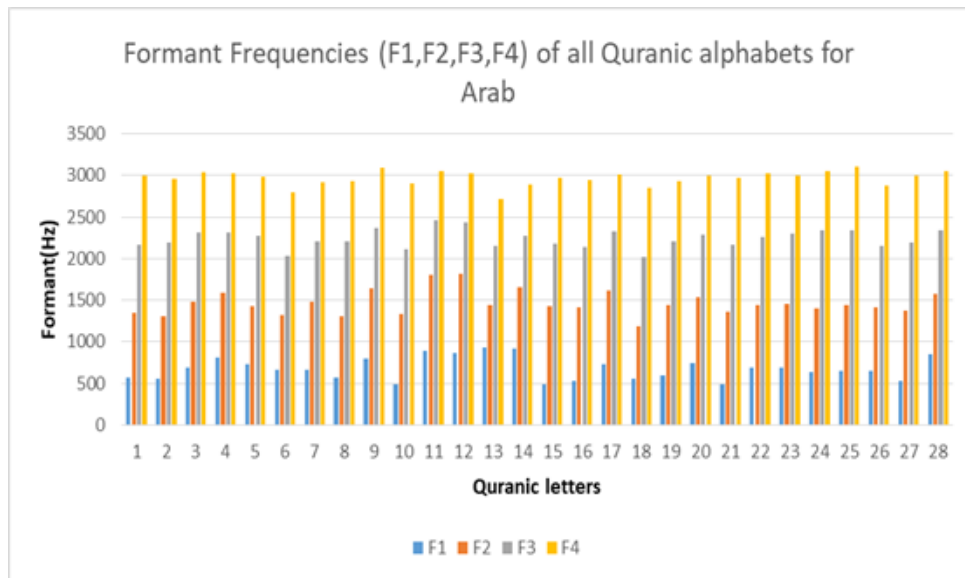


Figure 4 Formant Frequencies of all alphabets for Arab speaker

The mean values and for all 28 alphabets of Arab and non-Arab speakers are shown in Figure 5 and 6. From the data, psd2 was the highest power spectrum for Quranic letters as compared with PSD₁ and PSD₃ is the lowest. The letter 'ن' holds the highest value of psd1 but lowest in psd2 values. This indicates that other than 'م' (mim), the letter 'ن' (nun) also can represent as a nasal phoneme.

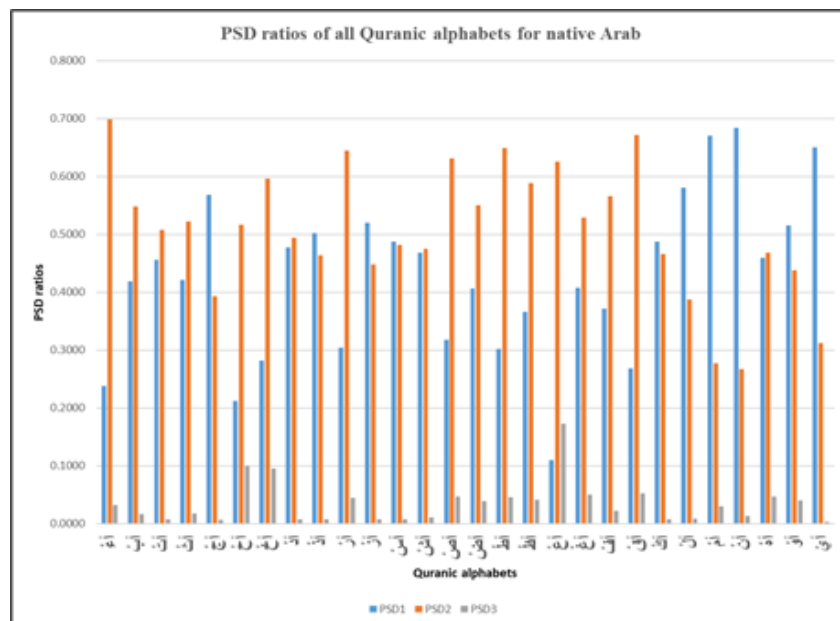


Figure 5 PSD ratios of all Quranic alphabets of Arab speakers

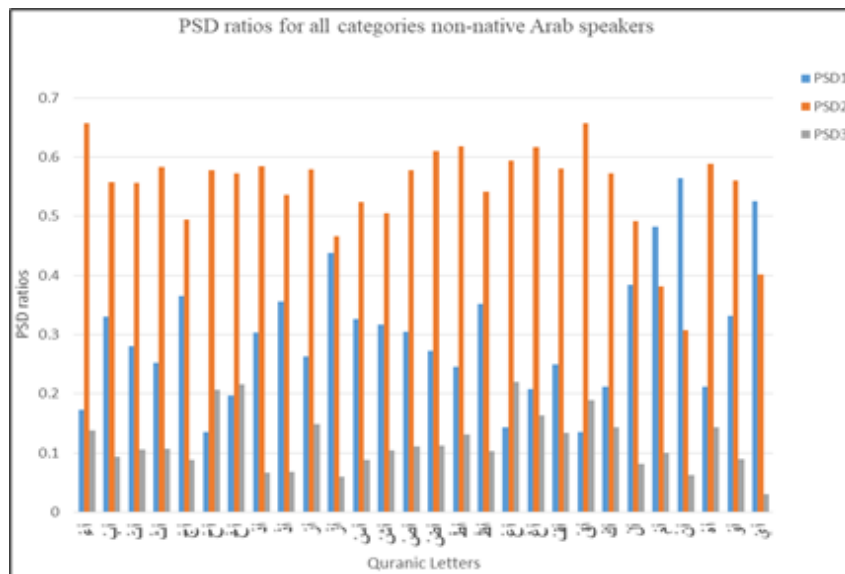


Figure 6 PSD ratios for 28 Quranic all alphabets of non-Arab speakers

3.2 LDA and QDA Classifications

For classification between the categories, the LDA and QDA with Jackknife resampling method were used to classify all the features that have been extracted. The features were evaluated and combined so that the best result will be obtained. All data are classified into Malay, Indian and Chinese category, according to each Quranic alphabets of *sukoon* (°) combinations. The classification resulted in the percentage of accuracy that represents the correct classification of the data into its class. There are 28 alphabets of Quranic represent non-Arab which is Malay, Indian and Chinese. An interactive GUI model was developed as an to provide the interactive platform for evaluation of the new data set for the pronunciation. The user can utilize the GUI to learn, train and evaluate the accuracy of Quranic alphabets pronunciation.

The first four formants and the first three psd values were evaluated and classified using discriminant analysis the plot of f1 and f2 with Linear and Quadratic boundaries using Jackknife method for the pronunciation of ‘اَبْ’, as shown in Figure 7 and Figure 8. The result shows that, out of 6 respective reciters, 6 Malay, and 5 Indian and Chinese are correctly classified using LDA and QDA.

For this study, the threshold was set to 83% percentage of the train set classification which means that the features combination results of the percentage of accuracy which are equal or greater than threshold values will be used to model and represent the actual alphabet in the GUI. Based on the result obtained from the classification on non-Arab speakers, some pronunciation can uniquely be represented by different features combination. The percentage of accuracy of Malay as compared with Indian and Chinese recorded and tabulated. Table 3 summarizes the result for the classification by LDA and QDA with Jackknife, where it shows the correct pronunciation and the combination of their features with the number of vector that is correctly classified from 6 reciters of each group.

The correct pronunciation was then selected to be the model reference for the pronunciation using MATLAB GUI since those pronunciations have achieved the threshold value and can be considered as correct classification of non-native Arab speaker. These results

of correct pronunciations indicate that the combination of f1, f2, f3, f4, psd1, psd2 and psd3 can be used to represent most of the pronunciation based on its respective *Makhrāj* except one from lips category, and one is originated from the side of the tongue and another one from the top part of the throat. The used of two classifiers were also significant so that more pronunciation are correctly classified.

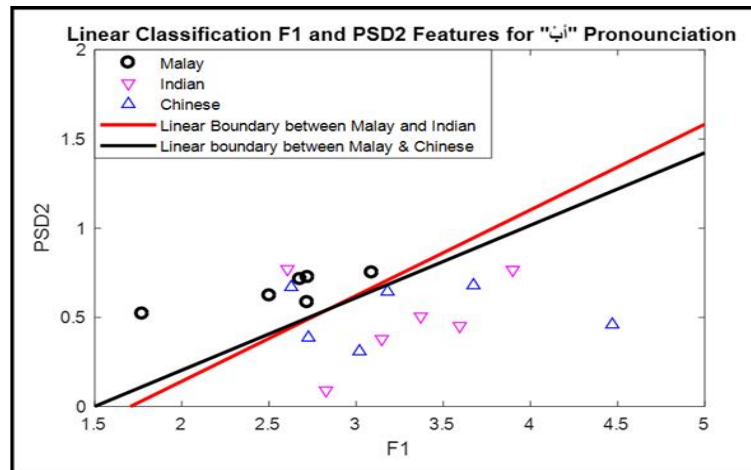


Figure 7 The plot of f1 with respect to psd2 and a linear boundary using Jackknife linear classifier for 'أب' pronunciation

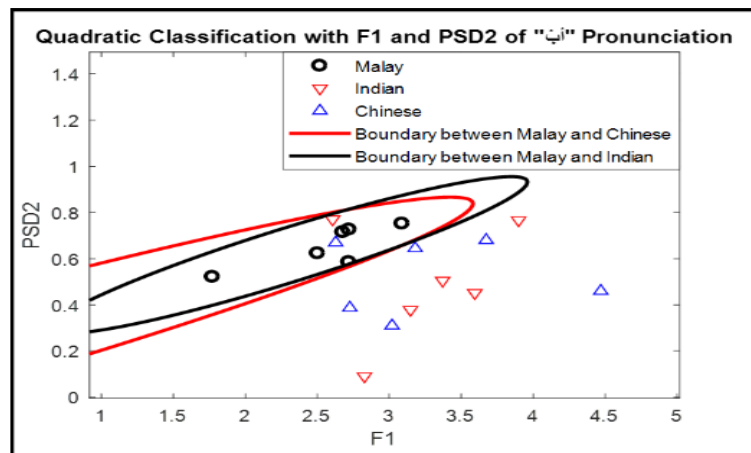


Figure 8 The plot of F1 with respect to psd2 and a Quadratic boundary using Jackknife linear classifier for 'أب' pronunciation

To visualize better evaluation stage, based on the result obtained, the GUI was developed in MATLAB software in providing the interactive learning system of the pronunciation for non-Arab speakers. The GUI will generate the accuracy of the user's pronunciation by referring to the training data. Figure 9 shows the excellent result with the accuracy of 94% obtained when the pronunciation recited by the random Malay experts similar with the data while Figure 10 shows the result with the accuracy of 25% calculated when the pronunciation recited by the Malay was incorrect and different from the actual pronunciation.

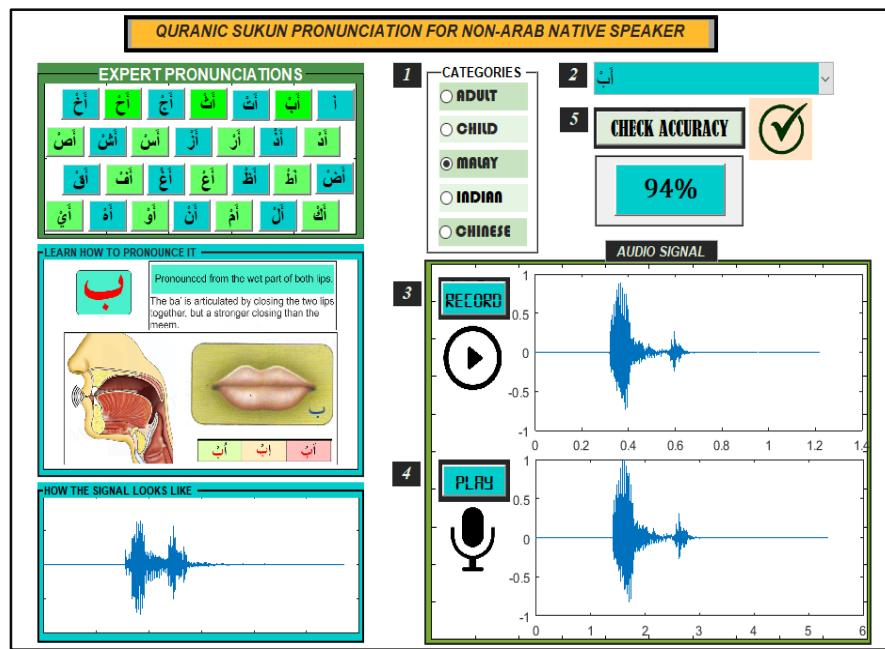


Figure 9 Fig-file of the percentage obtained for for 'ب' pronunciation from a Malay user

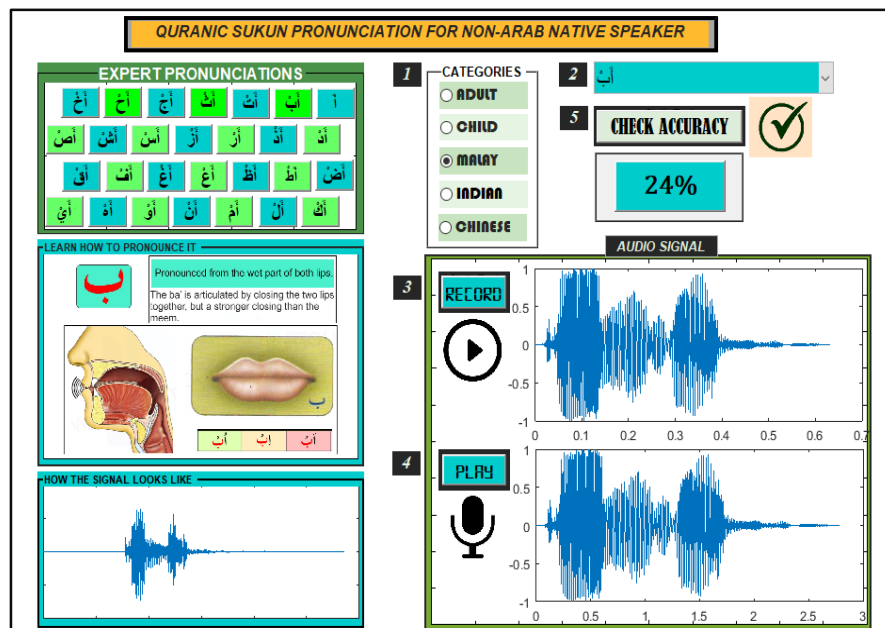


Figure 10 The percentage obtained from wrong pronunciation from Malay user

Table 3 The combination and number of the vector of the correct features of Malay, India and Chinese classified using Jackknife method

Letters	Classifier	MALAY		INDIA		CHINESE	
		Feature combination	Total correct	Feature combination	Total correct	Feature combination	Total correct
اَء	LDA	F1PSD1	6	F1PSD2	5	F1PSD1	6
	QDA	F1PSD2	6	F1F3	5	F1PSD2	6
اَبْ	LDA	F1PSD2	6	F2PSD3	6	F2PSD3	5
	QDA	F1PSD2	5	F2PSD3	5	F2PSD3	5
اَثْ	LDA	F2PSD3	6	F1F2	5	F2F4	6

	QDA	F2PSD3	5	F1PSD2	5	F2F4	6
اَ	LDA	F1PSD3	5	F4PSD1	5	F4PSD2	5
	QDA	F3PSD3	6	NA		F3PSD3	6
اِ	LDA	F3PSD3	6	F2F4	5	F3PSD3	6
	QDA	F3PSD3	6	F2F4	5	F3PSD3	6
اُ	LDA	F2PSD1	6	F3PSD2	5	F1F2	5
	QDA	F1F4	5	NA		F1PSD2	6
اُ	LDA	F4PSD2	6	F2F4	5	F2PSD3	6
	QDA	F4PSD3	5	F2F4	5	F2PSD2	5
اُ	LDA	F3PSD3	6	F4PSD3	5	F4PSD3	6
	QDA	F3PSD3	6	F4PSD3	5	F4PSD3	6
اُ	LDA	F4PSD3	6	F1F2	6	F2PSD2	5
	QDA	F4PSD3	6	F1F4	6	F2PSD2	5
اُ	LDA	F2PSD1	6	F1F4	6	F2PSD3	6
	QDA	F2PSD1	5	F1F4	5	F2PSD3	5
اُ	LDA	F3F4	6	F1F2	5	F4PSD1	6
	QDA	F3F4	6	F1F2	5	F1F2	6
اُس	LDA	PSD2PSD3	5	F1PSD1	6	F2F3	5
	QDA	PSD2PSD3	5	F1PSD1	5	F1F4	6
اُس	LDA	PSD1PSD3	6	F1PSD3	5	F3PSD2	6
	QDA	PSD1PSD3	5	F1PSD3	5	PSD1PSD3	6
اُص	LDA	F2F4	5	F4PSD1	5	F1F2	5
	QDA	F2F4	5	F2F4	5	F3PSD2	6
اُط	LDA	F3PSD1	6	F1PSD1	6	F2PSD1	5
	QDA	F3PSD1	5	F1PSD1	5	F2PSD1	6
اُظ	LDA	F4PSD3	6	F3PSD2	6	F3PSD2	5
	QDA	F4PSD3	6	NA		F3PSD2	5
اُغ	LDA	PSD1PSD3	5	F1PSD2	6	F1PSD2	6
	QDA	PSD1PSD3	5	F1PSD2	6	F1PSD2	5
اُق	LDA	F2PSD2	5	F4PSD3	6	F4PSD3	6
	QDA	NA		F4PSD3	5	F4PSD3	6
اُك	LDA	F4PSD3	6	PSD1PSD3	5	PSD1PSD3	5
	QDA	F4PSD3	6	F1PSD3	5	PSD1PSD3	5
اُن	LDA	F2PSD3	6	F4PSD2	5	F2PSD3	5
	QDA	F2PSD3	6	F1PSD1	5	F2PSD3	6
اُم	LDA	F3PSD3	6	F1PSD3	5	F4PSD3	6
	QDA	F3PSD3	5	F1PSD3	6	F4PSD3	6
اُن	LDA	F1PSD1	6	F1F3	5	F1PSD1	5
	QDA	F1PSD2	5	NA		F1PSD1	5
اُه	LDA	F2PSD3	6	F4PSD1	5	F2PSD3	6
	QDA	F2PSD3	6	F4PSD1	6	F2PSD3	5
اُو	LDA	NA		F1F4	5	PSD2PSD3	5
	QDA	F4PSD2	6	F3PSD3	5	PSD2PSD3	6
اُي	LDA	F1F4	6	F4PSD3	5	F3PSD1	6
	QDA	F1F4	5	F4PSD3	5	NA	

4. CONCLUSION

In conclusion, LDA and QDA were successfully implemented in this study to classify the actual pronunciation of Quranic alphabets that differentiate the non-Arab speakers classified

as Malay, Indian and Chinese, which produce 25 correct pronunciations, which those alphabets were uniquely represented by features combinations of formants and psd. It can be assumed that the remaining three alphabets may possess almost similar features among the three categories. The results show that the different combination features were able to indicate the pronunciation of 25 Quranic letters between non-native Arab speakers. The result obtained was implemented in the GUI developed and it was able to record, analyze and evaluate the new recording audio into the correct percentage of similarity as compared with the reference model of correct pronunciation. This GUI is considered as the new approach to help in supporting the Quranic learning among Muslims. For better performance, the intelligent technique of classification and another additional feature will be implemented soon where much data are needed.

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