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Improved Malay Vowel Feature Extraction Method Based on First and Second Formants

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***Abstract* - There are many speech recognition applications that use vowels phonemes. Among them are speech therapy systems that improve utterances of word pronunciation especially to children. There are also systems that teach hearing impaired person to speak properly by pronouncing words with a good degree of intelligibility. All of these systems require high degree of vowel recognition capability. This paper presents a new method of Malay vowel feature extraction based on formant and spectrum envelope called First Formant Bandwidth (F1BW). It is an effort to increase Malay vowel recognition capability by using a new speech database that consist of words uttered by Malaysian speakers from the three major races, Malay, Chinese and Indians. Based on single frame analysis, F1BW performs better than MFCC by more than 9% based on four classifiers of Levenberg-Marquart trained Neural Network, K-Nearest Neighbours, Multinomial Logistic Regression and Linear Discriminant Analysis.**

Keywords-component; Malay Vowel, Spectrum Envelope, Speech Recognition

I. INTRODUCTION

In human language, a phoneme is the smallest structural unit that distinguishes meaning. Normally, language like English commonly combines phonemes to form a word. In many languages, the Consonant-Vowel (CV) units have the highest frequency of occurrence among different forms of subword units. Therefore, recognition of CV units with a good accuracy is crucial for development of a speech recognition system. Recognition of these subword units is a large class set pattern classification problem because of the large number (typically, a few thousands) of units [1]. In this case, if ASR recognizes the vowel with a good accuracy, system can reduce region of search and improve accuracy and time.

English uses a combination of phonemes to form words which may not exactly follow the characters of the words. Because of this, a large database of vocabulary is needed in order to represent each individual word. Standard Malay (SM) on the other hand can be uttered properly based on the combination of CV phonemes. One advantage Bahasa Malaysia has over English is the numbers of vowel phoneme that need to be considered. The proper Bahasa Malaysia has only 6 vowels phonemes which are /a/, /e/, /i/, /o/, /u/ and /ə/ [2] whereas typical American English has 20 vowel phonemes [3].

Applications that use vowel phonemes require high degree of Standard Malay vowel recognition capability. In Malaysia, researches in vowel recognition is still lacking especially in the usage of Malay vowels, independent speaker systems, recognition robustness and algorithm speed and accuracy. There is a need to develop a better algorithm of Malay vowel recognition in terms of accuracy and robustness. Although there are studies concerning Malay phoneme recognition, it is still at its infancy [4] and multiple frame analysis is mostly in use by Malaysian researcher. Accuracy and processing time is a concern when developing speech therapy systems. More efforts are needed to be taken in order to develop Malay speech recognition system and this study is an effort to improve Malay vowel recognition.

This study is an effort to increase Malay vowel recognition capability by using a new speech database that consist of words uttered by Malaysian speakers from the three major races, Malay, Chinese and Indians. The main objective of this study is to increase independent speaker Malay vowel recognition capability in terms of accuracy. This paper will present an improved feature extracting algorithms for Malay vowels using independent speaker database based on first and second formants.

II. LITERATURE REVIEW

There are many researches on the topic of vowel recognition. Qin Yan and Vaseghi (2003) studied formant features of formant frequency, bandwidth, and intensity to classify accents conversions between British, Americans and Australian speakers [5]. Carlson and Glass (1992) also analyzed Formant Amplitude for vowel classification while Vuckovic and Stankovic (2001) researched on automatic vowel classification based on 2-dimensional formant Euclidean distance [6, 7]. Liu and Ng (2009) obtained the first three formant values of F1, F2, and F3 using Praat's linear predictive coding algorithm to study formant characteristics of vowels produced by mandarin esophageal speakers [8].

According to Hillenbrand and Houde (2003), majority of vowel identification models assumed that the

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recognition process is driven by either the formant frequency pattern of the vowel (with or without a normalizing factor of fundamental frequency) or by the gross shape of the smoothed spectral envelope [9]. Several other researchers have made excellent reviews of this literature. The main idea underlying formant representations is the notion that the recognition of vowel identity is controlled not by the detailed shape of the spectrum but rather by the distribution of formant frequencies, chiefly the three lowest formants (F1, F2 and F3).

In Malaysia itself, among the active Malaysian Universities in researching Speech Recognition are Universiti Teknologi Malaysia (UTM), Universiti Kebangsaan Malaysia (UKM), Universiti Putra Malaysia (UPM), Universiti Sains Malaysia (USM) and Multimedia University (MMU). For example, UTM did research into Malay plosives sounds and Malay numbers [10]. UTM also did a study on Malay vowels based on cepstral coefficients and fusion of Dynamic Time Warping (DTW) and Hidden Markov Model (HMM) [11, 12]. USM experimented with 200 vowel signals using wavelet de-noising approach and Probabilistic Neural Network Model [13]. UPM investigated on using Neural Networks to recognized SM digits [14]. Ting and Mark (2008) converted LPC coefficients into cepstral coefficients before being fed into a Multi-layer Perceptron with one hidden layer for training and testing [15]. The Multi-layer Perceptron was able to recognize the all speech sounds.

Table 1. Recent related literature on vowel recognition

Reference	Speaker Type	Frame Analysis	Accuracy %
Mohammad Nazari et. al., 2008 [16]	Independent	Multi Frame	93.9%
Ting & Mark, 2008 [15]	Dependent	Multi Frame	98-100%
Mara Carvalho [17]	Dependent	Multi Frame	89-96%
Bresolin et.al, 2007 [18]	Independent / Dependent	Multi Frame	91.01% / 98.07%
Muralishankar, 2005 [19]	Independent	Multi Frame	71.72%
Merkx and Miles, 2005 [20]	Independent	Multi Frame	91.5%
Ting & Yunus, 2004 [12]	Independent	Single Frame	76.25%

Although automatic speech recognition has been in existence since before the 1950s, Standard Malay was actively used as the choice of language by Malaysian researchers since the late 1990s. Table 1 summarizes some of the important aspects of vowel recognition from recent literatures. It addresses the issues of speaker type, analysis frame and accuracy of the recognition capability. From this table, most of the recent researchers studied on both dependent and independent speaker systems using mostly multi frame analysis. The accuracy obtained was in between 89 to 100% for dependent speaker system and between 70 to 94% for an independent speaker and multi framed analysis system. From this list, the only literature that uses independent and single framed analysis system only obtained an accuracy of only 76.25%.

III. METHODOLOGY

A. *Introduction*

This chapter presents the methodology used in the research including the experimental setup, the feature extraction methods, experimental work of the paper. This chapter will also explains the database, front-end pre-processing techniques, segmentation process and also the classification processes used in the experiments.

B. *Vowel Recognition Process*

Vowel Recognition process starts with the Data Acquisition process followed by filtering, pre-processing, frame selection, Auto-regressive modelling, and feature extraction process. These processes are shown in Fig.1 and their details will be explained in the rest of this chapter. Data Collection process was taken from a total of 80 individuals consisting of students and staff from Universiti Malaysia Perlis (UniMAP) and Universiti Utara Malaysia (UUM). The speakers consist of individuals from both male and female genders. They are from the three main races of Malaysia which are Malay, Chinese and Indians.

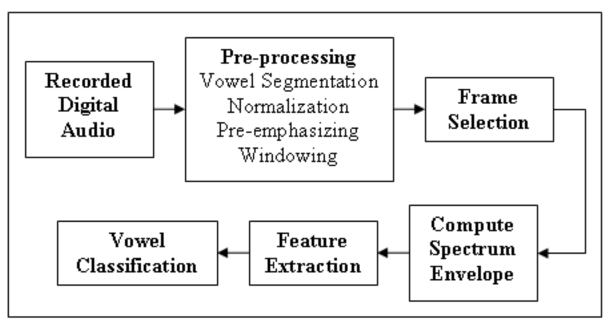

Figure 1. Vowel recognition process

The recordings were done using a conventional microphone and a laptop computer with a sampling frequency of 8000Hz. The words “ka, ke, ki, ko, ku, kə” were used to represent the six vowels of /a/, /e/, /i/, /o/, /u/ and /ə/ because vowels have significantly more energy than consonants. Different combinations of consonants and vowels were tested but yield similar results in terms of portion of vowel obtained. Based on [7, 21-23], the first three formants for vowels are situated within 4 kHz and so are vowel's main characteristics. For this study, a sampling frequency of 8 kHz was used to sample the vowels. The recordings were done 2 to 4 times per speaker depending on situation convenience. The details of the data collection are listed in Table 2.

Table 2. Data collection details

Information	1st Data Collection	2nd Data Collection
Sources	40 UniMAP students	20 UUM staff and 40 students
Recorded utterances	640	728
Sampling Frequency	8000 Hz	8000 Hz
Vowels uttered	/a/, /e/, /i/, /o/, /u/, /ə/	/a/, /e/, /i/, /o/, /u/, /ə/

C. Spectral Envelope

The vocal tract can be viewed as an acoustic tube of varying diameter. Depending on the shape of the acoustic, a sound wave travelling through it will be reflected in a certain way so that interferences will generate resonances at certain frequencies. These resonances are called formants. Their location largely determines the speech sound that is heard. The source-filter model can be used to model the spectral envelope for the voice. The spectral envelope is the transfer function of the filter part of the source-filter model. The spectral envelope in this paper is generated using *MATLAB* built-in functions.

The steps to generate the spectral envelope model are listed here.

i. Multiply signal with a hamming window
ii. Compute the 10th order auto-regressive (AR) model of vowel
iii. Compute the transfer function.
iv. Compute the frequency response the filter transfer function based on 512-point FFT.
v. Plot the spectral envelope using the real component of the frequency response.

The smooth spectral-shape or the spectral envelope plotted from each speaker showed similar characteristics. Fig. 2 shows the characteristics of formants (resonant frequency) for different speakers match up. This plot is fairly demonstrative of the similarities in the vowel speech patterns of various speakers. The plotted outputs are scaled using *x*-axis of frequency between 0 to 4000Hz and *y*-axis in log scale. In terms of differentiating vowels, these plotted differences can be used as features then can be extracted and used to classify these vowels.

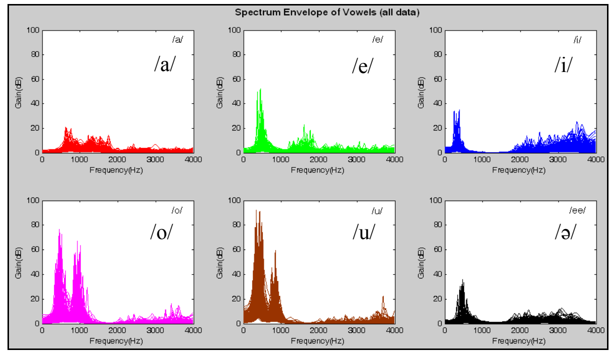

Figure 2. Spectrum envelope of vowels

Fig. 3 shows that except for vowel /i/, the other five vowels' frequency energy has at least two resonances or formant frequencies located at difference frequency location. Even the formant intensity is different between each of the vowels. F1-F2 formant features have been previously studied in detail in two dimensions (2-D) clustered analysis.

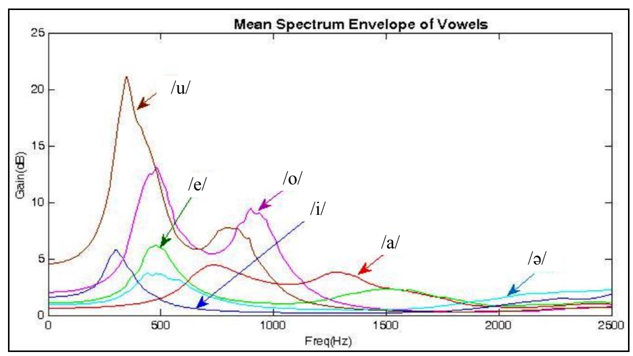

Figure 3. Mean spectrum envelope of vowels

D. Improved Vowel Feature Extraction Method

Bandwidth is the difference between the upper and lower cutoff frequencies of a signal spectrum and measured in hertz. In signal processing, the bandwidth is the frequency at which the closed-loop system gain drops 3dB below peak given by equation (1) [24].

$$K_{BW} = \frac{1}{\sqrt{2}} K_{peak} \tag{1}$$

K_{peak} denotes the intensity value at a formant frequency. K_{BW} is the resultant -3dB value of K_{peak}. Two features were extracted from each vowel. The first feature was extracted based on the energy of the first formant (F1) peak and denoted by $F1BW_1$.

The steps of computing $F1BW_1$ is as follows:

i). Locate 1st formant peak ($F1_{pk}$) and its intensity ($F1_{int}$).
ii). Calculate the -3dB intensity ($BW1_{int}$) from (1).
iii). Determine the frequency range (F_{low1} < freq < F_{high1}) of $F1_{pk}$ where spectrum intensity is greater than intensity of $BW1_{int}$.

iv). Calculate mean intensity of $F1BW_1$ for each vowel using (2) where *SI* is the spectrum intensity.

$$F1BW_1(vowel) = \frac{1}{N}\sum_{f=F_{low1(vowel)}}^{f=F_{high1(vowel)}} SI(f) \qquad (2)$$

The second feature was extracted from the valley between the first (F1) and the second formant (F2) peaks and denoted by $F1BW_2$.

The steps of computing $F1BW_2$ is as follows:

i). Locate 1st formant peak ($F1_{pk}$), 2nd formant peak ($F2_{pk}$) and the valley or lowest intensity between them (FV_{low}). Their intensities are $F1_{int}$, $F2_{int}$ and FV_{int} respectively.

ii). Calculate -3dB intensity ($BW2_{int}$) value based on difference between $F2_{int}$ and V_{int} is calculated based on:

$$BW2_{\text{int}} = F2_{pk} - \frac{((F2_{\text{int}} - FV_{\text{int}})}{\sqrt{2}} \qquad (3)$$

iii). Determine the frequency range (F_{low2} < freq < F_{high2}) of FV_{int} where spectrum intensity is lower than intensity of $BW2_{int}$.

iv). Calculate mean intensity of $F1BW_2$ for each vowel using (3) where *SI* is the spectrum intensity.

$$F1BW_2(vowel) = \frac{1}{N}\sum_{f=F_{low2(vowel)}}^{f=F_{high2(vowel)}} SI(f) \qquad (3)$$

SI(f) is the spectrum intensity at frequency location *f* for each vowel of /a/, /e/, /i/, /o/, /u/, /ə/. *N* is the number of spectrum intensity values within frequency subband of *BW2* for each vowel. Six Malay vowels were represented by a total of twelve features of *F1BW1a*, *F1BW2a*, *F1BW1e*, *F1BW2e*, *F1BW1i*, *F1BW2i*, *F1BW1o*, *F1BW2o*, *F1BW1u*, *F1BW2u*, *F1BW1ə* and *F1BW2ə*,.

E. Classification Techniques Used

In this study, three non-linear classifiers of Levenberg-Marquart trained Neural Network (LM), K-Nearest Neighbours (KNN), Multinomial Logistic Regression (MLR) and a linear classifier of Linear Discriminant Analysis (LDA) will be used to classify all the features in this study. These classifiers were chosen based on their popularities in speech recognition researches. All the features in this paper are classified using MATLAB built-in functions for all the four classifiers.

IV. RESULTS

A. Feature Analysis

Bandwidth is the difference between the upper and lower cutoff frequencies of a signal spectrum and measured in hertz. In signal processing, the bandwidth is the frequency at which the closed-loop system gain drops 3dB below peak. Altogether, there are twelve ranges of frequency used to extract intensity features from the vocal tract model. Features of each of the vowels is extracted from two frequency bands which is the first formant peak band and the frequency band between the first formant and second formant peak. The ranges of frequency band that were used to extract the mean intensity values from each vowel are obtained directly from the spectrum envelope of the vowels. These frequency bands will be used to obtain the F1BW features.

To determine if the features of the proposed feature extraction methods significantly affect vowel classification an ANOVA analysis was done for all the features using a statistical application called SPSS. In the rest of the ANOVA analysis, *main effect* is the effect of an independent variable or a factor on a dependent variable, determined separate from of the effects of other independent variables. The *F*-value signifies whether the model as a whole has statistically significant prediction capability. Degree of Freedom (*df*) refers to the number of independent measurements used in calculating a Sum of Squares. *df1* refers to degree of freedom between groups and *df2* refers to degree of freedom within groups. ANOVA assumptions were fulfilled for all the features used in this study. Based on ANOVA analysis on Table 3, there are very significant main effects from all the individual features of the proposed F1BW method with *p* value less than 0.001. This shows that all the features used in this method have significantly different mean values.

Table 3. ANOVA analysis of F1BW features

Main Effect	***df1***	***df2***	***F***	**Sig. (*p*)**
$F1BW_{1a}$	5	1310	516.42	<0.001
$F1BW_{2a}$	5	1310	372.91	<0.001
$F1BW_{1e}$	5	1310	600.85	<0.001
$F1BW_{2e}$	5	1310	447.16	<0.001
$F1BW_{1i}$	5	1310	811.72	<0.001
$F1BW_{2i}$	5	1310	461.03	<0.001
$F1BW_{1o}$	5	1310	144.15	<0.001
$F1BW_{2o}$	5	1310	388.92	<0.001
$F1BW_{1u}$	5	1310	549.96	<0.001
$F1BW_{2u}$	5	1310	160.41	<0.001
$F1BW_{1ə}$	5	1310	772.82	<0.001
$F1BW_{2ə}$	5	1310	478.67	<0.001

B. F1BW Overall Vowel Classification

Classifications results were based on repeated random sub-sampling validation. This method randomly splits the dataset into training and validation data. For each such split, the model is fit to the training data, and predictive accuracy is assessed using the validation data. The results are then averaged over the splits. The database is randomly divided into training and testing sets in the ratio of 7:3. This was done for each cross validation run where each training set will be used in training the classifier model and the other 30% of the data was treated as unseen testing inputs. A total of 20 iterations were done and their averaged vowel classification results were computed for each classifier. Fig. 4 shows that MLR obtained an overall accuracy of 94.39% which was 1.12% better than LM's performance of 93.27%. KNN gave 91.98% followed by LDA of 90.00%. Table 4 shows that among all the vowels, vowel /i/ was best classified by all classifiers except LDA while MLR gave the highest result of 98.96%. Vowel /o/ gave the worst classification rate for all the classifiers in which LDA gave the worst result of 78.72%.

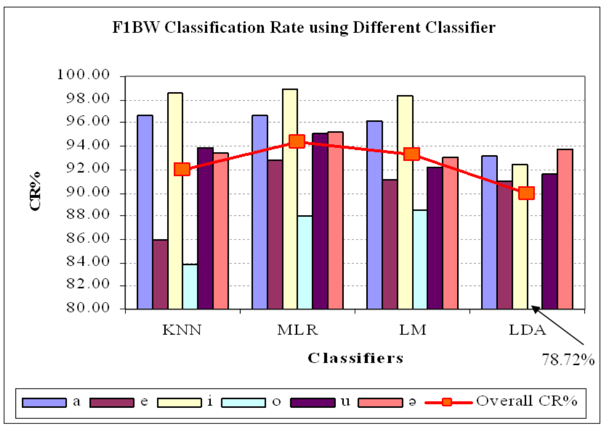

Figure 4. Result of F1BW classification rate using different classifiers

Table 4. Vowel classification result for F1BW features

	Best Recognition Performance for Vowel		Worst Recognition Performance for Vowel	
Classifier	**Vowel**	**CR%**	**Vowel**	**CR%**
KNN	/i/	98.60	/o/	83.81
MLR	/i/	98.96	/o/	88.02
LM	/i/	98.29	/o/	88.50
LDA	/ə/	93.76	/o/	78.72

For F1BW, MLR gave the best overall vowel classification rate of 94.39% which is 4.39% better than LDA. Overall, all the classifiers were able to obtain good classification rate of 90% and above for all the vowels using F1BW.

C. MFCC Overall Vowel Classification

MFCC is most commonly used as a features extraction method by speech recognition researchers. For this study, a single frame MFCC is used as a conventional feature extraction method where its classification performance will be compared to the proposed methods. Based on Fig. 5, both MLR and LM appear to give the best classification rate for overall performance of vowel classification. 2-tail *t*-test shows a non-significant difference between overall accuracy of KNN and MLR with a probability of 0.301. This means that both KNN and MLR performed best in overall vowel classification.

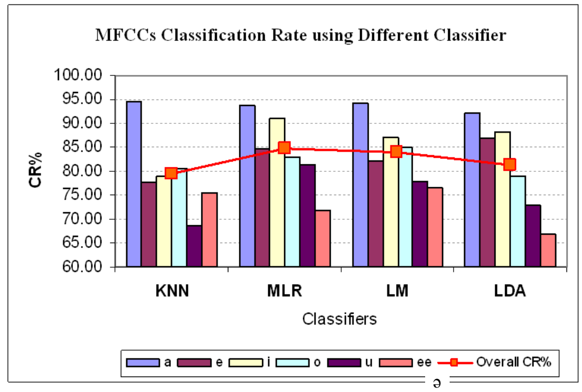

Figure 5. Result of MFCC classification rate using different classifiers

Table 5 shows that among all the vowels, vowel /a/ gave the best classification accuracy for all classifiers in which, KNN gave the best performance of 99.40%. Vowel /ə/ gave the worst classification rate for MLR, LM and LDA classifiers in which LDA gave the worst result of 66.76%. For KNN, vowel /u/ performs the worst with 68.71%. For MFCCs features, MLR and LM gave the best overall vowel classification rate but needed more time to train.

Table 5. Vowel classification result for MFCCs features

	Best		Worst	
Classifier	**Vowel**	**CR%**	**Vowel**	**CR%**
KNN	/a/	94.40	/u/	68.71
MLR	/a/	93.74	/ə/	71.81
LM	/a/	94.32	/ə/	76.46
LDA	/a/	92.18	/ə/	66.76

Based on Table 6 and Fig. 6, single framed features of F1BW performs better in overall vowel classification than single framed MFCCs by more than 9% for all four classifiers. Biggest improvement was seen for KNN where the improvement was 12.44% and LDA showed the smallest improvement of an impressive 8.6%.

Table 6. Overall vowel classification improvement

Classifier	Improvement of F1BW over MFCCs
KNN	12.44 %
MLR	9.75 %
LM	9.34 %
LDA	8.6 %

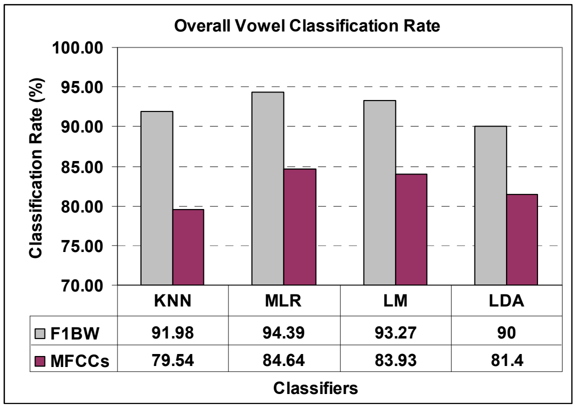

Figure 6. Result of F1BW vs. MFCC overall vowel classification rate using different classifiers

V. CONCLUSION

This paper presents a new method of vowel feature extraction based on formant and spectrum envelope called First Formant Bandwidth (F1BW). In terms of specific vowel classification performance of F1BW, vowel /i/ was best classified by all four classifiers with KNN gave the highest result of 98.96% classification rate. For MFCCs, vowel /a/ gave the best classification accuracy for all classifiers in which, KNN gave the best performance of 99.40%. Vowel /ə/ gave the worst classification rate for MLR, LM and LDA classifiers in which LDA gave the worst result of 66.76%. From the results presented in this paper, it can be concluded that F1BW performs better than MFCCs by more than 9% on all four classifiers of LM, MLR, LDA and KNN.

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