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Abstract - Each person's voice is different. Thus, the Quran sound, which had been recited by most of recitors will probably tend to differ a lot from one person to another. Although those Quranic sentence were particularly taken from the same verse, but the way of the sentence in Al-Ouran been recited or delivered may be different. It may produce the difference sounds for the different recitors. Those same combinations of letters may be pronounced differently due to the use of harakates. This paper explores the viability of Mel-Frequency Cepstral Coefficient (MFCC) technique to extract features from Quranic verse recitation. Features extraction is crucial to prepare data for classification process. MFCC is one of the most popular feature extraction techniques used in speech recognition, whereby it is based on the frequency domain of Mel scale for human ear scale. MFCCs consist of preprocessing, framing, windowing, DFT, Mel Filterbank, Logarithm and Inverse DFT.

Keywords: Quranic verse recitation recognition, speech recognition, Mel-Frequency Cepstral Coefficient (MFCC), DFT.

I. INTRODUCTION

The automated speech recognition is one of the popular research domains since the beginning of the computer industry. There are a lot of problems and difficulties arise, when dealing with the Arabic language. Arabic is one of the languages that often described as morphologically complex language. Furthermore, the problem of Arabic language modeling is also compounded by dialectal variation and due to the differences between written and recites the Al-Quran [4] [24]. According to the ASR perspective, those differences occurs while the same combination of letters may be pronounced differently due to the use of *harakates* [4].

In addition, most of Al-Quran learning process is still handled with manual method, through reading the Al-Quran skills with *talaqqi* and *musyafahah* methods. These methods are described as face to face learning process between students and teachers, where listening, correction of Al-Quran recitation and recite again the correct Al-Quran recitation took place [3]. This factor is important, so that students will know how the

hijaiyah letters are pronounced correctly. The process only can be done, if the teachers and students follow the art, rules and regulations while reading the Al-Quran, known as "Rules of Tajweed" [4].

In this research, the process of the features extraction technique was presented, which inherent with Quranic Arabic in particular, as part of speech recognition system [18]. Thus, the implementation of MFCC features extraction from Quranic verse recitation were discovered and explored, due to convert the speech signal into a sequence of acoustic feature vectors. The MFCC features extraction techniques is implemented using the Programming language of MATLAB. This implementation is easy to use and can easily be extended with new features [13]. Features extraction is crucial to prepare data for classification process. It also can recognize and extract the Quran recitation features not just the phonemes but also checks for the Tajweed Rules [6] such as 'Mad Asli' and basic mad.

II. SPEECH RECOGNITION

In recent years, speech recognition has reached a very high level of performance, with word-error rates dropping by a factor of five in the past five years. This current state of performance is increased due to improvements in the algorithms and techniques that are used in this field. This technology also had been implemented into various fields with different languages. Most of research which had been successfully implemented is English language. Thus, the developments of other language based on speech recognition techniques are also applied.

A. Quranic Verse Recitation Recognition Systems.

H. Tabbal et al. [4] have conducted the Quranic verse recitation recognition, which covered the Quran verse delimitation system in audio files using speech recognition techniques. The Holy Quran recitation and pronunciation as well as software used for recognition purposes had been discussed in this research. The Automatic Speech Recognizer

(ASR) has been developed by using the open source Sphinx framework as the basis of this research. The scope of this project more focus into the automated delimiter, which can extract the verse from the audio files. Research techniques for each phase were discussed and evaluated using implementation of various techniques for different recitors, which recite sourat "Al-Ikhlas". Here, the most important tajweed rules and tarteel, which can influence the recognition of a specific recitation, can be specified. In this research, the use of the MFCC has proven the remarkable result in the field of speech recognition. It is because, the behavior of the auditory system had been tried to emulate by transforming the frequency from a linear scale to a non-linear one.

A comprehensive evaluation of Quran recitation recognition techniques was provided by A.M. Ahmad et al. [8]. The survey provides recognition rates and descriptions of test data for the approaches considered between LPCC and MFCC in the feature extraction process. Focusing on Quran Arabic recitation recognition, it incorporates background on the area, discussion of the techniques, and potential research directions. The result obtained, shown that the LPCC is the best performance for recognizing the Arabic alphabets of Quran, with 50 hidden units (99.3%) more efficient compared to MFCC. But, MFCC is still the most popular feature set with 50 hidden units (98.6%) efficient, which computed on a warped frequency scale based on known human auditory perception.

According to the A.Youssef & O.Emam [11], 12 Dimensional Mel Frequency Cepstral Coefficients (MFCCs) is been coded for recorded speech data. Pitch marks were produced using Wavelet transform approach, by using the glottal closure signal. This signal is obtained from the professional speaker during the recording. Under this condition, the overall voice quality was better than the tested system.

B. English Language based on Speech Recognition system

O.Khalifa et al. [7] had identified the main steps for MFCCs are clearly shown in Figure 1.

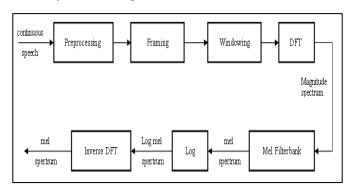


Figure 1: Block diagram of the computation steps of MFCC [7]

Those steps in MFCC include the followings:

- 1. Preprocessing
- 2. Framing
- 3. Windowing [12]
- 4. DFT
- 5. Mel Filterbank
- 6. Logarithm
- 7. Inverse DFT.

MFCC becomes more robust to noise and speech distortion, once the Fast Fourier Transform (FFT) and Mel scale filter applied. MFCCs use Mel scale filter bank, where higher frequency filter have greater bandwidth than the lower frequency filter, but their temporal resolutions are the same.

III. SPEECH SIGNAL ANALYSIS

Quranic Arabic recitation is best described as long, slow pace rhythmic, monotone utterance [18] [19]. The sound of Quranic recitation recognizably unique and reproducible according to a set of pronunciation rules, tajweed, designed for clear and accurate presentation of the text. The input to the system is the speech signal and phonetic transcription of the speech utterance. The overall process of this system is briefly described as block diagram shown below:

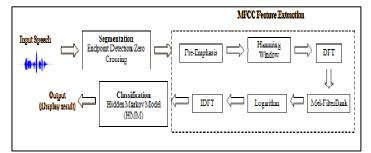


Figure 2: Quranic R.R. Block Diagram

A. Input Speech Signal

In this process, input speech samples are recorded in a constraint environment and the speech sample is 16 000 Hz for 2 second of time length. This was verified on speech inputs for different speakers who recited "Quranic verse" of approximately 2 minutes each. Sampling rate of 16 000 Hz is a high fidelity microphone, which has the capability of 16 kHz sampling rate of microphone speech [12] [26]. This sampling frequency would be necessary for complete accuracy and Nyquist rate. Thus, the typical sampling rate, 16 000 samples per second, is adequate. Some systems have used over sampling plus a sharp cutoff filter to reduce the effect of noise [12].

The sample resolution is the 8 or 16 bits per second that *sound cards* can accomplish. This process of representing real-valued numbers as integers is called quantization because there is a minimum granularity (the quantum size) and all values

which are closer together than this quantum size are represented identically [12]. Due to proceed for further process, the speech regions need to be identified and ignore the non-speech area.

B. Segmentation

The speech utterances need to be segmented through the segmentation process, in order to detect the boundaries of each phoneme within the speech signal. The property of speech signal changes markedly as a function of time. To study the spectral properties of speech signal, the concept of time varying Fourier representation is used. However, the temporal properties of speech signal such as energy, zero crossing, correlation etc are assumed constant over a short period. Those characteristics were belonging to short-time stationary [2]. The algorithm used for both energy and zero-crossing thresholds to detect the beginning and end of the speech, at the segmentation part.

Therefore, by using hamming window [5] at MFCC part, speech signal is divided into a number of blocks of short duration, which allow us to use the normal Fourier transform. Overlapping process as well as add the method to extract the spectral properties of speech signal also has done here. Those processes can be briefly described based on the figure 2 shown above.

IV. THE PROPOSED FOR MEL-FREQUENCY CEPSTRAL COEFFICIENT (MFFC)

The purpose of this research is to convert the speech waveform to some type of parametric representation. Thus, the viability of Mel-Frequency Cepstral Coefficient (MFCC) technique to extract features from Ouranic verse recitation can be explored and investigated. MFCC is perhaps the best popular features extraction method used recently [25] [26], and this feature will be used in this paper. MFCC's are based on the known variation of the human ear's critical bandwidths with frequency. Speech signal had been expressed in the Mel frequency scale, in order to capture the important characteristic of phonetic in speech. This scale has a linear frequency spacing below 1000 Hz and a logarithmic spacing above 1000 Hz. Normal speech waveform may vary from time to time depending on the physical condition of speakers' vocal cord. Rather than the speech waveforms themselves, MFFCs are less susceptible to the said variations [9] [10].

A. MFCCs Block Diagram.

According to Quranic R.R. Feature Extraction shown in figure 3, the MFCCs feature extraction methods were implemented in this research also consists of 8 main computation steps, which include the following: preprocessing, framing and windowing using Hamming Window, performing Discrete Fourier Transform (DFT), applying the Mel-scale

filter bank in order to find the spectrum as it might be perceived by the human auditory system, performing the Logarithm, taking the inverse DFT of the logarithm of the magnitude spectrum and finally deltas which also correspond with energy. Those MFCCs computation steps were able to compute the log-energy at the output of each filter, where the filter energy is more robust to noise and spectral estimation errors. This algorithm been extensively used as a feature vector for speech recognition systems. Overviews of the MFCC computation process were described as below:

1) Preprocessing

Preprocessing is considered as the first step of speech signal processing, which involve with the analog signal to digital signal conversion, which had been described by E. C. Gordon (1998) [14]. The continuous time signal (speech) is sampled at discrete time point and then, the samples are quantized due to obtain a digital signal.

The sequence of samples x[n] is obtained from the continuous time signal x (t), which stated clearly in the relationship below:

$$x[n] = x(nT) \tag{1}$$

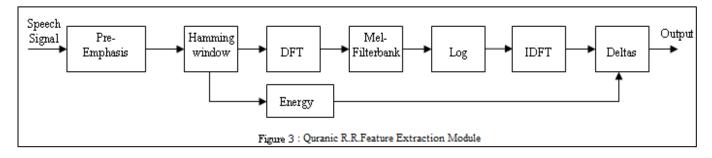
Where, T is the sampling period and 1/T =fs is the sampling frequency, in samples/sec. n is represent as the number of samples. The above equation is mainly used to obtain a discrete time representation of a continuous time signal through periodic sampling. The size of the sample for digital signal is determined by the sampling frequency and the length of the speech signal in seconds.

At the first stage in MFCC feature extraction is to boost the amount of energy in the high frequencies. It turns out that if we look at the spectrum for speech segments like vowels, there is more energy at the lower frequencies than the higher frequencies. This drop of energy across frequencies is caused by the nature of the glottal pulse [20]. This preemphasis is done by using a filter, using the equation below:

$$y[n] = x[n] - \alpha x[n-1]$$
 (2)

2) Framing

Process of segmenting the speech samples obtained from the analog to digital conversion (ADC), into the small frames with the time length within the range of 20-40msec, also known as Framing. Framing enables the non-stationary speech signal to be segmented into quasi-stationary frames, and enables Fourier Transformation of the speech signal. It is because, speech signal is known to exhibit quasi-stationary behavior within the short time period of 20-40msec. Thus, it is rationale if the Fourier Transformation of the speech signal was enable, because a single Fourier Transform of the entire speech signal cannot capture the time varying frequency due to the non-stationary behavior of the speech signal [21].



3) Windowing

Windowing step is meant to window each individual frame, in order to minimize the signal discontinuities at the beginning and the end of each frame. If we define the window as w(n), $0 \le n \le N-1$, where N is the number of samples in each frame. Thus, the result of the windowing can be shown based on equation below:

$$y(n) = x(n) * w(n), 0 \le n \le N-1$$
 (3)

Here, hamming window most commonly used as window shape in speech recognition technology, by considering the next block in the feature extraction processing chain, integrates all the closest frequency lines. Impulse response of the Hamming window was shown, based on the equation (4) below:

$$w(n) = \begin{cases} 0.54 - 0.46 \cos(\frac{2\pi n}{N - 1}), & 0 \le n \le N - 1 \\ 0 & \text{Otherwise} \end{cases}$$
 (4)

For this reasons, Hamming window is commonly used in MFCC extraction, which shrinks the values of the signal toward zero at the window boundaries and avoiding discontinuities.

4) Discrete Fourier Transform (DFT)

Discrete Fourier Transform (DFT) is normally computed via Fast Fourier Transform (FFT) algorithm, which is widely used for evaluating the frequency spectrum of speech [15]. Besides, the amount of energy signal contains at different frequency bands also can be determined via DFT. FFT converts each frame of N samples from the time domain into the frequency domain. Furthermore, FFT is a fast algorithm which exploits the inherent redundancy in the DFT and reduces the number of calculations. It provides exactly the same result as the direct calculation.

In this research, we added the basis of performing Fourier Transform, which had been implemented before by Alexander and Sadiku (2000) [16]. Here, the Fourier Transform is to convert the convolution of the glottal pulse u[n] and the vocal

tract impulse response h[n]in the time domain. This statement supports the equation below:

$$Y(w) = FFT[h(t)*x(t)] = H(w) \times X(w)$$
(5)

If X(w), H(w) and Y(w) are the Fourier Transform of x(t), h(t) and y(t) respectively.

Discrete Fourier Transform (DFT) is used instead using the Fourier Transform during analyzing speech signals. It is because the speech signal is in the form of discrete number of samples due to preprocessing. The input of the DFT is a windowed signal x[n]...x[m], and the output, for each of N discrete frequency bands, is a complex number X[k] representing the magnitude and phase of that frequency component in the original signal. The discrete Fourier Transform is represented by the equation below, where X(k) is the Fourier Transform of x(n).

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\frac{\pi}{N}kn}$$
 (6)

Mathematical details of DFT, includes the note of Fourier analysis, also relies on Euler's formula stated below:

$$e^{j\theta} = \cos\theta + j\sin\theta \tag{7}$$

5) Mel Filterbank

The useful information that carried by the low frequency components of the speech signal is more important compared to the high frequency components. Thus, Mel scale is applied in order to place more emphasizes on the low frequency components. The speech signal consists of tones with different frequencies. For each tone with an actual Frequency, f, which measured in Hz, a subjective pitch is measured on the 'Mel' scale. A mel (Stevens et al., 1937) [22] [23] is a unit of pitch defined, so that pairs of sounds which are perceptually equidistant in pitch are separated by an equal number of mels.

Mel scale is a unit of special measure or scale of perceived pitch of a tone. It does not correspond linearly to the normal frequency, but behaves linearly below 1 kHz and logarithmically above 1 kHz. This frequency range is based on the studies of the human perception of the frequency perception of the frequency content of sound. Therefore we can use the following formula to compute the mels for a given frequency f in Hz [17]:

Frequency (Mel scale) =
$$[2595* \log_{10}(1+f)700]$$
 (8)

This formula shows the relationship between both the frequency in hertz and Mel scale frequency. Particularly, for the filterbanks implementation, the magnitude coefficient of each Fourier Transform speech segment is binned by correlating them with each triangular filter in the filterbank. In order hand, due to perform Mel-scaling, a number of triangular filter or filterbank is used.

Therefore, a bank of filters was created during the MFCC computation, in order to collect energy from each frequency band, with 10 filters spaced linearly below 1000 Hz, and the remaining filters spread logarithmically above 1000 Hz.

The results of the FFT will be information about the amount of energy at each frequency band. Human hearing, however, is not equally sensitive at all frequency bands. It is less sensitive at higher frequencies, roughly above 1000 Hertz. It turns out that modeling this property of human hearing during feature extraction improves speech recognition performance.

6) Logarithm

The logarithm has the effect of changing multiplication into addition. Therefore, this step simply converts the multiplication of the magnitude in the Fourier transform into addition.

Here, the logarithm of the Mel filtered speech segment is carried out using the Matlab command "log", which return the natural logarithm of the elements of the Mel filtered speech segment. In general, the human response to the signal level of logarithmic. It is because humans are less sensitive to slight differences in amplitude at high amplitudes compared to the low amplitudes. In addition, using a log makes the feature estimates less sensitive to variations in input (for example power variations due to the speaker's mouth moving closer or further from the microphone) [20].

7) Inverse of Discrete Fourier Transform (IDFT)

IDFT is the final procedure for the Mel Frequency cepstral coefficients (MFCC) computation. It consists of performing the

inverse of DFT on the logarithm of the inverse of DFT on the logarithm of the Mel filterbank output. The speech signal is represented as a convolution between varying vocal tract impulse response and quickly varying glottal pulse. The glottal source waveform of a particular fundamental frequency is passed through the vocal tract; regardless to glottal shape with particular filtering characteristics.

But many characteristics of the glottal are not important for distinguishing different phones. Instead, the most useful information for phone detection is the filter, i.e. the exact position of the vocal tract. If we knew the shape of the vocal tract, we would know which phone was being produced [20].

Therefore, by taking the inverse of DFT in logarithm of the magnitude spectrum, the glottal pulse and the impulse response can be separated and show us only the vocal tract filters. As the result, Mel cepstrum signal may be obtained. This is the final stage of MFCC, where it required computing the inverse Fourier Transform of the logarithm of the magnitude spectrum, in order to obtain the Mel frequency cepstrum coefficients. At this stage, MFCCs are ready to be formed in a vector format known as features vector. This features vector is considered as an input for the next stage, which are concern with training the features vector and pattern recognition. The cepstrum is more formally defined as the inverse DFT of the log magnitude of the DFT of a signal. The windowed frame of speech, x[n] is described in equation below:

$$c[n] = \sum_{n=0}^{N-1} \log \left(\left| \sum_{n=0}^{N-1} x[n] e^{-j\frac{2\pi}{N}kn} \right| \right) e^{j\frac{2\pi}{N}kn}$$
(9)

8) Deltas and Energy

Energy was correlates with phone identity and it is a useful cue for phone detection. The energy in a frame for a signal x in a window from time sample t1 to time sample t2, is represented at the equation below:

Energy =
$$\sum_{t=t_1}^{t_2} x^2[t]$$
 (10)

Moreover, the speech signal is not constant from frame to frame. This is the important fact about the speech signal and the frames changes, such as the slope of a formant at its transitions, or the nature of the change from a stop closure to stop burst, can provide a useful cue for phone identity. For this reason we also add features related to the change in cepstral features over time.

In this research, we add for each of the 13 features (12 cepstral features plus energy) a delta or velocity feature, and a double delta or acceleration feature [12]. Each of the 13 delta features represents the change between frames in the

corresponding cepstral/ energy feature, while each of the 13 double delta features represents the change between frames in the corresponding delta features. A simple way to compute deltas would be just to compute the difference between frames; thus the delta value d(t) for a particular cepstral value c(t) at time t can be estimated as:

$$d(t) = \frac{c(t+1) - c(t-1)}{2} \tag{11}$$

CONCLUSION

In this research, we presented a features extraction method for Quranic Arabic recitation recognition, by using the Melfrequency Cepstral Coefficients (MFCC). The main contribution of the proposed speech recognition system is encouraged to recognize and differentiate the Quranic Arabic utterance and pronunciation based on the features vectors output produce, by using the MFCC features extraction method.

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