

Voice Recognition Based on Adaptive MFCC and Deep Learning

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Abstract—In this paper, we propose an enhanced voice recognition method using Adaptive MFCC and Deep Learning. To improve the voice recognition rate, it is important to extract the audio data from original signal. However the existing Algorithms which is used to remove the noise of particular band deteriorate the audio signal. Differently from the existing MFCC, the proposed filter is built up compactly in the data density area to reduce data loss, and impose the weighted value to the data area. As a result, it prevents the data loss which results in improving the recognition rate. In addition the Deep Learning makes it possible to use the Voice recognition without DB. Therefore, it can be effectively used for electronic devices with small memory.

Keywords— Voice recognition, MFCC, Deep Learning, Noise, Filter

I. INTRODUCTION

The Voice recognition technology to transform the voice signal into text is applied to mobile communication, home application, navigation equipment and robot. The voice recognition methods generally are based on comparison between ‘the audio signal to be recognized’ and ‘the audio signal to be set’. In ideal case, embedded system can be used for this purpose. However, the noised voice signal results in fatal error in voice recognition. The speech enhancement method is proposed to eliminate the noise from the audio signal itself,[1][2][3][4]. To compensate for the damaged model for the effects of noise, ‘The model compensation’ method is effective. [5][6]. In addition, The inherently robust speech feature method extracts the feature vector for the robust noise, [7][8], etc. ‘The speech enhancement’ method is Spectral Subtraction[1], MMSE(Minimum Mean Square Error), Wiener filtering[2], Adaptive noise Cancelling[3], Microphone Array[4], etc. The model compensation method deals with is HMM decomposition[5], PMC(Parallel Model Compensation) [6]. The inherently robust speech feature method includes MFCC(Mel-Frequency Cepstral Coefficient), PLP (Perceptual Linear Prediction)[7], SMC(Short-time Modified

Coherence)[8], and Cepstral Compensation[9]. Recently, the MFCC method is relatively popular than other methods. Basically the MFCC calculates the Logarithm energy of the filter bank configured in consideration of human auditory characteristics using DCT(Discrete Cosine Transform). Even though the recognition performance is decreased in the signals with low signal to noise ratio, this method shows good performance. Noise removal filter that is proposed in this paper extracts the higher frequency band over certain decibel by DFT of audio signal. With a different weighting to each extracted frequency, it is distinguished from any other band. In addition, the Filterbank uses the triangle band-pass filter. **The MFCC is common that the middle value of the n-th bandpass filter is the first value of (n+1) th filter. However, since in proposed algorithm, the last value of the n-th filter is the first value of the (n+1)th filter, the filter is not overlapped to remove the noise, and extract the cepstrum for voice recognition.** By applying the cepstrum value obtained through the DCT to Deep Neural Network of the Neural Network Algorithm, we can build a speech recognizer which can be used in the Embedded system with small memory capacity, and improves the recognition rate.

II. ADAPTIVE MFCC

The average amplitudes of typical noise is much smaller than the average amplitudes of the input signal. Such a small noise is eliminated using ‘Smooth’ in the input signal.

$$s(n) = \begin{cases} s(n) & s(n) \geq \text{value} \\ 0 & s(n) \leq \text{value} \end{cases} \quad (2-1)$$

The signal without small size noise using a ‘Smooth’ is applied to the Adaptive MFCC Algorithm which converts the inputted voice data to the Mel-scale Algorithm. We can recognize the voice even if the noise is mixed in the sound by using this principle. This method shows excellent performance even in noisy environments due to the processing of non-linear frequency scale which is log scale. The equation 2-2 converts the inputted voice signal to the Mel-scale which is robust to noise.

$$f_{mel} = 2595 \times \log_{10} \left(1 + \frac{f}{700} \right) \quad (2-2)$$

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Where f is the frequency.

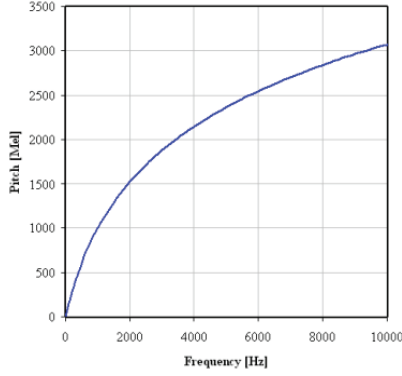


Fig. 1. The relation between Mel-scale and linear frequency

The Figure 1 shows the relation between Mel-scale and linear frequency.

Since the voice signal is continuous input. it is hard to process at once. it is divided in scale of the **frame in 25ms ~ 30ms using the 'Window'**. In this case, for the continuity of the start and the end, the Hamming Window as in the equation (2-3) is used.

$$w(n) = 0.54 - 0.46 \cos\left(\frac{2\pi n}{N-1}\right) \quad 0 \leq n \leq N \quad (2-3)$$

where 'N' is the length of Window function. 'Figure 2' shows the characteristic curve of Hamming window.

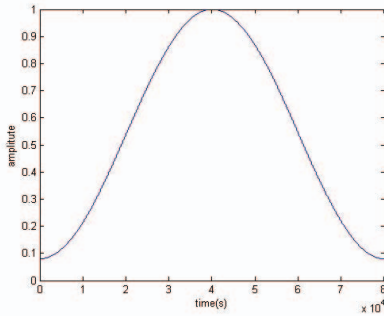


Fig. 2. Characteristic curve of Hamming window

In the Adaptive MFCC method, the frames which is divided by the Hamming window is applied in the Filterbank which consists of Triangle bandpass and filters out the noise. In this case, the intervals of the frequency band become wider in the higher frequency band because Mel-scale is applied. In the Figure 3 which shows the characteristic curve of the Triangle Bandpass Filterbank in the existing MFCC, we can see the overlap between filter.

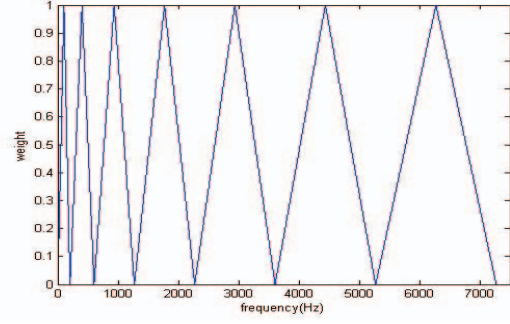


Fig. 3. Characteristic curve of Filterbank

However, in the Adaptive MFCC, if the pass band of the n -th filter was 500 ~ 600 Hz, the pass band of the $(n+1)$ th filter should be designed 600 ~ 750Hz so as not to overlap the each of filters. With this process the noise is eliminated effectively.

Figure 3 shows the characteristic of the modified Filterbank without overlapped filter.

$$y(k) = w(k) \sum_{n=1}^N x(n) \cos \frac{\pi(2n-1)(k-1)}{2N}, k = 1, \dots, N \quad (2-4)$$

$$w(k) = \begin{cases} \frac{1}{\sqrt{N}} & k = 1 \\ \sqrt{\frac{2}{N}} & 2 \leq k \leq N \end{cases} \quad (2-5)$$

In equation 2-4 and 2-5, N , k , and $x(n)$ describe the number of filters, the degree of feature vector, and the n -th filter value, respectively. **The result obtained by the DCT filtered signal was learned by using the DNN(Deep Neural Network) based on the Back propagation.** The hidden layer is updated using equation (2-6).

$$\nabla w_{ij}(t+1) = \nabla w_{ij}(t) + \eta \frac{\partial C}{\partial w_{ij}} \quad (2-6)$$

Using the learning, updated value of the hidden layer calculates the value of output layer to calculate the result of the speech recognizer.

III. EXPERIMENT

To prove the efficiency of the proposed algorithm, the result is obtained under irregular noise environments using MATLAB. In the experiment, the Senheiser e835s was used in dynamic MIC system. Especially, the DNN algorithm was used for efficient speech recognition. **The DNN with 16 hidden layer for a given number of inputs and 13th filter were use.**

A. Removing noise using Adaptive MFCC

In this experiments, the 6 words such as 'Hello', 'Turn On', 'Turn Off', 'Up', 'Down', and 'Good bye' are recorded and used as data. **The frame was divided by 30ms by using Hamming Window.** The Figure 4 indicates the voice

signal of ‘Hello’ recorded in the general laboratory environment.

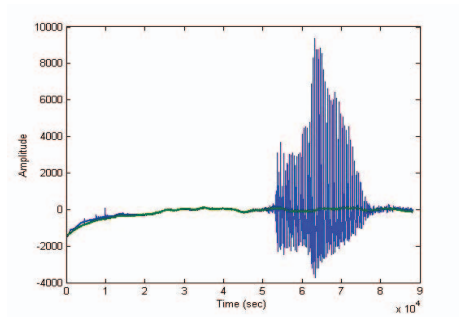


Fig. 4. Voice data for ‘Hello’

In this experiments, after the voice signal of ‘Hello’ is converted to the Mel-scale which is robust to noise, the time domain was converted to the Frequency domain based on DFT. The noise was eliminated using the Filterbank which consists of the Triangle bandpass filter. Figure 5 shows the audio signal after the recorded audio signal is converted into Mel-scale and the converted data using DFT.

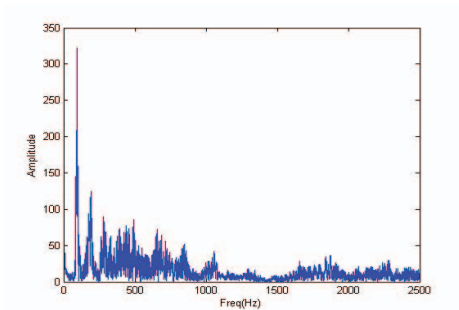


Fig. 5. DFT conversion of the original signal

The noise in the signal that is converted by DFT is eliminated using the Mel-scale Filterbank. Figure 9 shows the signal which passed through the each Filterbank.

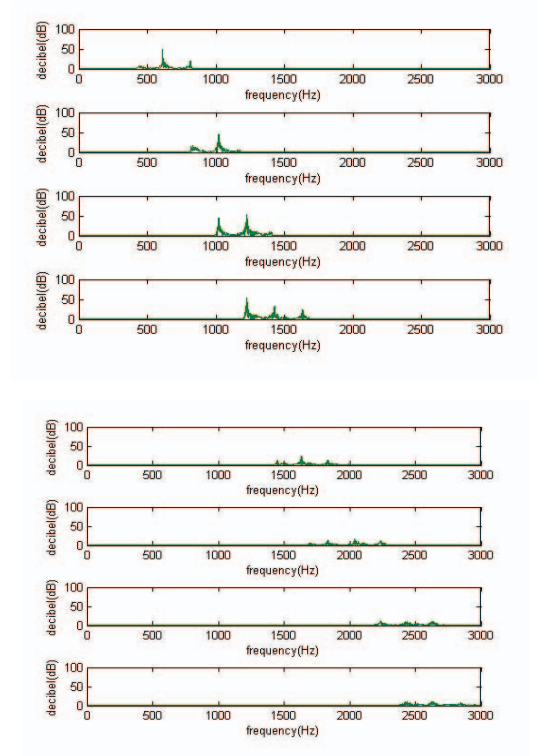
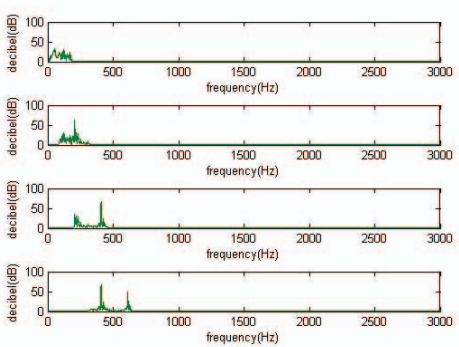


Fig. 6. DFT signal passed through Filterbank

Table 1. Table Type Styles

68Hz	73 Hz	77 Hz	95 Hz
101 Hz	106 Hz	131 Hz	132 Hz
133 Hz	178 Hz	256 Hz	421 Hz
422 Hz	423 Hz	479 Hz	613 Hz
622 Hz	645 Hz	673 Hz	742 Hz
803 Hz	804 Hz	805 Hz	835 Hz
836 Hz	852 Hz	853 Hz	869 Hz
870 Hz	884 Hz	911 Hz	912 Hz
944 Hz	948 Hz	980 Hz	981 Hz
1058 Hz	1059 Hz	1067 Hz	1272 Hz
1275 Hz	1289 Hz	1462 Hz	1543 Hz
1546 Hz	1693 Hz	1695 Hz	1847 Hz
1849 Hz	1852 Hz		

As shown in Table 1, the bigger weight is imposed to the higher frequency range because it has higher probability to contain more audio data. In order to calculate the each cepstrum using the signal obtained through the Filterbank, the DCT transform was applied. Figure 7 and Figure 8, show the voice signal passed through Filterbank and DFT conversion of filtered signal.

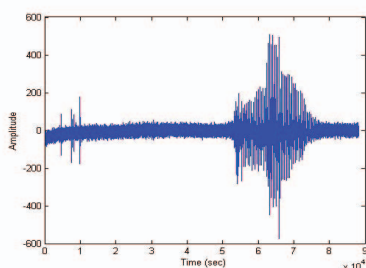


Fig. 7. Voice signal passed through Filterbank

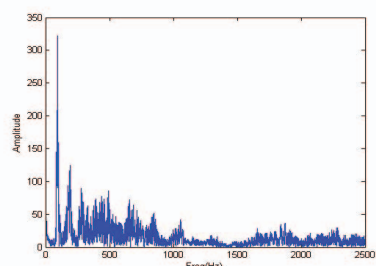


Fig. 8. DFT conversion of filtered signal

In this process, the 13 order MFCC with lower DCT coefficients can be obtained from the coefficients by 20 Filterbanks. Figure 9 shows the capstrum obtained by Adaptive MFCC.

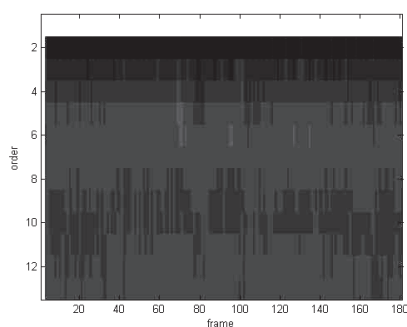


Fig. 9. Capstrum by Adaptive MFCC

B. Recognition of the MFCC and Adaptive MFCC

The analyzer learned 10000 learning data by using the same DNN algorithm with 6 words with the noise of the random frequency of 0.1dB, 10dB, 50dB.

Table 2. Recognition of the MFCC and Adaptive MFCC

	MFCC	Adaptive MFCC
Hello	96.7%	98%
Turn On	96.2%	96%
Turn Off	96.5%	97.2%
Up	96.4%	97.6%
Down	96.3%	98%
Good bye	96%	97.4%

Table 2 shows 96% recognition rate of the MFCC and about 96~98% of Adaptive MFCC.

IV. CONCLUSION

In voice recognition method, comparing the input audio signal through Mic or specific input device with the data of existing Database is the most widely used. In this method, to remove noise from the obtained signal is one of the most important parts.

In this paper, the enhanced MFCC effectively removes the noise for robust voice recognition. The recognized voice through the Deep Learning, the results are compared in terms of the recognition rate. Especially, to improve the recognition rate, the noise is eliminated without data loss by using ‘Smooth’ and ‘Adaptive filter’. The conventional MFCC which has the disadvantage in removing the specific band noise, has inherently low recognition rates. However, the Adaptive MFCC removes noise in all bands without damaging the audio data by removing the small size noise through the ‘Smooth’ in advance. For robust voice recognition in all frequency range, the average and the variance of about 50 frequency band with bigger magnitude are calculated. The adaptive filter which is robust to in all frequency range is designed by imposing the weighting factor to each filter.

A more advanced adaptive filter is under going to remove white noise especially for home appliances.

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