Modified Mel Filter Bank to Compute MFCC of Subsampled Speech

Kiran Kumar Bhuvanagiri  
TCS Innovation Lab-Mumbai, Tata Consultancy Services  
Yantra park, Thane, Maharastra, India  
Email: kirankumar.bhuvanagiri@tcs.com

Sunil Kumar Kopparapu  
TCS Innovation Lab-Mumbai, Tata Consultancy Services  
Yantra park, Thane, Maharastra, India  
Email: sunilkumar.kopparapu@tcs.com

Abstract—Mel Frequency Cepstral Coefficients (MFCCs) are the most popularly used speech features in most speech and speaker recognition applications. In this work, we propose a modified Mel filter bank to extract MFCCs from subsampled speech. We also propose a stronger metric which effectively captures the correlation between MFCCs of original speech and MFCC of resampled speech. It is found that the proposed method of filter bank construction performs distinguishably well and gives recognition performance on resampled speech close to recognition accuracies on original speech.

I. INTRODUCTION

Time scale modification (TSM) is a class of algorithms that change the playback time of speech/audio signals. By increasing or decreasing the apparent rate of articulation, TSM on one hand, is useful to make degraded speech more intelligible and on the other hand, reduces the time needed for a listener to listen to a message. Reducing the playback time of speech or time compression of speech signal has a variety of applications that include teaching aids to the disabled and in human-computer interfaces. Time-compressed speech is also referred to as accelerated, compressed, time-scale modified, sped-up, rate-converted, or time-altered speech. Studies have indicated that listening to teaching materials twice that have been speeded up by a factor of two is more effective than listening to them once at normal speed [1]. Time compression techniques have also been used in speech recognition systems to time normalize input utterances to a standard length. One potential application is that TSM is often used to adjust Radio commercials and the audio of television advertisements to fit exactly into the 30 or 60 seconds. Time compression of speech also saves storage space and transmission bandwidth for speech messages. Time compressed speech has been used to speed up message presentation in voice mail systems [2].

In general, time scale modification of a speech signal is associated with a parameter called time scale modification (TSM) factor or scaling factor. In this paper we denote the TSM factor by $\alpha$. There are a variety of techniques for time scaling of speech out of which, resampling is one of the simplest techniques. Resampling of digital signals is basically a process of decimation (for time compression, $\alpha > 1$) or interpolation (for time expansion, $\alpha < 1$) or a combination of both. Usually, for decimation, the input signal is subsampled. For interpolation, zeros are inserted between samples of the original input signal. For a discrete time signal $x[n]$ the restriction on the TSM factor $\alpha$ to obtain $x[\alpha n]$ is that $\alpha$ be a rational number. For any $\alpha = \frac{p}{q}$ where $p$ and $q$ are integers the signal $x[\alpha n]$ is conducted by first interpolating $x[n]$ by a factor of $p$, say $x^p = x[n \uparrow p]$ and then decimating $x[n]$ by a factor of $q$, namely, $x^q = x[n \downarrow q]$. It should be noted that, usually interpolation is carried out before decimation to eliminate information loss in the pre-filtering of decimation.

Most often, cepstral features are the speech features of choice for many speaker and speech recognition systems. For example, the Mel-frequency cepstral coefficient (MFCC) [3] representation of speech is probably the most commonly used representation in speaker recognition and speech recognition applications [4]–[6]. In general, cepstral features are more compact, discriminable, and most importantly, nearly decorrelated such that they allow the diagonal covariance to be used by the hidden Markov models (HMMs) effectively. Therefore, they can usually provide higher baseline performance over filter bank features [7].

In [8] 6 types of filter banks were proposed to calculate MFCC’s on subsampled speech and used Pearson coefficient as a measure of similarity to compare the MFCC of subsampled speech and the MFCC of original speech. In the present work, a Mel filter bank construct is presented that is able to extract significantly more correlated MFCC’s of the subsampled speech with respect to the MFCC’s of original speech. We also experimentally show that the new Mel filter bank construction performs better than all the six approaches mentioned in [8] in addition we perform speech recognition experiments on AN4 speech database [9] using open source ASR engine [10] to show the recognition performance on resampled speech is as good as the recognition accuracy on original speech. One of the application of this work is in the scenario where training is done on original speech and decoding has to be done on subsampled speech.

In Section II procedure to compute MFCC features is discussed. In Section III we derive a relationship between the MFCC parameters computed for original speech and the time scaled speech. In Section IV, new filter bank approach is proposed. Section V gives the details of the experiments conducted to substantiate advantage of proposed modified filter bank and we conclude in Section VI.
II. COMPUTING THE MFCC PARAMETERS

The outline of the computation of Mel frequency cepstral coefficients (MFCC) is shown in Figure 1. In general, the MFCCs are computed as follows. Let \( x[n] \) be a speech signal with a sampling frequency of \( f_s \), and is divided into \( P \) frames each of length \( N \) samples with an overlap of \( N/2 \) samples such that \( \{\tilde{x}_1[n], \tilde{x}_2[n], \cdots, \tilde{x}_p[n], \cdots, \tilde{x}_P[n]\} \), where \( \tilde{x}_p[n] \) denotes the \( p^{th} \) frame of the speech signal \( x[n] \) and is \( \tilde{x}_p[n] = \{x[p \cdot \frac{N}{2} - 1 + i]\}_{i=0}^{N-1} \) Now the speech signal \( x[n] \) can be represented in matrix notation as \( X = [\tilde{x}_1, \tilde{x}_2, \cdots, \tilde{x}_p, \cdots, \tilde{x}_P] \). Note that the size of the matrix \( X \) is \( N \times P \). The MFCC features are computed for each frame of the speech sample (namely, for all \( \tilde{x}_p \)).

In speech signal processing, in order to compute the MFCCs of the \( p^{th} \) frame, \( \tilde{x}_p \) is multiplied with a hamming window \( w[n] = 0.54 - 0.46 \cos\left(\frac{n\pi}{N}\right) \), followed by the discrete Fourier transform (DFT) as shown in (1).

\[
X_p(k) = \sum_{n=0}^{N-1} x_p[n]w[n] \exp^{-j \frac{2\pi n k}{N}} \tag{1}
\]

for \( k = 0,1,\cdots, N-1 \). If \( f_s \) is the sampling rate of the speech signal \( x[n] \) then \( k \) corresponds to the frequency \( f_k(k) = \frac{f_s}{N}k \). Let \( \bar{X}_p = [X_p(0), X_p(1), \cdots, X_p(N-1)]^T \) represent the DFT of the windowed \( p^{th} \) frame of the speech signal \( x[n] \), namely \( \tilde{x}_p \). Accordingly, let \( X = [\bar{X}_1, \bar{X}_2, \cdots, \bar{X}_p, \cdots, \bar{X}_P] \) represent the DFT of the matrix \( X \). Note that the size of \( X \) is \( N \times P \) and is known as STFT (short time Fourier transform) matrix.

The modulus of Fourier transform is extracted and the magnitude spectrum is obtained as \( |X| \) which again is a matrix of size \( N \times P \).

The modulus of Fourier transform is extracted and the magnitude spectrum is obtained as \( |X| \) which is a matrix of size \( N \times P \). The magnitude spectrum is warped according to the Mel scale in order to adapt the frequency resolution to the properties of the human ear.

Note that the Mel \( (\phi_f) \) and the linear frequency \( (l_f) \) are related, namely, \( \phi_f = 2595\log_{10}(1 + l_f/700) \) where \( \phi_f \) is the Mel frequency and \( l_f \) is the linear frequency. Then the magnitude spectrum \(|X|\) is segmented into a number of critical bands by means of a Mel filter bank which typically consists of a series of overlapping triangular filters defined by their center frequencies \( l_{fc}(m) \).

The parameters that define a Mel filter bank are (a) number of Mel filters, \( F \), (b) minimum frequency, \( l_{fmin} \) and (c) maximum frequency, \( l_{fmax} \). For speech, in general, it is suggested in (4) that \( l_{fmin} > 100 \text{ Hz} \). Furthermore, by setting \( l_{fmin} \) above 50/60Hz, we get rid of the hum resulting from the AC power, if present. (4) also suggests that \( l_{fmax} \) be less than the Nyquist frequency. Furthermore, there is not much information above 6800 Hz. Then a fixed frequency resolution in the Mel scale is computed using \( \delta f_f = (\phi_f_{max} - \phi_f_{min})/(F + 1) \) where \( \phi_f_{max} \) and \( \phi_f_{min} \) are the frequencies on the Mel scale corresponding to the linear frequencies \( l_{fmax} \) and \( l_{fmin} \) respectively. The center frequencies on the Mel scale are given by \( \phi_{fc}(m) = m.\delta \phi \) where \( m = 1,2,\cdots,F \). To obtain the center frequencies of the triangular Mel filter bank in Hertz, we use the inverse relationship between \( l_f \) and \( \phi_f \) given by \( l_f(m) = 700(10^{\phi_{fc}(m)/2595} - 1) \). The Mel filter bank, \( M(m,k) \) is given by

\[
M(m,k) = \begin{cases} 
0 & \text{for } l_f(k) < l_{fc}(m-1) \\
\frac{l_f(k)-l_{fc}(m-1)}{l_f(m)-l_{fc}(m-1)} & \text{for } l_{fc}(m-1) \leq l_f(k) < l_{fc}(m) \\
\frac{l_f(k)-l_{fc}(m+1)}{l_f(m)-l_{fc}(m+1)} & \text{for } l_{fc}(m) \leq l_f(k) < l_{fc}(m+1) \\
0 & \text{for } l_f(k) \geq l_{fc}(m+1)
\end{cases}
\]

The Mel filter bank \( M(m,k) \) is an \( F \times N \) matrix.

The logarithm of the filter bank outputs (Mel spectrum) is given in (2).

\[
\Phi_p \{x[n]\} = \sum_{m=1}^{F} L_p(m,k) \cos\left\{r\frac{(2m-1)\pi}{2F}\right\} \tag{3}
\]

where \( r = 1,2,\cdots,F \) and \( \Phi^r_p \{x[n]\} \) represents the \( r^{th} \) MFCC of the \( p^{th} \) frame of the speech signal \( x[n] \). The MFCC of all the \( P \) frames of the speech signal are obtained as a matrix \( \Phi \)

\[
\Phi \{X\} = \Phi_1, \Phi_2, \cdots, \Phi_p, \cdots, \Phi_P \tag{4}
\]

Note that the \( p^{th} \) column of the matrix \( \Phi \), namely \( \Phi_p \) represents the MFCC of the speech signal, \( x[n] \), corresponding to the \( p^{th} \) frame, \( x_p[n] \).

III. MFCC OF RESAMPLED SPEECH

In this section, we show how the resampling of the speech signal in time effects the computation of MFCC parameters. Let \( y[s] \) denote the time scaled speech signal given by

\[
y[s] = x[\alpha n] = x \downarrow \alpha \tag{5}
\]

where \( \alpha \) is the scaling factor. Let \( y_p[s] = x_p[\alpha n] = x_p \downarrow \alpha \) denote the \( p^{th} \) frame of the time scaled speech where \( s = 0,1,\cdots,S-1 \), \( S \) being the number of samples in the time scaled speech frame given by \( S = \frac{N}{\alpha} \). If \( \alpha < 1 \) the signal is expanded in time while \( \alpha > 1 \) means the signal is compressed in time. Note that if \( \alpha = 1 \) the signal remains unchanged. DFT of the windowed \( y_p[n] \) is calculated from the DFT of \( x_p[n] \). Assuming that \( \alpha \) is an integer and using the scaling property
of DFT, we have,

$$Y_p(k') = \frac{1}{\alpha} \sum_{l=0}^{\alpha-1} X_p(k' + lS)$$  \hspace{1cm} (6)

where $$k' = 1, 2, \ldots, S$$. The MFCC of the time scaled speech are given by

$$\Phi_p^r(n) = \Phi_p^r \{ x \downarrow \alpha \} = \sum_{m=1}^{F} L_p^r(m, k') \cos \left( \frac{r(2m-1)\pi}{2F} \right)$$  \hspace{1cm} (7)

where $$r = 1, 2, \ldots, F$$ and

$$L_p^r(m, k') = \ln \left\{ \sum_{k' = 0}^{S-1} M'(m, k') \left| \frac{1}{\alpha} \sum_{l=0}^{\alpha-1} X_p(k' + lS) \right| \right\}$$  \hspace{1cm} (8)

Note that $$L_p^r$$ and $$M'$$ are the log Mel spectrum and the Mel filter bank of the resampled speech. We propose a filter bank, $$M'(m, k')$$ which is used in the calculation of MFCC of the resampled speech. Note that a good choice of the Mel filter bank is the one which gives (a) the best Pearson correlation between the MFCC of the original speech and the MFCC of the resampled speech and (b) best speech recognition accuracies when trained using the original speech and decoded using the subsamples speech.

IV. MODIFIED FILTER BANK

One of the major steps in the computation of MFCC of subsampled speech is through construction of the Mel filter bank. The proposed Mel filter bank $$M_{new}(m, k')$$ for subsampled speech is given as

$$M_{new}(m, k') = \begin{cases} M(m, ak') & \text{for } l_f(k') \leq \left( \frac{f_s}{2\alpha} \right) \\ 0 & \text{for } l_f(k') > \left( \frac{f_s}{2\alpha} \right) \end{cases}$$

where $$k'$$ ranges from 1 to $$N/2$$. Notice that the modified filter bank is the subsampled version of original filter bank with bands above $$f_s/2\alpha$$ set to 0. In other words the center frequencies and bandwidths of proposed filter bank and original filter bank are the same for $$f_c < f_s/2\alpha$$. In order to keep the total number of filter bank outputs same as original we fill in the remaining filter bank outputs in the following manner. Let $$F_c$$ be the number of filter banks whose $$f_c$$ is below $$f_s/2\alpha$$ and let $$L_{new,p}(m, k')$$ be output of the $$p^{th}$$ Mel filter bank. Then we define outputs of Mel filter banks

$$L_{new,p}(m, k') = (0.95)^{m-F_c} L_{new,p}(F_c, k')$$  \hspace{1cm} (9)

where $$F_c < m \leq F$$.

In all our experiments, we assume, (a) $$\alpha = 2$$, (b) the number of Mel filters used for the feature extraction of original speech and that of the resampled speech are same and, (c) the window length reduces by half, namely, $$N/2$$.

V. EXPERIMENTAL RESULTS

We conducted experiments on AN4 audio database. It consists of 948 train and 130 test audio files and the test audio files contain 773 spoken words or phrases. The recognition results are based on these 773 words and phrases. All the speech files in the AN4 database are sampled at 16 KHz. The Mel filter bank used has $$F = 30$$ bands spread from $$f_{min} = 130$$ Hz to a maximum frequency of $$f_{max} = 6800$$ Hz and the frame size if of 32 ms. The MFCC parameters (denoted by $$\Phi\{x[n]\} = \{\Phi_1, \Phi_2, \ldots, \Phi_m, \ldots \Phi_F\}$$) are computed for the 16 KHz speech signal $$x[n]$$, as described in Section II. We then subsampled $$x[n]$$ by a factor of $$\alpha = 2$$ and constructed $$y[s] = x \downarrow 2 = x[2n]$$. The MFCC parameters of $$y[s]$$ (denoted by $$\Phi\{y[s]\} = \{\Phi_1', \Phi_2', \ldots, \Phi_m', \ldots \Phi_F'\}$$) are calculated using the proposed Mel filter bank (9). We conducted two types of experiments to evaluate the performance of using the proposed Mel filter bank construction. We used, as done in [8]. Pearson coefficient to compare the MFCC of the subsampled speech with the MFCC of the original speech; in addition we used speech recognition accuracies to compute the appropriateness of the Mel filter bank construction. Pearson correlation coefficient (denoted by $$r$$) is computed between the MFCC parameters of the subsampled speech (using different Mel filter bank constructs) and the MFCC of the original speech in two different ways and the speech recognition experiments were done using Sphinx ASR. We trained HMM models using train data set using the Sphinx toolbox and accuracies were calculated on the test data using Sphinx.

A. Comparison using Pearson Coefficient

We considered two types of evaluations. In Case I the $$F$$-dimensional MFCC vector of each frame is concatenated and the $$r$$ between the MFCC of the original speech and the MFCC of the subsampled speech is computed. The mean and variance of Pearson correlation coefficients, $$r$$ for the proposed method and 6 methods of [8] are shown in Table I for 130 test samples. In Case II instead of concatenating MFCCs of all the frames, we computed $$r$$ for MFCCs of each frame of subsampled speech and the original speech. The mean and variances of $$r$$ are shown in Table I. Clearly the proposed Mel filter bank construction performs better than the ones suggested in [8] in both the cases. Compare 0.986 of the proposed method to the 0.913 best of [8] for Case I and 0.961 compared to 0.756 for Case II.

1Note that $$\Phi_m$$ is a vector formed with the $$m^{th}$$ MFCC of all the speech frames

### Table I

| Filter bank | Case I | Case II |
|-------------|--------|---------|
| Type        | mean variance | mean variance |
| Proposed    | 0.986 0.00004 | 0.961 0.00433 |
| A [8]       | 0.868 0.00196 | 0.692 0.14715 |
| B [8]       | 0.913 | 0.756 0.07570 |
| C [8]       | 0.906 0.00104 | 0.746 0.08460 |
| D [8]       | 0.842 0.00266 | 0.662 0.16834 |
| E [8]       | 0.756 0.00572 | 0.619 0.15979 |
| F [8]       | 0.798 0.00431 | 0.680 0.10893 |
TABLE II
RECOGNITION ACCURACIES (PERCENTAGE)

| Filter bank Type | Case A | Case B |
|------------------|--------|--------|
| Original (16 kHz) |        |        |
| Proposed (8 kHz) | 43.21  | 81.63  |
| A (8 kHz)        | 37.00  | 77.62  |
| B (8 kHz)        | 2.72   | 11.00  |
| C (8 kHz)        | 3.88   | 11.90  |
| D (8 kHz)        | 0.78   | 2.85   |
| E (8 kHz)        | 1.68   | 1.03   |
| F (8 kHz)        | 1.94   | 2.46   |

B. Speech recognition Performance

We used 948 training speech samples of AN4 database to build acoustic models using Sphinx train tool box. Training is done using speech features calculated on the 16 kHz (original) speech files. Recognition is performed on the 130 test speech samples, both for the original (16 kHz) and subsampled (8 kHz) speech. In Case A we extracted 30 MFCC’s while in Case B we extracted 30 MFCC and used only the first 13 of them and appended them with 13 velocity and 13 acceleration coefficients to form a 39 dimensional feature vector. Recognition accuracies are shown in Table II as word recognition rate on the 773 words in the 130 test speech files. It can be observed that word recognition accuracies using the proposed Mel filter bank on subsampled speech is closer to the baseline word recognition accuracies calculated on the original speech for both Case A and Case B and much higher than the best Mel filter bank in [8]. Compare 37% to 3.88% and 77.62% to 11.90% in Table II for Case A and Case B respectively. The improved performance of the proposed Mel filter bank in terms of recognition accuracies can be explained by looking at a sample filter bank output shown in Fig.2. Filter bank output of the proposed Mel filter bank construct (red line; ‘+’) closely follows that of the original speech Mel filter bank output (blue line; ‘x’), while that of C (best in [8]) filter bank (black line; ‘o’) shows a shift in the filter bank outputs. This is primarily because the center frequencies and bandwidths of filter bank (C in [8]) are different from original filter bank, but this is not true in the method proposed in this paper.

VI. CONCLUSION

We proposed a modified Mel filter bank to extract MFCC from subsampled speech which correlates well with the MFCC of the original speech. We showed that the proposed Mel filter bank outperforms all the Mel filter banks developed in [8] experimentally both in terms of correlation with the MFCC of the original speech and also through word recognition accuracies. The primary importance of this work is when there are available trained models for speech of one sampling frequency and the recognition has to be performed at a subsampled or compressed speech. The suggested Mel filter bank makes it possible to use the HMM models of the original speech without having to train the speech engine again with the subsampled speech.

REFERENCES

[1] B. Arons, “Techniques, perception, and applications of time-compressed speech,” Proceedings of American Voice I/0 Society, pp. 169–177, Sep. 1992.
[2] D. J. Hejna, “Real-time time-scale modification of speech via the synchronized overlap-add algorithm,” Master’s thesis, MIT, Department of Electrical Engineering and Computer Science, 1990.
[3] S. B. Davis and P. Mermelstein, “Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences,” IEEE Trans. Acoust. Speech Signal Processing, vol. 28, no. 4, pp. 357–366, 1980.
[4] D. A. Reynolds and R. C. Rose, “Robust text-independent speaker identification using Gaussian mixture speaker models,” IEEE Transactions on Speech and Audio Processing, vol. 3, No. 1, January 1995.
[5] M. R. Hasan, M. Jamil, M. G. Rabban, and M. S. Rahman, “Speaker identification using Mel frequency cepstral coefficients,” 3rd International Conference on Electrical & Computer Engineering ICECE 2004, 28-30 December 2004, Dhaka, Bangladesh.
[6] H. Seddik, A. Rahmouni, and M. Sayadi, “Text independent speaker recognition using the Mel frequency cepstral coefficients and a neural network classifier,” First International Symposium on Control, Communications and Signal Processing, pp. 631–634, 2004.
[7] Z. Jun, S. Kwong, W. Gang, and Q. Hong, “Using Mel-frequency cepstral coefficients in missing data technique,” EURASIP Journal on Applied Signal Processing, vol. 2004, no. 3, pp. 340–346, 2004.
[8] S. Kopparapu and L. Narayana, “Choice of Mel filter bank in computing MFCC of a resampled speech,” International Conference on Information Science, Signal processing and their applications (ISSPA), 2010.
[9] CMU. AN4 database. [Online]. Available: http://www.speech.cs.cmu.edu/databases/an4/
[10] ——, Sphinx. [Online]. Available: http://www.speech.cs.cmu.edu/
[11] Oppenheim and Schafer, Discrete Time Signal Processing. Prentice-Hall, 1989.
[12] S. Molau, M. Pit, R. S. Uter, and H. Ney, “Computing Mel-frequency cepstral coefficients on the power spectrum,” Proc. Int. Conf. on Acoustic, Speech and Signal Processing, pp. 73 – 76, 2001.
[13] T. F. Quatieri, “Discrete-time speech signal processing: Principles and practice,” Pearson Education, vol. II, pp. 686, 713, 1989.
[14] CMU. Mel filter bank. [Online]. Available: http://cmusphinx.sourceforge.net/sphinx4/javasrc/edu/cmu/sphinx/frontend/frequencywarp/MelFrequencyFilterBank.html
[15] S. Sigurdsson, K. B. Petersen, and T. L. Schiller, “Mel frequency cepstral coefficients: An evaluation of robustness of MP3 encoded music,” Conference Proceedings of the Seventh International Conference on Music Information Retrieval (ISMIR), Victoria, Canada, 2006.