Filterbank-based Feature Extraction for Speech Recognition and Its Application to Voice Mail Transcription

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ABSTRACT

In this paper, we propose a filterbank-based technique to extract more robust and discriminative features for the application of telephony speech recognition. First, we propose an extended Lerner grouping method to approximate the shape of the Mel filters in MFCC while reducing the cross-correlation between filterbank outputs. Then we used Welch processing to reduce the variance of the spectral features while retaining the spectral resolution. Finally, we describe experiments where we augment the cepstral features with formant related features, computed using an adaptive filterbank. The new features represent the trajectory of the frequency components within different formant bands. Experimental results showed that the Welch processing consistently improved the word error rate on a task of large vocabulary voice mail transcription and the formant related features provide higher discriminability than the MFCC features.

1. INTRODUCTION

Conventional speech features are extracted based on the power spectrum which contains information related to the source signal and the vocal tract. Typically, the power spectrum of a speech frame is computed via an FFT or a filter-bank analysis, and a number of studies have shown that perceptually based filter-bank analysis is more robust than an FFT-based representation. In the original Lerner grouping design, each bandpass filter was realized by a weighted sum of adjacent parallel second-order biquadratic filters with the weighting coefficients alternating in sign for adjacent resonators. All the weights were +1 except for the bandpass-edge resonators, for which the weights were +0.5. In our method, we use an “extended” Lerner design technique in which each Lerner weighting coefficient can have an arbitrary value constrained by the fact that the alternating sign condition is still maintained. In our experiment, we want to design a set of Lerner coefficients which has a passband similar to the Mel filters, and that also provide low sidelobes. In section 3, we introduce a Welch processing technique to get smoother speech features. A new set of features based on locating spectral peaks is proposed in section 4. We present some experimental results in voice mail transcription and discriminant analysis (LDA) of the new feature in section 5.

2. LERNER GROUPED FEATURES

Lerner grouping is a method of realizing bandpass filters with relatively low sidelobes, by grouping together the outputs of uniformly spaced element bandpass filters. The Lerner grouping design was originally proposed for realizing continuous-time filter-banks having almost linear-phase bandpass outputs with good stopband performance. In the original Lerner grouping method, each bandpass filter was realized by a weighted sum of adjacent parallel second-order biquadratic filters with the weighting coefficients alternating in sign for adjacent resonators. All the weights were +1 except for the bandpass-edge resonators, for which the weights were +0.5. In our method, we use an “extended” Lerner design technique in which each Lerner weighting coefficient can have an arbitrary value constrained by the fact that the alternating sign condition is still maintained. In our experiment, we want to design a set of Lerner grouping coefficients which has a passband similar to the Mel filters in MFCC feature extraction. The criterion to design the Lerner coefficients is now given by:

\[
\hat{l}_{kN}^{(i)} = \arg \min_{l_{kN}^{(i)}} \left\| l_{kN}^{(i)} - \hat{h}_{kN}^{(i)} F_{kN}^{-1} \right\| , \quad k = 1, 2, \ldots, K
\]

subject to

\[
\hat{h}_{iL}^{(i)} = \hat{l}_{iL}^{(i)} \cdot \text{sign}(\hat{h}_{iL}^{(i)}) \times \text{sign}(\hat{l}_{iL}^{(i)}) = -1
\]
Where $\hat{h}^{(k)}_{\text{Mel}}$ is the desired impulse response of the $k$-th Mel filter in the time-domain; $K$ is the number of channels; $F_{N \times N}$ is the DFT matrix; $\tilde{i}^{(k)}_{\text{lth}}$ is the lerner grouping of coefficients for the $k$-th channel. This is a least-squares problem and we can get a closed form solution:

$$\tilde{g}^{(k)} = \hat{h}^{(k)} F^{-1}, \quad \tilde{g}^{(k)} = [g^{(k)}_1, g^{(k)}_2, \ldots, g^{(k)}_N]$$

(3)

$$\tilde{i}^{(k)}_l = [I^{(k)}_1, I^{(k)}_2, \ldots, I^{(k)}_N], \quad I^{(k)}_l = g^{(k)}_l$$

(4)

$$I^{(k)}_{lj} = I^{(k)}_{l-1,j} = (-1)^j \frac{1}{2} (g^{(k)}_{lj} + g^{(k)}_{lj-1}), \ j = 1, 2, \ldots, D$$

(5)

In our experiment, we use lerner coefficients computed in Eqs. (3)-(5) to group the real part of the spectrum of the speech signal, then pass it through a DCT transformation matrix to get features similar to MFCC speech feature. The experimental results on voice mail transcription are given in section 5.

3. WELCH PROCESSING

In our experiment, we found that the log operation that follows the binning of the power spectrum outputs causes the variance of the features to increase greatly. In order to get a smoother feature while keeping the spectral resolution, we applied a lowpass filter to smooth the feature before the log operation. As in [6], we used a simple average for the lowpass filtering operation. The binned outputs were computed every 2 ms, and then averaged over 10 ms to yield an estimate of the binned outputs every 10 ms. Experimental results using this welch processing on voice mail transcription are presented in section 5.

4. PSEUDO-GRADIENT-BASED NEW SPEECH FEATURES

4.1 Pseudogradient of the resonator filter-bank

It is well known that spectral transitions and dynamics play an important role in the perception of speech [9]. In this paper, we propose a set of new features based on an adaptive filter to capture the dynamics of the local concentration of energy within different formant bands of the speech signal. The adaptive filter comprises of a number of digital resonators in a feedback loop [5] – the result being a multiple notch transfer function with notches at the resonator frequencies. The adaptive algorithm adapts these resonator frequencies to minimize the power at the notch output – hence the resonator frequencies track the frequencies of the sinusoidal components in the input. The $i$'th resonator frequency is controlled by a single coefficient, $k_i$, and a gradient or “pseudo-gradient” method can be used to adapt the parameter $k_i$:

$$k_i(n + 1) = k_i(n) - \mu \nabla_i(\omega)$$

(6)

Where $\nabla_i(\omega)$ denotes the gradient of the error power $E[\epsilon_i^2]$ with respect to the coefficient $k_i$, $\mu$ is the step size. As the error surface is extremely multimodal, gradient descent techniques could lead to the filter converging to local minima, consequently we use a pseudogradient (rather than the gradient) to adapt the parameters $k_i$. It was proved in [6] that this pseudogradient can guarantee global convergence under certain conditions, and has lower computational complexity ($O(N)$) as compared to the true gradient. The pseudogradient is computed by correlating the error signal $\epsilon_i$ with the output of a pseudo-sensitivity filter:

$$\nabla_p(\omega) = \frac{1}{2\pi} \int H(z^{-1}) H_p(z) \bar{X}(z) z e i \omega d\omega$$

(7)

where $\bar{X}(z)$ denotes the $z$-transform of the input signal. For a single sinusoidal input signal with frequency $\omega$, the pseudogradient $\nabla_p(\omega)$ is given by:

$$\nabla_p(\omega) = -2G \frac{d\omega}{d\omega} \left[2\cos(\omega) - 2\omega \right]$$

(8)

In order to reduce the variance of the instantaneous pseudo-gradient estimates, and to normalize out the amplitude of the input signal, we used a normalized version of the pseudogradient, given by:

$$\hat{\nabla}_p(\omega) = \frac{E[H_p(\omega) \dot{H}_p(\omega) \phi]}{E[H_p(\omega) \dot{H}_p(\omega) \phi]}$$

(9)

where $x(t)$ and $x_p(t)$ denote the error signal and the $t$-th pseudo-sensitivity filter output of the $t$-th input data sample, respectively. $T$ is the number of samples in a speech frame.
Fig. 6. Pseudogradient (a) and normalized pseudogradients (b)

Fig. 6(a) and 6(b) show the pseudogradients and normalized pseudogradients for a two-resonator system with two closely spaced normalized resonator frequencies \( f_1 = 0.0804 \) and \( f_2 = 0.10 \), respectively. We can see from these two figures that for both the pseudogradients and the normalized pseudogradients, the sign of the signal correlates with whether the input frequency is greater or less than the resonator frequency, in the neighbourhood of the resonator frequency, there is in fact a linear relationship between the pseudogradient and the input sinusoidal frequency. Consequently, the pseudogradient can be used to get an estimate of the input sinusoidal frequency. Further, the pseudogradient has a much stronger dependence on the amplitude of the input sinusoidal frequency. Indeed, the pseudogradient can be used to get an estimate of the input sinusoidal frequency.

4.2 Linear discriminant analysis (LDA)

Phonemes.

For these new features to distinguish between different classes, we use linear discriminant analysis (LDA) to quantify the ability of the linear projection \( \tilde{v}_i \) which is called the leading linear discriminant of the data set. We’ll compare the leading eigenvalue \( d_1 \) of the new feature set with the MFCC feature set in the next section.

5. EXPERIMENTAL RESULTS

5.1 Experiment results on voice mail transcription

In this part, we present results on a large vocabulary, speaker-independent, conversational telephone speech recognition (voicemail transcription) task. We primarily report results of speech recognition experiments that used the Welch smoothing technique on baseline MFCC features, and some preliminary analysis of the discriminability of the new pseudo-gradient features. The vocabulary size of the voice mail database is 20K words. The recognition system has 2313 context-dependent states and about 70K Gaussians. The language model perplexity is about 100. The baseline extracted features consist of 13 MFCC and their first and second temporal derivatives. We experimented with two different training and test sets - the first training set “vmtrgabcd” has 20 hours of telephone speech and the second set “vmtrgabcd” contains 70 hours of telephone speech. The first test data set “vmt.test2b” has 43 phone-mail messages with 1986 words and the second test data set “vmt.test2c.sort” has 86 phone-mail messages with 6925 words. Experimental results of the phone recognition accuracy and word error rate (WER) are listed in Table I and II, respectively.

| Table I. Phone recognition accuracy of the baseline and welch processing |
|-----------------------------|-----------------------------|
| Vmt.test2b (baseline)       | Vmtrgabcd                   |
| 28.43%                      | 28.88%                      |
| Vmt.test2b (welch)          | 28.64%                      |
| Vmt.test2c (baseline)       | 30.35%                      |
| Vmt.test2c (welch)          | 30.55%                      |

The dimension of the feature space is \( K \), we can define the within-class covariance matrix, respectively. If the parameters \( d_i \) by:

\[
d_i = \max_i \left( \frac{\tilde{v}_i^T B_{\tilde{v}_i}}{\tilde{v}_i^T W_{\tilde{v}_i}} \right), \quad i = 1, 2, \ldots, K
\]

Then \( d_i \) for \( i = 1 \) denotes the maximum of the ratio of the inter-class distance and the average within class variance. Hence, \( d_1 \) is a measure of the discriminative ability of the linear projection \( \tilde{v}_i \) which is called the leading discriminant of the data set.
Table II. WER of the baseline and the welch processing

<table>
<thead>
<tr>
<th>Vmt.test2b+Vmt.test</th>
<th>Vmtrgab</th>
<th>Vmtrgabcd</th>
</tr>
</thead>
<tbody>
<tr>
<td>2c (baseline)</td>
<td>43.72%</td>
<td>43.74%</td>
</tr>
<tr>
<td>Vmt.test2b+Vmt.test</td>
<td>43.68%</td>
<td>43.52%</td>
</tr>
</tbody>
</table>

We can see from Table I and II that welch processing consistently improves the phone accuracy over the baseline for different combinations of training and testing conditions. The WER of the lerner grouped features is 47.89% with the training set “vmtrgab” and test set “vmt.test2b”. The higher error rate appears to be because the lerner features have a much larger variance than the Mel features (possibly because the binning is done in the amplitude domain, rather than in the power domain, leading to much smaller-valued features as the input to the log function).

5.2 LDA of the pseudo-gradient-based feature set
In this part, we carried out some experiments on the LDA analysis of the pseudo-gradient-based feature set and its combination with the conventional MFCC feature set. First, we try to augment the conventional MFCC features (MFCC1-12+C0) with the two pseudo-gradient-based features and to compare the leading eigenvalue of LDA analysis for the new feature (MFCC1-12 + pseudo-gradients 1-2+ C0) and the MFCC feature (MFCC1-12 + C0). The leading eigenvalue of the first 3 MFCC features and the first 3 augmented features are listed in Table III.

Table III. LDA measurement $d_i$ of the MFCC feature and new augmented feature.

<table>
<thead>
<tr>
<th>MFCC+C0(1-5)</th>
<th>2.9414</th>
<th>2.3814</th>
<th>1.9402</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augmented feature (1-5)</td>
<td>2.9466</td>
<td>2.4313</td>
<td>1.9922</td>
</tr>
</tbody>
</table>

Furthermore, we replace the last two components (MFCC 11 - 12) of the MFCC features by the first two pseudo-gradient-based features. We call the new features mixed features. The leading eigenvalue of the mixed features and the MFCC features are listed in Table IV.

Table IV. LDA measurement $d_i$ of the MFCC feature and new mixed feature.

<table>
<thead>
<tr>
<th>MFCC+C0(1-5)</th>
<th>2.9414</th>
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<th>1.9402</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mixed feature (1-5)</td>
<td>2.9453</td>
<td>2.4310</td>
<td>1.9904</td>
</tr>
</tbody>
</table>

We can see from Table III and Table IV that both the augmented features and the mixed new features help to increase the discriminative ability of the features over conventional MFCC features.

6. DISCUSSION
The welch processing helps to decrease the variance of the speech features and consistently improve the phone recognition accuracy and the WER by some extend. The pseudo-gradient-based features represent the trajectory of the movement of the frequency components within different formant bands. LDA analysis shows that this new feature improves the discriminative ability to distinguish between different phone classes. Future work includes incorporating this new feature into a speech recognition system to improve the recognition performance.

REFERENCES