Bark-shift based nonlinear speaker normalization using the second subglottal resonance*

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Abstract

In this paper, we propose a Bark-scale shift based piecewise nonlinear warping function for speaker normalization, and a joint frequency discontinuity and energy attenuation detection algorithm to estimate the second subglottal resonance (Sg2). We then apply Sg2 for rapid speaker normalization. Experimental results on children’s speech recognition show that the proposed nonlinear warping function is more effective for speaker normalization than linear frequency warping. Compared to maximum likelihood based grid search methods, Sg2 normalization is more efficient and achieves comparable or better performance, especially for limited normalization data.

Index Terms: speaker normalization, speech recognition, nonlinear normalization, VTLN, speaker adaptation

1. Introduction

Speaker normalization is widely used to reduce spectra variations caused by speaker variabilities through frequency warping. One of the most popular normalization approaches is linear frequency warping based vocal tract length normalization (VTLN) [1–5], which assumes that differences in the speakers’ vocal tract lengths result in linearly scaled spectra of each other. Motivated by studies on speech analysis, many nonlinear speaker normalization methods have been proposed. A simple exponential warping function was described in [6] which provided more adjustment at high frequencies than at low frequencies. The work was further extended in [7] to preserve bandwidth after warping. Normalization methods in [8] used the bilinear transform and the more general all-pass transform. However, a comparison in [9] observed no significant performance differences between bilinear and piecewise linear warping functions.

Based on psycho-acoustical observations in [10], authors in [11,12] proposed to use offsets in the Bark scale for speaker normalization, while [9] applied speaker-specific Bark- and Mel-scale based normalization approaches. These Bark-scale based methods directly modified the Hz-Bark conversion formula with a warping factor. On another scale referred to as the ‘speech scale’, which is essentially equivalent to the Mel scale except for a constant coefficient with a value of one, [13,14] proposed a shift-based nonlinear frequency warping function. All of these nonlinear normalization methods have been reported to perform better than linear warping.

To estimate an optimal warping factor, a maximum-likelihood (ML) based grid search is usually applied. Another promising warping factor estimation method is proposed in [15], which uses speaker-specific but content-independent subglottal resonances to calculate a warping factor. Compared to conventional linear VTLN, comparable or better performance has been reported using the second subglottal resonance. In such a method, however, a reliable detection of subglottal resonances is critical to the normalization performance.

In this paper, we propose two novel ideas: 1) a bark-shift based piecewise nonlinear warping function for speaker normalization, and 2) a joint F2 frequency discontinuity and energy attenuation estimation method for Sg2 detection. The Sg2 normalization is compared with ML-based methods for linear, Mel-shift and Bark-shift based warping functions.

2. Speaker normalization through nonlinear frequency warping

Given a warping function \( W(f) \), the spectrum \( S(f) \) is transformed into

\[
S'(f) = S(W(f))
\]

where \( f \) is the frequency scale in Hz. For computational efficiency, \( W(f) \) usually involves only one parameter, the warping factor \( \alpha \). A simple yet effective warping function is a linear scaling function:

\[
W(f) = W_\alpha(f) = \alpha \cdot f
\]

In conventional VTLN, the optimal warping factor is usually estimated using a grid search to maximize the likelihood of warped observations given an acoustic model \( \lambda \):

\[
\alpha = \arg \max_{\alpha \in \mathcal{G}} \sum_{r=1}^{R} \log p(O_r(W_\alpha(f))|\lambda,s_r)
\]

where \( s_r \) is the transcription of the \( r \)th speech file \( O_r \), and \( \mathcal{G} \) is the search grid.

Though widely used, the linear scaling model in Eq. 2 is known to be a crude approximation of the way vocal tract variations affect spectrum. The warping factor between speakers is also observed to be frequency dependent [13]. Motivated by speech analysis, [13, 14] proposed a shift-based nonlinear frequency warping, i.e., to shift upward or downward the Mel scale, which results in nonlinear warping in Hz. As opposed to a linear \( W_\alpha(f) \), the warping function is defined as:

\[
W_\alpha(z) = z + \alpha
\]

where \( z \) is in Mel scale: \( z = Mel(f) = 1127 \log(1 + \frac{f}{700}) \)

The Mel-shift function corresponds to a non-linear relationship in Hz:

\[
f' = e^{\frac{z}{120.7}} \cdot f + 700(e^{\frac{z}{120.7}} - 1)
\]

\*[1] In [13], the coefficient 1127 is changed to 1. Throughout this paper, the standard Mel scale in Eq. 5 is used.
Similar to the linear warping method, the optimal warping factor $\alpha$ for shift-based methods can be estimated using the ML criterion.

In this paper, we propose a Bark-scale shift based warping function defined as in Eq. 4, but where $z$ is now in Bark scale:

$$z = \text{Bark}(f) = 6 \log(f + \sqrt{(f^2 + 1)})$$  \hspace{0.5cm} (7)

Inserting Eq. 7 into Eq. 4, we can derive the frequency (Hz) domain relationship corresponding to a Bark shift:

$$6 \log(f + \sqrt{(f^2 + 1)} = 6 \log(f + \sqrt{(f^2 + 1)} + \alpha$$

$$f' = 600 \cdot 10^{\frac{z - z_{min}}{636}} \cdot f, \quad \text{for } f \gg 600 \text{ Hz}$$

$$f' = 600 + 600(e^{\frac{z}{636}} - 1), \quad \text{for } f \ll 600 \text{ Hz}$$  \hspace{0.5cm} (10)

For high frequency $f \gg 600$ Hz, the Bark shift corresponds to a linear scaling in Hz to 600 Hz; while for low frequency $f \ll 600$ Hz, the Bark shift results in an affine relationship in Hz as the Mel shift (Eq. 6). In general, the Bark shift warping function stretches or compresses lower frequencies more than higher frequencies.

To preserve the frequency bandwidth after warping, a piecewise nonlinear warping function, shown in Fig. 1, is applied such that the lower boundary frequency $f_{min}$ (or $z_{min}$) and the upper boundary frequency $f_{max}$ (or $z_{max}$) are always mapped to themselves, i.e.,

$$W_\alpha(z) = \begin{cases} 
\frac{z - z_{min}}{z_{max} - z_{min}} \cdot (z - z_{min}) + z_{min}, & \text{if } z \leq z_1 \\
\frac{z + \alpha}{z_{max} - z_{min}} \cdot (z - z_{min}) + z_{min} + \alpha, & \text{if } z_1 < z < z_u \\
\frac{z_{max} - z_{min} - \alpha}{z_{max} - z_{min}} \cdot (z - z_u) + z_u + \alpha, & \text{if } z \geq z_u
\end{cases}$$

$$Sg_2 = \beta \times F_2 + (1 - \beta) \times F_2$$

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\end{cases}$$

The proposed Bark-shift based piecewise nonlinear warping function differs from previous Bark-scale based approaches [9, 11, 12] in two aspects. First, the previous methods apply modifications to the Hz-Bark conversion formula directly, which make it difficult to implement in an uniform filter bank.

3. Sg2 detection based on joint frequency and energy measurement

The coupling of the subglottal system to the vocal tract introduces additional pole-zero pairs in the vocal tract transfer function, corresponding to the subglottal resonances. Speech analysis studies have shown that discontinuities and attenuations of formant prominence typically occur near resonances of the subglottal system [16]. To avoid errors, which has been more thoroughly studied than other subglottal resonances. When the second formant (F2) approaches Sg2, an attenuation of 5-12dB in F2 energy prominence (E2) is always observed, while an F2 frequency discontinuity in the range of 50-300Hz often occurs.

Based solely on F2 frequency discontinuities, an automatic Sg2 estimation algorithm (Sg2DF) was developed in [15]. Sg2DF uses a formula (Eq. 14) as a starting point, searches within ±100 Hz around the starting point for a F2 discontinuity in the F2 track, and estimates Sg2 as:

$$Sg_2 = \beta \times F_2^{high} + (1 - \beta) \times F_2^{low}$$

where $F_2^{high}$ and $F_2^{low}$ are the F2 values on the high and low frequency side of the discontinuity, respectively; $\beta$ is a weight in the range (0, 1) that controls the closeness of the detected Sg2 value to $F_2^{high}$. The optimal value of $\beta$ is estimated using the minimum mean square error criterion on training data:

$$\hat{\beta} = \arg \min_\beta E\{(Sg_2 - Sg_2)^2\}$$

If no such discontinuity is detected, Sg2DF is approximated as in [17]:

$$Sg_2 = 0.636 \times F_3 - 103$$

Though simple and efficient, Sg2DF may produce unreliable estimates in cases where F2 discontinuities are not detectable. Since E2 attenuation always occurs when F2 crosses Sg2, a joint F2 and E2 measurement (Sg2DF) is proposed here to improve the reliability of Sg2 estimation. The detection algorithm works as follows:

1. Track F2 and E2 frame by frame using LPC analysis and dynamic programming. The F2 tracking algorithm is similar to that used in Snack [19], with parameters specifically tuned to provide reliable F2 tracking results on children’s speech. Manual verification and/or correction is applied through visually checking the tracking contours against spectrogram.

2. Search within ±100 Hz around $Sg_2$ (Eq. 14) for F2 discontinuities (F2d) and E2 attenuation (E2a). Apply decision rules for Sg2 estimation.

The decision rules are biased toward E2 attenuations, since E2 attenuations are more correlated with Sg2. If the time information of F2 discontinuity matches that of E2 attenuation, as shown in Fig. 2, Eq. 12 is used for Sg2 estimation. Otherwise, if F2 discontinuities are not detectable or F2 discontinuities and E2 attenuations disagree, as shown in Fig. 3, the estimation will only rely on E2 attenuation, and uses the average F2 value around E2a as Sg2. If in some extreme cases E2 attenuation is
Sg2 value for a test speaker, tend that work to nonlinear speaker normalization. Given the frequency warping, and shown to be promising [15]. Here, we ex-

The automatically estimated Sg2 has been applied for linear fre-

Most of the improvements occur in cases where F2 disconti-

the warping factor

Figure 2: Example of the joint estimation method where F2 dis-

Figure 3: Example when there is a discrepancy between loca-

E2 attenuation (at frame 51). The average F2 value within the dotted box is then used as the Sg2 estimate.

not detectable, which rarely occur in our experiments, then Eq. 14 would be used for Sg2 estimation.

The algorithm was tested on children’s data with estimated ground truth Sg2 values using an accelerometer [15, 17]. Com-

F2 and E2 tracking based on LPC analysis, which can be done efficiently. Since Sg2 has been shown to be content independent and remains constant for a given speaker [15, 16], Sg2 estimation doesn’t require large amounts of data, and theoreti-

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5. Experimental results

For computational efficiency, all normalization methods are im-

Figure 3: Example when there is a discrepancy between loca-

and remains constant for a given speaker [15, 16], Sg2
tions of F2 discontinuity (not detectable) and E2 attenuation (at frame 51). The average F2 value within the dotted box is then used as the Sg2 estimate.

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Sg2 is calculated as:

\[ \alpha = \begin{cases} 
\frac{S_{g2,\text{ref}} - S_{g2}}{S_{g2,\text{ref}}} & \text{for linear scaling} \\
\text{Mel}(S_{g2,\text{ref}}) - \text{Mel}(S_{g2}) & \text{for Mel shift} \\
\text{Bark}(S_{g2,\text{ref}}) - \text{Bark}(S_{g2}) & \text{for Bark shift} 
\end{cases} \]  

\[ (15) \]

The ML-based speaker normalization method (Eq. 3) in-

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4For most reliable estimation, the Sg2 detector requires F2 transition crossing Sg2, e.g., as in a diphthong /ai/.
WER is 7.75% using MFCC features and 8.35% using PLPCC features. Three randomly chosen words (including at least one diphthong word) were used for normalization. The ML search grid is [0.9, 1.1] for linear scaling, [-0.7, 0.7] for Bark shifting, and [-100, 100] for Mel shifting. For comparison, the Bark offset method in [12] was also evaluated using PLPCC features.

All experiments were performed in an unsupervised way, and the recognition output from the baseline models (without normalization) was used as transcription during ML grid searching.

Tables 1 and 2 show results on TIDIGITS with various amounts of normalization data for MFCC and PLPCC features, respectively. LS-ML means linear scaling with ML-based warping factor estimation; LS-Sg2 means linear scaling with Sg2-based warping factor estimation; MS represents Mel-shift based nonlinear warping; BS is Bark-shift based nonlinear warping; BO-ML is the method in [12] using ML grid search.

For ML-based warping methods, comparing LS vs. MS for MFCC (rows 1 and 2 in Table 1) and LS vs. BS for PLPCC features (rows 1 and 2 in Table 2), it can be seen that nonlinear frequency warping provides better performance than linear warping in all conditions, which is in agreement with literature.

Due to the bandwidth compensation, the proposed piecewise Bark shift method (BS-ML) outperforms BO-ML except for the case of one normalization digit.

Compared to ML-based methods, Sg2 normalization performs significantly better for up to seven normalization digits with all three warping functions (LS, MS, and BS). With more data, ML-based methods tend to produce close or superior performance, though for the case of Bark shift (BS-ML vs. BS-Sg2, rows 3 and 5 in Table 2), Sg2 outperforms ML in all testing conditions for up to 15 digits. Similar performance trends are observed on TBall data in Table 3.

### Table 1: WER on TIDIGITS using MFCC features with varying normalization data from 1 to 15 digits.

<table>
<thead>
<tr>
<th>Warping</th>
<th>1</th>
<th>4</th>
<th>7</th>
<th>10</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS-ML</td>
<td>7.48</td>
<td>6.34</td>
<td>5.42</td>
<td>4.99</td>
<td>4.91</td>
</tr>
<tr>
<td>MS-ML</td>
<td>6.33</td>
<td>5.47</td>
<td>4.48</td>
<td>4.11</td>
<td>4.08</td>
</tr>
<tr>
<td>LS-Sg2</td>
<td>6.11</td>
<td>5.57</td>
<td>5.05</td>
<td>5.07</td>
<td>5.03</td>
</tr>
<tr>
<td>MS-Sg2</td>
<td>5.29</td>
<td>4.81</td>
<td>4.05</td>
<td>4.13</td>
<td>3.99</td>
</tr>
</tbody>
</table>

### Table 2: WER on TIDIGITS using PLPCC features with varying normalization data from 1 to 15 digits.

<table>
<thead>
<tr>
<th>Warping</th>
<th>1</th>
<th>4</th>
<th>7</th>
<th>10</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS-ML</td>
<td>7.62</td>
<td>6.90</td>
<td>5.78</td>
<td>5.64</td>
<td>5.25</td>
</tr>
<tr>
<td>BS-ML</td>
<td>6.21</td>
<td>5.63</td>
<td>4.56</td>
<td>4.30</td>
<td>4.13</td>
</tr>
<tr>
<td>BO-ML</td>
<td>6.00</td>
<td>5.94</td>
<td>5.33</td>
<td>4.96</td>
<td>4.65</td>
</tr>
<tr>
<td>LS-Sg2</td>
<td>6.15</td>
<td>5.71</td>
<td>5.31</td>
<td>5.47</td>
<td>5.39</td>
</tr>
<tr>
<td>BS-Sg2</td>
<td>5.17</td>
<td>4.76</td>
<td>4.09</td>
<td>4.11</td>
<td>4.05</td>
</tr>
</tbody>
</table>

### Table 3: WER on TBall children’s data using MFCC and PLPCC features with 3 normalization words.

<table>
<thead>
<tr>
<th>MFCC</th>
<th>WER</th>
<th>PLPCC</th>
<th>WER</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS-ML</td>
<td>5.91</td>
<td>BS-ML</td>
<td>5.82</td>
</tr>
<tr>
<td>-</td>
<td>-</td>
<td>BO-ML</td>
<td>6.08</td>
</tr>
<tr>
<td>LS-Sg2</td>
<td>6.10</td>
<td>LS-Sg2</td>
<td>6.33</td>
</tr>
<tr>
<td>MS-Sg2</td>
<td>4.89</td>
<td>BS-Sg2</td>
<td>4.71</td>
</tr>
</tbody>
</table>

### 6. Summary and discussion

In this study, a Bark-scale shift based nonlinear frequency warping is proposed for speaker normalization. The technique preserves frequency bandwidth and can be efficiently implemented through modification of a filter bank analysis. Instead of using maximum likelihood (ML) based grid search for warping factor estimation, the second subglottal resonance (Sg2) is applied to calculate the warping factor. For reliable Sg2 estimation, a joint frequency discontinuity and energy attenuation detection algorithm is proposed. Experiments on two children’s speech recognition tasks show that nonlinear frequency warping outperforms linear warping, and Sg2 normalization is more efficient than ML-based methods, with comparable or better recognition performance, especially when a limited amount of data is available. In future work, we’ll evaluate this method on noisy data sets.

### 7. References