Feature Extraction Combining Spectral Noise Reduction and Cepstral Histogram Equalization For Robust ASR

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Introduction

- Results for Noisy TI-Digits at ICASSP’02
  - Histogram Equalization (HE) can reduce the mismatch of noisy speech better than CMS and CMVN
  - Its performance is increased when applied over partially compensated speech features
- In this work we explore HE performance in combination with Spectral Subtraction
Outline

- System description
- Front-End Spectral Noise Reduction
  - Speech/Non-Speech Detection
  - Spectral Subtraction
- Back-End Processing
  - Frame-Dropping
  - Feature Normalization
- Experimental set-up
- Results and discussion
System Description

Speech signal → FFT → NS → logE → SND → SS → MFCC

Front-End

Back-End

Recog. → FD → SND2 → HE
Spectral Subtraction

- Standard implementation on the magnitude spectrum

\[
|\hat{X}_t(w)| = \max \left\{ \left( |Y_t(w)| - \alpha |\hat{N}_t(w)| \right), \beta |Y_t(w)| \right\}
\]

\[
|\hat{N}_t(w)| = \begin{cases}
    \lambda |\hat{N}_{t-1}(w)| + (1 - \lambda) |Y_t(w)| & \text{Non - Speech} \\
    |\hat{N}_{t-1}(w)| & \text{Speech}
\end{cases}
\]

Over - subtraction \( \alpha = 1.1 \)
Maximum attenuation \( \beta = 0.3 \)
Forgetting factor \( \lambda = 0.95 \)

\( \hat{N}(w) \): Noise estimate
\( Y(w) \): Noisy speech
\( \hat{X}(w) \): Clean speech estimate
Speech/Non-Speech Detection (I)

- Based on log-Energy quantile difference

- Quantiles are estimated over a sliding window of 21 frames (at a frame rate of 100Hz)
  - $Q_{0.5}$ (median) is used to track the noise level $B$
  - $Q_{0.9}$ is used to track the speech level

- $Q_{SNR} = Q_{0.9} - B$ is thresholded to detect speech

- Noise level $B$ is updated with $Q_{0.5}$ whenever non-speech is detected
Speech/Non-Speech Detection (II)

- Characteristics of the SND algorithm
  - Easy and fast implementation
  - Fast tracking of noise level
  - $Q_{SNR}$ is smooth enough to prevent false speech detections
  - Implicit symmetric hang-over
Speech/Non-Speech Detection (III)
Frame-Dropping

- The objective is to remove long speech pauses

- Based on same SND algorithm
  - It works over the noise reduced speech

- One frame is removed only if in the middle of a non-speech segment of predefined length
  - This prevents over-dropping
  - 11 frames are used in this work
**Feature Normalization (I)**

- **CDF-matching for non-linear distortion compensation**

  ★ Given a zero-memory one-to-one general transformation $y = T[x]$

\[
\begin{align*}
    x & \rightarrow p_X(x) \quad \quad \quad \quad \quad \quad \quad y = T[x] \rightarrow p_Y(T[x]) = p_Y(y) \\
    C_X(x) = \int_{-\infty}^{x} p_X(u) \, du \quad \quad \quad \quad \quad C_Y(y) = \int_{-\infty}^{y} p_Y(u) \, du \\
    C_X(x) = C_Y(y) \quad \quad \quad \quad \quad \Rightarrow \quad x = T^{-1}[y] = C_X^{-1}(C_Y(y))
\end{align*}
\]
Feature Normalization (II)

- Two ways of using CDF-matching for mismatch reduction

- CDF-matching for feature compensation
  - $C_X(x)$ is estimated during training
  - During test, $C_Y(y)$ estimate is used to compensate for the mismatch
    \[
    \hat{x} = \hat{T}^{-1}[y] = C_X^{-1}(\hat{C}_Y(y))
    \]

- CDF-matching for feature normalization
  - A predefined $C_X(x)$ is selected (usually Gaussian)
  - For both training and test, features are transformed to match the reference distribution using an estimate of $C_Y(y)$
  - Can be viewed as an extension of CMVN
Feature Normalization (III)

- Previous works: Feature compensation
  - R. Balchandran, R. Mammone. *Non-parametric estimation and correction of non-linear distortion in speech systems* [ICASSP’98]
    - Domain: Speech samples
    - Task: Speaker ID / Sigmoid and cubic distortions
  - S. Dharanipragada, M. Padmanabhan. *A nonlinear unsupervised adaptation technique for speech recognition* [ICSLP’00]
    - Domain: Cepstrum
    - Task: Speech Recognition / Handset / Speaker-phone mismatch
  - F. Hilger, H. Ney. *Quantile based histogram equalization for noise robust speech recognition* [EUROSPEECH’01]
    - Domain: Filter-bank Energy
    - Task: Speech Recognition / AURORA task
Feature Normalization (IV)

- Previous works: Feature normalization
  
  ★ J. Pelecanos, S. Sridharan. *Feature warping for robust speaker verification* [Speaker Odyssey’01]
  - Domain: Cepstrum
  - Task: NIST 1999 Speaker Recognition Evaluation database

  ★ B. Xiang, U.V. Chaudhari,… *Short-time gaussianization for robust speaker verification* [ICASSP’02]
  - Domain: Cepstrum / Short-time
  - Task: Speaker Verification

  ★ J.C. Segura, A. de la Torre, M.C. Benítez,… *Non-linear transformations of the feature space for robust speech recognition* [ICASSP’02]
  - Domain: Cepstrum
  - Task: Speech Recognition / AURORA
Feature Normalization (V)

\[ y = \log(\exp(x + h) + \exp(n)) \quad h = 0.8 \quad n = 3.5 \]
Feature Normalization (VI)

- Implementation details
  - CDF-matching is applied in the cepstrum domain in a feature transformation scheme
  - Each cepstral coefficient is transformed independently to match a Gaussian reference distribution

- Algorithm
  - \( C_y(y) \) is estimated for each feature of each utterance using cumulative histograms
  - The bins centers are transformed and a piecewise linear transformation is constructed
  - The transformation is applied to the input features to get the transformed ones
Feature Normalization (VII)
Experimental set-up

- Database end-pointing
  - Noisy TI-digits and SpeechDat Car databases have been automatically end-pointed
  - SND algorithm is used on clean speech (channel 0) utterances
  - 200ms of silence have been added at the end-points

- Acoustic features
  - Standard front-end: 12 MFCC + logE
  - Delta and acceleration coefficients are appended at the recognizer with regression lengths of 7 and 11 frames respectively

- Acoustic modeling
  - One 16 emitting states left-to-right continuous HMM per digit
  - 3 Gaussian mixture per state
## Aurora 2 results

### TI-Digits Multi-condition Training

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>Average</th>
<th>Rel.Imp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>88.07</td>
<td>87.22</td>
<td>84.56</td>
<td>87.03</td>
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</tr>
<tr>
<td>SS</td>
<td>90.94</td>
<td>88.69</td>
<td>86.29</td>
<td>89.11</td>
<td>9.43%</td>
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<tr>
<td>SS+HE</td>
<td>90.72</td>
<td>89.74</td>
<td>90.03</td>
<td>90.19</td>
<td>15.42%</td>
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<tr>
<td>SS+FD+HE</td>
<td>90.89</td>
<td>89.80</td>
<td>90.11</td>
<td>90.30</td>
<td>17.99%</td>
</tr>
</tbody>
</table>

### TI-Digits Clean-condition Training

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>Average</th>
<th>Rel.Imp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>58.74</td>
<td>53.40</td>
<td>66.00</td>
<td>58.06</td>
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</tr>
<tr>
<td>SS</td>
<td>73.71</td>
<td>69.35</td>
<td>75.63</td>
<td>72.35</td>
<td>37.71%</td>
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<tr>
<td>SS+HE</td>
<td>82.08</td>
<td>82.61</td>
<td>81.73</td>
<td>82.22</td>
<td>55.59%</td>
</tr>
<tr>
<td>SS+FD+HE</td>
<td>82.51</td>
<td>82.78</td>
<td>81.87</td>
<td>82.49</td>
<td>56.45%</td>
</tr>
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</table>

23.57%  
35.51%  
37.22%
### Aurora 3 results

<table>
<thead>
<tr>
<th></th>
<th>WM</th>
<th>MM</th>
<th>HM</th>
<th>Average</th>
<th>Rel. Imp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>92.74</td>
<td>80.51</td>
<td>40.53</td>
<td>75.41</td>
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</tr>
<tr>
<td>SS</td>
<td>95.09</td>
<td>78.80</td>
<td>69.19</td>
<td>82.91</td>
<td>21.92%</td>
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<tr>
<td>SS+HE</td>
<td>94.58</td>
<td>86.53</td>
<td>74.20</td>
<td>86.67</td>
<td>35.10%</td>
</tr>
<tr>
<td>SS+FD+HE</td>
<td>94.58</td>
<td>86.73</td>
<td>73.11</td>
<td>86.46</td>
<td>35.00%</td>
</tr>
</tbody>
</table>

#### Finnish

<table>
<thead>
<tr>
<th></th>
<th>WM</th>
<th>MM</th>
<th>HM</th>
<th>Average</th>
<th>Rel. Imp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>92.94</td>
<td>83.31</td>
<td>51.55</td>
<td>79.22</td>
<td>-----</td>
</tr>
<tr>
<td>SS</td>
<td>95.58</td>
<td>89.76</td>
<td>71.94</td>
<td>87.63</td>
<td>39.00%</td>
</tr>
<tr>
<td>SS+HE</td>
<td>96.15</td>
<td>93.15</td>
<td>86.77</td>
<td>93.00</td>
<td>57.00%</td>
</tr>
<tr>
<td>SS+FD+HE</td>
<td>96.65</td>
<td>94.10</td>
<td>87.03</td>
<td>93.35</td>
<td>61.95%</td>
</tr>
</tbody>
</table>

#### Spanish

<table>
<thead>
<tr>
<th></th>
<th>WM</th>
<th>MM</th>
<th>HM</th>
<th>Average</th>
<th>Rel. Imp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>91.20</td>
<td>81.04</td>
<td>73.17</td>
<td>83.14</td>
<td>-----</td>
</tr>
<tr>
<td>SS</td>
<td>93.41</td>
<td>86.60</td>
<td>84.32</td>
<td>88.75</td>
<td>30.70%</td>
</tr>
<tr>
<td>SS+HE</td>
<td>94.79</td>
<td>88.58</td>
<td>89.32</td>
<td>91.25</td>
<td>45.29%</td>
</tr>
<tr>
<td>SS+FD+HE</td>
<td>94.57</td>
<td>88.07</td>
<td>88.95</td>
<td>90.89</td>
<td>43.00%</td>
</tr>
</tbody>
</table>

#### German
20 mixtures Aurora 2 results

### Features

<table>
<thead>
<tr>
<th>Features</th>
<th>Clean Condition</th>
<th>Multi Condition</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Absolute</td>
<td>Relative</td>
</tr>
<tr>
<td>BL 3mix</td>
<td>58.06</td>
<td>--.--</td>
</tr>
<tr>
<td>BL 20mix</td>
<td>58.04</td>
<td>4.51%</td>
</tr>
<tr>
<td>SS+FD+HE 3mix</td>
<td>82.49</td>
<td>56.45%</td>
</tr>
<tr>
<td>SS+FD+HE 20mix</td>
<td>83.22</td>
<td>62.67%</td>
</tr>
</tbody>
</table>
Gaussian class distortion

- Gaussian class densities are transformed into non-Gaussian ones
Conclusions

- A simple and effective SND algorithm based on logarithmic energy quantile difference is presented.

- HE is evaluated in combination with classical spectral subtraction with mean relative improvements of 37.22% and 46.65% for AURORA 2 and 3 tasks.

- Performance for the 20 mixtures system suggest the need of a higher number of Gaussians after HE.
This slides are available at
http://sirio.ugr.es/segura/pfd/docs/icslp02_sl.pdf