Classifier-based Mask Estimation for Missing Feature Methods of Robust Speech Recognition

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Missing Feature Compensation

“Even then, if she took one step forward”

• Noise corrupts some time-frequency locations more than others
Consider noisy regions “missing”

- All regions of local SNR less than 0 dB considered missing.
- Missing Feature Methods perform compensation using remaining reliable regions.
- No stationarity assumptions are made.
Missing Feature Compensation

- For missing feature methods to be successful, we need a *spectrographic mask*, a binary mask that accurately labels the reliable and corrupt features.
How do we estimate masks?

• Conventional mask estimation methods estimate local SNR
  – Methods assume noise is pseudo-stationary

• Is this really a noise estimation problem?
  – No!
  – Mask estimation is a binary decision process

• Solution: Build a 2-class classifier
  – Use all available information to make a decision
  – No stationarity assumptions about noise
Voiced Speech Feature Extraction

- Most of the energy of voiced speech is centered around the harmonics of the fundamental frequency.

- Noise may or may not contain energy at these frequencies.

- Can we measure how much energy is at the harmonics (**speech**) and how much is not (**noise**)?
Yes! Use Comb Filters

- Capture the energy at and between the harmonics
  - The ratio of the energies of these two filters give us a measure of noise content, the Comb Ratio.

\[
H_{\text{comb}}(z) = \frac{z^{-p}}{1 - g z^{-p}} \quad \quad H_{\text{combshift}}(z) = \frac{-z^{-p}}{1 + g z^{-p}}
\]
Comb Ratio as a measure of SNR

- Average Comb Ratio vs. global SNR for the voiced frames of a single utterance
  - Clear relationship between SNR and the Comb Ratio

**SNR vs. Comb Ratio**

![SNR vs. Comb Ratio diagram]

- **Music**
- **White Noise**
What about the pitch?

- Comb filtering assumes we know the fundamental frequency of the speech signal. (We don’t.)

- There are several pitch tracking algorithms that we can use to estimate the pitch.
More Voiced Speech Features

- Voiced speech has a distinctive spectral contour
  - Noise will change this contour.

/EH/ in “then”

Features to capture spectral contour

- Sub-band Energy to Frame Energy Ratio
- Flatness: variance of the energy in a local spectrographic region
Voiced Speech Feature Summary

- Voiced Feature Set:
  - Comb Ratio
  - Sub-band Energy to Frame Energy Ratio
  - Flatness
  - Ratio of secondary and primary autocorrelation peaks
  - Ratio of sub-band energy to estimate of noise floor energy

- Using *ratios* rather than absolute values for features enables the classifier to be *invariant to overall signal level*
What about the unvoiced speech?

- For unvoiced speech we only use the features that characterize spectral shape:
  - Sub-band Energy to Frame Energy Ratio
  - Flatness
  - Sub-band Energy to Sub-band Noise Floor Ratio
Classification Strategy

- Multivariate Gaussian classifier
- Separate classifier for voiced and unvoiced regions
- Separate classifier per sub-band
- Trained with oracle masks that label training data as reliable or unreliable
How well do we do?

- Speech corrupted by noise
  - 3 noise environments: white noise, factory noise, music
    - Assumption: Known operating environment

  - Training Set:
    - 2880 utterances from Resource Management corrupted with noise at various SNRs.

  - Test Set:
    - 1600 utterances from Resource Management corrupted with noise at a single SNR

- Oracle masks for Evaluation:
  - If local SNR is < -5dB, consider mask location to be corrupt
## Mask Estimation Performance

- Performance compared to “oracle masks” via confusion matrix.

<table>
<thead>
<tr>
<th></th>
<th>AWGN</th>
<th></th>
<th>Factory</th>
<th></th>
<th>Music</th>
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<tr>
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<td>21% 79%</td>
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<tr>
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<tr>
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<td>13% 87%</td>
<td>0</td>
<td>22% 78%</td>
<td>0</td>
<td>28% 72%</td>
</tr>
</tbody>
</table>
Speech Recognition with Estimated Masks

- Speech + White Noise

Recognition Accuracy vs. SNR

Accuracy (%)

Oracle Masks
Classifier Masks
Spec Sub Masks
Baseline

SNR (dB)
Speech Recognition with Estimated Masks

- Speech + Factory Noise

Recognition Accuracy vs. SNR

![Graph showing recognition accuracy vs. SNR]

- Oracle Masks
- Classifier Masks
- Spec Sub Masks
- Baseline
Speech Recognition with Estimated Masks

- Speech + Music

Recognition Accuracy vs. SNR

![Graph showing recognition accuracy vs. SNR](image_url)
Conclusions

- Missing Feature Methods have great potential for compensation for *stationary and non-stationary noises*, if the spectrographic masks are known.

- We have developed a classification scheme for mask estimation that is *free of the stationarity assumptions* made by previous methods.

- We obtained substantial improvements in recognition accuracy with classifier-based masks over conventional mask estimation methods in *all three noise conditions*. 