BBN+UMD Rich Transcription System for Broadcast News

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RT-03F Workshop
Washington, DC
13 November, 2003
Outline

• Broadcast News (BN) System
  – Overview
  – Speaker Recognition
  – Sentence Boundary Detection

  (Speech-to-Text was from RT03S, Disfluency Detection will be given by Matt/Rich)

• Evaluation Results

• Conclusion
BN System Overview

Audio

Speech Detection/Speaker Recognition

Speech Recognition

Sentence Boundary Detection

Disfluency Detection

RT Composer

Rich Transcription

A = Speech/Speaker Information
B = Word Transcriptions
C = Sentence Boundaries
D = Filler Words, Edit Words and IP
Speaker Recognition

- Improved version of the system used in December 2002 dry-run
- rteval_v2.3.pl as the scoring tool for development
- System Diagram for speech detection and speaker recognition:

```
Audio
  ↓
Bandwidth detector
  ↓
Gender detector/
  Speech detector
  ↓
Speaker change detector
  ↓
Speaker clustering
  ↓
Speech segments with
  bandwidth/gender/cluster ids
```
Bandwidth Detection (new for RT03F)

- 2-class GMM model for wide and narrow-band
  - Training Data from 3 languages, English, Chinese, Arabic
  - 20hrs for narrow-band, 40hrs for wide-band
  - 256 GMM components
  - 20-state HMM: 0.2sec minimum duration
  - Viterbi decode

- Benefit
  - Simpler model
  - More general and robust
  - 0.2% improvement on speaker recognition (SR) score
Gender/Speech Detection (unchanged for RT03F)

- Detect within bandwidth-specific segments
- Phoneme decode with 11 classes
  - speech phones: MV, MF, MO, FV, FF, FO
  - non-speech phones: music, silence, breath, lip-smack, laughter
- Training from Hub4 98, 80hrs, male:female =~ 2:1
- Output:
  sequence of broad phoneme classes
Speaker Change Detection (unchanged for RT03F)

- Goal was to find speaker changes within bandwidth-gender specific speech segments
- Hypothesize speaker change on every phoneme class boundary. On average, reduce computation by a factor of 10
- Generalized Likelihood Ratio (GLR) test with duration penalty:
  \[
  \frac{L(z; \mu_z, Z_z)}{L(x; \mu_x, Z_x) L(y; \mu_y, Z_y)} \cdot \left( \frac{1}{N} \right)
  \]
- Non-speech frames not used for GLR tests
- Biased to find more changes on non-speech phonemes

D. Liu, F. Kubala, “Fast Speaker Change Detection for Broadcast News Transcription and Indexing,”
*EUROSpeech'99*, Budapest, Hungary, Volume 3, Page 1031-1034, September 5-9, 1999
Speaker Clustering (improved for RT03F)

- **Online speaker clustering**
  - Clustering decisions are made on the fly
  - Causal process with no latency. Decision cannot be changed later
  - Cannot change bandwidth and gender boundaries
  - Can change speaker boundaries detected by speaker change detection

- **Benefit compared to offline hierarchical-style speaker clustering**
  - Simpler approach
  - Consistently more accurate
  - Run faster
  - No stopping criterion is needed

- **Recent improvement**
  - Distance measure uses the same duration-penalized GLR as used in speaker change detection. (Previous system omitted the penalty term)
  - First and Second order cepstral derivatives added as new features

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D. Liu, F. Kubala, “Online Speaker Clustering,” ICASSP’03, Hong Kong, May, 2003
## Improvement Summary for Speaker Recognition

- STT segmentation from RT03S evaluation as the baseline
- Dev03F: 1.5hrs from ABC, NBC, CNN
- Scored by rteval_v2.3.pl

<table>
<thead>
<tr>
<th>Improvements</th>
<th>SR</th>
<th>RT 1</th>
<th>RT03</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. STT segmentation (baseline)</td>
<td>32.2</td>
<td>12.7</td>
<td>42.7</td>
</tr>
<tr>
<td>2. Bandwidth viterbi decode</td>
<td>32.0</td>
<td>12.7</td>
<td>42.5</td>
</tr>
<tr>
<td>3. Online speaker clustering*</td>
<td>30.9</td>
<td>12.7</td>
<td>40.5</td>
</tr>
<tr>
<td>4. Turning clustering parameters</td>
<td>27.9</td>
<td>12.7</td>
<td>39.2</td>
</tr>
<tr>
<td>5. Duration-penalized GLR for clustering</td>
<td>26.6</td>
<td>12.7</td>
<td>38.0</td>
</tr>
<tr>
<td>6. Improved STT from RT03S</td>
<td>25.1</td>
<td>11.2</td>
<td>35.0</td>
</tr>
<tr>
<td>7. Add derivatives as clustering feature</td>
<td>23.4</td>
<td>11.2</td>
<td>32.4</td>
</tr>
</tbody>
</table>

Relative improvement to baseline: 25% 12% 24%

*The initial parameters for 3. was tuned on Hub4 1996 evaluation data, with reference segmentation*

## Conclusions

- Tuning resulted in the biggest gain of 3% absolute
- Online speaker clustering was 1.1% better than offline speaker clustering in terms of SR scores
- Cepstral derivatives gave a big gain of 1.7% absolute
- RT03 improvement tracks the SR improvement
Sentence Boundary Detection (SBD)

- System is the same as that used in CTS, except for the following differences
  - Sentence boundary decisions were made on bandwidth, gender, and speaker boundaries detected by speaker recognition
  - Linguistic subsystem was only word-based. Part-of-Speech (POS) was not implemented for BN
  - No system combination
Training Data

- **Acoustic training**
  - 17 hours of MDE training data released by LDC, which conforms to "MDE Annotation Spec v5"
  - 70 hours of Hub4 acoustic training data

- **Language model training**
  - All acoustic training data
  - TDT4 transcripts
  - 3 million words
  - Additional PSM data did not help
Improvement Summary for SBD

Baseline uses a silence chopper on the gender decode output
chop on longer silence first
average sentence duration was 4 second

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<tr>
<td>Silence chopper (baseline)</td>
<td>66.5</td>
<td>11.2</td>
<td>32.4</td>
</tr>
<tr>
<td>SBD with CTS settings</td>
<td>64.0</td>
<td>11.2</td>
<td>32.1</td>
</tr>
<tr>
<td>SBD parameters tuning for BN</td>
<td>61.8</td>
<td>11.2</td>
<td>32.1</td>
</tr>
<tr>
<td>Cleanup language model training</td>
<td>61.0</td>
<td>11.2</td>
<td>31.8</td>
</tr>
<tr>
<td>Add PSM language model training</td>
<td>62.3</td>
<td>11.2</td>
<td>32.1</td>
</tr>
<tr>
<td>More Neural Net training epochs (from 130 to 143)</td>
<td>58.5</td>
<td>11.2</td>
<td>31.6</td>
</tr>
<tr>
<td>Relatively improvement</td>
<td>12%</td>
<td>-</td>
<td>2%</td>
</tr>
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</table>

Conclusions

- **Parameter tuning for BN resulted in a gain of 2.2%**
- **More epochs gave a big gain of 2.5%. However no significant gain was observed beyond 143rd epoch**
- **RT03 score was not sensitive to SBD score changes due to the fact that SBD had a much smaller denominator**
Evaluation Results

- Eval03F: 1.5hrs from PRI, VOA, MSNBC

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<tr>
<td>Dev03F</td>
<td>58.5</td>
<td>98.7</td>
<td>81.4</td>
<td>96.2</td>
<td>23.4</td>
<td>11.2</td>
<td>31.6</td>
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<td>Eval03</td>
<td>63.8</td>
<td>94.5</td>
<td>78.8</td>
<td>85</td>
<td>15</td>
<td>11.7</td>
<td>24.3</td>
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Conclusions

- **Good**
  - Very good speaker recognition result. Apparently Eval03F set was easier than Dev03F set
  - Edit performance was better for Eval03F
  - RT03 was also much better, mainly due to better SR

- **Could be better**
  - SBD was about 10% relatively worse for Eval03F
  - Filler performance was about the same, but ... (next slide)
### Problem with filled pauses

- Filled pause detection solely depends on STT, which is not tuned to recognize filled pauses. For STT, pauses are optionally deletable.
- Dev03F and Eval03F are very different on filled pauses (why?)

<table>
<thead>
<tr>
<th>set</th>
<th>#ref</th>
<th>#hyp</th>
<th>#corr</th>
<th>#ins</th>
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<tr>
<td>Dev03F</td>
<td>45</td>
<td>107</td>
<td>36 (80%)</td>
<td>71 (158%)</td>
</tr>
<tr>
<td>Eval03F</td>
<td>204</td>
<td>280</td>
<td>176 (86%)</td>
<td>104 (51%)</td>
</tr>
</tbody>
</table>

### Decision made based on Dev03F
- Stripped out all the uhs before submission (~90% of filled pauses hypothesized). Filler errors dropped from 129% to 81%.
- For Eval03F, the effect is the opposite. If uhs are preserved, filler error would be 57%, rather than 79%. Most of other conditions also gained

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<td>uh-preserved Dev03F</td>
<td>59.4</td>
<td>98.7</td>
<td>128.6</td>
<td>125.5</td>
<td>23.2</td>
<td>11.1</td>
<td>31.6</td>
</tr>
<tr>
<td>uh-preserved Eval03F</td>
<td>64.0</td>
<td>93.9</td>
<td>57.2</td>
<td>70.1</td>
<td>14.1</td>
<td>10.9</td>
<td>23.6</td>
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Conclusion

- We participated in RT03F evaluation for all conditions in BN
- The final RT-03 error is 24.3%. STT RT1 error (11.7%) accounts for less than 50% of the total error. Most of the errors would be due to SR errors.
- Most CTS technologies applicable to BN
- We had less than 1 person-month effort on BN system development for this evaluation. Most of time spent on understanding the new scoring tools and new training data
- We hope the Dev data could be statistically close to Eval data, especially on those features to be evaluated.