Evaluating Automatic Speech Recognition Systems in Comparison with Human Perception Results Using Distinctive Feature Measures

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Abstract

- Using measures derived from linguistic distinctive features to evaluate automatic speech recognition (ASR) systems.
- Presenting Error patterns in terms of manner, place and voicing, along with an examination of confusion matrices via a distinctive-feature-distance metric.

Motivation

Word error rate(WER) and phone error rate(PER) are the most popular methods. However, there are two drawbacks.

- The phone sequence for a produced word may vary widely, so that direct comparison of pronunciation variants becomes difficult.
- It is not possible to measure how similar two phones are to each other using phones as analysis units.

Experimental Setup

- **Databases** TIMIT & LAFF VCV
- **Conversion of Miller & Nicely results**
- **Human perception of LAFF VCV in noise** six syllables **/aa-b-aa/**, **/aa-d-aa/**, **/aa-s-aa/**, **/aa-m-aa/**, **/aa-ch-aa/** and **/aa-sh-aa/**, each of which was embedded in full-band white noise ranging from **30dB** SNR to **-20dB** SNR in 10dB decrements.
- **Hidden Markov Model(HMM)-based ASR system & Deep Neural Network(DNN)-based system** detection of consonants and glides, selecting 36 speech files from the LAFF database, each of which included a consonant or glide between two **/aa/** phones, such as **/aa-z-aa/**, **/aa-b-aa/**, etc. White noise at various levels from **40dB** SNR to **-20dB** SNR at 10dB decrements were added to form the test data set.
- **Evaluating system** All results were tabulated in terms of error types and into grey-scale confusion matrices

Distinctive Feature Distance

The distinctive feature distance $D(i,j)$ between phonemes i and j can be written as $D(i,j) = \sum_f(1-\delta(d(i,j)d(j,f)))$, where $d(i,f)$ is the fth distinctive feature of the phoneme i, $f \in$ {vowel, glide, consonantal, ...}, and $\delta(i,j)$ is the Kronecker delta,

$$\delta(i,j) = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases}.$$

In our study, the total number of distinctive features is 24.

Results

Manner Place and Voicing error patterns

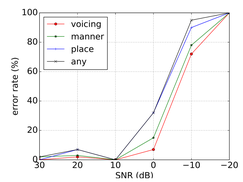


Figure 1: Error patterns for human perception results

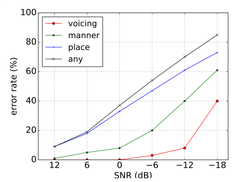


Figure 2: Error patterns for Miller & Nicely results

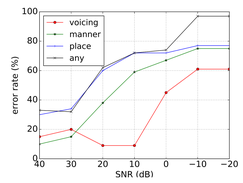


Figure 3: Error patterns for HMM-based system results

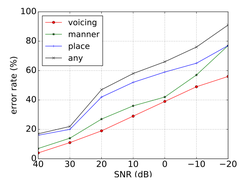
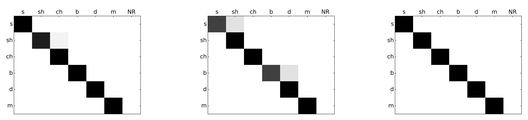


Figure 4: Error patterns for DNN-based system results

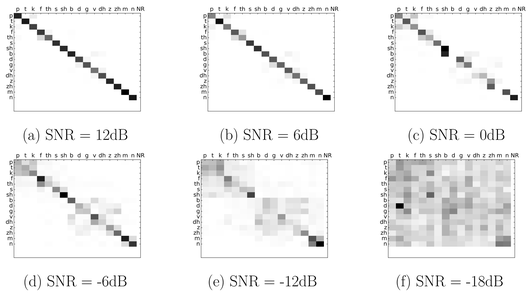
Comparison of confusion matrices in white noise



(a) SNR = 30dB (b) SNR = 20dB (c) SNR = 10dB

(d) SNR = 0dB (e) SNR = -10dB (f) SNR = -20dB

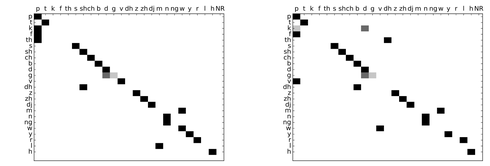
Figure 5: Confusion matrices for human perception results



(a) SNR = 12dB (b) SNR = 6dB (c) SNR = 0dB

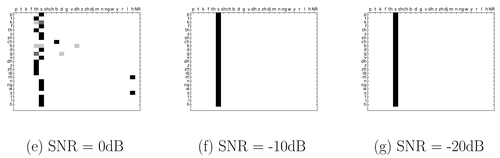
(d) SNR = -6dB (e) SNR = -12dB (f) SNR = -18dB

Figure 6: Confusion matrices for Miller & Nicely results



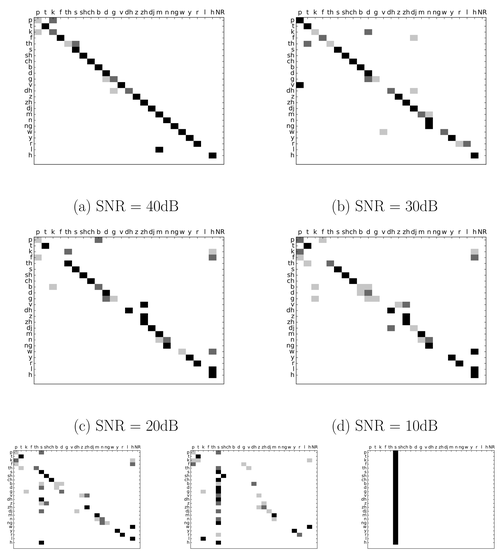
(a) SNR = 40dB (b) SNR = 30dB

(c) SNR = 20dB (d) SNR = 10dB



(e) SNR = 0dB (f) SNR = -10dB (g) SNR = -20dB

Figure 7: Confusion matrices for HMM-based system results



(a) SNR = 40dB (b) SNR = 30dB

(c) SNR = 20dB (d) SNR = 10dB

(e) SNR = 0dB (f) SNR = -10dB (g) SNR = -20dB

Figure 8: Confusion matrices for DNN-based system results

Distinctive-Feature-Distance results

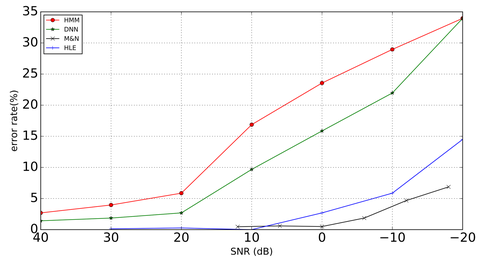


Figure 9: Plot of distinctive-feature-distance results of human perception and HMM- and DNN- based ASR systems

Conclusion

- Human perception results show that place features are most susceptible to misperception in white noise, followed by manner features, then voicing features. The DNN-based system showed similar patterns, although with more errors.
- The HMM-based system had less consistency in the error patterns. In the confusion matrices, human perception results show that most errors occur near the diagonal regions, with blocking effects around -10dB SNR, which indicate correct voicing detections at that level
- Point to the possibility of incorporating parameters specifically related to voicing, manner, and place into acoustic models, and/or incorporating distinctive-feature-distance measures as training criteria for closer modeling of ASR systems to human perception patterns.

Future Work

- Extend this comparison to include results for larger databases and other types of noise, e.g. babble and bandpass noise.

Contact Information

- The authors want to thank Dr. Rachel Theodore and Nicholas Monto at the University of Connecticut-Storrs for their expertise in conducting the human listening experiments