OBJECTIVE COMPARISON OF SPEECH ENHANCEMENT ALGORITHMS WITH HEARING LOSS SIMULATION

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Introduction

One goal of the current study is to compare many traditional and newly-emerged speech enhancement algorithms, using a large database that contains diverse mixtures of speech and background noise under a broad range of SNRs. A second goal of this study is to evaluate the performance of these algorithms for people with hearing impairments. Most previous studies evaluated speech-enhancement outcomes using metrics developed for healthy young adults, such as the widely-adopted perceptual evaluation of speech quality (PESQ). It is not clear whether the findings using these metrics hold for the hearing-impaired population. The current study includes evaluations using the hearing-aid speech quality index (HASQI) (Kates and Arehart, 2014).

Speech Enhancement Algorithms

Active Set Newton Algorithm (ASNA) (Virtanen et al., 2013):
It applies the Newton method to update the weights more efficiently than other NMF approaches. Parameters match those of the original study.

DNN-based ideal ratio mask estimation (D-IRM) (Wang et al., 2014):
This DNN-IRM network has three hidden layers with 1024 units each. The rectified linear (ReLU) activation function is applied to the hidden layers and a linear activation function is applied to the output layer. The mean square error is used as the cost function.

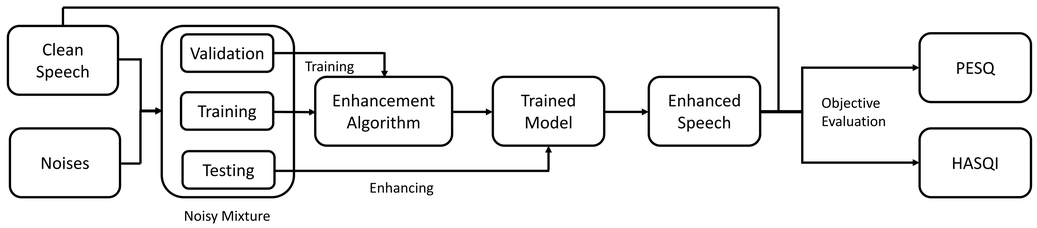
DNN-based complex ideal ratio mask estimation (D-cIRM) (Williamson et al., 2016):
The cIRM is predicted with a network that has three hidden layers with 1024 units each. All hidden layers use ReLU activation functions. The output layer uses a linear activation function.

LSTM-based ideal ratio mask estimation (L-IRM) (Weninger et al., 2014):
The network has two LSTM layers with 256 nodes in each layer, followed by a third sigmoidal layer. Mask approximation (MA) is used as the cost function.

BLSTM-based phase-sensitive mask estimation (BL-PSM) (Erdogan et al., 2015):
The network has two BLSTM layers with 256 nodes in each layer, followed by a third sigmoidal layer. Phase-sensitive spectrum approximation (PSA) is used as the cost function.

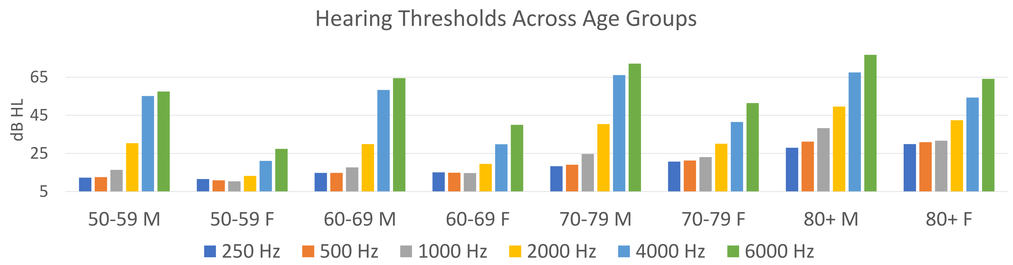
A Mel-frequency domain implementation is applied for all DNN and RNN-based methods.

Experiment Design and Results

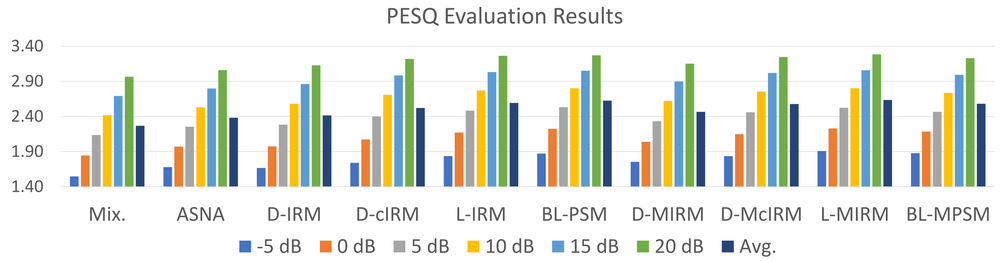


Experimental Design

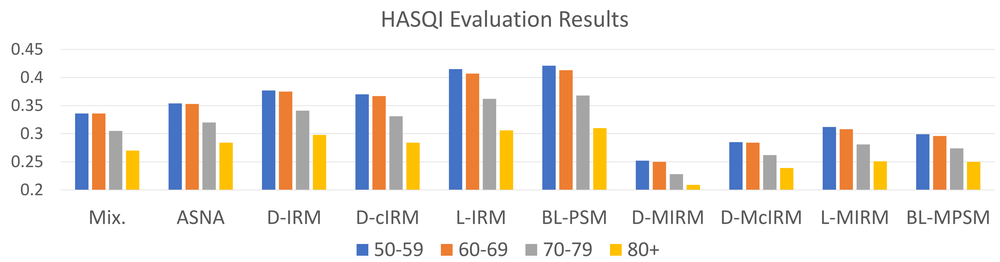
Hearing thresholds (dB HL) of male (M) and female (F) subjects across age groups (Schmiedt 2010):



PESQ (-0.5 to 4.5) evaluation results are averaged across noise types for brevity:



HASQI (0 to 1) evaluation results are averaged across noise types, genders and SNRs for brevity:



Materials

The speech data includes 1440 IEEE utterances, 250 utterances from the Hearing in Noise Test (HINT) corpus and 2342 utterances from the TIMIT database. 70% of them are used for the training set and 15% are used for both the testing and development sets. The clean utterances are further corrupted by four types of noises at different levels [-5 dB to 20 dB], including airplane, babble, dog barking, and train noises.

Conclusions

- We investigated the performance of several speech enhancement algorithms on a diverse speech dataset, with a particular interest in simulated hearing loss environments.
- The RNN-based methods result in significantly higher PESQ and HASQI scores for normal-hearing listeners.
- For hearing-impaired listeners, the BLSTM method achieves the best performance in all age groups for both genders.
- We also found that for both DNN- and RNN-based methods, Mel-frequency domain processing can often lead to improved PESQ scores, but reduced HASQI scores.
- Future studies that include subjective evaluations are warranted to confirm the performance of these algorithms for normal and hearing-impaired listeners.

Acknowledgements

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