MBI-Net: A Non-Intrusive Multi-Branched Speech Intelligibility Prediction Model for Hearing Aids

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Introduction

• A fair way to assess speech intelligibility is critical for a variety of speech-related applications.

• The most direct measure of speech intelligibility is the subjective listening test.

• However, conducting large-scale hearing tests is prohibitive.
Introduction

• A series of **speech intelligibility measures based on signal processing** have been proposed:

  - Speech intelligibility index (SII)
  - Extended SII (ESII)
  - Speech transmission index (STI)
  - Short-time objective intelligibility (STOI)
  - Modified binaural short-time objective intelligibility (MBSTOI)
Introduction

• With the advent of deep learning (DL) models, several studies have used DL models to deploy non-intrusive speech intelligibility prediction models.

  - To predict STOI [1,2,3]
  - To predict subjective listening test results [4,5]

• Few studies have focused on designing speech intelligibility prediction models for HA users.
  - HASA-Net [6]: formulates the hearing loss pattern as a vector, which is combined with speech signals.
Introduction

• In our previous study, a multi-objective speech assessment model (MOSA-Net) [7] was proposed to predict objective quality and intelligibility metrics for normal hearing individuals.
Introduction

• In this study, we extend MOSA-Net and develop a speech intelligibility prediction model for HA, called the **multi-branched speech intelligibility prediction model (MBI-Net)**.
MBI-Net

• MBI-Net consists of **two branches of model**, each characterizing one channel of speech signals in a binaural HA system.

• Each branch of MBI-Net consists of an MSBG model [8], a cross-domain feature extraction module, and a frame-level speech intelligibility prediction model.

• The MSBG model **modifies the speech signal according to the HA pattern** and serves as a **simulator to simulate the hearing ability** of HA users.
MBI-Net

Figure 1: Architecture of the MBI-Net model.

\[ O = \frac{1}{U} \sum_{u=1}^{U} [(I_u - \hat{I}_u)^2 + \frac{\alpha_u}{F_u} \sum_{f=1}^{F_u} (I_u - \hat{I}_f)^2] + L_{left} + L_{right} \]
\[ L_{left} = \frac{\alpha_l}{F_u} \sum_{f=1}^{F_u} (I_u - \hat{I}_f)^2 \]
\[ L_{right} = \frac{\alpha_r}{F_u} \sum_{f=1}^{F_u} (I_u - \hat{I}_r f)^2 \]

Figure 2: Illustration of extraction cross-domain feature and obtaining frame-level intelligibility score on CNN-BLSTM+AT architecture.
Experiments

Experimental Setup

• The Clarity Prediction Challenge dataset 2022 included ten HA systems from the previous Clarity Enhancement Challenge 2021 [9].

• Twenty-five HA users participated in the listening test, and each listener was asked to answer what she/he heard from a played speech sample.

• The intelligibility score ranges from 0 to 100 (the higher the better).

• The training set consisted of two tracks, Track 1 and Track 2. Track 1 consisted of 4863 training utterances, and Track 2 consisted of 3580 training utterances.
Experiments

Experimental Results

Table 1: RMSE, Standard Deviation, and LCC scores of Left-Branch, Right-Branch, MBI-Net (Ave), and MBI-Net (Lin) on the closed-set (Track 1) dataset.

| Systems          | RMSE | STDERR | LCC |
|------------------|------|--------|-----|
| Left-Branch      | 25.33| 0.51   | 0.73|
| Right-Branch     | 26.24| 0.52   | 0.72|
| MBI-Net (Ave)    | 25.12| 0.51   | 0.74|
| MBI-Net (Lin)    | 24.65| 0.50   | 0.74|
Experiments

Experimental Results

Table 2: RMSE, Standard Deviation, and LCC scores of Baseline, MBI-Net (Hub), and MBI-Net (WavLM) on the closed-set (Track 1) dataset.

| Systems            | RMSE  | STDERR | LCC  |
|--------------------|-------|--------|------|
| Baseline           | 28.52 | 0.58   | 0.62 |
| MBI-Net (Hub)      | 24.65 | 0.50   | 0.74 |
| MBI-Net (WavLM)    | 24.06 | 0.49   | 0.75 |
| MBI-Net (WavLM+)   | 23.05 | 0.46   | 0.78 |

Table 3: RMSE, Standard Deviation, and LCC scores of Baseline, MBI-Net (Hub), and MBI-Net (WavLM) on the open-set (Track 2) dataset.

| Systems            | RMSE  | STDERR | LCC  |
|--------------------|-------|--------|------|
| Baseline           | 36.52 | 1.35   | 0.53 |
| MBI-Net (Hub)      | 30.72 | 1.22   | 0.59 |
| MBI-Net (WavLM)    | 28.90 | 1.09   | 0.65 |
| MBI-Net (WavLM+)   | 24.36 | 0.96   | 0.75 |
Figure 3: Scatterplots of two speech intelligibility prediction models: Baseline and MBI-Net (WavLM+).
Conclusion

• In this study, we presented MBI-Net, a multi-branched speech intelligibility prediction model for binaural HA users.

• MBI-Net adopts two-branches of models corresponding to two speech channels of the binaural HAs.

• Each branch of MBI-Net consists of an MSBG model, a cross-domain feature extraction module, and the CNN-BLSTM+AT model architecture.

• The outputs of the two branches are then fused through a linear layer to obtain the final speech intelligibility score.
Conclusion

• Experimental results from both Track 1 and Track 2 have confirmed the advantages of implementing the multi-branched model and using cross-domain features for achieving a better intelligibility prediction score.

• Furthermore, experimental results confirm the advantages of WavLM in deploying representative SSL features.
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Thank You