

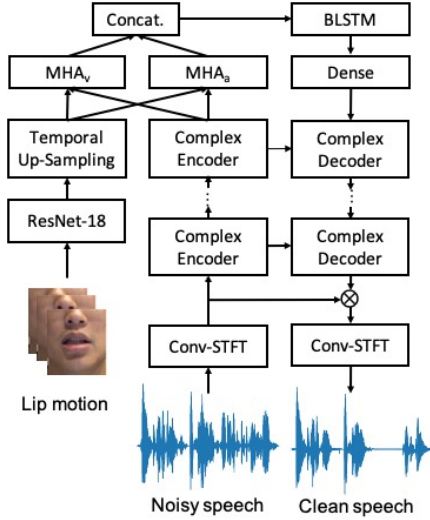
# A DCCRN-BASED AUDIO-VISUAL SPEECH ENHANCEMENT APPROACH FOR THE 1<sup>ST</sup> COG-MHEAR AVSE CHALLENGE

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## 1. PROPOSED APPROACH

Our proposed approach is based on deep complex convolution recurrent network (DCCRN) [1], which has been shown to be effective for speech enhancement (SE) by predicting target complex spectrum via complex-valued operation. We incorporate additional visual information (e.g. lip motion) into a DCCRN model as an audio-visual speech enhancement (AVSE) approach for the 1<sup>st</sup> COG-MHEAR AVSE Challenge. The entry associated with this report is `BioASP_CITILCE2`. Our proposed model, AV-DCCRN, is shown in Figure 1. Noisy speech is converted into complex spectrum and processed via a U-net like complex encoder-decoder architecture, where the latent representations are processed with a bi-directional long short-term network (BLSTM). The visual features of the lip motion and the speech features are fed into cross-attention modules, which consist of multi-head attention (MHA), to better couple the audio-visual features. The training objective is to minimize a weighted sum of the scale-invariant signal-to-noise ratio (SI-SNR) loss and the  $L1$  loss between the predicted speech and the clean speech.



**Fig. 1.** Our proposed AV-DCCRN model. MHA represents Multi-Head Attention.

## 2. EXPERIMENTAL RESULTS

The experimental results on the development set is shown in Table 1. We can observe that the inclusion of MHA blocks for audio-visual feature coupling can obtain a performance boost compared to naive cross-modal feature fusion. In addition, we adopt noise augmentation within each mini-batch during training to improve model generalization. The noise is from the training set, and the probability to conduct noise augmentation is set as 0.5 for each iteration. Our experimental results show the proposed model can significantly outperform the baseline model with a 40.7% and 23.9% improvement in perceptual evaluation of speech quality (PESQ) and short-time objective intelligibility (STOI), respectively. The number of trainable parameters of the proposed model is 18.6M.

| Methods                              | PESQ        | STOI        |
|--------------------------------------|-------------|-------------|
| Noisy speech                         | 1.15        | 0.64        |
| Baseline                             | 1.30        | 0.67        |
| AV-DCCRN (w/o MHA)                   | 1.62        | 0.81        |
| AV-DCCRN (w/ MHA)                    | 1.80        | 0.83        |
| <b>AV-DCCRN (w/ MHA, noise aug.)</b> | <b>1.83</b> | <b>0.83</b> |

**Table 1.** Comparison of the evaluation scores of the enhanced speech on the development set. The baseline model is the one provided by the challenge organizers.

## 3. REFERENCES

- [1] Yanxin Hu, Yun Liu, Shubo Lv, Mengtao Xing, Shimin Zhang, Yihui Fu, Jian Wu, Bihong Zhang, and Lei Xie, “Dccrn: Deep complex convolution recurrent network for phase-aware speech enhancement,” *INTERSPEECH*, 2020.