Deep Learning-based Non-Intrusive Multi-Objective Speech Assessment Model with Cross-Domain Features

Ryandimas E. Zezario, Student Member, IEEE, Szu-Wei Fu, Fei Chen, Senior Member, IEEE
Chiou-Shann Fuh, Hsin-Min Wang, Senior Member, IEEE, and Yu Tsao, Senior Member, IEEE

Abstract—Most conventional speech assessment metrics require a golden clean reference to calculate the evaluation score. This condition limits their applicability in real-world scenarios because a clean reference may not always be available. Hence, non-intrusive speech assessment metrics have garnered significant attention in recent years, and several deep learning-based models have been developed accordingly. Although these models are more flexible than conventional speech assessment metrics, most of them are designed to estimate a specific evaluation score, whereas speech assessment generally involves multiple facets. Herein, we propose a cross-domain multi-objective speech assessment model, i.e., the MOSA-Net, which can estimate multiple speech assessment metrics simultaneously. More specifically, the MOSA-Net is designed to estimate speech quality, intelligibility, and distortion assessment scores based on a test speech signal as input. It comprises a convolutional neural network and bidirectional long short-term memory (CNN-BLSTM) architecture for representation extraction, as well as a multiplicative attention layer and a fully-connected layer for each assessment metric. In addition, cross-domain features (spectral and time-domain features) and latent representations from self-supervised learned models are used as inputs to combine rich acoustic information from different speech representations to obtain more accurate assessments. Experimental results reveal that the MOSA-Net can precisely predict perceptual evaluation of speech quality (PESQ), short-time objective intelligibility (STOI), and speech distortion index (SDI) scores when tested on both noisy and enhanced speech utterances under either seen test conditions (where the test speakers and noise types are involved in the training set) or unseen test conditions (where the test speakers and noise types are not involved in the training set). In light of the confirmed prediction capability, we further adopt the latent representations of the MOSA-Net to guide the speech enhancement (SE) process and derive a quality-intelligibility (QI)-aware SE (QIA-SE) approach accordingly. Experimental results show that QIA-SE provides superior enhancement performance compared with the baseline SE system in terms of objective evaluation metrics and qualitative evaluation test.

Index Terms—non-intrusive speech assessment models, deep learning, multi-objective learning, speech enhancement.

I. INTRODUCTION

Speech assessment metrics are indicators that quantitatively measure the specific attributes of speech signals. These metrics are vital to the development of speech-related application systems. A direct assessment approach measures the difference between the distorted/processed speech and clean reference at the signal level. The speech distortion index (SDI) [1] is a well-known example that calculates the distortion of the distorted/processed speech compared with the clean speech. Meanwhile, the signal-to-noise-ratio (SNR) [2] and segmental SNR [3] are other well-known metrics that indicate the difference in the SNR and segmental SNR between processed and noisy speech, respectively. Scale-invariant source-to-noise ratio (SI-SNR) [4] and optimal scale-invariant signal-noise ratio (OSI-SNR) [5] are improved versions of the SNR that have been proven effective in assessing speech signals more fairly. Although these signal-level metrics can directly indicate the distortion or SNR of the distorted/processed speech compared to the clean reference, they may not fully reflect the quality and intelligibility of the distorted/processed speech. Therefore, many evaluation metrics have been proposed for measuring speech quality and intelligibility.

Existing speech quality and intelligibility evaluation metrics can be classified into two categories: subjective and objective metrics. The subjective evaluation metrics are based on test scores from human listeners. To obtain subjective scores, speech samples are played to a group of human subjects, and these subjects provide feedback regarding the quality or intelligibility levels of the played speech signals. In terms of speech quality, the mean opinion score (MOS) is a typical numerical indicator in listening tests. In most cases, the MOS metric categorizes speech quality into five levels, ranging from one to five, with a higher score indicating better quality. By contrast, the intelligibility score is typically calculated by the ratio of the number of accurately recognized words to the total number of words in the played speech samples. To attain an unbiased assessment of speech quality and intelligibility, it is necessary to recruit a sufficient number of human subjects, and each subject must listen to a significant amount of speech utterances encompassing diverse acoustic conditions, including speakers and distortion sources. This testing strategy is prohibitive and may not always be feasible. Hence, several objective evaluations metrics have been developed as surrogates for human listening tests [6]–[31].
Generally, a conventional objective quality evaluation metric comprises two stages. The first stage includes a series of signal processing units designed to convert speech waveforms into handcrafted acoustic/auditory features. The second stage derives a mapping function to predict the speech quality score based on acoustic/auditory features. The mapping function can be implemented via linear regression \cite{6,7}, polynomial regression \cite{6,7}, multivariate adaptive regression spline \cite{14}, and machine learning methods, such as Gaussian mixture models \cite{9,17,18}, support vector regression \cite{10,15}, and artificial neural networks \cite{19,21}. Depending on whether clean reference speech is required, objective speech quality metrics can be further classified into two categories: intrusive metrics \cite{6} and non-intrusive metrics \cite{7,15}. Compared with intrusive evaluation metrics, non-intrusive evaluation metrics do not require a clean reference; therefore, they are more suitable for real-world scenarios, but typically have lower assessment capabilities.

Objective intelligibility evaluation metrics can be classified into two categories. One category first segregates the speech signal under analysis into frequency subbands, and assumes that each subband independently contributes to the intelligibility. Next, the long-term subband SNR is calculated and then normalized to a value between 0 and 1. Finally, the intelligibility score is obtained using the perceptually weighted average of the normalized subband SNRs. Notable examples of this category include the articulation index (AI) \cite{22}, speech intelligibility index (SII) \cite{23}, extended SII (ESII) \cite{24}, and coherence SII (CSII) \cite{27}. The other category is derived based on the observation that reverberation and/or additive noise tends to reduce the modulation depth of the distorted signal, compared with the clean reference signal. Well-known approaches of this category include the speech transmission index (STI) \cite{25}, spectro-temporal modulation index (STMI), normalized-covariance measure (NCM) \cite{26}, short-time objective intelligibility (STOI) \cite{28}, extended STOI (eSTOI) \cite{29}, polynomial measure (SOPM) \cite{32}, and weighted spectro-temporal modulation index (wSTMI) \cite{33}. To avoid the necessity for clean reference speech, several non-intrusive approaches have been proposed. Most of them adopt statistical models of clean speech signals or psychoacoustic features for speech understanding \cite{34}. Notable non-intrusive speech intelligibility metrics include modulation-spectrum area (ModA) \cite{30}, speech-to-reverberation modulation energy ratio (SRMR) \cite{31}, and the non-intrusive STOI \cite{35}.

Recently, the emergence of deep learning algorithms has resulted in the development of many deep learning-based speech assessment models. These models are trained to predict subjective assessment scores \cite{36,41} or objective evaluation scores, in terms of speech quality \cite{42,43} and intelligibility \cite{44,45}. To attain a higher assessment accuracy, the MBNet adopts the BiasNet architecture to compensate for the biased scores of a certain judge \cite{46}. In addition, the multi-task learning criterion that simultaneously optimizes multiple metrics is used to train the assessment model \cite{44,47}. Meanwhile, different acoustic features are used as input to the assessment model to consider information from different acoustic domains \cite{48,49}.

In this paper, we propose a cross-domain multi-objective assessment model, the MOSA-Net, which aims to predict multiple objective assessment metrics simultaneously, including speech quality, intelligibility, and distortion scores. To enrich acoustic information from multiple domains, the MOSA-Net uses cross-domain features, including traditional spectral features, learnable end-to-end features (based on the Sinc convolutional network) \cite{50} applied to the waveform, and latent representations from self-supervised trained models (Wav2vec 2.0 \cite{51} and Hubert \cite{52}). The MOSA-Net is composed of a convolutional neural network and a bidirectional long short-term memory (CNN-BLSTM) with an attention mechanism. It has three outputs corresponding to three assessment scores, namely quality, intelligibility, and distortion scores. A multi-task learning criterion is used to train the MOSA-Net model. We systematically compared the performance of the MOSA-Net based on various model architectures, training targets, and acoustic features. Experimental results (in terms of mean square error (MSE), linear correlation coefficient (LCC), and Spearman’s rank correlation coefficient (SRCC) scores) demonstrate the advantages of cross-domain features, multi-tasking learning, and attention mechanism. In our previous study, we confirmed the effectiveness of using a speech assessment model to guide the speech enhancement (SE) process \cite{53,54}. Herein, we propose integrating the latent representation of the MOSA-Net model into the SE system, and derive a novel quality-intelligibility-aware (QIA)-SE system. Experimental results show that QIA-SE achieves notable improvements over the baseline SE systems and several existing SE systems, which confirms the advantage of combining the knowledge in the speech assessment model to improve the enhancement capability.

The remainder of this paper is organized as follows. We first review related work in Section II. Subsequently, we elaborate the proposed methods in Section III. In Section IV, we describe the experimental setup, report the experimental results, and discuss our findings. Finally, we conclude our work in Section V.

II. RELATED WORK

A. Deep Learning-based Assessment Metrics

To date, deep learning models have been widely used to build speech assessment systems. In this section, we review several deep learning-based assessment metrics based on different targets and model architectures.

As mentioned earlier, the assessment targets can be classified into two types. The first type is human subjective assessment scores, and the second is objective assessment scores. When the target is the human subjective assessment score, the learned assessment metric through appropriate modeling can directly predict the human assessment result \cite{41,46,49,55,57}. However, a significant number of subjective listening tests encompassing many listeners and acoustic conditions must be conducted in advance to prepare ground-truth labels for an unbiased training set. In addition, it is difficult to extend the dataset to new domains, because additional subjective tests must be conducted. According to
the training target criterion, the subjective assessment scores can be classified into two categories: quality and intelligibility scores. Notable systems associated with subjective quality metrics include the following: (1) The MOSNet [55], which combines the utterance-level and frame-level scores to estimate the MOS of an utterance; (2) the DNSMOS [41], which uses the teacher-student architecture to eliminate subjective bias; and (3) the MBNet [46], which compensates for individual judgement biases using a BiasNet architecture. Compared with speech quality assessment, there is less work on predicting subjective intelligibility scores. For example, (1) Andersen et al. [56] used a CNN model to accommodate the entire signal composed of multiple sentences to estimate the scalar value of the intelligibility score. (2) Pedersen et al. [57] used a CNN architecture to calculate scores locally in a short time to achieve more efficient learning with limited listening test data.

The second group adopts objective speech assessment metrics as the ground-truth labels for model training. Similar to the first group, the objective speech assessment metrics can also be divided into two categories: quality and intelligibility. For objective speech quality assessment, the PESQ [42]–[44], POLQA [58], and HASQI [44] scores obtained by comparing the test speech with the reference speech are often used as the ground-truth scores for training the deep-learning-based assessment metrics. For speech intelligibility assessment, the STOI [43]–[45] and hearing-aid speech perception index (HASPI) [59] scores are used as the training targets.

Many model architectures have been used to construct the deep learning-based assessment metrics, e.g., BLSTM [42], pyramid BLSTM [60], CNN [39], [41], and CNN-BLSTM [46], [55]. In addition, attention mechanism [44], [45], multitask learning [44], [47], and additional network that compensates for score biases [46] have been used to improve assessment capabilities. In terms of input, different acoustic features have been explored, which can be classified into three categories. The first category includes traditional spectral features such as log Mel features [41] and power spectral (PS) features [42], [45], [55]. The second category uses learnable filters to extract features from raw waveform [43], [61]. The third category is based on the end-to-end features of the self-supervised pre-trained network [49].

B. Incorporating Speech Assessment Metrics to SE

The idea of incorporating informative latent representations from pre-trained models to guide target speech processing tasks has been extensively studied. For example, SE systems using speaker embedding [62]–[65] and noise embedding [66] have been shown to provide improved SE performance. Since the goal of speech assessment metrics is to estimate speech quality/intelligibility attributes given a distorted/processed speech signal, it is feasible to use the information from these assessment metrics to guide the SE process to achieve better speech quality and intelligibility. These approaches can be classified into two categories. The first category directly uses speech assessment metrics as training targets to train the SE system [67]–[69]. The second category uses assessment metrics to determine the best model architecture or select the most appropriate output [53], [54], [70].

III. PROPOSED METHODS

In this section, we first present the proposed MOSA-Net model. Subsequently, we will explain how to use latent representations for obtaining better speech quality or intelligibility.

A. Multi-Target Speech Assessment Model with Cross-Domain Features (MOSA-Net)

Fig. 1 shows the overall architecture of the MOSA-Net model. As shown in the figure, the MOSA-Net adopts cross-domain acoustic features and predicts multiple assessment scores. Given a speech waveform $X = [x_1, \ldots, x_n, \ldots, x_N]$, the model takes two branches of the input. In the first branch, the speech waveform $X$ is processed by STFT and learnable filter banks (LFB) separately. Subsequently, the estimated spectral and filtered signal features are concatenated and fed into a convolution layer. In the second branch, the speech waveform $X$ is processed by a self-supervised pre-trained model (HuBert [52] or Wav2vec 2.0 [51]). The two branches of input are combined and further processed by a bidirectional layer and a fully connected layer. Subsequently, a set of attention layers is used for the corresponding objective assessment metrics. In our implementation, multiplicative attention is used in the attention layers because of its high efficiency and decent performance. Next, for each metric, a fully connected layer is used to generate the frame-wise scores. Finally, based on the frame-level scores, a global average operation is applied to calculate the final predicted PESQ, STOI, and SDI scores.
Considering that speech utterances may contain stationary and/or non-stationary noise in different segments of frames, directly estimating the utterance level score may result in less accurate estimation. Therefore, the MOSA-Net aims to combine utterance-level and frame-level score estimations. Accordingly, the objective function of MOSA-Net is defined as follows:

\[
O = L_{\text{PESQ}} + L_{\text{STOI}} + L_{\text{SDI}}
\]

\[
L_{\text{PESQ}} = \frac{1}{N} \sum_{n=1}^{N} [ (Q_n - \hat{Q}_n)^2 + \frac{1}{U(n)} \sum_{l=1}^{U(n)} \alpha_Q(Q_n)(q_l - q_{nl})^2 ]
\]

\[
L_{\text{STOI}} = \frac{1}{N} \sum_{n=1}^{N} [ (I_n - \hat{I}_n)^2 + \frac{1}{U(n)} \sum_{l=1}^{U(n)} \alpha_I(I_n)(i_l - i_{nl})^2 ]
\]

\[
L_{\text{SDI}} = \frac{1}{N} \sum_{n=1}^{N} [ (S_n - \hat{S}_n)^2 + \frac{1}{U(n)} \sum_{l=1}^{U(n)} \alpha_S(S_n)(s_l - s_{nl})^2 ]
\]

(1)

where \( \{Q_n, \hat{Q}_n\}, \{I_n, \hat{I}_n\}, \) and \( \{S_n, \hat{S}_n\} \) are the true and predicted utterance-level scores of the PESQ, STOI, and SDI, respectively; \( N \) denotes the total number of training utterances; \( L(U_n) = L(\hat{X}_n) + L(C_n) \) denotes the number of frames in the \( n \)-th training utterance; \( L(\hat{X}_n) \) and \( L(C_n) \) are the number of frames of speech features generated by STFT/LFB and the self-supervised pre-trained model, respectively; \( q_{nl}, i_{nl}, \) and \( s_{nl} \) are the predicted frame-level scores of the PESQ, STOI, and SDI of the \( l \)-th frame of the \( n \)-th training utterance, respectively; \( \alpha_Q, \alpha_I, \alpha_S \) denote the weight of each training utterance, which is determined by the attention mechanism. In Eq. [1] for each metric, the first and second terms estimate the accuracy of the utterance-level and the frame-level scores, respectively.

**B. QIA-SE Model**

The QIA-SE model is designed to incorporate the latent representation from MOSA-Net to guide the SE. The overall QIA-SE architecture is illustrated in Fig. 2. As shown in the figure, the noisy speech waveform is first converted to spectral features, \( \mathbf{Y} = [y_1, \ldots, y_n, \ldots, y_N] \), where \( N \) is the total number of frames. QIA-SE aims to convert \( \mathbf{Y} \) to enhanced spectral features \( \hat{\mathbf{X}} \), referring to the latent representation features \( \mathbf{A} = [a_1, \ldots, a_n, \ldots, a_N] \) extracted by the MOSA-NET from the input noisy speech waveform. The latent representation \( \mathbf{A} \) is incorporated into the middle layer of the QIA-SE to guide the enhancement process:

\[
\mathbf{H}_1 = F_\theta^{(1)}(\mathbf{Y})
\]

\[
\ldots
\]

\[
\mathbf{H}_k = F_\theta^{(k)}(\mathbf{H}_{k-1})
\]

\[
\mathbf{H}_{k+1} = F_\theta^{(k+1)}(\mathbf{H}_k, \mathbf{A})
\]

\[
\ldots
\]

\[
\mathbf{H}_K = F_\theta^{(K)}(\mathbf{H}_{K-1})
\]

\[
\hat{\mathbf{X}} = F_\theta^{(K+1)}(\mathbf{H}_K)
\]

(2)

where \( k \) denotes the layer index, and \( F_\theta^{(k)} \) indicates the transformation model of the \( k \)-th hidden layer. Parameter \( \theta \) is optimized by minimizing the following loss function based on the MSE, as follows:

\[\theta = \arg\min_{\theta} L(\mathbf{X}, \hat{\mathbf{X}}),\]

where \( \mathbf{X} \) denotes the clean speech reference. In the testing stage, noisy speech is first input into MOSA-Net to generate the latent representation \( \mathbf{A} \), and then input into the QIA-SE model to obtain the enhanced spectral features, as defined in Eq. [2]. The enhanced speech waveform is generated by performing ISTFT on the enhanced spectral features along with phase information from the noisy speech.

**IV. EXPERIMENTS**

**A. Analysis of MOSA-Net**

In this section, we systematically investigate the correlations between the achievable performance of the MOSA-Net and different input features, model architectures, and output labels. A fair comparison of MOSA-Net with related neural evaluation metrics is presented.

1) **Experimental Setup:** To evaluate MOSA-Net, we adopted the Wall Street Journal (WSJ) dataset [72], which comprises 37,416 training utterances and 330 test utterances. The training and test utterances were recorded at a sampling rate of 16 kHz. To prepare noisy utterances, we artificially contaminated the clean training utterances with 100 types of noises [72] at 31 different SNR levels, ranging from -10 to 20 dB with an interval of 1 dB. To prepare enhanced utterances, we adopted a pre-trained SE model, constructed by a BLSTM model with two bidirectional hidden layers, each containing 300 neurons, to process the noisy utterances. The SE model was trained by 37,416 utterances from the WSJ dataset with 100 noise types and covering -10 to 20 dB SNR levels. Finally, we randomly sampled 15,000 noisy utterances, 15,000
enhanced utterances, and 1,500 clean utterances to form the training set. To prepare the training targets, we computed the PESQ, STOI, and SDI scores of these training utterances.

We prepared two sets of testing data to evaluate the deep learning-based evaluation metrics, i.e., a seen testing set and an unseen testing set. For the seen testing set, we randomly selected 2,350 noisy, 2,350 enhanced, and 300 clean utterances from the remaining utterances in the training set. For the unseen testing set, we selected 300 utterances from the test set of the WSJ and artificially contaminated them with four unseen noise types (i.e., car, pink, street, and babble) at six SNR levels (i.e., -10, -5, 0, 5, 10, and 15 dB), amounting to 7,200 noisy utterances. It is noteworthy that the speakers in this unseen testing set were not involved in the training set. The same SE model was applied to generate enhanced utterances for the seen and unseen testing sets. Finally, 2,350 noisy, 2,350 enhanced, and 300 clean utterances were generated to form the unseen test set.

To evaluate the proposed MOSA-Net model, we adopted three evaluation metrics, namely the MSE, LCC, and SRCC [73]. Lower MSE scores indicate that the predicted scores are closer to the ground-truth assessment scores (the lower the better), whereas higher LCC and SRCC scores indicate that the predicted scores are of higher correlations to the ground-truth assessment scores (the higher the better).

2) MOSA-Net with different model architectures: First, we compared the MOSA-Net with different model architectures, including the CNN [67], BLSTM [42], CNN-BLSTM [55], and CNN-BLSTM+ATT [45]. For a fair comparison, we adopted the same acoustic features PS and a single-metric (either the PESQ or STOI scores) learning criterion to train the model. To extract the PS features, each speech waveform was converted into a 257-dimensional spectrogram by applying a 512-point STFT with a Hamming window of 32 ms and a hop of 16 ms. The results of the MOSA-Net using the CNN, BLSTM, CNN+BLSTM (denoted as CRNN), and CNN+BLSTM with the attention mechanism (denoted as CRNN+AT) are shown in Table I, where the results of both the seen and unseen tests are reported. For CNN, the model was constructed by convolutional layers completely. As shown in Fig. 1, the CRNN+AT model included 12 convolutional layers, each comprising four channels 16, 32, 64, and 128, a one-layered BLSTM (with 128 nodes), and a fully connected layer (with 128 neurons). An attention layer was used to estimate the assigned objective assessment metric. Finally, the output of the attention layers was forwarded to a fully connected layer (with one neuron), and a global average operation was applied to generate the prediction score. The CRNN model architecture resembled CRNN+AT, where no attention layer was involved. For the CNN, we used the same model architecture as that reported in [67]. The model comprised of four two-dimensional convolutional layers with the following filters and kernels configurations: [15, (5, 5)], [25, (7, 7)], [40, (9, 9)], and [50, (11, 11)]. In addition, the two-D global average pooling was added to fix feature dimension into 50, and the feature was mapped into three fully connected layers with the following configurations: 50 and 10 LeakyReLU nodes, and one linear node. For BLSTM, we used the same model architecture as that reported in [42]. The model comprised of one bidirectional LSTM layer with 100 nodes, followed by two fully connected layers with 50 exponential linear unit (ELU) nodes and one linear node.

As shown in Table I, CRNN slightly outperformed the CNN and BLSTM, in terms of both the PESQ and STOI predictions for the seen and unseen testing sets. The results suggest that combining the abilities of the CNN in extracting local invariant features and BLSTM to characterize temporal characteristics can yield better performance than using individual CNN and BLSTM in this task. Additionally, CRNN+AT outperformed the CRNN. This indicate that by incorporating the attention mechanism, the model can focus on the more important regions and hence allow the MOSA-Net to achieve better prediction performance. To qualitative analyze the advantages of CRNN+AT, we used scatter plots to compare MOSA-Net with two systems, which have been published earlier: Quality-

| Model       | Seen Noises |       |       | Unseen Noises |       |       |
|-------------|-------------|-------|-------|---------------|-------|-------|
|             | LCC         | SRCC  | MSE   | LCC           | SRCC  | MSE   |
| Quality-Net | 0.975       | 0.959 | 0.055 | 0.947         | 0.931 | 0.117 |
| STOI-Net    | 0.964       | 0.945 | 0.074 | 0.957         | 0.932 | 0.075 |
| MOSA-Net    | 0.981       | 0.965 | 0.042 | 0.966         | 0.949 | 0.078 |
| CRNN+AT     | 0.982       | 0.967 | 0.040 | 0.965         | 0.954 | 0.092 |

![PESQ Prediction](image1)

![STOI Prediction](image2)

Fig. 3. Scatter plots of speech assessment models between MOSA-Net and Quality-Net [42] and STOI-Net [45].

TABLE I

LCC, SRCC, AND MSE RESULTS OF MOSA-Net USING CNN, BLSTM, CNN-BLSTM (CRNN) AND CRNN WITH ATTENTION (CRNN+AT) MODEL ARCHITECTURES. THE PESQ FEATURES ARE USED AS THE INPUT, AND A SINGLE METRIC (EITHER PESQ OR STOI SCORES) IS USED TO TRAIN MOSA-Net.
As shown in Fig. 3, we can note that the predicted PESQ and STOI scores by MOSA-Net achieved higher correlations than Quality-Net [42] and STOINet [45], respectively. In the following discussion, we will fix the CRNN+AT as the model architecture for the MOSA-Net.

3) MOSA-Net with single- and multi-task training: Next, we aim to compare the performance of the MOSA-Net with single- and multi-task training criteria. In the previous section, we used a single-task training criterion. Specifically, when the prediction task was the PESQ/STOI, the MOSA-Net was trained using PESQ/STOI labels. In this section, we used multiple assessment targets to train the MOSA-Net, and the model architecture is shown in Fig. 1. The results of single, double, and triple-task learning are shown in Tables II, III, and IV, where the prediction targets are the PESQ, STOI, and SDI, respectively.

As shown in Table II, the MOSA-Net trained with a double-task criterion (PESQ and STOI) yielded overall better results than that trained with a single-task criterion (PESQ only). The triple-task learning criterion yielded only marginal LCC and SRCC improvements for the seen testing condition. Similar trends are presented in Table III, whereas the MOSA-Net trained with the double-training (the PESQ and STOI) criterion can achieve better performance than that trained with the STOI alone in the seen testing condition; however, the additional SDI score did not further improve the STOI predictions. As shown in Table IV, when predicting the SDI scores, it is beneficial for MOSA-Net to consider PESQ and STOI during training to achieve better performance. The results from Tables II-IV suggest that the PESQ and STOI computations are correlated to some degree and that it is beneficial to adopt the multi-task learning criterion when training the speech assessment models.

In addition to quantitative analyses, we conducted qualitative analyses on the MOSA-Net trained with single- and multi-task training criteria. As shown in Fig. 4, the MOSA-Net can estimate the assessment score more accurately than the three assessment models, as indicated by the better convergence of the scatter plots. This demonstrates the benefit of sharing an important feature when training the model.

To develop a comprehensive analysis, we visualized the hidden layer representation of the MOSA-Net with single-task and triple-task learning. We extracted the output of the attention layer from each of the models. In addition, we present the scatter plots of MOSA-Net trained with single and multi-task in Fig. 5. From the figure, the representations of the single-task MOSA-Net trained with individual PESQ, STOI, and SDI values yielded different patterns when predicting the individual metrics (the PESQ, STOI, and SDI). This shows that the MOSA-Net trained with a distinct metric is learned to focus on particular regions. By contrast, as shown in Fig. 6, the

| Label     | Seen Noises |          |            |            |          |            |          |            |            |
|-----------|-------------|----------|------------|------------|----------|------------|----------|------------|------------|
|           | LCC         | SRCC     | MSE        | LCC         | SRCC     | MSE        | LCC       | SRCC       | MSE        |
| Q         | 0.982       | 0.965    | 0.043      | 0.965       | 0.954    | 0.092      |          |            |            |
| Q+I       | 0.987       | 0.974    | 0.028      | 0.966       | 0.952    | 0.068      |          |            |            |
| Q+I+D     | 0.987       | 0.975    | 0.031      | 0.965       | 0.951    | 0.058      |          |            |            |

| Label     | Seen Noises |          |            |            |          |            |          |            |            |
|-----------|-------------|----------|------------|------------|----------|------------|----------|------------|------------|
|           | LCC         | SRCC     | MSE        | LCC         | SRCC     | MSE        | LCC       | SRCC       | MSE        |
| D         | 0.883       | 0.904    | 0.045      | 0.826       | 0.823    | 0.050      |          |            |            |
| Q+I+D     | 0.941       | 0.949    | 0.024      | 0.863       | 0.871    | 0.035      |          |            |            |

Fig. 4. Scatter plots of speech assessment models between single task and multi-task models.

Fig. 5. Scatter plots of speech assessment models between single task and triple-task models.
Fig. 5. Representations of a speech utterance at the hidden layers of (a) Single-task (PESQ) (b) Single-task (STOI) (c) Single-task (SDI)

Fig. 6. Representations of a speech utterance at the hidden layers of (a) Multi-task (PESQ) (b) Multi-task (STOI) (c) Multi-task (SDI)

multi-task MOSA-Net which was trained simultaneously on three assessment metrics yielded different visualization results. Unlike the single-task speech assessment model, the multi-task based MOSA-Net model yielded a similar pattern in each of the branches. Therefore, it may further suggest that the MOSA-Net aims to share useful representations and achieve more general weights by optimally considering all metrics.

4) Comparison with another multi-task method: In this section, we compare the performance of the MOSA-Net with that of another multi-task speech assessment model, namely, attention enhanced multi-task speech assessment (AMSA) [44]. Specifically, we compared two different strategies to update the objective functions. In our proposed work, we combined the estimated loss from the utterance and frame-level scores to define the objective functions. By contrast, the AMSA uses the regression loss based on the utterance level score and classification loss based on the classification-aided model to define the objective functions. For a fair comparison, the same model architecture with the same number of assessment targets was used in both systems. When training the AMSA system, we followed the same parameters as defined in [44] to adjust the classification-aided model.

As shown in Table V, the proposed MOSA-Net can achieve better performance in almost all objective assessment metrics. In terms of the LCC, SRCC, and MSE metrics, the MOSA-Net consistently outperformed the performances of AMSA in almost every evaluation, except for the case of estimating STOI-score under seen noises. Therefore, these evaluation results demonstrate the benefit of combining the utterance level-score and the frame level-score to form the objective function.

5) MOSA-Net with cross-domain features: In this section, we investigate the effects of different acoustic features on the achievable performance of the MOSA-Net. In addition, we investigated whether a combination of multiple acoustic features can allow the MOSA-Net to obtain more accurate prediction scores. In addition to PS features, which have been used in the previous two sets of experiments, the MOSA-Net adopted complex features (termed complex), learnable filter banks (termed LFB features) and the output of a self-supervised pre-trained model (termed SSL features). The goals of using these three features are as follows: (1) Complex features can reserve the phase information; (2) the LFB features can retain the raw-waveform information more completely; (3) the SSL features can exploit the context-information of phones. In this study, we used real and imaginary (RI) spectrograms to deploy complex features. Next, we used SincNet [50] as a learnable feature extraction model. Furthermore, we adopted two types of self-supervised models, namely Wav2vec 2.0 [51] and HuBert [52], to generate the SSL features. The corresponding features are terms SSL(W2V) and SSL(Hub), respectively. The results of the MOSA-Net using PS, Complex, LFB, SSL(W2V), and SSL(Hub) features are shown in Table VI.
As shown in Table VI, the PS features tended to achieve slightly better performances than the other features when estimating the PESQ. By contrast, in assessing the STOI score, the SSL(Hub) features achieved better performance in both the seen and unseen environments. Meanwhile, in assessing the SDI score, the complex and PS features achieved better performances in the seen and unseen environments, respectively. Hence, it is indicated that these acoustic features have different and complementary information for speech assessment. In addition, by considering phase information, it can reserve useful information that is particularly more useful when conducting assessment evaluations in seen environments. In addition, because SSL(Hub) generally provides better performance than SSL(W2V). Therefore, SSL(Hub) is used as the representative SSL features in the following discussion.

Based on the findings shown in Table VI, we further investigated that the MOSA-Net combines cross-domain features as input. The results of the MOSA-Net with different combinations of acoustic features are listed in Table VI. As shown in Fig. 1, the STFT and learnable neural network (SincNet in this study) were applied to the speech waveform to obtain the PS/Complex and LFB features, which were then used as the input to the MOSA-Net. For the SSL(W2V) and SSL(Hub) features, the speech waveforms were processed using the Wav2vec 2.0 and HuBert models, respectively, and the latent representations were input to the middle layer of the MOSA-Net model. The results of the different forms of cross-domain features are shown in Table VII.

Comparing the results in Tables VII and Table VI, the benefits of incorporating cross-domain features to train the MOSA-Net model were evident. For example, the combination of Complex with SSL(Hub), denoted as Complex+SSL(Hub) in Table VI, consistently outperformed the individual Complex and SSL(Hub) in terms of the PESQ, STOI, and SDI predictions in both the seen and unseen environments. Fur-
thermore, Table VII shows that the Complex+Hub features achieved the best performance among other combinations for STOI and SDI predictions in the seen environments. Finally, the combination of three acoustic features, namely Complex+LFB+SSL(Hub) / PS+LFB+SSL(Hub), consistently achieved better performance in the unseen environments as compared with Complex+SSL(Hub) / PS+SSL(Hub). We also present the scatter plots of MOSA-Net using single input (PS) and using cross domain features (PS+SSL(Hub)). The plots are shown in Fig. 7. From the figure, the MOSA-Net trained with cross-domain features can achieve a more accurate estimation than the single-domain feature. Therefore, these results confirm the benefit of cross-domain features with more complete information for the speech assessment model.

### B. Experiments of SE with assessment information

We further propose the QIA-SE system that incorporates the knowledge from the MOSA-Net model to improve the better SE performance. To date, several SE systems have been proposed to incorporate the knowledge from the speech assessment models into an SE system, e.g., [53], [54]. In this section, we intend to compare the proposed QIA-SE with the comparative SE systems. We tested the proposed QIA-SE systems on two SE datasets, the WSJ and the Taiwan Mandarin version of the Hearing in Noise Test (TMHINT) datasets [74].

PESQ, STOI, and SDI scores were used to evaluate the SE performance.

1) Experiments on WSJ dataset: For the WSJ dataset, we prepared 37,416 noisy training utterances by artificially adding 100 noise types to clean utterances at 31 SNR levels, ranging from 20 to -10 dB with an interval of 1 dB. For the testing set, we prepared 330 testing utterances by adding four seen (i.e., white, engine, bell, and traffic noises) and four unseen (i.e., car, pink, street, and babble noises) noise types to clean utterances, from the WSJ testing set at six SNR levels (i.e., -10, -5, 0, 5, 10, and 15 dB). All of the training and testing utterances were converted to 257-dimensional log-power-spectra (LPS) features with a Hamming window of 32 ms, a hop size of 16 ms, and a 512-point STFT. For the baseline SE system, we adopted the CNN model, which comprised 12 convolutional layers, followed by a fully connected layer consisting of 128 neurons. Each convolutional layer contained four channels \{16, 32, 64, 128\} with three types of strides \{1, 1, 3\} in each channel. Next, two comparative systems, namely specialized speech enhancement model selection (SSEMS) [53] and zero-shot model selection ZMOS [54], were constructed to evaluate the effectiveness of the proposed QIA-SE system. In the SSEMS, multiple component SE models were prepared, with each model characterizing a particular noisy-clean mapping. Subsequently, a speech assessment model was incorporated to select the most suitable component model based on the estimated PESQ scores. For the ZMOS SE system, the latent representation of a speech assessment model was used to prepare multiple component models in the offline. In the online process, the noisy speech was input into the speech assessment model to obtain the latent representation, which was then used to select the most suitable component model to perform SE. By contrast, the proposed QIA-SE approach directly applies latent representation into the hidden layer of the SE model. Therefore the overall system is a speech-assessment-aware SE system. The enhancement results in terms of the PESQ and STOI for the SSEMS, ZMOS, and QIA-SE at different SNR levels are shown in Tables VIII and IX, respectively.

As shown in Table VIII, we first note that both the SSEMS and ZMOS achieved better performances than the baseline CNN model. Next, the proposed QIA-SE significantly outperformed the SSEMS and ZMOS in both the seen and unseen environments. Similar trends were observed from Table VIII, i.e., the SSEMS, ZMOS, and QIA-SE outperformed the baseline CNN, whereas the QIA-SE achieved the best performance. The results confirmed the benefits of applying the speech assessment model as a supportive tool for the main SE task. It is noteworthy that the SSEMS and ZMOS adopted the deep learning based-speech assessment model to prepare multiple component models offline and selected the best one online, where additional models and selection computations are required. By contrast, the QIA-SE directly incorporates the latent representation from the assessment model. The results suggest that directly combining the assessment model into the SE system can be a more feasible and hardware-friendly approach.
2) Experiments on TMHINT dataset: In this experiment, we adopted TMHINT dataset to evaluate the proposed QIA-SE to fulfill three objective: (1) To further verify the effectiveness of the QIA-SE on a different SE task (from a Mandarin corpus); (2) to confirm the effectiveness of speech assessment code for cross-language corpora; and (3) to verify the correlations of the SE performance with the MOSA-Net trained with different training criteria (single-task and multi-task learning). The TMHINT dataset comprised of 1,200 utterances recorded by three male and three female speakers (each speaker provided 200 utterances) for the training stage. We injected 100 types of noises [72] at 31 SNR levels (from -10 dB to 20 dB, with a step of 1 dB), resulting in 120,000 training utterances. For the test set, it comprised 120 utterances recorded by two speakers (one male and one female). It is noteworthy that the speaker and speech content did not overlap with the training set. Subsequently, we selected four seen (i.e., white, engine, bell, and traffic noises) and four unseen (i.e., car, pink, street, and babble) noise types to evaluate the systems. Specifically, we injected noise at six SNR levels (i.e., -10, -5, 0, 5, 10, and 15 dB).

Similar to the previous experiments, we intended to use the same model architecture to develop the baseline CNN systems. We denote the QIA-SE with the MOSA-Net trained with single-task and multi-task criteria as QIA-SE(S) and QIA-SE(M), respectively. All the QIA-SE models were constructed based on the same model architecture used in the baseline system. The MOSA-Net was constructed based on the best model architecture. The PESQ and STOI results under the seen and unseen noise types are shown in Figs. 8 and 9, respectively. It is noteworthy that QIA-SE(S-PESQ) and QIA-SE(S-STOI) imply that the PESQ and STOI scores were used to train the single-task MOSA-Net, respectively.

As shown in Fig. 8, we note that QIA-SE(S-PESQ) and QIA-SE(S-STOI) and QIA-SE(M) outperformed the baseline CNN, whereas QIA-SE(M) achieved better performance than the other two in certain region. The results again confirm the effectiveness of the QIA-SE, which leverages the speech
assessment model to attain better SE capability. Meanwhile, as shown in Tables II and III, the multi-task learning criterion allows the MOSA-Net to more accurately predict the speech assessment scores. The results in Figs. 8 and 9 show that an SE system with a better speech assessment model can achieve better enhancement performance.

3) Qualitative Analysis: In addition to objective evaluation, Figs 10, 11, and 12 demonstrate the waveform, spectrogram, and amplitude envelope plots of a clean utterance, respectively, along with its noisy version (car noise), and the enhanced utterances (by the CNN and QIA-SE). As shown in From Fig. 10, both the CNN and QIA-SE effectively removed the noise components from noisy input. Compared with CNN, the QIA-SE preserves more structures (please refer to the red rectangles in Fig. 10 (a), (c), and (d)).

Furthermore, as shown in Fig. 11, we again note that both the CNN and QIA-SE effectively reduced noise components, and the QIA-SE preserves more speech structures than the CNN (please compare the red rectangles in Fig. 11 (a), (c), and (d)).

In addition, several previous works have shown that the amplitude envelope of the middle-frequency bands contributed significantly to the speech intelligibility process. In this study, we adopted the four-channel tone-vocoder used in [75] to extract an amplitude envelop that encompassed 457–1202 Hz from the speech waveforms. Fig. 12 shows the amplitude envelopes of the clean, noisy, and enhanced utterances processed by the CNN and QIA-SE, where the x- and y-axes denote the time index and amplitude magnitude, respectively. The results shown in Fig. 12 (a), (c), and (d) confirm that the amplitude envelopes produced by the QIA-SE can yield a similar pattern to the original clean waveform. The results further confirmed the benefits of the QIA-SE approach.

V. CONCLUSION

In this paper, we proposed a cross-domain speech assessment metric, i.e., MOSA-Net. We first systematically investigated the performance of MOSA-Net with different model architectures and compared the prediction capability based on different training criteria (single-task vs. multi-task training). Experimental results showed that the CRNN with the attention mechanism achieved the best performance as compared with the other models in terms of the LCC, SRCC, and MSE scores. Next, the MOSA-Net with multitask training consistently and significantly outperformed that with single-task training. Finally, we tested the MOSA-Net based on different acoustic features, including spectral features, waveform processed by learnable filter banks, and representation from a SSL model. The results showed that using a cross-domain feature (combining information from spectral features, complex features, raw-waveform, and SSL features), the MOSA-Net achieved the best performance.

In the second part, we proposed QIA-SE, an SE system that incorporates the information from the MOSA-Net. Experimental results showed that the QIA-SE, which jointly combined the latent representations from the MOSA-Net, yielded better performance than previous works of SSEMS and ZMOS, which utilized speech assessment models for offline ensemble model preparation and online model selection. In addition to better performances, the QIA-SE required less model storage requirements and online computation. Finally, we observed that when using a better speech assessment, the SE systems yielded better performance.

In the future, we will investigate the applicability of the MOSA-Net in estimating the assessment scores under a cross-corpora scenario and then further improve its performance robustness based on real-world scenarios. Additionally, we plan to extend the MOSA-Net to predict other subjective assessment scores.

REFERENCES

[1] J. Chen, J. Benesty, Y. Huang, and S. Doclo, “New insights into the noise reduction wiener filter,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 14, no. 4, pp. 1218–1234, 2006.
[2] P. Scalart and J. Vieira Filho, “Speech enhancement based on a priori signal to noise estimation,” in Proc. ICASSP, 1996, vol. 2, pp. 629–632.
[3] J. Hansen and B. Pellom, “An effective quality evaluation protocol for speech enhancement algorithms,” in Proc. International Conference on Spoken Language Processing, 1998, vol. 7, pp. 2819–2822.
[4] J. L. Roux, S. Wisdom, H. Erdogan, and J. R. Hershey, “Sdr – half-baked or well done?,” in ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 626–630.
[5] C. Ma, D. Li, and X. Jia, “Optimal scale-invariant signal-to-noise ratio and curriculum learning for monaural multi-speaker speech separation in noisy environment,” in 2020 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), 2020, pp. 711–715.
[6] A. Rix, J. Beerends, M. Hollier, and A. Hekstra, “Perceptual evaluation of speech quality (pesq), an objective method for end-to-end speech quality assessment of narrowband telephone networks and speech codecs,” in ITU-T Recommendation, 2001, p. 862.
[7] T. Murphy, D. Picovici, and A. E. Mahdi, “A new single-ended measure for assessment of speech quality,” in Proc. INTERSPEECH, 2006, pp. 177–180.
[8] D. Sharma, L. Meredith, J. Lainez, D. Barreda, and P. A. Naylor, “A non-intrusive pesq measure,” in Proc. GlobalSIP, 2014, pp. 975–978.
13

[55] C.-C. Lo, S.-W. Fu, W.-C. Huang, X. Wang, J. Yamagishi, Y. Tsao, and H.-M. Wang, “Mosnet: deep learning-based objective assessment for voice conversion,” in Proc. INTERSPEECH, 2019, pp. 1541–1545.

[56] A. H. Andersen, J. M. De Haan, Z. H Tan, and J. Jensen, “Nonintrusive speech intelligibility prediction using convolutional neural networks,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 26, no. 10, pp. 1925–1939, 2018.

[57] M. B. Pedersen, A. Heidemann Andersen, S. H. Jensen, and J. Jensen, “A neural network for monaural intrusive speech intelligibility prediction,” in Proc. IEEE ICASSP, 2020, pp. 336–340.

[58] G. Mittag and S. Möller, “Non-intrusive speech quality assessment for super-wideband speech communication networks,” in Proc. IEEE ICASSP, 2019, pp. 7125–7129.

[59] J. M. Kates and K. H. Arehart, “The hearing-aid speech perception index (haspi) version 2,” Speech Communication, vol. 131, pp. 35–46, 2021.

[60] X. Dong and D. S. Williamson, “A pyramid recurrent network for predicting crowdsourced speech-quality ratings of real-world signals,” in arXiv preprint arXiv:2106.07474, 2021, pp. 4631–4635.

[61] Z. Zhang, P. Vyas, X. Dong, and D. S. Williamson, “An end-to-end non-intrusive model for subjective and objective real-world speech assessment using a multi-task framework,” in ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2021, pp. 316–320.

[62] F.-K. Chuang, S.-S. Wang, J. w. Hung, Y. Tsao, and S.-H. Fang, “Speaker-aware deep denoising autoencoder with embedded speaker identity for speech enhancement,” in Proc. INTERSPEECH, 2019, pp. 3173–3177.

[63] Y. Koizumi, K. Yatabe, M. Delcroix, Y. Masuyama, and D. Takeuchi, “Speech enhancement using self-adaptation and multi-head self-attention,” in Proc. IEEE ICASSP. 2020, pp. 181–185.

[64] M. Delcroix, K. Zmolikova, K. Kinoshita, A. Ogawa, and T. Nakatani, “Single channel target speaker extraction and recognition with speaker beam,” in Proc. IEEE ICASSP. 2018, pp. 5554–5558.

[65] K. Zmolikova, M. Delcroix, K. Kinoshita, T. Ochiai, T. Nakatani, L. Burget, and J. Cernocky, “Speakerbeam: Speaker aware neural network for target speaker extraction in speech mixtures.” IEEE Jnl. of Selected Topics in Signal Process., 2019.

[66] J. Lee, Y. Jung, M. Jung, and H. Kim, “Dynamic noise embedding: Noise aware training and adaptation for speech enhancement,” in arXiv preprint arXiv:2008.11920, 2020.

[67] S.-W. Fu, C.-F. Liao, Y. Tsao, and S.-D. Lin, “Metricgan: Generative adversarial networks based black-box metric scores optimization for speech enhancement,” in arXiv preprint arXiv:1905.04874, 2019.

[68] S.-W. Fu, C. Yu, T.-A. Hsieh, and et.al., “Metricgan+: An improved version of metricgan for speech enhancement,” in arXiv:2104.03538, 2021, 2021.

[69] K. M. Nayem and D. S. Williamson, “Incorporating Embedding Vectors from a Human Mean-Opinion Score Prediction Model for Monaural Speech Enhancement,” in Proc. Interspeech 2021, 2021, pp. 216–220.

[70] Y.-T. Chang, Y. H. Yang, Y.-H. Peng, S.-S. Wang ang, T.-S. Chi, Y. Tsao, and H. M. Wang, “Mohev: A mixture of experts voice conversion system with sparse gating mechanism for online computation acceleration,” in Proc. International Symposium on Chinese Spoken Language Processing (ISCSLP). IEEE, 2021, pp. 1–5.

[71] D. Paul and J. Baker, “The design for the wall street journal-based csr corpus,” in Proc. ICSLP, 1992, pp. 899–902.

[72] D. Hu, “100nonspeechenvironmentalsounds2004[online].” [http://www.cse.ohio-state.edu/pml/corpus/HuCorpus.html], 2004.

[73] C. Spearman, “The proof and measurement of association between two things,” The American journal of psychology, vol. 15, no. 1, pp. 72–101, 1904.

[74] M. Huang, “Development of taiwan mandarin hearing in noise test,” Department of speech language pathology and audiology. National Taipei University of Nursing and Health Science, 2005.

[75] S.-W. Fu, P.-C. Li, Y.-H. Lai, C.-C. Yang, L.-C. Hsieh, and Y. Tsao, “Joint dictionary learning-based non-negative matrix factorization for voice conversion to improve speech intelligibility after oral surgery,” IEEE Transactions on Biomedical Engineering, vol. 64, no. 11, pp. 2584–2594, 2017.