Attention-based multi-task learning for speech-enhancement and speaker-identification in multi-speaker dialogue scenario

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Abstract—Multi-task learning (MTL) and the attention technique have been proven to effectively extract robust acoustic features for various speech-related applications in noisy environments. In this study, we integrated MTL and the attention-weighting mechanism and propose an attention-based MTL (ATM) approach to realize a multi-model learning structure and to promote the speech enhancement (SE) and speaker identification (SI) systems simultaneously. There are three subsystems in the proposed ATM: SE, SI, and attention-Net (AttNet). In the proposed system, a long-short-term memory (LSTM) is used to perform SE, while a deep neural network (DNN) model is applied to construct SI and AttNet in ATM. The overall ATM system first extracts the representative features and then enhances the speech spectra in LSTM-SE and classifies speaker identity in DNN-SI. We conducted our experiment on Taiwan Mandarin hearing in noise test database. The evaluation results indicate that the proposed ATM system not only increases the quality and intelligibility of noisy speech input but also improves the accuracy of the SI system when compared to the conventional MTL approaches.

Index Terms—Speech enhancement, speaker identification, multi-task learning, attention weighting, neural network.

I. INTRODUCTION

Speech signals propagating in an acoustic environment are inevitably deteriorated by environmental noises and degrade the performance of various speech-related applications such as automatic speech recognition (ASR) [1], and speaker verification [2, 3]. To address this issue, speech enhancement (SE) is one of the widely used approaches to extract clean utterances from noisy inputs. Conventional SE techniques including the signal subspace method [4], power spectral subtraction [5], Wiener filtering [6], and minimum mean square error based estimations [7, 8] are suitably employed in stationary environments to reduce noise components from applied statistical assumptions between environmental noises and human speech [9, 10, 11]. In contrast, deep learning (DL) methods are designed to transfer the noisy source to a clean target in terms of powerful nonlinear capabilities to implicitly model the statistical properties of acoustic signals. For example, the work in [12, 13] proposes a deep-neural-network (DNN)-based deep denoising autoencoder (DDAE) to encode an input noisy speech into a series of frame-wise speech codes, and then perform a decoding process to retrieve the clean part from the system output. Another study in [11] apply long short-term memory (LSTM) to integrate the context information for improving sound quality and intelligibility in SE while achieving a low word error rate in an ASR system. In [14], the transformer technique utilizes an attention mechanism for computing attention weights, which are used to emphasize related context symbols and fuse them to extract clean components.

A single SE can be extended to multiple applications by concatenating different tasks at the system output side and forming a multi-task learning (MTL) model [15, 16]. In such a model, the purpose of MTL is to look for purified representations between related tasks to boost the performance of major tasks [17]. Considering this viewpoint, some proposed techniques [18, 19] leverage visual modality as a second regression task to promote an SE system. Consequently, both audio and visual cues work together to derive more representative acoustic features in a DL model to enhance SE performance.

On the other hand, MTL has been applied to a speaker recognition task [20, 21, 22] for identifying or to confirming the identity of a person in terms of input speech segments. The recognized accuracy of a speaker-identification (SI) task is dependent on the extracted speaker features. Therefore, most of the proposed techniques realize the decent speaker representations from a text-independent waveform input. Over the years, combination of i-vector with a probabilistic linear discriminant analysis [23] has become a famous feature extraction criteria in conventional approaches. Recently, d-vector [24] and x-vector [25] features extracted by DL models have been proven to provide more abundant speaker information and thus show superior identification performances.

Inspired by the transformer model structure, this study proposes a novel system called attention-based MTL (ATM) to extract the shared information between SE and SI and to improve their performance. The system outputs are SE and SI, while the input is noisy speech in the frequency domain. In addition, an attention-based network (AttNet) is used to integrate both speech and speaker cues between SE and SI models to extract robust acoustic features. For ATM, two DL-based models are created: the first LSTM enhances the input noisy spectra, while the second DNN is used for classifying the speaker identity and extracting the attention weight from the major task, that is, SE. The objective evaluations on the Taiwan Mandarin hearing in noise test (TMHINT) corpus [26] showed that the proposed ATM can improve not only the quality and intelligibility of distorted utterances but also the accuracy of speaker identity classification in the test set.

The remainder of this paper is organized as follows. Section II reviews the related work, including LSTM-based SE and DNN-based SI. Section III introduces the proposed ATM architecture. Experiments and the respective analyses are given in Section IV. Finally, Section V presents the conclusions and future research directions.

II. RELATED WORK

This section briefly reviews the processes in the LSTM-SE and DNN-SI systems. In noisy environments, the received noisy speech is provided by contaminating clean utterances with background noises. A short-time Fourier transform (STFT) is applied to the time-domain signals to provide the noisy and clean logarithmic power spectra (LPS), Y and S, respectively, while preserving the noisy phase component. In addition, there are \( N \) frames in the paired Y–S.
The context feature of noisy LPS is then generated by concatenating the adjacent $M$ static feature frames at the associated feature vector $Y'[n]$, that is, $Y'[n] = [Y[n-M]; \cdots; Y[n]; \cdots; Y[n+M]]$, where “;” denotes the vertical-concatenation operation.

A. Speech enhancement

In this study, the baseline SE system composed of an $L$-hidden-layer LSTM and a feed-forward layer is trained for shrinking noise components from a noisy input. This SE system is denoted as LSTM-SE, in which the input-output relationship $(z_{L+1}[n], z_L[n])$ at $n$-th frame and the arbitrary $\ell$-th hidden layer is formulated by

$$z_{\ell+1}[n] = LSTM_{\ell}[z_{\ell}[n]], \quad \ell = 1, 2, \cdots, L.$$  

(1)

Notably, the input in the first LSTM layer is $Y$, i.e. $z_{t=1}[n] = Y[n]$. The output $z_{L+1}[n]$ is then processed by

$$\hat{S}[n] = Wz_{L+1}[n] + b,$$  

(2)

where $W$ and $b$ are the weighted matrix and bias vector, respectively. In the training stage, the parameters of the baseline SE system are provided by minimizing the distance between $\hat{S}[n]$ and $S[n]$ in terms of the mean square error (MSE). On the other hand, the output $\hat{S}$ in the testing stage is combined with the preserved noisy phase and then processed with an inverse STFT to produce the enhanced time-domain signal $\hat{s}$.

B. Speaker identification

This subsection introduces the frame-based DNN-SI system. The objective of the DNN-SI is to classify input $Y[n]$ at $n$-th frame into a specific speaker identity. In addition, this study assumes these non-speech frames to be uttered by a single virtual speaker. Therefore, the dimension of DNN-SI output is the number of speakers plus one.

The DNN SI contains $D$ layers, in which the input-output relationship $(z_{d}[n], z_{d+1}[n])$ at $d$-th layer and $n$-th frame is formulated by

$$z_{d+1}[n] = \sigma^{(d)}(F^{(d)}(z_{d}[n])), \quad d = 1, \cdots, D,$$  

(3)

where $\sigma^{(d)}(\cdot)$ and $F^{(d)}(\cdot)$ are the activation and linear transformation functions, respectively. The activation function is set to softmax for the output layer, that is, $d = D$, while the rectified linear units (ReLU) function is used for all hidden layers. Meanwhile, the input and output of DNN correspond to $z_{(1)}[n] = Y[n]$ and $z^{(D+1)}[n] = I$, respectively. To obtain DNN parameters in Eq. (3), the categorical cross-entropy loss function is used in the training stage.

III. THE PROPOSED APPROACH

In this section, the block diagram of the ATM is depicted in Fig. 1. According to the figure, the proposed ATM that utilizes MTL to present the representative feature is composed of SE, SI, and AttNet modules. The system input is a noisy LPS $Y$, while the outputs are enhanced LPS in SE and speaker identity vector in SI. Meanwhile, two different ATM architectures are implemented and introduced in the following two sub-sections.

A. The first type of ATM system

Figure 2 illustrates the block diagram of the first ATM approach. As shown in the figure, the SE model is used to provide the embedded speech code vector, $z_{L+1}[n]$, from the output of the $L$-th LSTM hidden layer. We then create the context information of speech by concatenating the adjacent $M$ $z_{L+1}[n]$ vectors and providing $[z_{L+1}[n-M]; \cdots; z_{L+1}[n]; \cdots, z_{L+1}[n+M]]$ to the SI to compute the speaker feature at the output of the last hidden layer (i.e., the penultimate layer or $z_{D}[n]$). Then, AttNet, which is a $J$-layer DNN model, takes the speaker feature as the input to extract the weighting vector, $\omega$, to reinforce the speaker-dependent nodes at the output of the $(L-1)$-th LSTM hidden layer of SE. The attention mechanism is used for the reinforcement process by simply performing $\omega[n] \odot z_L[n]$, where $\odot$ is an element-wise multiplication operator. Consequently, the enhanced speech and classified speaker identity are obtained in terms of the derived speaker-attention speech features at the $L$-th LSTM hidden layer. As the attention operation is performed before extracting the acoustic feature representation, we denote the approach as “ATM$_{se}$”.

To train ATM$_{se}$, we first prepare noisy LPS, speaker-identity vectors, and clean speech features to form the training set. Then, an iterative training is applied to individual SI and SE–AttNet models in the following steps: (1) The categorical cross-entropy loss function is used to optimize the SI model parameters, wherein the model input and output are the contextual embedding features and the speaker-identity vectors, respectively. (2) We extract the speaker features, $z_{(D)}$, using the SI model. (3) The training proceeds with $Y$ and $z_{(D)}$ on the input side of SE and AttNet, respectively, to produce an enhanced output that approximates $S$. Notably, the SE and AttNet models are jointly trained with an MSE loss function.

B. The second type of ATM system

In contrast to ATM$_{se}$, the second proposed ATM architecture named ATM$_{dec}$ performs shared acoustic feature extraction and the
On the other hand, the dynamic weighted loss function [27] proposed to address the scale issue between classification and regression tasks is minimized in this study for ATM_{ide} in the training phase. The loss function is formulated in Eq. (4) with two additional trainable parameters, $\sigma_1$ and $\sigma_2$.

$$L(\Theta, \sigma_1, \sigma_2) = \frac{1}{2\sigma_1^2}L_1(\Theta) + \frac{1}{\sigma_2^2}L_2(\Theta) + \log\sigma_1 + \log\sigma_2,$$

where $L_1$ and $L_2$ are the MSE and categorical cross-entropy loss functions, respectively; the $\Theta$ represents all parameters in ATM_{ide}.

### IV. Experiments and Analyses

In the following subsections, we first introduce the experimental setup of MTL-based SE and SI tasks and then provide the experimental results together with a discussion on the presented systems.

#### A. Experimental setup

We evaluated the system’s performance on the TMHINT database. The disjointed training and testing scripts of TMHINT were recorded by eight different speakers at a 16 kHz sampling rate in a noise-free environment. A total of 1,560 clean utterances were pronounced by three males and three females ($K = 6$ in Section IV-A), with each of them reading 260 TMHINT utterances for the training set. From these clean data, we randomly concatenated three different recordings to simulate the dialogue scenario and subsequently generated 520 clean training utterances, wherein each speech contained exactly three different speakers. Noisy utterances were generated by artificially adding 100 different types of noises [28] at six signal-to-noise ratio (SNR) levels (15, 10, 5, 0, −5, and −10 dBs) to the prepared 520 clean training utterances, and thus provide 312,000 (= 520 × 100 × 6) noisy–clean training pairs. Among them, we randomly selected 500 speech pairs to form the validation set. Meanwhile, two different testing configurations were applied to each SE and SI tasks. For SE, the testing set contains one additional male and female speech. We randomly concatenated one utterance of the male speaker with a speech recorded by the female and ultimately generated 60 clean testing waveforms. Noisy testing utterances were determined by deteriorating these clean data with four additive noises ("engine", "pink", "street", and "white") at three SNRs (5, 0, and −5 dBs). Therefore, we have 720 (= 60 × 4 × 3) noisy testing samples. In contrast to SE, the testing set for evaluating SI comprises the same speakers from the training set. However, we prepared 120 clean dialogue waveforms from testing utterances, with each dialog utterance containing three different speakers. Then, we manually added four additive noises ("engine", "pink", "street", and "white") at three SNRs (5, 0, and −5 dBs) to these clean testing sets to form the noisy data. Therefore, we have 1440 noisy testings for the SI task. Notably, no overlapping speaker is observed in the sound segment of an utterance in all training and testing sets.

A speech utterance in the training and test sets was first windowed to overlapping frames, with the frame size and the shift being 32 ms and 16 ms, respectively. Then, a 257-dimensional LPS was derived through a 512-point discrete Fourier transform. The context feature for each frame was created for $M = 5$ and extended to $2,827 = 257(2 × 5 + 1)$ dimensions. Accordingly, the input- and output-layer sizes of SE were 257, while those of SI were 2,827 and 7 (i.e., $K + 1 = 6 + 1$), respectively. For ATM, the input size was 257 and the output size was 257 in SE and 7 in SI. The network configuration is as follows:

- The SE model consists of two LSTM layers ($L = 2$) with 300 cells in each layer, followed by a 257-node feed-forward layer.
- The SI model comprises four hidden layers ($D = 4$) in the order of 1024, 1024, 256, and 7 nodes.
- The AttNet in each of the ATM models contains two hidden layers ($J = 2$) with each layer having 300 nodes.

In this study, we applied three metrics to evaluate all system performances: perceptual evaluation of speech quality (PESQ) [29], short-time objective intelligibility (STOI) [30], and segmental SNR index (SSNRI) [31]. The score ranges of PESQ and STOI are [−0.5, 4.5] and [0, 1], respectively. Higher PESQ and STOI scores denote better sound quality and intelligibility. Regarding SSNRI, a higher score indicates a decent SNR improvement.

#### B. Experimental results

In this subsection, we split the evaluation results into two parts. We report the SE evaluation results in the first subsection while the

|   | Noisy | LSTMS-E | MTL | ATM_{ide} | ATM_{ide} |
|---|-------|---------|-----|-----------|-----------|
| PESQ | 1.25  | 1.86   | 1.86 | 1.94      | 1.98      |
| STOI | 0.72  | 0.73   | 0.74 | 0.74      | 0.75      |
| SSNRI| −     | 7.39   | 7.61 | 7.57      | 8.05      |
SI performances are listed in the second part.

1) The performance of SE: Table I lists the averaged PESQ, STOI, and SSNRI results with respect to all tested utterances of the noisy baseline (denoted as “Noisy”) and those processed by conventional LSTM-SE and both ATM systems (ATM_{lbf} and ATM_{ldc}). In addition, the results of MTL, which is composed of only SE and SI models in Fig. 1 are also listed for comparison. From the table, most evaluation metrics on MTL-based approaches, that is, MTL, ATM_{lbf}, and ATM_{ldc}, show better results than those provided by Noisy and LSTM-SE, except the PESQ score of MTL. This observation suggests the capability of MTL-based models to improve the sound quality, intelligibility, and background noise reduction in terms of the representative features. In addition, ATM_{lbf} and ATM_{ldc} provide decent results on all evaluation metrics while ATM_{ldc} yields superior scores than ATM_{lbf}. These observations clearly indicate that the SE performance of MTL can be further improved by applying the attention-weighting technique.

The detailed PESQ and STOI scores of Table I are presented in Tables II and III, respectively. We compared the performance of Noisy, LSTM, MTL, ATM_{lbf}, and ATM_{ldc} with respect to four testing noise environments over all SNR levels. From both tables, we observe that all DL-based approaches provide better PESQ and STOI scores on all evaluated conditions than those achieved by the noisy baseline while the metric scores of ATM_{ldc} are the highest. This observation confirms the capability of the proposed ATM approach to extract robust features for SE to improve sound quality and intelligibility in noisy environments.

2) The performance of SI: Figure 4 illustrates the frame-wise SI accuracy of the DNN-SI baseline, MTL, ATM_{lbf}, and ATM_{ldc}. The evaluation were conducted on “engine”, “pink”, “street”, and “white” noise backgrounds, among which street is considered to be the most complicated testing environment. From the figure, we first observe that MTL-based approaches (MTL, ATM_{lbf}, and ATM_{ldc}) provide a higher SI accuracy than those achieved by DNN-SI. In addition, ATM_{ldc} shows the highest recognized accuracy in the street background, and competes with MTL in other noise environments.

![Frame-wise SI accuracy of DNN-SI, MTL, ATM_{lbf}, and ATM_{ldc} in four testing noise environments.](image)

**TABLE II**

| Noise Environment | Noisy | LSTM-SE | MTL | ATM_{lbf} | ATM_{ldc} |
|-------------------|-------|---------|-----|-----------|-----------|
| WHITE             | 1.25  | 2.01    | 2.00| 2.08      | 2.13      |
| PINK              | 1.28  | 1.88    | 1.88| 1.96      | 2.02      |
| STREET            | 1.32  | 1.84    | 1.83| 1.89      | 1.92      |
| ENGINE            | 1.16  | 1.72    | 1.71| 1.81      | 1.84      |

**TABLE III**

| Noise Environment | Noisy | LSTM-SE | MTL | ATM_{lbf} | ATM_{ldc} |
|-------------------|-------|---------|-----|-----------|-----------|
| WHITE             | 0.75  | 0.75    | 0.75| 0.76      | 0.77      |
| PINK              | 0.72  | 0.72    | 0.73| 0.73      | 0.74      |
| STREET            | 0.72  | 0.74    | 0.75| 0.75      | 0.76      |
| ENGINE            | 0.69  | 0.70    | 0.71| 0.71      | 0.73      |

In this study, we proposed a novel ATM approach that integrates MTL and the attention-weighting mechanism for SE and SI tasks. ATM is composed of SE, SI, and AttNet modules, and is used to extract representative and robust acoustic features in a noisy environment. Experimental results on the TMHINT database simulate the dialog conditions and confirm that the newly proposed ATM significantly reduced the noise components from the noisy speech, while simultaneously improving quality and intelligibility. In addition, the recognized accuracy of the SI system can be further improved through the proposed ATM approach. In the future, we plan to apply ATM to another language. Furthermore, the presented ATM architecture will be tested on speaker-diarization and speech-source separation tasks.

![Statistical analysis of DNN-SI and ATM_{ldc} extracted speaker features with t-SNE dimension-reduction technique.](image)
