



On the Efficacy and Noise-Robustness of Jointly Learned Speech Emotion and Automatic Speech Recognition

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Abstract

New-age conversational agent systems perform both speech-emotion recognition (SER) and automatic speech recognition (ASR) using two separate and often independent approaches for real-world applications in noisy environments. In this paper, we investigate a joint ASR-SER multitask learning approach in a low-resource setting and show that improvements are observed not only in SER but also in ASR. We also investigate the robustness of such jointly trained models to the presence of background noise, babble, and music. Experimental results on the IEMOCAP dataset show that joint learning can improve ASR word error rate (WER) and SER classification accuracy by 10.7% and 2.3% respectively in clean scenarios. In noisy scenarios, results on data augmented with MUSAN show that the joint approach outperforms the independent ASR and SER approaches across many noisy conditions. Overall, the joint ASR-SER approach yielded more noise-resistant models than the independent ASR and SER approaches.

Index Terms: Speech emotion recognition, automatic speech recognition, multitask learning, noise robustness, conversational agents.

1. Introduction

Nowadays, modern AI-based conversational agents employing ASR are also equipped with emotional awareness using SER to improve the overall user experience. These agents are indispensable in real-world applications such as call centers, automotive voice assistants, and voice-enabled home automation systems. For instance, in call centers, conversational AI agents that automatically transcribe the customers' requests using ASR also detect their emotions using SER to ensure customer satisfaction. Therefore, it is essential to build reliable systems that can perform ASR and SER jointly to simplify the computational requirements in scenarios where both tasks are necessary.

However, integrating ASR and SER presents significant challenges, since (i) their underlying approaches have traditionally been developed separately, (ii) corpora that contain both transcriptions and emotion annotations are scarcely available, limiting their performance in joint-use scenarios. There has been limited research in this area, with only a few studies [1, 2]. The authors of [1] demonstrated that multitasking ASR and SER jointly during training can enhance SER performance. In [2], the authors showed an improvement in SER performance by fusing acoustic embeddings with linguistic embeddings generated from the ASR output and jointly training the ASR and

SER end-to-end model. In both works, ASR was considered as an auxiliary task to SER, i.e. there is no clear emphasis on the ASR performance. Moreover, the noise robustness of these models has not been studied. Operating in a real-world setting requires the models to be robust to background conditions, most typically noise, music, and babble. While several approaches exist that improve the robustness of individual ASR and SER systems in noisy environments, the noise robustness of joint modeling has not been studied.

With this motivation, our research presents two main contributions. Firstly, we utilize a multitask joint ASR-SER learning architecture [2], with both of them as primary tasks, with a minor modification in the fusion strategy of acoustic and linguistic information in addition to the existing fusion approach in [2]. This approach overcomes the problem of data scarcity by utilizing pre-trained models, specifically wav2vec2. Furthermore, we investigate and present our results on noise robustness analysis carried out to assess the resilience of the multitasking approach to various typical noise kinds, in comparison to the single-tasking baseline approaches.

The rest of the paper is organized as follows: related work is introduced in Sec. 2, the multitask-based joint learning approach is described in Sec. 3, the experimental settings and results are presented in Sec. 4, analysis is presented in Sec. 5 and the conclusions are presented in Sec. 6.

2. Related Work

According to the literature [3], ASR can benefit from modeling variability among data, such as speaker-related (e.g., i-vectors, x-vectors) and channel-related information (through multi-condition training). Several studies have investigated multitasking with various speech tasks, including age, gender, and speaker verification. In [4], improvements were observed in both ASR and text-dependent speaker verification when performed together. Multitasking with tasks similar to ASR, such as phone label, phone context, and state context prediction, can also improve ASR performance, as demonstrated in [5] and [6]. Thus, one can expect that modeling emotion variability by multitasking with emotion recognition can benefit ASR. Correspondingly, for SER, multi-task learning models have been introduced to predict gender, age, accent, and emotion in a joint manner, and these models demonstrated an enhanced SER performance [7, 8, 9, 10]. As mentioned above, although ASR and SER have been multitasked with other tasks separately, there is also research that combines ASR and SER tasks together which has demonstrated to improve the performance of SER task alone [1, 2, 11], but the improvements on the ASR side have not been systematically evaluated.

In addition to multitasking ASR and SER using acous-

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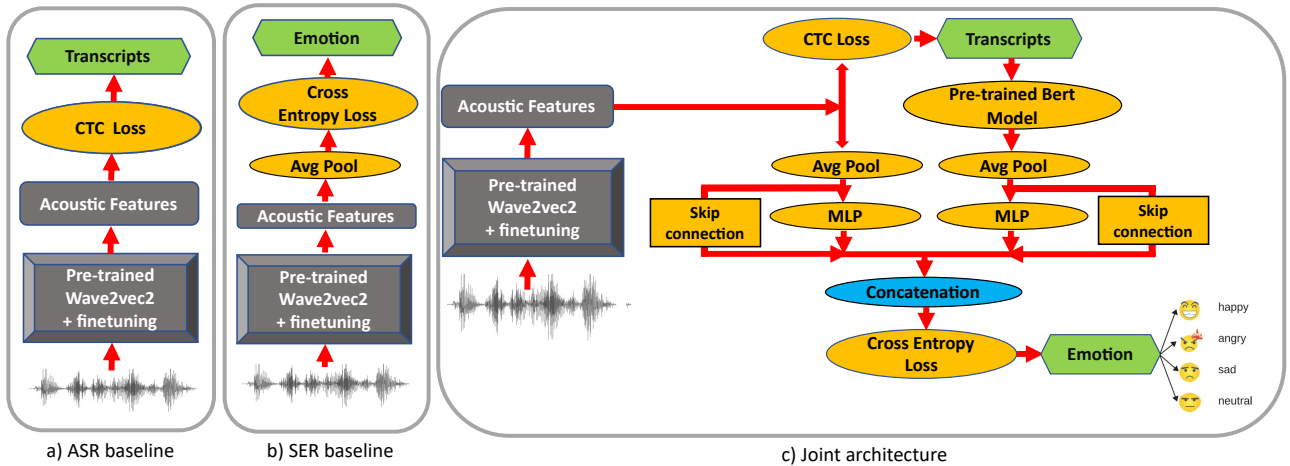


Figure 1: Architectures.

tic embeddings, recent studies have emphasized the fusion of acoustic and linguistic embeddings to improve SER performance. Linguistic embeddings offer additional information about spoken words, leading to better emotion recognition accuracy. Combining both acoustic and linguistic embeddings has been demonstrated to enhance SER classifier performance in comparison to using acoustic embeddings alone. Numerous fusion methods, including the Gated Bidirectional Alignment Network (GBAN) proposed by [12], the deep dual recurrent encoder model proposed by [13], and the fusion techniques proposed by Sebastian et al. [14], have displayed the potential for improving emotion recognition using multiple modalities. Following the previous fusion methods, we present a simple modification to the architecture by incorporating skip connections in conjunction with feed-forward layers. This revised approach entails processing the two embeddings separately using the skip connection-based feed-forward layer before concatenating them.

As advancements have been made in ASR and SER for noise-free environments, there have also been independent studies on ASR and SER in noisy environments. Several techniques were proposed to improve noise robustness in ASR, such as the interactive feature fusion network (IFF-Net) [15], the multitask-based method with dual-channel data augmentation [16], and an online speech distortion module with an encoder [17], to name a recent few. On the other hand, techniques like the adversarial joint training framework with the self-attention mechanism [18] and data augmentation techniques, including overlaying background noise and loudness variations, have been proposed to improve noise robustness in SER models [19]. Additionally, a feature selection technique based on the noise robustness of individual low-level descriptors in noisy conditions has been proposed to improve SER performance without using any compensation methods or a noisy training set [20].

Since we have observed improvements in ASR-SER models through joint training, it is important to investigate the effect of joint ASR-SER training on noise robustness in real-world settings where ASR-SER applications are typically used. In such scenarios, it is critical to ensure that ASR-SER joint models are able to perform accurately in noisy environments.

3. Approach

We begin with the description of the baseline models for ASR and SER tasks, which will serve as a point of comparison for the joint architecture. Then, we will present the joint architecture for a multitask-based joint learning approach. Figure 1 shows the overall architecture of the joint multitasking model along with the ASR baseline and SER baseline models. In our experiments, we employed the SpeechBrain toolkit [21] for both the joint architecture and baselines, since its recipes are considered state-of-the-art. We used the recipes provided by the toolkit as-is for the baselines, which included the ASR and SER baselines. To implement the joint-training approach, we introduced modifications to the same recipe to attain the desired joint architecture. More comprehensive explanations of these modifications will be provided in Sec. 3.2.

3.1. Baseline for ASR and SER

The ASR baseline involves performing data augmentation using Time Domain Spec Augment with three different speed values 95, 100, and 105, followed by acoustic feature extraction using the Hugging Face wav2vec2-large-960h-lv60-self wav2vec2 model [22]. The wav2vec2 encoder was fine-tuned while keeping the convolutional part of the model frozen. The training (fine-tuning) was performed using connectionist temporal classification (CTC) loss [23] and the decoded transcripts were obtained using the corresponding decoding algorithm. The SER baseline involves acoustic feature extraction using the same wav2vec2 encoder, with its fine-tuning with the convolutional part of the encoder frozen. It is followed by an average pooling layer and an output MLP for emotion classification into anger, happiness, sadness, and neutral categories.

3.2. Joint architecture

The joint multitasking architecture aims to improve the performance of both ASR and SER tasks. Firstly, the ASR baseline approach is followed, which involves data augmentation and fine-tuning a pre-trained wav2vec2 model as a shared acoustic feature extractor for both tasks, while freezing the convolutional part of the model. These acoustic feature embeddings are then processed through two parallel and interlinked channels, one for ASR and the other for SER. The ASR channel utilizes a

Table 1: Results of 10-fold cross-validation on IEMOCAP dataset for all the models trained on Clean and Noise data and evaluated at seven test scenarios. Rel Imp refers to relative improvement (%).

10 Fold Cross Results	ASR Performance: Metric Word Error Rate (WER)						SER Performance: Metric - Accuracy					
	Trained on Clean			Trained on Noise			Trained on Clean			Trained on Noise		
Test Dataset	Baseline	Joint	Rel Imp	Baseline	Joint	Rel Imp	Baseline	Joint	Rel Imp	Baseline	Joint	Rel Imp
Clean	16.8	15.0	10.7	19.8	15.6	21.2	71.9	74.2	2.3	70.2	71.7	1.5
SNR 15 Noise	22.2	19.3	13.1	19.8	18.4	7.1	69.8	71.8	2.0	69.0	70.6	1.6
SNR 5 Noise	33.6	29.3	12.8	26.0	25.8	0.8	62.0	66.8	4.8	66.1	68.7	2.6
SNR 15 Music	21.7	19.6	9.9	19.1	18.3	4.3	68.8	72.1	3.3	68.7	71.1	2.4
SNR 5 Music	37.4	35.8	4.3	27.9	29.2	-4.6	60.8	64.2	3.4	65.1	68.4	3.3
SNR 15 Speech	36.9	42.0	-13.8	20.6	22.4	-8.6	66.7	67.6	0.9	67.4	70.0	2.6
SNR 5 Speech	74.6	86.4	-15.8	36.3	51.3	-41.3	53.3	52.4	-0.9	58.1	62.3	4.2

CTC-based decoder [23] to decode the acoustic features and obtain speech transcriptions. The transcriptions contain emotional content as specified in lexical dictionaries [24, 25, 26, 27]. To leverage this information, linguistic embeddings are extracted from the ASR transcriptions using a pre-trained BERT encoder, which has a greater representation capability than other types of embeddings due to its context-aware representations, resulting in more robust and accurate embeddings. Then these BERT-based linguistic embeddings are used in a fusion network for feature-level fusion with the acoustic embeddings. The fusion approach we utilized processes linguistic and acoustic embeddings separately through multi-layer perceptron (MLP). To enhance the robustness, and information flow of these layers, we incorporate skip connections [28] across them that results in more accurate and reliable embeddings. We concatenate the processed embeddings to obtain the final embeddings for SER classification. Finally, a cross-entropy loss-based emotion classifier is used for SER classification. For the training of the joint architecture, we used the following multitasking loss function:

$$\mathcal{L}_{joint} = \alpha \mathcal{L}_{SER} + (1 - \alpha) \mathcal{L}_{ASR} \quad (1)$$

Where \mathcal{L}_{SER} is the SER cross-entropy loss, \mathcal{L}_{ASR} is the ASR CTC loss and α is a scaling factor that determines the contribution of the SER and ASR components. We used $\alpha = 0.1$ that gave the best results (analysis not shown) for both the tasks as primary tasks.

4. Experiments and Results

4.1. Dataset preparation and Experimental setup

For our study, we utilized the IEMOCAP dataset [29], which consists of approximately 12 hours of data from ten actors in five dyadic sessions. The dataset contains 10,039 turns or utterances, sampled at 16 kHz. We used Speechbrain toolkit [21] for experimentation - specifically the ‘IEM4’ categories which include happy, sad, angry, and neutral emotions. In total, we used 5500 utterances in the IEM4 categories for training and evaluation. Further, to generate noise in the data we used MUSAN (Music, Speech, and Noise) dataset [30]. The MUSAN dataset is a large-scale corpus of various types of audio signals, such as music, speech, and noise. The dataset includes more than 8,000 audio files, each 10 seconds long, sampled at 16 kHz. The audio files are categorized into three groups, namely music, speech, and noise, and further sub-categorized based on various properties such as genre, language, and type of noise.

For training the baseline and joint models, we used two types of data: clean data and noisy data. The IEMOCAP IEM4

data was used as the clean set, while the noisy data was created by superimposing the IEM4 data with audio files from the MUSAN dataset, resulting in noisy files with speech-to-noise ratio (SNR) values ranging from 5 to 35 dB and noise types including music, background speech (babble), and background noise. Using these two types of datasets, we trained three types of models (joint architecture, SER, and ASR baseline), resulting in six types of trained models. To evaluate these models, we prepared seven test scenarios with 15 and 5 dB SNR levels across noise types. The joint and baseline methods were evaluated using 10-fold cross-validation. Following the standard practice, one speaker was excluded for testing in each fold, while the remaining nine speakers were used for training. We applied this evaluation approach to the IEMOCAP dataset, which consists of 10 speakers. In each fold of cross-validation, we held out one speaker at a time for testing and utilized the remaining nine speakers for training. During this process, we collected and stored the predictions for emotion and transcription. This hold-and-training procedure was repeated for all ten folds, and finally, the overall performance was assessed by analyzing the predictions.

4.2. Results

Table 1 showcases the outcomes of the aforementioned experiments. The ASR performance is measured in word error rate (WER) (the lower the better), while the SER performance is determined by classification accuracy (the higher the better). The relative performance improvement was calculated by comparing the clean-trained joint model to the clean-trained baseline models and the noise-trained joint model to the noise-trained baseline models.

The results of training testing performed on clean data show that the joint model significantly outperformed the baseline models for both ASR and SER. In terms of ASR, there was a 10.7% improvement in the WER, from 16.8 to 15, and a 2.3% improvement in SER accuracy, from 71.9% to 74.2%.

5. Analysis

In this section, we examine the variation in performance between the baseline and joint models that were trained on clean and noisy data. We use the baseline models trained on clean data as the reference point for the other three types of models, which include the noise-trained baseline models, the clean-trained joint model, and the noise-trained joint model. Fig.2(a) and (b) show these comparisons.

First, we evaluate the impact of noise inclusion in the training data for the seven test scenarios. Fig.2(a) shows that, ir-

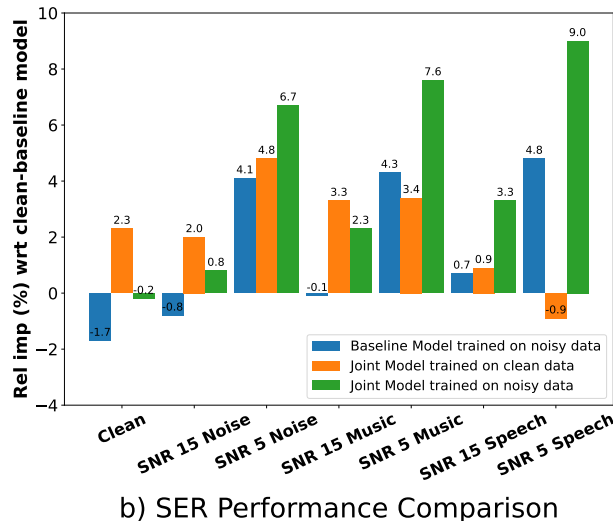
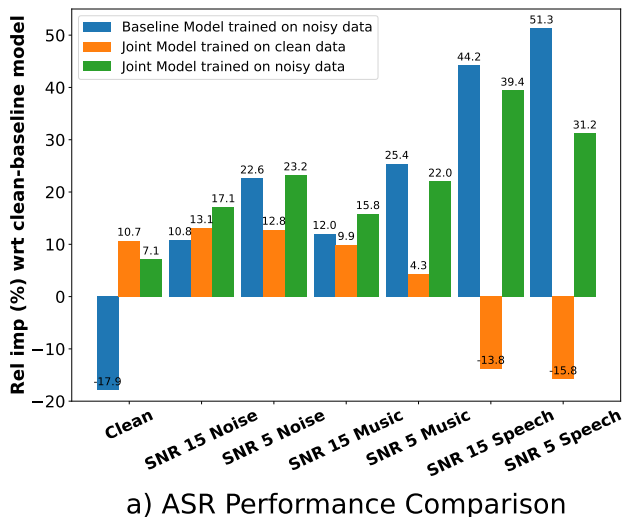


Figure 2: Relative comparison among the baseline models and joint architecture trained with the two training strategies: Clean and Noisy dataset.

respective of the baseline or joint model, training on a noisy dataset yields better performance in all the ASR test cases, except for clean test speech.

Furthermore, when we compare the baseline model to the joint model, regardless of clean or noisy training data, the joint model performs better when there is music and background noise mixed with the data, across all levels of SNR except for scenario SNR 5 Music, where there is a slight improvement in baseline in comparison to the joint model. In Table 1, we can observe a significant relative improvement of the clean-trained joint model over the clean-trained baseline model in the case of noise and music in the background, with a huge improvement across all SNR levels, and the highest improvement of 13.1% for the SNR 15 noise case. Similarly, for the comparison between noise-trained joint and noise-trained baseline models, we can see a significant improvement for the clean test as well as the noise and music-contaminated test set across all SNR levels, with a remarkable improvement of 21.2% for the clean data and significant improvement across other mentioned data sets. Hence, it can be concluded that the joint model always outperforms the baseline model for all SNR levels for music and noise speech contamination scenarios. However, in the case of speech in the background, the baseline model performs better than the joint model, regardless of training type and SNR level. This observation requires further investigation.

In the case of SER, we first focus on the impact of a clean versus noisy training approach. As shown in Figure 2(b), with the exception of the clean test and SNR 15 noise and SNR 15 Music scenarios, the noisy training approach outperforms the clean training approach for both the joint and baseline models. The joint model trained with noisy data exhibits exceptional performance, particularly in the babble scenario and even in highly contaminated scenarios such as the SNR 5 level across all noise types. The most notable improvement is observed in the SNR 5 Noise case, where it outperforms the clean-trained joint model by 9.9% and the noise-trained baseline model by 5.2%. Additionally, the comparison between the noise-trained SER baseline and the clean-trained SER baseline indicates a trend similar to that found in the joint model’s noise versus clean case. This suggests that noise training enhances the noise robustness of the model, regardless of the baseline or joint ar-

chitecture, particularly at low SNR levels and babble scenarios. However, in other cases, the clean-trained models perform better than the noise-trained models.

Finally, we analyze the performance of the joint architecture versus the baseline architecture for both clean and noise-trained scenarios. As shown in the plot, the joint model consistently outperforms the baseline model with significant margins (except for the clean training at SNR 5 speech). This observation indicates that the joint architecture is more robust than the baseline architecture for all types of noise at all SNR levels. Overall for SER, the joint architecture demonstrates better noise robustness than the baseline model regardless of the training strategy.

6. Conclusions

The results conclude that joint modeling of ASR-SER improves both tasks in clean conditions over the single-tasking baselines. In the case of ASR, training on a noisy dataset results in better performance for all test scenarios except clean speech, regardless of whether it is a baseline or joint model. Additionally, the joint model consistently exhibits better performance than the baseline model in most of the test scenarios, except for the babble scenario and the SNR 5 Music scenario (when noise training is used). For the babble scenario, regardless of the training approach, ASR performance degrades at both 15 and 5 SNR, with higher degradation at 5 SNR. Further, in the case of SER, noise training enhances the noise robustness of the model in low SNR levels and babble, and the joint architecture consistently outperforms the baseline architecture for all types of noise and SNR levels.

Finally, we found that joint architectures are generally more noise robust than baseline architectures, but there are still some scenarios where the baseline outperforms the joint model, particularly for ASR tasks having babble test scenarios and Music with lower SNR. Further research could investigate why this is the case and develop strategies to improve joint models’ performance in these scenarios.

7. References

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