Improving speakers separation with additional speech recognition task

Legchenko Anton
Novosibirsk State University
a. legchenko@g. nsu. ru

Pavlovskiy Evgeniy
Novosibirsk State University
e. pavlovskiy@g. nsu. ru

Abstract

In the paper, we propose a method of multi-task learning in the cocktail party problem with a single microphone. The task of automatic speech recognition for each of the speakers in the audio signal was chosen as an additional one. The paper presents two different approaches to the hierarchy of tasks in which speech recognition follows the separation of speech signals or done simultaneously with it. Training and testing of models was carried out on open resources and public datasets.

The proposed method showed an improvement in results compared to the single-task model and gave an increase of about 1% SDR and PESQ according to various estimates of the quality of speaker separation. To confirm the results, a hierarchical model was trained using only the loss function of the speech recognition task, which also improved the quality of speaker separation by 0.4% SDR and PESQ.

Keywords: Automatic speech recognition, cocktail-party problem, deep learning, multi-task learning, source separation

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Легченко Антон
Новосибирский
Государственный Университет
a.legchenko@g.nsu.ru

Евгений Павловский
Новосибирский
Государственный Университет
e.pavlovskiy@g.nsu.ru

Аннотация

В данной работе мы предлагаем метод многозадачного обучения в задачи коктейльной вечеринки с единственным микрофоном, в качестве дополнительной задачи была выбрана задача автоматического распознавания речи для каждого из дикторов в звуковом сигнале. В работе представлены два различных подхода к иерархии задач, в которых распознавание речи производиться после разделения речевых сигналов или же одновременно с ним. Обучение и тестирование моделей проводилось на открытых ресурсах и наборах данных.

Предложенный метод показал улучшение результатов по сравнению с однозадачной моделью, дав прирост около 1% по различным оценкам качества разделения дикторов. Для подтверждения результатов был произведено дообучение иерархической модели используя только функцию потерь задачи распознавания речи, что дало также дало улучшение качества разделения дикторов на 0.4%.

Ключевые слова: Автоматическое распознавание речи, проблема коктейльной вечеринки, глубокое обучение, многозадачное обучение, разделение сигналов

1 Introduction

Automatic speech recognition (ASR) is one of the important problems in the modern world. There are many solutions that allow it to be solved with high accuracy for speech signals of good quality. However, in the real world, speech recognition systems face contamination of the speech signal by different noise. Especially the case of the extraneous speaker voices presence is difficult. To solve this task, we used the systems that implement signal separation by differentiating speakers. In consistent speech cases, the task is well studied and known as the speaker diarization problem. In cases of significant overlap of the speaker's speech signals, the task becomes much more difficult and is known as the cocktail party problem. To solve the problem of a cocktail party with one microphone, various approaches were used. Most modern solutions are based on deep learning. This approach allows us to achieve high results, but it is associated with problems such as overfitting, which are especially acute with a small amount and variety of training data, which are often unavailable. Examples of low generalizing ability of models are their instability on data containing other dialects or the underrepresentation of speech examples of one of the sexes in the training dataset. One of the methods to improve the generalizing ability of deep learning models is the method of multi-task learning, when one model is trained to solve various problems from the same subject area, so that the model can use the similarities and differences between them. In many cases, the method of multi-task learning allows us to achieve better model predictions results from specific tasks compared to the models trained for one specific task. In this work, we propose a method of

multi-task learning in a cocktail-party problem with a single microphone. The task of automatic speech recognition for each of the speakers in the audio signal was chosen as an additional one in two different formulations. Firstly, when speech recognition is carried out on the basis of signals predicted by the separation model. Secondly, when the transcription of the speech of individual speakers is predicted simultaneously with the prediction of the separated speech signals of speakers.

The main goal of the work is to implement the proposed model and compare the results to show the advantages of the multi-task approach in the speaker separation task with mono-channel signals.

1 Literature review

Currently, many end-to-end models have been proposed to solve the cocktail party problem. The models that use multi-task learning with the solution of speech separation and recognition problems are the most interesting in this work. For a problem with multiple microphones, a MIMO-Speech model [1] was proposed in 2019. This model implements a hierarchical approach to the problem when the speech recognition task is solved after the speaker separation problem. For a more complex task with a single microphone, in 2018 it was proposed a model [2] that does not use multi-task learning, but solves the problem of speech recognition of multiple speakers with end-to-end approach. Unlike MIMO-Speech, which implements a hierarchical approach to multi-task learning, an alternative is to use a single block of feature extraction block for heads solving various equal tasks. An example of such an approach is Multi-task BERT model from [3] for the natural language understanding (NLU) task. Thus, work [2] shows the possibility of considering the recognition problem as one of the independent tasks and using an additional head to the block of the feature extractors of the original problem to solve it. Models [1] and [2] are based on the Transformer architecture, which makes it difficult to train in conditions of limited computing resources. Therefore, attention was drawn to earlier and simpler models that solve individual problems. To solve the separation problem in 2017, the Conv-TasNet [4] model based on the CNN architecture was proposed, due to which its training time is significantly shorter, while the model shows good quality evaluations (15.5 SDRi on the Librimix while state of the art models shows 20 SDRi). Modern approaches to the task of automatic speech recognition are also based on the Transformer architecture, for example, Wav2Vec2.0 [5]. However, within the framework of this work, the use of this architecture is laborious. Therefore, a model based on the CNN Wav2Latter [6] architecture was chosen as a speech recognition model. In the paper we also used the PIT [7] method, which has become standard for solving the separation problem and significantly improves the convergence of model used in [4]. For the training separation models there are many synthetic datasets based on existing speech corpora, similar in principle to generation. Librimix is the largest public dataset [8], based on the English language speech corpus of recordings from LibriSpeech [9] that contains high quality speech examples from audio books.

2 Method

In the paper we compare three different composite models. The common part of the models which solves the speech signals separation task have the same architecture. The architecture is Conv-TasNet reduced to 0.6M parameters to decrease training time. Reducing the complexity of the model naturally led to a decrease in the quality of separation to 11 SDR, which is still an acceptable quality when listening to a person. To train all models, we use the PIT method, the sources are rearranged based on comparing the outputs of the separation block with the target signals. The differences of the models are in the part of the model solving the speech recognition task.

The hierarchical model is a sequential connection of Conv-TasNet and Wav2Letter models adapted to the sampling rate of 8khz.

For the common feature space model we use Conv-TasNet with an additional decoder block, which implements end-to-end speech recognition. In such a model, both tasks are solved on the basis of the same features, so that the features should be more representative.

The baseline is the component model with Conv-TasNet and Wav2Letter as in hierarchical model, which are trained in alternating periods.

When training models, we use the gradient clipping technique and the Knowledge Distillation method [10] for the speech recognition block, which allows to improve the convergence of the model, the Wav2Vec 2.0 model was used as a teacher.

All models were implemented in the PyTorch framework.

4 Experiments and results

The experiments are done on a synthesized data set based on the LibriSpeech public corpus containing audio recordings of English speech with a low noise level, part of train-clean-100 was used for training and validation and test-dev-clean was used for the test. The synthesis of examples for the data set was similar to LibriMix, to reduce the learning time, speech examples were limited in duration to four seconds, in this regard, the markup of the speech recognition task for each individual speaker's speech example was carried out synthetically using a modern Wav2Vec 2.0 model with high accuracy on LibriSpeech, WER 1.7%, which significantly exceeds the possible quality indicators of the models considered in this paper. in total, 27,000 examples were synthesized for training and 4,000 examples each for testing and validation.
One model was trained for one day on one Nvidia Tesla V-100 with batch size 32 for 100 epochs. In the experiments, model indicators were considered for different values of the multiplier k with an additional loss function of the transcription task, Table 1 shows PESQ indicators for different values of the parameter k.

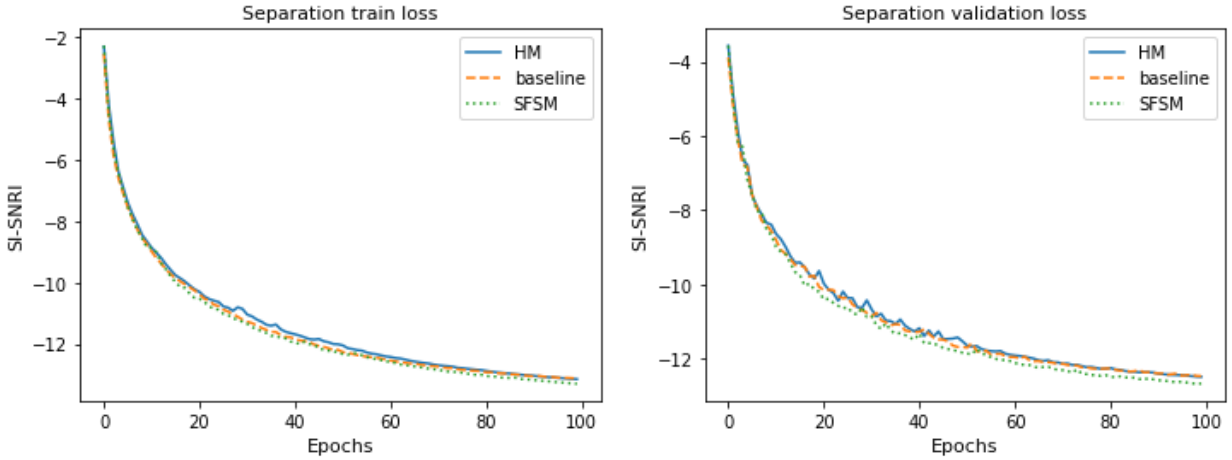
Table 1: PESQ score of separation block

Model	**k = 10**	**k = 1**	**k = 0.1**
HM	2.12	2.31	2.39
SFSM	2.02	2.29	2.38

The results obtained show that in both approaches, the best separation result corresponds to a lower coefficient k for the loss function of the ASR task.

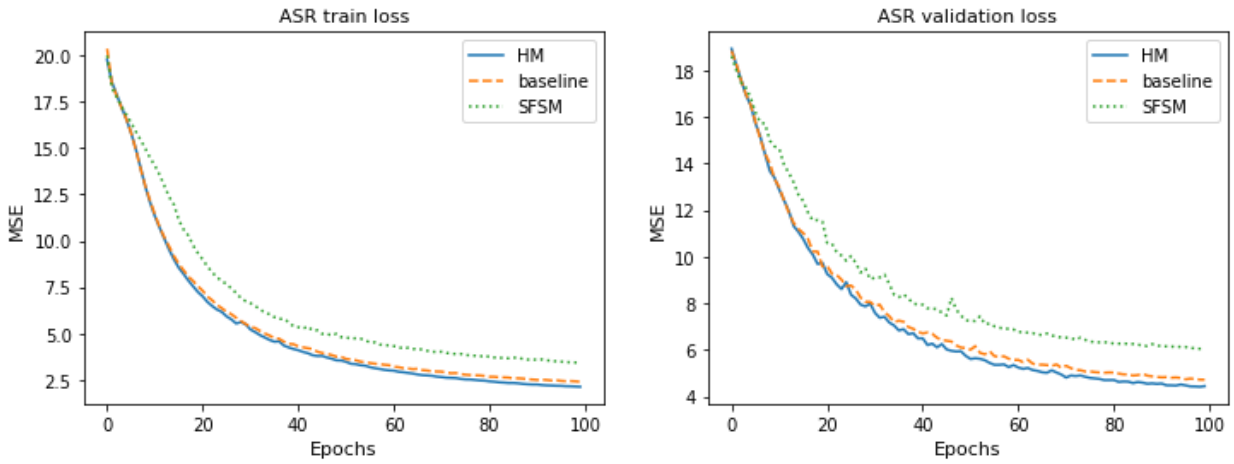
4.1 Base experiment

Figure 1 shows the convergence graphs of the separation block, Figure 2 shows the convergence graphs of the speech recognition block, both figures show models with the optimal parameter.



(a) Training loss (b) Validation loss

Figure 1: The separation block training curves



(a) Training loss (b) Validation loss

Figure 2: The transcription block training curve

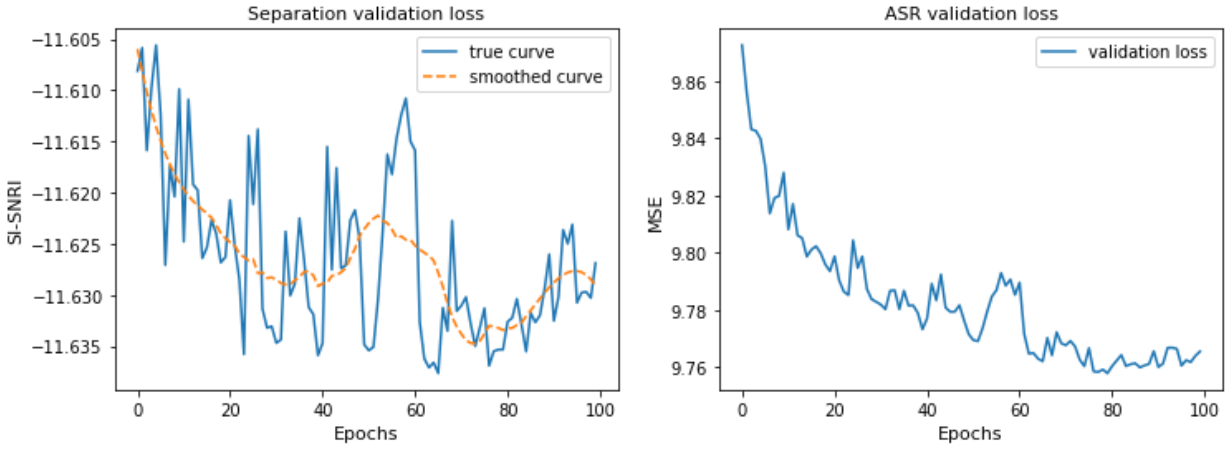
Table 2 shows the various metrics of the trained models on the test dataset. The results show that both multitasking methods yielded results superior to the base solution in terms of separation quality, and the hierarchical model outperformed the component system in terms of CER for the ASR problem as well.

Table 2: Architecture comparison on test dataset

Model	PESQ	SI-SDR	CER
baseline	2.37	11.11	0.42
HM	2.39	11.33	0.43
SFSM	2.38	11.16	0.49

4.2 Fine-tuning experiment

To confirm the relationship of improved results with the use of an additional loss function, an experiment was conducted on tuning the base solution using only the loss function of the speech recognition problem. The learning process is shown in Graph 3, the metrics obtained before and after the fine-tuning are shown in Table 3.



(a) Separation task loss on validation set (b) ASR task loss on validation set

Figure 3: Tuning separation model only with ASR task loss

Table 3: ASR task fine-tuning results on test

Model	PESQ	SI-SDR	CER
Model before tuning	2.33	10.73	0.44
Model after tuning	2.34	10.81	0.43

The loss function curve for the separation block was unstable during the training process, but the final result showed improvement in the metrics, which confirms the feasibility of the hierarchical multitasking approach.

5 Discussion

Both proposed methods of multi-task learning showed an increase in results with the correct choice of the relationship between the loss functions. At the same time, the model with a common feature space showed noticeably higher quality indicators in the validation data containing the voices present in the training sample. However, it is inferior to the hierarchical model on the test dataset, which may indicate an increased tendency of this model to overfit due to a more accurate learning of the individual speaker's speech characteristics. Unfortunately, the increase was not so large, only about 1%. Perhaps great results could be achieved using models with a larger number of parameters and a more advanced architecture, as in MIMO-Speech. Since both approaches gave improved results, it was also worth considering the third statement of the problem. It combines both approaches into the architecture, to consider the first transcription output as a preliminary prediction, such as in the Inception networks [11].

6 Challenges and unrealized plans

During the research, the main problem was the lack of computing resources, which led to a significant simplification of the model's architecture and datasets. This did not allow us to use the models that can solve individual problems well and can significantly reduce the possible number of experiments.

7 Conclusion

In this study, we show the possibility of improving the speaker separation quality using the additional task of transcription of the received signals, as well as the possibility of tuning already trained models. Based on the results obtained, it is necessary to test this method for modern architectures adding more tasks, such as speaker verification. Then the method may possibly give relatively significant increase in metrics. Another important task for subsequent work is to study the changes in the hidden space of models introduced by the method of multi-task learning, and the establishment of interconnections between various speech processing tasks. Another interesting direction is to consider the problem in a multimodal formulation, when the resulting transcriptions are analyzed using a language model. Feedback between the semantic coherence of the received transcriptions and the separation block can improve the quality of the extracted signals. This direction will be the next stage of our research.

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