Multi-task Learning Deep Neural Networks For Speech Feature Denoising

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Abstract

Traditional automatic speech recognition (ASR) systems usually get a sharp performance drop when noise presents in speech. To make a robust ASR, we introduce a new model using the multi-task learning deep neural networks (MTL-DNN) to solve the speech denoising task in feature level. In this model, the networks are initialized by pre-training restricted Boltzmann machines (RBM) and fine-tuned by jointly learning multiple interactive tasks using a shared representation. In multi-task learning, we choose a noisy-clean speech pair fitting task as the primary task and separately explore two constraints as the secondary tasks: phone label and phone cluster. In experiments, the denoised speech is reconstructed by the MTL-DNN using the noisy speech as input and it is respectively evaluated by the DNN-hidden Markov model (HMM) based and the Gaussian Mixture Model (GMM)-HMM based ASR systems. Results show that, using the denoised speech, the word error rate (WER) is respectively reduced by 53.14% and 34.84% compared with baselines. The MTL-DNN model also outperforms the general single-task learning deep neural networks (STL-DNN) model with a performance improvement of 4.93% and 3.88% respectively.

Index Terms: multi-task learning, feature denoising, deep neural networks

1. Introduction

Speech denoising has become increasingly important for building a robust automatic speech recognition (ASR) system, since the noise presenting in speech makes the accuracy drop down in the ASR system. This has sparked a lot of related researches on speech noisy reduction and speech enhancement.

Traditional mathematical methods are mainly focused on statistical relationship between noise and speech, such as spectral subtraction, Wiener filtering, wavelet speech enhancement, subspace based methods and so on [1, 2, 3, 4]. These methods substantially analyze the shallow statistics of stationary noise in speech under the assumption that noisy and speech are separable, which limits their generalizations.

In recent years, the deep neural network (DNN) has promoted performance on speech recognition accuracy [5], since the DNN has a better ability of capturing the essential and abstract structure of targets. There has also been recent work on speech enhancement and speech denoising using deep autoencoder (DAE) [6, 7], which has obtained better performance than the traditional mathematical methods. In these methods, the DAE is trained by greedy layer-wise pre-training and fine-

tuning. In the DAE's training of each layer, noisy-clean speech pairs are used as input and output. Therefore, the DAE can be treated as a sort of single-task learning (STL)-DNN and its unique task is minimizing the difference between noisy-clean speech pairs.

Though the STL-DNN performs well in the speech denoising task, they only take advantage of low level speech information without any other assistant constraints. They can be improved by jointly learning multiple related tasks, which is called multi-task learning in machine learning.

Multi-task learning attempts to jointly learn additional interactive tasks to augment the primary task and has been applied to various areas [8, 9, 10]. The DNN architecture can be used for multi-task learning in several different ways which are appealing approaches to well leverage data. It has been previously reported that the multi-task learning (MTL)-DNN can improve performance in speech and language related tasks [11, 12, 13]. In multi-task learning, it is always technical to choose interactive tasks and effectively combine them with existed STL systems.

In this paper we propose a new MTL-DNN model applied to the task of speech denoising for a robust ASR system. In this model, the MTL-DNN is trained with the primary task of noisy-clean speech pair fitting. Meanwhile, two candidate secondary tasks are explored to augment this primary task. One of the secondary tasks is the phone label classification. In this task, the networks are supposed to predict extra phone labels of input noisy-clean speech pairs. Each noisy-clean speech pair is grouped according to its phone label. It enables the networks to learn phonetic structures in noisy-clean speech pairs and substantially increases the phonetic discrimination of reconstructed speech. The other secondary task is the phone cluster classification. It extends the phone label task with relaxed constraints. Each noisy-clean speech pair is divided into several phone clusters instead of one phone label. The phone clusters consisting of phone labels are manually built based on phonology knowledge.

The rest of the paper is organized as follows. In section 2, we introduce the multi-task learning. Section 3 describes the model structure and training procedures of the proposed MTL-DNN model. The experiments and results are given in Section 4. Finally we make conclusions and point out the future work in section 5.

2. Multi-task learning

The multi-task learning approach attempts to solve the primary task by jointly learning multiple related tasks using a shared

representation. When these additional tasks have been properly organized, it achieves better performance than general single task learning methods.

In this work, in order to augment the primary task of noisy-clean speech pair fitting, we explore two secondary tasks: phone label and phone cluster classification.

2.1. Noisy-clean speech pair fitting task

In this paper, our goal is to denoise speech features. It can be done by directly mapping noisy speech features to clean ones via neural networks. To this end, we minimize the difference between the networks' output and the expected clean speech.

A Mean Square Error (MSE) is taken as the objective function:

$$E_1 = \frac{1}{2} \sum_{i=1}^N \|\mathbf{a}_i - \mathbf{f}_i\|^2 \quad (1)$$

where N is the number of frames, and $\mathbf{f}_i$ is the i -th frame clean speech feature. $\mathbf{a}_i$ represents the networks' output vector:

$$\mathbf{a}_i = \mathbf{W} \cdot \mathbf{z}_i \quad (2)$$

where $\mathbf{z}_i$ is the output vector of the DNN' penultimate layer, and $\mathbf{W}$ is this layer's weight matrix.

The derivative of E_1 wrt. $\mathbf{a}_i$ is as follows:

$$\frac{\partial E_1}{\partial \mathbf{a}_i} = \mathbf{a}_i - \mathbf{f}_i \quad (3)$$

2.2. Phone label task

The phone label classification is a higher level task compared with the feature pair fitting one. Each phone label represents a specified phonetic collection. In this paper, we focus on Mandarin speech denoising. A Mandarin phone list is shown in Table 1. The phone list contains 36 vowels and 24 consonants.

We apply one-hot encoding to the phone label targets. The k -th bit is set when the input speech frame belongs to the k -th phone label.

During propagation, the posterior probability of the j -th phone label of the i -th speech frame gets evaluated via softmax:

$$y_{i,j} = \frac{\exp(a_{i,j})}{\sum_{j=1}^D \exp(a_{i,j})} \quad (4)$$

where D is the dimensionality of phone label targets.

We use the Cross-Entropy (CE) as the objective criterion between the networks' output and the phone label targets:

$$E_2 = - \sum_i^N \sum_j^D t_{i,j} \log y_{i,j} \quad (5)$$

where $t_{i,j}$ is the j -th phone target of the i -th speech frame, and the Cross-Entropy can be differentiated wrt. vector $\mathbf{a}_i$ as:

$$\frac{\partial E_2}{\partial \mathbf{a}_i} = \mathbf{y}_i - \mathbf{t}_i \quad (6)$$

2.3. Phone cluster task

The phone cluster task is an extension of the phone label task. It takes into consideration the phonological knowledge. As is shown in Table 2, each phone cluster contains several phone labels sharing similar phonological characteristics.

Table 1: Phone label list of Mandarin.

Vowel	Consonant
a ai an	b c
ang ao e	ch d
ei en eng	f g
er i ia	h j
ianiang iao	k l
ib ie if	m n
in ing iong	p q
iou o ong	r s
ou u ua	sh t
uai uan uang	w x
uei uen uo	y z
van ve vn	v zh

Notice that since one speech frame may be divided into several phone clusters, using the one-hot encoding for the multiple targets is not feasible. We propose a block encoding method using two bits to represent the phone cluster states. The active phone clusters are encoded by (1,0), otherwise (0,1). The propagation is slightly different from the one in the phone label task, and the posterior probability of the c -th phone cluster of i -th speech frame is as follows:

$$y_{i,c,j} = \frac{\exp(a_{i,c,j})}{\sum_{k \in \{0,1\}} \exp(a_{i,c,k})}, \forall j = 0, 1 \quad (7)$$

where $a_{i,c,j}$ is the networks' output corresponding to the i -th speech frame, and c is the frame's phone cluster. The objective criterion becomes:

$$E_3 = - \sum_{i=1}^N \sum_{c=1}^{N_c} \sum_{j \in \{0,1\}} t_{i,c,j} \log y_{i,c,j} \quad (8)$$

where N_c is the total number of clusters, and $t_{i,c,j}$ is the corresponding target.

The derivative of E_3 wrt. $\mathbf{a}_i$ is:

$$\frac{\partial E_3}{\partial \mathbf{a}_i} = \mathbf{y}_i - \mathbf{t}_i \quad (9)$$

3. Training an MTL-DNN Denoising Model

The proposed MTL-DNN denoising model is a multi-layer perception (MLP) with hidden sigmoid neurons. The structure of the model is shown in Figure 1. The networks in this model consist of two parts: the task independent hidden layers and the multi-task dependent output layers. The hidden layers are initialized by pre-training, and then the whole networks are fine-tuned with multi-task learning.

3.1. Pre-training DNN

Randomly initialized multi-layer networks often get stuck in local optimum in gradient-based training. Therefore, we use a common pre-training method called the Restricted Boltzmann Machine (RBM) to initialize the hidden layers. Each pair of layers in the network can be treated as a RBM, which can be trained using an objective criterion of contrastive divergence [14]. In the pre-training stage, we use the noisy speech as the RBMs' input.

Table 2: Phone clusters of Mandarin. The vowels in front of ' _ ' mean leading vowels, otherwise trailing vowels.

Cluster	Phonemes
a_	a ai an ang ao
_a	a ia ua
e_	e ei en eng er
_e	e ie ue
i_	i ia ian iang iao ib ie if in ing iong iou
_i	i ai ei uai uei
o_	o ong ou
_o	o ao uo iao
u_	u ua uai uan uang uei uen uo
_u	u iou ou
v	v van ve vn
Nasal	n an ang en eng ian iang in ing iong ong uan uang uen van vn
Labial	b p m f
Apical	d t n l
Velar	g k h
Palatal	j q x
Spirant	zh ch sh r z c s
Other	y w

3.2. Fine-tuning with Multi-task learning

The structure used for fine-tuning is shown in Figure 1. After pre-training, an affine layer is appended to the output layer of RBMs. This layer is shared by the primary and the secondary tasks. What's more, in the secondary tasks, another softmax layer is appended to the shared affine layer and the softmax transformations are different between these secondary tasks.

In the primary task of noisy-clean speech pair fitting, the output of the affine layer is directly used as the reconstructed feature fitting to the expected clean speech feature and they have the same dimensionality.

In the secondary tasks, the networks have to predict the posterior probabilities of phone labels or phone clusters, so a softmax layer is appended to the shared affine layer. However, the softmax transformations are different between the phone label task and the phone cluster task. In the phone label task, the

Figure 1: The MTL-DNN denoising model structure.

softmax operation is performed on all output units of the affine layer, whereas in the phone cluster task, we perform softmax operations on blocks of the affine layer's output units separately. Each block corresponds to a specified phone cluster. The output part of the secondary task is dropped out in testing.

The networks are fine-tuned by back propagation with mini-batch Stochastic Gradient Descent (SGD) algorithm. Notice that different error criteria are applied in the primary task and the secondary task. The primary task is a typical fitting task and uses a Minimum Mean Squared Error (MMSE) criterion, while the secondary classification task uses a Minimum Cross Entropy (MCE) criterion. The dimensions between the MMSE and the MCE are much different. We present a combination method as follows:

$$E = (1 - \alpha) \cdot W_p \cdot E_p + \alpha \cdot W_s \cdot E_s \quad (10)$$

where E is the error sum of the networks. E_p and E_s indicate the primary task error and the secondary task error respectively. α is a trade-off weight between the primary task and the secondary task. W_p and W_s are balance weights to solve the dimension mismatch problem.

We can deduce the derivative of E wrt. $\mathbf{a}_i$ as:

$$\frac{\partial E}{\partial \mathbf{a}_i} = (1 - \alpha) \cdot W_p \cdot \frac{\partial E_p}{\partial \mathbf{a}_i} + \alpha \cdot W_s \cdot \frac{\partial E_s}{\partial \mathbf{a}_i} \quad (11)$$

We choose a form of W_p and W_s as:

$$W_p = \sqrt{\frac{1}{N_m} \sum_{j \in M} \left\| \frac{\partial E_p}{\partial \mathbf{a}_j} \right\|^2} \quad (12)$$

$$W_s = \sqrt{\frac{1}{N_m} \sum_{j \in M} \left\| \frac{\partial E_s}{\partial \mathbf{a}_j} \right\|^2} \quad (13)$$

where M is a mini-batch training set with a size of N_m . Applying (3), (6), (9), to (11), (12) and (13), we get:

$$W_p = \sqrt{\frac{1}{N_m} \sum_{j \in M} \|\mathbf{y}_j - \mathbf{t}_j\|^2} \quad (14)$$

$$W_s = \sqrt{\frac{1}{N_m} \sum_{j \in M} \|\mathbf{a}_j - \mathbf{f}_j\|^2} \quad (15)$$

$$\frac{\partial E}{\partial \mathbf{a}_i} = (1 - \alpha) \cdot W_p \cdot (\mathbf{a}_i - \mathbf{f}_i) + \alpha \cdot W_s \cdot (\mathbf{y}_i - \mathbf{t}_i) \quad (16)$$

where W_p and W_s can be automatically updated during the back propagation.

4. Experiments and results

4.1. Data preparation

Experiments are conducted on a Mandarin corpus. This corpus is contributed by 48 different native students with 11069 utterances. We build two types of corpora: a clean speech corpus and a noisy speech corpus. The clean speech is recorded in quiet background with a 16 kHz sample rate and a mono channel while the noisy speech is made up by adding random road and bus noise to the clean one. The training set consists of 43 speakers and 8600 utterances while the test set is built with 5 speakers and 2469 utterances.

We use the 39 dimensional Mel-frequency cepstral coefficient (MFCC) feature with a 20 ms frame window and a 10 ms frame shift. A splice operation that concatenates adjacent

5 frames with the central frame is performed on the raw input MFCC feature, which results in a 429 dimensional feature vector.

All the experiments are conducted using the Kaldi toolkit [15].

4.2. Baseline systems

The baseline systems consist of a Gaussian mixture model and hidden Markov model (GMM-HMM) ASR system and a DNN-HMM ASR system.

The GMM-HMM ASR system using 2500 senones is trained on the clean training set. It is used to generate forced alignments for training DNN and obtaining frame-level phone label information. In the DNN-HMM ASR system, we use a shared HMM trained in the GMM-HMM ASR system. The DNN is configured with 5 hidden layers and 1024 hidden units in each layer and is pre-trained using the RBM method. We use a learning rate of 0.008 in the fine-tuning stage. The DNN-HMM ASR system is also trained on clean test set.

Using the word error rate (WER) as the criterion, we evaluate the performance of the trained DNN-HMM and GMM-HMM ASR systems on noisy test set as baselines.

4.3. MTL-DNN denoising model

The necessary phone label information of each frame is obtained via the previously trained HMM triphone system. Several MTL-DNN models are trained on the noisy training set. They use the same schedule with the DNN-HMM system in pre-training the DNN. We choose 0.00001 as the start learning rate and use the learning rate halving strategy.

In order to evaluate the performance of the MTL-DNN model, we reconstruct the denoised test set by passing the noisy test set to the trained MTL-DNN denoising system and then test it on the previously trained DNN-HMM and GMM-HMM ASR systems respectively.

4.4. Effect of the secondary task weight

We first explore the relationship between the WER and the secondary task weight. From (10) we learn that the secondary task weight α determines how much the secondary task affects the networks. When α is larger than 0.5, the secondary task is dominant and becomes the primary task. Figure 2 shows the curve of WER of DNN-HMM ASR along with the secondary task weight ranging from 0.1 to 0.9. In the phone label MTL-DNN, the WER of DNN-HMM baseline system reaches the minimum of 21.03% at 0.2, while in the phone cluster MTL-DNN the minimum of 21.28% at 0.5. There is an increasing trend of WER with the secondary weight growing, which verifies our hypothesis above.

4.5. Performance comparison

The experimental results of performance comparison are shown in Table 3. The baseline DNN-HMM and GMM-HMM systems have a WER of 9.36% and 16.95 on the clean MFCC test set respectively. However, both of their performance sharply drop on the noisy MFCC test set and get a WER of 44.88% and 47.19% respectively.

The DNN based denoising models including STL-DNN and MTL-DNN significantly improve the performance. Using the denoised speech, the WER of the DNN-HMM baseline is relatively reduced by 50.71%-53.14%, while the WER of the GMM-HMM baseline is relatively reduced by 31.72%-34.84%.

Figure 2: Relationship between the Word Error Rate (WER) and the secondary task weight in MTL-DNNs using different secondary tasks.

Besides, the MTL-DNN model using the phone label as the secondary task outperforms the STL-DNN model using noisy-clean speech pair fitting as the unique task with a relative improvement of 4.93% and 3.88% on the WER of the DNN-HMM system and the GMM-HMM system respectively. It shows the superior effectiveness of our proposed MTL-DNN model in the speech denoising task.

Table 3: The WER (%) of the DNN-HMM system and the GMM-HMM system with different types of features. The secondary task weights selected for the phone label and the phone cluster task are 0.2 and 0.5 respectively.

Feature	Task	GMM-HMM	DNN-HMM
Clean MFCC	-	16.95	9.36
Noisy MFCC	-	47.19	44.88
STL-DNN	Pair fitting	31.99	22.12
MTL-DNN	Phone label	30.75	21.03
MTL-DNN	Phone cluster	32.22	21.28

5. Conclusions

In this paper, we propose a new MTL-DNN method and apply it to the speech denoising task. In the proposed model, we design a primary task of noisy-clean speech pair fitting and explore two secondary tasks: phone label and phone cluster classification. Experiments are conducted to analyze the relationship between the primary task and the secondary task. Experimental results of performance comparison prove the superior effectiveness of our proposed MTL-DNN model. It significantly reduces the WER of baseline systems and outperforms the STL-DNN model in speech denoising task.

In the future, we will try to integrate the denoising module into the ASR system and investigate other related secondary tasks such as state-level posteriors and Gauss-level posteriors.

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