MULTI-TASK METRIC LEARNING FOR TEXT-INDEPENDENT SPEAKER VERIFICATION

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ABSTRACT
In this work, we introduce metric learning (ML) to enhance the deep embedding learning for text-independent speaker verification (SV). Specifically, the deep speaker embedding network is trained with conventional cross entropy loss and auxiliary pair-based ML loss function. For the auxiliary ML task, training samples of a mini-batch are first arranged into pairs, then positive and negative pairs are selected and weighted through their own and relative similarities, and finally the auxiliary ML loss is calculated by the similarity of the selected pairs. To evaluate the proposed method, we conduct experiments on the Speaker in the Wild (SITW) dataset. The results demonstrate the effectiveness of the proposed method.

Index Terms— Speaker verification, multi-task learning, metric learning, pair mining, pair weighting

1. INTRODUCTION
During the last decade, i-vector based systems [1, 2] in combination with verification back-ends such as probabilistic linear discriminant analysis (PLDA), [3] has been the dominating paradigm of speaker verification (SV) tasks. With the great success of deep neural networks (DNNs) in machine learning, more efforts have been focused on how to learn deep speaker representations, known as speaker embeddings. Many novel DNN embedding-based systems have been proposed, and they have achieved comparable or even better performance with the traditional i-vector paradigm [4, 5, 6]. The most representative system is the x-vector framework [7].

For most DNN embedding systems, the networks are trained to classify speakers with cross entropy (CE) loss. However, SV aims to verify the claimed identity of a person for a given speech, where the test process calculates the similarity of the embeddings of enrollment/test pairs. If a network could integrate the learning of this pairwise similarity in model training, the speaker embeddings could be more discriminative. Metric learning (ML) approaches, where loss functions can be expressed in terms of pairwise similarity in the embedding space, have been brought into SV fields and improved the recognition accuracy in various tasks. This family includes triplet loss [8] contrastive loss [9], prototypical network loss [10], etc. To address the exponential growth of training pairs in ML multi-similarity loss is proposed to collect informative pairs and weight these pairs through their own and relative similarities [11] in image retrieval.

Inspired by the abovementioned works, we integrated the learning of pairwise similarity into conventional CE loss under the multi-task metric learning (MTML) framework. The main task is the same as that of deep neural speaker embedding system architecture using CE loss. The auxiliary task learns a more discriminative embedding space using ML loss, which is implemented using pair sampling and weighting. Unlike the random data processing in the conventional ML process, we carefully controlled the utterances of the same speaker in a mini-batch, which can increase the ratio of positive to negative samples and selected the more informative pairs in the following pair sampling and weighting step.

We executed the experiments on the Speaker in the Wild (SITW) [12] dataset. The results show that our proposed method obtains 20.9% and 19.52% relative improvement in terms of equal error rate (EER) in SITW development and evaluation.

The remainder of this paper is organized as follows. In section 2, we briefly introduce the related work about the baseline system and two classical pair-based loss functions. In section 3, we describe the proposed pair selecting, weighting strategy and MTML architecture in SV. The experimental set up and results are presented in section 4. Finally, conclusions are given in section 5.

2. RELATED WORK
2.1. Baseline
The network architecture of our baseline system could be partitioned into frame and segment level layers. We use ResNet [13] to extract frame-level features, and a detailed configuration is listed in Table 1. A statistics pooling layer converts frame-level input to an utterance-level speaker representation. Then, two fully connected layers map the utterance-level features to speaker embeddings that is finally passed into a softmax output layer. CE loss is used to train the system.

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In table 1, $T$ denotes variable-length data frames. The input layer consists of a single convolutional layer with kernel size of $7 \times 7$, stride of $2 \times 2$ and channel dimension of 64. Four residual stages include [2, 3, 4, 2] basic blocks with 64, 128, 256, 512 channels respectively, and each basic block has 2 convolutional layers with filter sizes of $3 \times 3$. Downsampling is performed by conv2-1, conv3-1, conv4-1 and conv5-1 with a stride of $1 \times 2$.

### 2.2. Classical Pair-based Loss Functions

In this section, we introduce two classical pairwise loss functions used in the SV field, namely, triplet loss and contrastive loss. The shortcomings of these two loss functions are also discussed.

**Triplet loss:** Triplet loss is defined on a set of triplets, each of which consists of an anchor sample $x_a$, a positive sample $x_p$ and a negative sample $x_n$. Triplet loss learns a deep embedding, which enforces the similarity of a negative pair to be smaller than that of a randomly selected positive one over a given margin $\nu$:

$$L_{triplet} := [S_{an} - S_{ap} + \nu]_+$$

where $S_{an}$ and $S_{ap}$ denote the similarity of a negative pair $\{x_a, x_n\}$ and a positive pair $\{x_a, x_p\}$, respectively. According to the gradient computed for Eq. 1, a triplet loss weights all pairs equally on the triplets which are selected by $S_{an} + \nu > S_{ap}$.

**Contrastive loss:** Contrastive loss is designed to encourage positive pairs to be as close as possible and the negative pairs to be far from each other over a given threshold $\mu$:

$$L_{contrast} := (1 - \sigma_{ij})[S_{ij} - \mu]_+ + \sigma_{ij}S_{ij}$$

where $\sigma_{ij} = 1$ indicates a positive pair, and 0 indicates a negative pair. By computing the partial derivative with respect to $S_{ij}$ in Eq. 2, we can find that all positive pairs and negative pairs are assigned with an equal weight when $S_{ij} > \mu$.

### 3. MULTI-TASK METRIC LEARNING

In this section, we will illustrate the proposed MTML system, as depicted in Fig. 1. The lower layers of the MTML system is the same as the baseline, and these layers serve as an utterance-level feature extractor. The top-left part of Fig. 1 is the same as the baseline described in section 2.1, and the classification of the speaker identity is the main task. The top-right part of Fig. 1 is the auxiliary task trained with metric learning loss function.

#### 3.1. Data Selection and Loss Function

The MTML system is based on processing a large number of utterances at once, in the form of a mini-batch that contains $M$ speakers, and $N$ utterances from each speaker in average. Vector $x_i (1 \leq i \leq M \times N)$ represents the $i^{th}$ feature extracted from $M \times N$ utterances in a mini-batch, and the output of the first fully connected layer of the MTML system serves as the speaker embedding vector $e_i$ of $x_i$. The similarity score of two samples is defined as $S_{ij} = < e_i, e_j >$, where $< \cdot, \cdot >$ denotes dot product, resulting in an $M \times N \times M \times N$ similarity matrix $S$ whose element at $(i, j)$ is $S_{ij}$.

Fig. 2 depicts the pair mining and weighting process. Assume $x_i$ is an anchor; then, the positive or negative pair...
Fig. 2. The strategy of pair mining and weighting.

\{x_i, x_j\} can be selected if \(S_{ij}\) satisfies the condition:

\[
\begin{aligned}
S_{ij}^+ &> \max_{y_k \neq y_j} S_{ik} + \varepsilon \\
S_{ij}^- &> \min_{y_i = y_j} S_{ik} - \varepsilon
\end{aligned}
\]

where \(\varepsilon\) is a given margin and \(y_k\), a one-hot vector, is the label of the \(k^{th}\) sample \(x_k\).

Pair mining can basically select more informative pairs and discard less informative pairs, while the pair weighting process can allocate more accurate weights to the selected pairs. This work adopts a soft weighting scheme similar to \[11\], which considers both the self-similarity and relative similarity. The self-similarity is computed from the pair itself, and the relative similarity is calculated by considering the relationship from neighboring pairs. The weight of a selected pair \(\{x_i, x_j\}\) can be computed as:

\[
\begin{aligned}
\omega_{ij}^+ &= \frac{1}{e^{\alpha(S_{ij}^- - S_{ij})}} + \sum_{k \in P_i} e^{-\alpha(S_{ik} - S_{ij})} \\
\omega_{ij}^- &= \frac{1}{e^{\beta(S_{ij}^- - S_{ij})}} + \sum_{k \in N_i} e^{\beta(S_{ik} - S_{ij})}
\end{aligned}
\]

where \(\alpha, \beta, \lambda\) are hyperparameters, and \(\omega_{ij}^+\) and \(\omega_{ij}^-\) are the weights of positive pairs and negative pairs, respectively. \(S_{ik}(k \in P_i)\) and \(S_{ik}(k \in N_i)\) denote the similarity scores of neighboring positive and negative pairs respectively. Finally, we integrate pair mining and pair weighting and provide a pair-based loss function called metric learning (ML) loss as follows.

\[
L_{ML} = \frac{1}{D} \sum_{i=1}^{D} \left\{ \frac{1}{\alpha} \log \left[ 1 + \sum_{k \in P_i} e^{-\alpha(S_{ik} - \lambda)} \right] + \frac{1}{\beta} \log \left[ 1 + \sum_{k \in N_i} e^{\beta(S_{ik} - \lambda)} \right] \right\}
\]

where \(D\) is the batch size.

3.2. Multi-task Learning Strategy

We integrate the pairwise similarity information into the baseline to obtain more discriminative speaker embeddings. As depicted in Fig. 1, the MTML system is trained to perform both primary speaker classification and auxiliary pairwise metric learning. For the primary classification task, the CE loss \(L_{CE}\) is defined as:

\[
L_{CE} = \frac{1}{D} \sum_{i=1}^{D} (y_i^T \log(p_i))
\]

where \(p_i\) is a vector representing the probability that sample \(x_i\) is assigned to the \(j^{th}\) class. Combined with the original CE loss, the final loss function can be written as:

\[
Loss = \eta L_{ML} + (1 - \eta)L_{CE}
\]

where \(0 \leq \eta \leq 1\) is a task weight that determines the influence of each task on the model.

4. EXPERIMENTS AND DISCUSSION

4.1. Experimental settings

4.1.1. Datasets and evaluation metrics

All the experiments were conducted on the SITW dataset. The development portion of VoxCeleb1 \[14\] and VoxCeleb2 \[15\] is used for training. There are 59 speakers included in both SITW and the development portion of Voxceleb1. These speakers are removed from the training dataset.

The results are reported in terms of three metrics, namely, the EER, and the minimum of the normalized detection cost function (minDCF) with two settings: one with the prior target probability \(P_{tar}\) set to 0.01 (DCF2), and the other with \(P_{tar}\) set to 0.001 (DCF3) \[16\].

4.1.2. Input Features

The audio signals are first transformed into frames of width 25ms with 10ms frame shift. Then, we select the 30-dimensional mel frequency cepstral coefficient (MFCC) features as the input acoustic features. An energy-based voice activity detection (VAD) is used to remove nonspeech frames.

4.1.3. Systems configuration

All systems are based on the TensorFlow \[17\] and Kaldi Toolkit \[18\]. The Kaldi Toolkit is used for data preprocessing, feature extraction and backend PLDA algorithm. TensorFlow is used to train the network and extracts speaker embeddings. The utterances from the training dataset are randomly cropped to lengths of 2-4s, and utterances with the same duration are grouped into a mini-batch with a batch-size=128. Other configurations of systems are listed as follows:

**TDNN system:** The time-delay neural network (TDNN) based x-vector is state-of-the-art architecture in the SV field. We use this contrastive system to demonstrate the effectiveness of ResNet. There are 5 TDNN layers for frame-level processing. The number of hidden nodes for the first four
frame-level layers is 512, and the last frame-level layer has 1536 hidden nodes. For the utterance-level learning, the output dimensions of the statistics pooling layer and two embedding layers are 3072, 512, 512, respectively.

**ResNet baseline:** It replace the TDNN of the classical x-vector with ResNet described in section 2.1. The other setup is same as that of the TDNN based system.

**MTML system:** This is the SV system with the proposed architecture as shown in Fig. 1. The configurations of the MTML system are the same as the ResNet system except for the auxiliary metric learning loss function. $M$ and $N$ are set to 32 and 4 respectively for every mini-batch. $\varepsilon$ in Eq. 3 is set to 0.1, and the hyperparameters in Eq. 4 are: $\alpha = 2, \beta = 50, \lambda = 1$.

All the networks are optimized using an Adam optimizer and the learning rate gradually decreases from 1e-3 to 1e-4. The embeddings are extracted from the first fully connected layer with a dimension of 512. The same type of batch normalization and L2 weight decay described in [19] are used to prevent overfitting.

**4.1.4. Backend Algorithm**

The embeddings are centered using the training set and are projected to a low-dimension space using LDA at first. The dimension of the speaker embedding is reduced to 100. After length normalization, we select the longest 200,000 recordings from the training set to train the PLDA backend.

**4.2. Results**

Table 2 presents the performance of the baseline and MTML system with different task weights on the SITW dataset. The proposed MTML system outperforms the baseline system with even a small weight auxiliary task, and we can obtain the best performance with $\eta = 0.3$. This system achieves 20.9%, 16.72% and 17.88% relative improvements in terms of EER and DCF2 and DCF3, respectively, in development set. Relative improvements of 19.52%, 19.38% and 18.23% are also obtained in terms of EER, DCF2 and DCF3, respectively, in evaluation set. These results make it clear that our MTML strategy makes the speaker embedding more discriminative by joint speaker classification and metric learning.

**Table 2.** Results of different systems on SITW with data augmentation. MTML-$\eta n$ denotes the MTML system with task weight $\eta = n/10$.

| systems   | Dev EER | DCF2 0.344 | DCF3 0.558 | Eval EER | DCF2 0.373 | DCF3 0.592 |
|-----------|---------|------------|------------|----------|------------|------------|
| TDNN      | 3.08    | 0.344      | 0.558      | 3.34     | 0.373      | 0.592      |
| ResNet    | 2.62    | 0.305      | 0.520      | 2.92     | 0.356      | 0.587      |
| MTML-$\eta1$ | 2.31  | **0.245**  | **0.402**  | 2.54     | **0.279**  | **0.461**  |
| MTML-$\eta3$ | **2.07** | 0.254      | 0.427      | **2.35** | 0.287      | 0.480      |
| MTML-$\eta10$ | 6.12  | 0.606      | 0.851      | 7.27     | 0.718      | 0.947      |

![Fig. 3. DET curve for SITW using PLDA backend.](image)

However, the performance dropped sharply with $\eta = 1$, where the whole network was difficult to converge when lacking a main task. Fig. 3 plots DET curves for various systems using PLDA backend for the SITW dataset.

The performance of the systems without data augmentation is also reported in Table 3, from which we can draw a similar conclusion as that drawn from Table 2. In SITW development set, the proposed method achieves 11.51%, 16.37% and 16.36% relative improvements over the baseline in terms of EER, DCF2 and DCF3, respectively. Similarly, in SITW evaluation set, it obtains a 14.91%, 20.66% and 23.77% improvement over the baseline in EER, DCF2 and DCF3, respectively.

**Table 3.** Results of different systems on SITW without data augmentation.

| systems   | Dev EER | DCF2 0.414 | DCF3 0.658 | Eval EER | DCF2 0.506 | DCF3 0.770 |
|-----------|---------|------------|------------|----------|------------|------------|
| TDNN      | 3.27    | 0.414      | 0.658      | 4.21     | 0.506      | 0.770      |
| ResNet    | 3.04    | 0.342      | 0.550      | 3.69     | 0.426      | 0.669      |
| MTML-$\eta1$ | 2.58  | **0.281**  | **0.438**  | 3.28     | 0.339      | 0.533      |
| MTML-$\eta3$ | 2.69  | 0.286      | 0.460      | **3.14** | **0.338**  | **0.510**  |
| MTML-$\eta10$ | 7.89  | 0.758      | 0.894      | 9.89     | 0.863      | 0.976      |

**5. CONCLUSION**

In this paper, we propose a novel MTML strategy based on deep embedding learning architecture. We integrated both the typical speaker classification and metric learning into one framework. The experimental results demonstrated the effectiveness of our proposed training strategy. The combination of the two supervisory signals leads to significantly more discriminative features than either of them individually.

In future work, we will continue to focus on the use of pairwise similarity information and investigate other useful multitask learning strategies in the SV field.
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