POWERSFUL SPEAKER EMBEDDING TRAINING FRAMEWORK BY ADVERSARILY
DISENTANGLING IDENTITY REPRESENTATION

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ABSTRACT
Irrelevant information in speeches can seriously interfere with the performance of speaker verification. Particularly, the most popular datasets do not contain enough labels to overcome this challenge. In order to solve this problem, we propose a novel speaker embedding training framework based on explicitly disentangled identity representation. Our key insight is to disentangle the speaker information from the feature perspective leveraging adversarial learning methods. The adversarial supervision signal is introduced to disperse identity information, which assists in obtaining a superior identity-purified feature. Experiments prove that the framework we propose can significantly improve the performance of speaker verification from the original models without adjusting the structure and hyper-parameters of them. This suggests that adversarially disentangled representation is extremely useful for alleviating the lack of speaker labels.

Index Terms— Speaker Embedding, Disentangled Representation, Adversarial Training

1. INTRODUCTION
Speaker recognition and verification have been topics of interest for their applications in high-security systems and forensic tests. With proposed in-the-wild datasets [1][2], recent studies have experienced rapid development for dealing with real-world scenarios. However, the task of in-the-wild speaker verification is not trivial. On the one hand, a person’s voice can vary differently under different situations, particularly with different intonations and emotions. On the other hand, background music and noise are all identity-irrelevant features that can severely contaminate speaker verification systems. Moreover, even though these datasets are already large-scale comparing with previous ones, they still cannot match the scale of face datasets, making it more difficult for learning uniform speaker embeddings.

With the recent development of deep learning, the convolutional neural network (CNN) has achieved great success in the face recognition and are gradually playing important roles in speaker verification with spectrogram inputs [1][2]. Excellent previous works [4][6][7][5] have been proposed one after another to further improve the performance of speaker verification. At the same time, disentangle learning has been explored in various computer vision applications [8][9][10][11]. For example, learning pose invariant features for face recognition [8] and person re-identification [11]. Also attribute transfer can be achieved with adversarial disentanglement [9][10]. Nevertheless, in the audio domain, works are mostly done in the field of voice conversion [12]. It is still worth exploring especially for speaker embeddings.

To this end, we propose to explicitly learn a speaker embedding that is free of speaker-irrelevant information. In other words, we take advantage of recent advances in adversarial training [13][10][9] and disentangle identity information within speaker embeddings. Hence we would like to utilize the identity labels of speakers for learning an additional feature representation which is orthogonal to our desired identity feature representation. In this way, both features can complement each other to learn a more comprehensive audio representation. Thus the identity information can be “purified”.

More specifically, we utilize only the identity labels and train Siamese networks, which take spectrograms as inputs and encode a pure identity feature and an identity dispersing one. While one network is learned through a simple recognition training scheme, the other network is forced to contain no information about identity through adversarial training. The two features from different branches are later combined together for the reconstruction process, which is to ensure the complement of them for original spectrograms. By extracting more information from the non-speaker branch, the speaker embedding can thus be further purified. Then take only the purified identity feature, speaker verification can be achieved in traditional ways.

The significant advantage of our training framework is that the identity-purify branch of our network can be set as an arbitrary network structure so that this framework can be easily applied to any existing network structure. With our disentangled representation, we prove that our learned features are more robust to identity-irrelevant information com-
paring with directly encoded ones, which shows competitive results especially for current research on speaker verification with limited labels. Experiments show that our method can significantly improve the performance on in-the-wild speaker verification datasets.

The contribution of our work can be highlighted as (1) We propose to disentangle identity-purified and identity-irrelevant information within audio representations through adversarial training. (2) We build a training framework with Siamese networks that specifically encode identity-purified information and identity-irrelated ones for speaker embeddings. (3) Extensive experiments validate the efficiency of our proposed method and improve the verification results on popular public datasets by a large margin.

2. RELATED WORKS

The emergence of high-quality speech datasets has greatly promoted the development of speaker verification. The VGG and ResNet structures are proposed in [1] and Chung et al. [2] propose to map voice spectrograms into a latent space for measuring feature distances. The triplet loss is introduced by [2] to map voice spectrograms into a latent space for measuring feature distances. The triplet loss is introduced by [2] to map voice spectrograms into a latent space for measuring feature distances. The triplet loss is introduced by [2] to map voice spectrograms into a latent space for measuring feature distances. The triplet loss is introduced by [2] to map voice spectrograms into a latent space for measuring feature distances.

3. APPROACH

In this section, we propose a Speaker Disentangled Representation Autoencoder (SDRA) training framework, an end-to-end trainable network for learning the disentangled speaker identity features by using external supervision signals from speaker labels, as shown in Figure 1.

![fig 1](image)

**Fig. 1.** The pipeline of Speaker Disentangled Representation Autoencoder (SDRA) framework.

Given an input spectrogram $S$ from speech, the speaker purifying encoder $E_p$ consists of multi-layer convolutional networks, and the speaker dispersing encoder $E_d$ is also composed of the same convolutional network structure as the purifying encoder $E_p$. The speaker purifying encoder $E_p$ embeds the identity-purified feature $f_p$ from the input spectrogram $S$, and the speaker dispersing encoder $E_d$ obtains the identity-irrelevant feature $f_d$. The speaker labels act as a supervisory signal on the training the identity-purified feature $f_p$, and also adversarially guide the training on the identity-irrelevant feature $f_d$. We combine $f_p$ with $f_d$ to the fused spectrogram feature $f_s$. The reconstruction decoder $D_r$ reconstructs the input spectrogram $S$ from the fused feature $f_s$ to ensure that $f_s$ contains the full information representation.

3.1. Purifying Encoder

The goal of the speaker purifying encoder is to achieve a more accurate speaker embedding by obtaining a identity-purified feature. The identity-purified feature is extracted by the speaker purifying encoder $E_p$ and can be written as $f_p = E_p(S)$. For the speaker verification task, $softmax$ is often chosen to nonlinearly map the identity-purified feature to the speaker prediction dimension $N_s$, which can be written as:

$$y_p = softmax(C_s(E_p(S))).$$  

(1)

The objective function of the training the speaker classifier $C_s$ is the same as the cross entropy loss. We compare the prediction result $y_p$ and the encoded speaker identity distribution $p_s$ by cross entropy which can be written as:

$$L_p = - \sum_{j=1}^{N_s} p_s^j \log (y_p^j).$$  

(2)

In order to improve the performance of speaker verification, previous outstanding work [4, 6] has made an improve-
ment to the native softmax function. We reproduce another common improved softmax functions $A - \text{softmax}^{14}$.

### 3.2. Dispersing Encoder

By suppressing identity-purified features, the speaker dispersing encoder extracts speech information that is complementary to the identity information. The identity-irrelated feature is extracted by the speaker dispersing encoder $E_d$ and can be written as $f_d = E_d(S)$. The adversarial classifier module $C_{adv}$ is designed to decouple identity-irrelated information from identity-purified information through an adversarial training method similar to the generative adversarial networks (GAN) $^{13}$.

The goal of the adversarial classifier $C_{adv}$ is to correctly classify the speaker based on the predicted distribution $y_d = \text{softmax}(C_{adv}(E_d(S)))$, and the speaker dispersing encoder $E_d$ tries to fool the classifier by introducing an adversarial supervision signal so that the classifier outputs the same probability on each prediction. The adversarial classifier needs to be trained to identity speakers based on feature $f_p$ extracted by the speaker dispersing encoder $E_d$, and constrained through the cross entropy loss written as

$$L_s^{adv} = -\sum_{j=1}^{N_s} t_j^d \log \left(y_d^j\right).$$

(3)

It is worth noting that the gradient of $L_s^{adv}$ only propagates back to the adversarial classifier $C_{adv}$ without updating layers of $E_d$. In contrast to the goal of $C_{adv}$, the speaker dispersing encoder is trained to fool the adversarial classifier, where speaker identity distribution $u_i$ is required to be assigned constant probabilities of each speaker label and equal to $\frac{1}{N_s}$ in the cross-entropy loss of $\text{softmax}$. In other words, this can also be written in the form of minimizing the negative entropy of the predicted speaker label distribution as follow:

$$L_d^{adv} = \sum_{j=1}^{N_s} u_i^d \log \left(y_d^j\right) = \frac{1}{N_s} \sum_{j=1}^{N_s} \log \left(y_d^j\right),$$

(4)

where the gradient of $L_d^{adv}$ is only propagated back to the speaker dispersing encoder $E_d$ while fixing the adversarial classifier $C_{adv}$. If we allow the gradient of the adversarial loss $L_d^{adv}$ to update the classifier $C_{adv}$ while remove the speaker identity loss $L_s^{adv}$, the encoder $E_d$ will easily cheat the classifier $C_{adv}$, for example, by only changing the classifier $C_{adv}$ to produce non-information output. However, the encoder $E_d$ can not ensure that feature $f_d$ will extract the information of dispelled identity under these circumstances. Therefore, by combining both $L_d^{adv}$ and $L_s^{adv}$, the framework can leverage the advantages of each of them and be coordinated to work together towards the identity-irrelated feature through disentangled information.

### 3.3. Reconstruction Decoder

Although the encoder $E_p$ and the encoder $E_d$ divide the input spectrogram $S$ into two features $f_p$ and $f_d$, they cannot guarantee that $f_p$ and $f_d$ embed a complete representation of the input spectrogram $S$. We fuse these two features into a complete feature $f_s$, and make the decoder $D_r$ to reconstruct the input spectrogram $S$ from input feature $f_s$. To simply measure the difference between reconstructed spectrogram $D_r(f_p, f_d)$ and input spectrogram $S$, we introduce $l_2$ distance as the reconstruction loss

$$L_r = \frac{1}{2}||D_r(f_p, f_d) - S||_2^2.$$ 

(5)

The adversarial supervision signal encourages the speaker dispersing encoder to extract identity-irrelated features, and the reconstruction loss guides the speaker purifying encoder to embed the remaining identity-purified features by constraining the quality of the spectrogram reconstruction. Therefore, during training the reconstruction decoder, the gradient of the reconstruction loss is propagated back to the encoder $E_p$ and the encoder $E_d$.

### 3.4. Learning Algorithm

We propose SDRA framework with the main goal for learning the disentangled speaker identity features. The full objective of SDRA framework consists of $L_p$, $L_s^{adv}$, $L_d^{adv}$ and $L_r$ with weight parameters $\lambda_p$, $\lambda_{adv}$ and $\lambda_r$, which can be written as:

$$L = \lambda_p L_p + \lambda_{adv} (L_s^{adv} + L_d^{adv}) + \lambda_r L_r.$$ 

(6)

In fact, the speaker purifying encoder needs to be trained first and reach a certain level in the task of speaker verification. The speaker dispersing encoder initiates networks by inheriting the weights from the speaker purifying encoder and begins the adversarial training, while the reconstruction decoder begins training the spectrogram reconstruction process. This training method can shorten the training time and ensure the feasibility of adversarial training.

### 4. EXPERIMENTS

#### 4.1. Datasets

Voxceleb1 $^{1}$ and Voxceleb2 $^{2}$ collected from videos uploaded to YouTube, and can be used for both speaker identification and verification. In our experiments, we only use audio files from Voxceleb1 and Voxceleb2 for speaker verification tasks. Voxceleb1 contains 153,516 utterances for 1,251 speakers, while Voxceleb2 contains 1,128,246 utterances for 6,112 speakers. We train our models on datasets Voxceleb1 and Voxceleb2 (the dev partition only, this partition contains speech from 5,994 speakers), which are large-scale text-independent speaker recognition databases. we choose two
Table 1. The performance for speaker verification of SDRA trained on Voxceleb1.

| Model            | Loss Function | Dims | Aggregation | Similarity Metric | EER (%) | \( C_{det} \) |
|------------------|---------------|------|-------------|-------------------|---------|-------------|
| Nagrani et al. [1] | VGG-M Softmax 1024 TAP Cosine | 10.2 | 0.75 |
| Nagrani et al. [1] | VGG-M Softmax 512 TAP Cosine | 7.8 | 0.71 |
| SDRA             | VGG-M Softmax 512 TAP Cosine | **6.57** | **0.619** |
| Cai et al. [6]   | ResNet-34 Softmax 128 TAP Cosine | 5.48 | 0.553 |
| SDRA             | ResNet-34 Softmax 128 TAP Cosine | **4.31** | **0.454** |
| Cai et al. [6]   | ResNet-34 Softmax 128 TAP PLDA | 5.21 | 0.545 |
| SDRA             | ResNet-34 Softmax 128 TAP PLDA | **4.45** | **0.479** |
| Cai et al. [6]   | ResNet-34 A-Softmax 128 TAP Cosine | 5.27 | 0.439 |
| SDRA             | ResNet-34 A-Softmax 128 TAP Cosine | **4.36** | **0.433** |
| Cai et al. [6]   | ResNet-34 Softmax 128 SAP Cosine | 5.51 | 0.522 |
| SDRA             | ResNet-34 Softmax 128 SAP Cosine | **4.18** | **0.455** |
| Cai et al. [6]   | ResNet-34 A-Softmax 128 SAP Cosine | 4.90 | 0.509 |
| SDRA             | ResNet-34 A-Softmax 128 SAP Cosine | **4.40** | **0.469** |
| Cai et al. [6]   | ResNet-34 A-Softmax 128 SAP Cosine | 4.39 | 0.507 |
| SDRA             | ResNet-34 A-Softmax 128 SAP Cosine | **4.29** | **0.437** |
| Cai et al. [6]   | ResNet-34 A-Softmax 128 SAP Cosine | 4.29 | 0.442 |
| SDRA             | ResNet-34 A-Softmax 128 SAP Cosine | **4.13** | **0.437** |

Key performance metrics the minimum of the detection cost function \( (C_{det}) \) [15] and the Equal Error Rate (EER) to evaluate our model performance for the speaker verification task.

4.2. Network Architecture

The SDRA framework we propose consists of five modules: the speaker purifying encoder \( E_p \), the speaker dispersing encoder \( E_d \), the speaker classifier \( C_s \) and the adversarial classifier \( C_{adv} \), as well as the reconstruction decoder \( D_r \).

The network architecture of the speaker purifying encoder \( E_p \) is determined according to the structure of the baseline model, and the speaker dispersing encoder \( E_d \) has a network architecture consistent with the speaker purifying encoder \( E_p \). The basic version of the encoders \( E_p \) and \( E_d \) we implemented to use the ResNet-34 [3] as the backbone and append the global temporal pool (TAP) layer to embed variable-length input speech into the fixed-length speaker feature. Furthermore, we introduce another self-attentive pooling (SAP) layer based on [6]. The speaker classifier \( C_s \) only has one fully connected layer and the adversarial classifier \( C_{adv} \) has 3 convolutional layers and 3 fully connected layers. We design the reconstruction decoder \( D_r \) with 3 fully connected layers and 10 fractionally-strided convolution layers [15] interlaced with batch normalization layers to obtain the output spectrogram.

4.3. Implementation Details

The whole model is trained on 3 NVIDIA Titan V GPUs with an end-to-end manner. During preprocessing, spectrograms of all input speech are extracted in a sliding window fashion by using a hamming window with width = 25ms and step = 10ms. and normalized to unit variance and zero-mean. Since the duration of the speech samples is different, we randomly choose the 3-seconds temporal segments from each spectrogram to ensure that the input size of the training samples is consistent. The batch size of input speech is set to 64 and the model is trained through SGD optimizer with momentum = 0.9 and weight delay = 5e - 4. The initial learning rate is set to \( 10^{-2} \), and it is reduced by 10% per cycle based on the previous learning rate (decaying to \( 10^{-6} \)). The weight parameters in the training process is set as \( \lambda_p = 1 \) for \( L_p \), \( \lambda_r = 0.02 \) for \( L_r \), and \( \lambda_{adv} = 0.1 \) for \( L_{adv} \) in the SDRA framework.

4.4. Model Evaluation

In our experiments, we reproduce several state-of-the-art speaker verification models [1, 2, 5, 6, 7] as the baselines. We ensure that the model structure, loss function, test dataset, and similarity metric are consistent with the original paper. Under this premise, we retrain the model through our pro-
Table 2. The performance for speaker verification of SDRA trained on Voxceleb2.

| Model          | Loss Function     | Dims | Aggregation | Test Set | EER (%) | $C_{det}$ |
|----------------|-------------------|------|-------------|----------|---------|---------|
| Xie et al. [5] | Thin ResNet-34    | 512  | TAP         | VoxCeleb1 | 10.48   | N/R     |
| SDRA           | Thin ResNet-34    | 512  | TAP         | VoxCeleb1 | 3.39    | 0.340   |
| Chung et al. [2] | ResNet-34        | 512  | TAP         | VoxCeleb1 | 5.04    | 0.543   |
| SDRA           | ResNet-34        | 512  | TAP         | VoxCeleb1 | 3.18    | 0.334   |
| Chung et al. [2] | ResNet-50        | 512  | TAP         | VoxCeleb1 | 4.19    | 0.449   |
| SDRA           | ResNet-50        | 512  | TAP         | VoxCeleb1 | 3.07    | 0.326   |
| Chung et al. [2] | ResNet-50        | 512  | TAP         | VoxCeleb1-H | 4.42    | 0.524   |
| SDRA           | ResNet-50        | 512  | TAP         | VoxCeleb1-E | 5.29    | 0.575   |

As a common indicator of speaker verification tasks, these and this are selected to evaluate the performance of our training framework. The formula of $C_{det}$ [15], where we assume $C_{miss}$ and $C_{fa}$ have equal weight parameter of 1.0, which satisfy the following relation:

$$C_{det} = C_{miss}P_{miss}^2 + C_{fa}P_{fa}^2 (1 - P_{tar}).$$

In order to compare experiment results expeditiously, we show the improved performance of baseline methods by using our proposed training framework SDRA under each of them. We choose the training set from Voxceleb1 and use test set of Voxceleb1 for the speaker verification task. Two metrics, Cosine and PLDA, are chosen to verify the similarity of speaker. As shown in Table 1, the experiment results prove that the SDRA training framework has an extraordinary performance on each original baseline method, and the SDRA training framework can improve its performance in different degrees, with the largest improvement margin of 35%.

To verify the performance of the SDRA training framework on a larger dataset, we choose the training set from Voxceleb1, and then choose three different test sets from Voxceleb1 and Voxceleb2: original Voxceleb1 test set, new Voxceleb1 − H test set and new Voxceleb1 − E test set [2]. Due to the limitation of the number of speakers in the original Voxceleb1 test set, one possible problem is that the model will be optimized to overfit a small number of speakers so that the comprehensive performance of the model can not be accurately evaluated through the test results. Unlike the original Voxceleb1 test set, new Voxceleb1 − H test set and new Voxceleb1 − E test set are derived from the entire Voxceleb1 dataset. It is worth mentioning that the test set limits each test pair to include the same nationality and gender, which requires the speaker verification model to learn a more precise speaker identity embedding.

As shown in Table 2, the SDRA training framework maintains an excellent performance on Voxceleb2. Although the accuracy of verification increases with the expansion of the dataset, the SDRA training framework can still further improve the performance of the original model, with the largest improvement margin of 68%. For new Voxceleb1 − E test set, experiment results prove that the SDRA training framework is capable of purifying the identity-related representation of speakers. To some extent, the SDRA training framework provides novel ideas for solving the problems of speaker verification in the wild and the lack of labeled speech database.

4.5. Feature Selectivity Study

We propose a SDRA training framework to learn complete and complementary speaker representations from an original speech by using the additional adversarially disentangled supervision. Successful extraction of disentangled features depends on several core components, such as two encoders $E_p$ and $E_d$ for feature selectivity and adversarial classifier $C_{adv}$ for identity dispersing.

Through experiments, we found that the speaker purifying encoder $E_p$ and the speaker dispersing encoder $E_d$ in-
deed have the ability to extract complementary speaker representations. To further demonstrate the difference between the two encoders in feature selectivity, we use T-SNE to reduce the dimension of high-level features and visualize these features in Figure 2. As shown in Figure 2(a), each speaker has a dense set of clustered features, and there are clear classification boundaries between the features of different speakers, which prove that the speaker purifying encoder $E_p$ can represent identity-related information. In Figure 2(b), each speaker’s identity is evenly distributed in the feature space, and different speaker features overlap with each other. Not surprisingly, experiments prove that the speaker dispersing encoder $E_d$ has an extraordinary ability to erase the speaker information from identity-irrelevant representations.

5. DISCUSSION AND CONCLUSION

In this paper, we present an adversarial training framework to disentangle identity information from identity-irrelevant ones from audio spectrograms. By using an auxiliary adversarial classifier, identity information can be erased from adversarial training. Through reconstruction learning, the speaker branch can be further purified. In this way, using only identity labels, our proposed method can naturally learn complementary feature representations for audio embeddings. Visualization results have revealed the effectiveness of our proposed disentangle mechanism, and extensive experiments have validated that through our training pipeline, a better embedding can be learned for speaker verification in the wild.

Diving deeper into the usage of the non-speaker feature we propose that by further tuning the reconstruction branch, it is possible that a new way for voice conversion can be achieved within our pipeline.

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