Optimization of the Area Under the ROC Curve using Neural Network Supervectors for Text-Dependent Speaker Verification

Victoria Mingote, Antonio Miguel, Alfonso Ortega, Eduardo Lleida

Abstract—This paper explores two techniques to improve the performance of text-dependent speaker verification systems based on deep neural networks. Firstly, we propose a general alignment mechanism to keep the temporal structure of each phrase and obtain a supervector with the speaker and phrase information, since both are relevant for a text-dependent verification. As we show, it is possible to use different alignment techniques to replace the average pooling providing significant gains in performance. Moreover, we present a novel back-end approach to train a neural network for detection tasks by optimizing the Area Under the Curve (AUC) as an alternative to the usual triplet loss function, so the system is end-to-end, with a cost function closed to our desired measure of performance. As we can see in the experimental section, this approach improves the system performance, since our triplet AUC neural network learns how to discriminate between pairs of examples from the same identity and pairs of different identities. The different alignment techniques to produce supervectors in addition to the new back-end approach were tested on the RSR2015-Part I database for text-dependent speaker verification, providing competitive results compared to similar size networks using the average pooling to extract supervectors and using a simple back-end or triplet loss training.

Index Terms—Text Dependent Speaker Verification, Supervectors, Alignment, Triplet Neural Network, AUC Function

I. INTRODUCTION

THE performance in many speaker verification tasks has improved thanks to deep learning advances in signal representations [1], [2] or optimization metrics [3]–[5] that have been adapted from the state-of-the-art deep learning face verification systems. In this paper we propose alternatives to the two following aspects. First, the generation of signal representations or embeddings which preserve the subject identity and uttered phrase. Second, a metric for training the system which, as we will show, is more appropriate for a detection task.

In many recent verification systems, deep neural networks (DNNs) are trained for multi-class classification. A common approach is to apply an average reduction mechanism [1], [2], [6], which produces a vector representing the whole utterance which is called embedding. A simple back-end as a similarity metric can be applied directly for the verification process [7] or more sophisticated methods like the one presented in [8]. However, this approach does not work efficiently in text-dependent tasks since the uttered phrase is a relevant piece of information to correctly determine the identities and the system has to detect a match in the speaker and the phrase to be correct [6], [9]. In our previous work [10], we have noted that part of the imprecisions may be derived from the use of the average as a representation of the utterance, and how this problem can be solved by integrating a new internal layer into the deep neural network architecture which uses an alignment method to encode the temporal structure of the phrase in a supervector. In this paper, we propose a generalization for the use of different alignment mechanisms that can be employed in combination with the deep neural network to generate a differentiable supervector with good performances as will be shown in the experiments.

The second proposal of the paper is an alternative to the triplet loss optimization, initially proposed in face recognition [3], [4]. The goal of the learning process using triplet loss is to maximize the similarity metric or minimize the distance between two examples that belong to the same identity while minimizing the similarity or maximizing the separation margin with the third example from a different identity. We propose the use of a novel method to combine the triplet philosophy with a loss function which approximates a differentiable function the Area Under the Receiver Operating Characteristic (ROC) Curve [11]–[13]. The Area Under the Curve (AUC) measures the area between the ROC and the axes, and the AUC is also a performance measure independent of the operating point. Therefore, by maximizing its value we can improve the overall performance as we will show in the paper.

The combination of i-vector extraction and Probabilistic Linear Discriminant Analysis (PLDA) [14], [15] is still dominant. Nonetheless, recently, several components have progressively been replaced by DNNs. Examples of this are the use of DNN bottleneck features instead of spectral parametrization or combined with it [15], the use of phonetic posteriors obtained by DNN acoustic models for alignment instead of Gaussian Mixture Model (GMM) in i-vector extractors [17], or replacing PLDA by a DNN [18]. More ambitious proposals have been proposed to train DNNs for speaker classification with a large number of speakers as classes, and then extract embeddings of an intermediate layer by reduction mechanisms [19], [20].

The application of the previous text-independent techniques for text-dependent speaker verification tasks has produced mixed results. Traditional techniques with specific modifications have achieved good performance for these tasks such as i-vector+PLDA [21], DNN bottleneck as features for i-vector extractors [22], posterior probabilities for i-vector extractors

V.Mingote, A. Miguel, A.Ortega and E. Lleida are with ViVoLab, Aragón Institute for Engineering Research (I3A), University of Zaragoza, Spain.
E-mail: {vmingote, amiguel, ortega, lleida}@unizar.es
or using the speaker and channel latent factor mechanism [24] with autoencoder DNNs [25]. On the other hand, when the task involves a large amount of data and only one phrase, good results have been provided by speaker embeddings obtained directly from a DNN [26]. While, in tasks with more than one phrase and smaller databases, the lack of data may lead to problems with the use of deep architectures due to overfitting. For this reason, these techniques have been shown ineffective [6], [9].

In our previous work [10] we explored another reason for the lack of effectiveness in these tasks. The order of the phonetic information of the uttered phrase is relevant for the identification. Most of the approaches to obtain speaker embeddings from an utterance reduce temporal information, so this kind of systems only maintain the information of who is speaking and they may not capture the phonetic information for the final identification process. Therefore, one of the objectives of this paper is to remark the relevance of keeping spoken and phrase information to achieve a correct verification process.

In summary, in this paper we propose a generalization of the frame-to-state alignment mechanism using a new alignment technique based on GMM posteriors that creates the supervector and encodes the speaker and phrase information, providing better performance on the RSR2015 dataset compared to previous similar approaches [6], [9]. Second, we propose a new optimization procedure that combines the triplet loss with the AUC as metric to maximize the inter-speaker similarity and minimize the intra-speaker similarity simultaneously as we show in the experiments.

This paper is organized as follows. In Section 2 we show our system and the different alignment strategies developed. Section 3 presents the triplet network method based on a novel triplet loss function. Section 4 presents the experimental data and explains the results achieved. Conclusions are presented in Section 5.

II. DEEP NEURAL NETWORK BASED ON ALIGNMENT

We have developed a differentiable alignment mechanism for neural networks to encode the phrase and speaker information from the audio file into a representation vector, usually called embedding. This representation has a common mechanism with the supervector in speaker verification. It has the advantage of being discriminative against differences in the phonetic information, which is needed in our task, and, at the same time, it is robust to other sources of variability like the speed or the way the utterance is pronounced, even by the same person.

In Fig. 1 we show the two architectures employed to develop our system, where the output of the front-end (FE) part is the supervector, which is obtained thanks to the alignment mechanism. The back-end (BE) could be any differentiable metric of similarity, in this work we use a cosine similarity metric. Since the alignment layer can propagate gradients, we can use this layer as a link between front-end and back-end parts which allows us to train the whole system to optimize any cost function we decide. In our previous work [10], we employed only the first architecture which is depicted in Fig. 1(a) with a classification cross-entropy as cost function, but in this paper as we describe in next section, we propose a second architecture with another function which is better integrated with the back-end and, therefore, closer to the objective of the task. In the architecture type B which we show in Fig. 1(b), one embedding is obtained for each utterance, and then the back-end is applied to provide the verification scores directly with the metric which allows us to have a end-to-end system.

In this work, we use a Hidden Markov Model (HMM) as well as a GMM combined with a Maximum a Posteriori (MAP) adaptation as the alignment techniques in the experiments. As the phrase transcription is known in text-dependent tasks, we could construct a specific left-to-right HMM model or a different GMM for each phrase of the data.

![Fig. 1. Two architectures used to create the whole system.](image)

(a) Architecture type A

(b) Architecture type B

A. HMM alignment mechanism

Firstly, in our previous work [10], we developed our experiments only with a phrase HMM-based alignment mechanism. Using this approach, the knowledge of the phonetic information is not needed in the training process, so we can train easily an independent HMM model for each different phrase. Furthermore, this kind of alignment mechanism has a left-to-right architecture which employs the Viterbi algorithm to provide a decoded sequence in which all the HMM states have correspondence to at least one frame of the utterance, so no state is empty.

The process followed to add this alignment to our system is detailed below. We obtained a sequence of decoded states $\vec{q} = (q_1, ..., q_t, ..., q_T)$ where $q_t$ indicates the decoded state at time $t$ with $q_t \in \{1, ..., Q\}$ from the HMM models and $Q$ is the number of states. After that, these decoded sequence vectors are converted into a matrix with ones at each state according to the frames that belong to this state and zeros in the rest of states, so we have the alignment matrix $A \in \mathbb{R}^{T \times Q}$ with its components $a_{jq} = 1$ and $\sum_j a_{jq} = l$ which means that only one state is active at the same time.

Once this process is over, a matrix is provided externally to the network for each utterance providing the supervector as output of a matrix product. This makes easier to differentiate and enables backpropagate gradients to train neural network as usual. The matrix multiplication assigns the sum of the
obtain the GMM alignment from the posterior probability of components for the whole sequence. The mixture, they can be distributed, and there might be empty a single frame might not correspond to only one component in the previous method. This method provides more flexibility since MAP adaptation \[27\]. To define how this layer operates, we employ the following expression:

$$x^{(l+1)}_{dq} = \sum_{t} \gamma_{t}(c) \cdot x^{(l)}_{dt} + \tau \cdot \mu_{dc},$$

where \(x^{(l+1)}_{dq}\) is the supervector of the layer \((l + 1)\) with dimensions \((D \times Q)\), \(\mu_{dc}\) is the running mean per component of the mixture which will be updated each minibatch in a similar manner to a batch normalization layer [28].

The MAP adaptation ensures that the components with a low count of activations in a sequence will be assigned the mean value of the corresponding supervector section, \(\mu_{dc}\), making the system more robust.

III. TRIPLET NEURAL NETWORK

The triplet neural network, referred to in Fig 2, as a back-end, defines a cost function to evaluate the embeddings provided by three instances of the same neural network with shared parameters. As input of this network three examples are used, an example from a specific identity \(e\) (an anchor), another example from the same identity \(e^+\) (a positive example), and an example from another identity \(e^-\) (a negative example). In most of the existing systems using this approach [5, 29–31], the network architecture has been trained with the triplet loss function [5] which maximizes the distance between the anchor and the negative example at the same time that the distance between the anchor and the positive example is minimized if it is greater than a margin. Unlike the previous systems, we decided to use a loss function which is more intuitive for the detection task, since this function allows us to optimize directly the AUC metric that measures the performance of our whole system.

Furthermore, another important point to train correctly this kind of systems is the triplet data selection applied to choose which are the examples that compose the triplets. We decided to use a similar approach to the triplet sampling strategy proposed in [4] which is usually called Hard Negative Mining instead of a random selection. This technique consists in selecting the anchor-negative pairs with the maximum similarity value (hard negative) for which the system triggers a false alarm, and the anchor-positive pairs with the minimum similarity value (hard positive) which the system can not detect and produces a miss.

The pipeline of the proposed scheme for training our triplet neural network back-end is depicted in Fig 2.

Fig. 2. Triplet neural network, the embeddings are grouped in triplets by the triplet selection to train the network and evaluated the two pairs of embeddings to optimize the objective function.

A. Optimization of the Area Under the ROC Curve

Verification systems are generally trained with discriminative paradigms to optimize the classification performance. However, in that way their training process does not consider the tradeoff between false alarms and misses. For that reason, we propose to optimize directly the AUC which is an operating point independent metric and measures the probability that pairs of examples are ranked correctly. Since this metric is not differentiable we propose an effective approximation as we show in the experiments.

For \(m\) training examples, the AUC is defined as the function that maximizes the average number of times the score for the anchor-positive pairs is greater than the score of the anchor-negative pairs. The anchor-positive score is given by the cosine similarity value \(s_\Theta(p^+_i)\) where \(p^+_i = (e, e^+)\) indicates each pair of anchor-positive embeddings with \(i \in \{1, \ldots, m^+\}\) and \(m^+\) is the total number of positive examples, and the anchor-negative score is provided by the cosine similarity value \(s_\Theta(p^-_j)\) where \(p^-_j = (e, e^-)\) represents the anchor-negative pairs with \(j \in \{1, \ldots, m^-\}\) and \(m^-\) is the total number of negative examples. Both values are also expressed as a function of the net learning parameters \(\Theta\). Therefore, given a set of network parameters \(\Theta\), the AUC function can be written as

$$AUC(\Theta) = \frac{1}{m^+ \cdot m^-} \sum_{i}^{m^+} \sum_{j}^{m^-} \mathbb{I}(s_\Theta(p^+_i) > s_\Theta(p^-_j)),\tag{3}$$

where \(\mathbb{I}(s)\) has a value equal to ‘1’ whenever \(s_\Theta(p^+_i) > s_\Theta(p^-_j)\), and ‘0’ otherwise. This function can be rewritten using the unit step function as
\[ AUC(\Theta) = \frac{1}{m^+ m^-} \sum_{i}^{m^+} \sum_{j}^{m^-} u(s_{\Theta}(p_i^+) - s_{\Theta}(p_j^-)). \] (4)

To enable the backpropagation of the gradients, this expression must be approximated in order to be differentiable. For that reason, we substitute the step function by a sigmoid function:

\[ \Theta^* = \arg \max_{\Theta} \frac{1}{m^+ m^-} \sum_{i}^{m^+} \sum_{j}^{m^-} \sigma(\alpha(s_{\Theta}(p_i^+) - s_{\Theta}(p_j^-)))). \] (5)

where \( \sigma(s) \) is the sigmoid function, and \( \alpha \) is an adjustable parameter which is set using development data.

IV. EXPERIMENTS

The experiments have been reported on the RSR2015 text-dependent speaker verification dataset [32]. This dataset comprises recordings from 157 male and 143 female. For each speaker, there are 9 sessions pronouncing 30 different phrases. This data is divided into three speaker subsets: background (bkg), development (dev) and evaluation (eval). We develop our experiments with Part I and we employ the bkg and dev data (194 speakers, 94 female/100 male) for training. The evaluation part is used for enrollment and trial evaluation.

To develop our experiments, we have employed the bkg partition to train two different alignment mechanisms, both were trained to obtain one model per phrase without the needed of knowing the phrase transcription. On the one hand, HMM models have been trained using a left-to-right model of 40 states for each phrase. On the other hand, a 64 component M GMM has been trained per phrase. With these models we can extract the alignment information to use inside our DNN architecture. A set of features composed of 20 dimensional Mel-Frequency Cepstral Coefficients (MFCC) with their first and second derivatives are employed as input to the DNN. The lack of data may lead to problems, so we try to avoid a possible overfitting in our models with a data augmentation method called Random Erasing [33] which is applied on the input features.

In our experiments, we compare an average pooling (avg) after the front-end network [6]. [9] to the feature input directly or the proposed alignments combined with the front-end network. We employed two different neural network alternatives for the front-end network of the architecture type A: the first one is a convolutional network with three layers (3C) and a kernel of dimension 3 [10], and the second one replicates this basic network using a teacher and student version, following the Bayesian Dark Knowledge approach (bdk) [34]. As reference, the proposed front-end and alignment combinations are tested firstly using only the architecture type A and a cosine similarity on the embeddings. Moreover, in the experiments, we contrast the architecture type A with the architecture type B with two dense layers (2D) as back-end network and cosine similarity as metric, and we also compare the proposed AUC optimization to the triplet loss (TrLoss). To initialize the second architecture, we employ a pre-train model with the architecture type A.

In Table 1, we can see the equal error rate (EER) and the AUC results for the experiments with the different architectures. As we showed, the embeddings from the average reduction mechanism do not represent correctly the relevant information of the speaker and the phrase due to the importance of keeping the temporal structure of the phrases in the supervectors with the alignment layer within the DNN architecture. We can observe that the proposed GMM with MAP alignment provides an additional performance improvement. Furthermore, we can see that if we apply the network back-end to the supervectors instead of using only the cosine similarity, we improve the ability to discriminate between different identities and phrases. This is due to the joint estimation of the front-end and back-end network parameters to optimize the AUC objective. Therefore, this is an end-to-end system since all the parameters are learned to jointly optimize the detection task. The best system performance is obtained when we use the end-to-end AUC optimization strategy to combine the front-end and back-end networks with the alignment mechanism, which plays the important role of encoding the features into the supervector communicating both networks. We achieve 11.11% and 13.89% relative improvement of EER% using HMM and GMM with MAP respectively.

| Architecture | Results (AUC%, EER%, minDCF) |
|--------------|-------------------------------|
| PE feats | NE feats | Type | Fem | Male |
| 3C avg | – | A | 97.91/9.11/0.96 | 97.21/8.66/0.96 | 97.13/8.87/0.96 |
| 3C | – | A | 99.95/0.85/0.10 | 99.96/0.70/0.16 | 99.95/0.72/0.14 |
| bdk | – | A | 99.95/0.73/0.12 | 99.94/0.79/0.14 | 99.95/0.79/0.15 |
| 3C | TrLoss | B | 99.94/0.89/0.21 | 99.93/0.89/0.24 | 99.93/1.06/0.26 |
| 3C | AUC | B | 99.96/0.52/0.10 | 99.97/0.67/0.14 | 99.96/0.64/0.13 |
| 3C | – | A | 99.95/0.79/0.17 | 99.94/0.99/0.23 | 99.94/0.92/0.20 |
| bdk | – | A | 99.98/0.51/0.12 | 99.96/0.78/0.15 | 99.97/0.65/0.13 |
| bdk | TrLoss | B | 99.96/0.63/0.14 | 99.97/0.76/0.16 | 99.96/0.72/0.17 |
| bdk | AUC | B | 99.98/0.40/0.09 | 99.99/0.65/0.14 | 99.98/0.56/0.12 |

V. CONCLUSION

In this paper we propose new alignment methods that incorporate the concept of supervector in text-dependent speaker verification to systems based on neural networks. The proposed alignment methods successfully encode the phrase and the identity in a supervector and are differentiable. Furthermore, we present a novel optimization procedure to optimize the AUC measure as an alternative to the triplet loss cost. Both proposals have been evaluated in the text-dependent speaker verification database RSR2015 part I. As we show, training the system end-to-end to maximize the AUC performance measure provides a better performance in the detection task.

ACKNOWLEDGMENT

This work has been supported by the Spanish Ministry of Economy and Competitiveness and the European Social Fund through the project TIN2017-85854-C4-1-R, by Gobierno de Aragón/FEDER (research group T36_17R) and by Nuance Communications, Inc. We gratefully acknowledge the support of NVIDIA Corporation with the donation of the Titan Xp GPU used for this research.
