ABSTRACT

In this paper, we propose a novel method that trains pass-phrase
specific deep neural network (PP-DNN) based auto-encoders for cre-
ating augmented data for text-dependent speaker verification (TD-
SV). Each PP-DNN auto-encoder is trained using the utterances of
a particular pass-phrase available in the target enrollment set with
two methods: (i) transfer learning and (ii) training from scratch.
Next, feature vectors of a given utterance are fed to the PP-DNNs
and the output from each PP-DNN at frame-level is considered one
new set of generated data. The generated data from each PP-DNN
is then used for building a TD-SV system in contrast to the con-
tentional method that considers only the evaluation data available.

In the proposed approach, data can be considered as the transforma-
tion of data to the pass-phrase specific space using a non-linear transfor-
mation learned by each PP-DNN. The method develops several TD-SV
systems with the number equal to the number of PP-DNNs sepa-
rately trained for each pass-phrases for the evaluation. Finally, the
scores of the different TD-SV systems are fused for decision mak-

1. INTRODUCTION

Speaker verification (SV) aims to verify a person based on their
voice signal. This is realized by using either text-independent (TI)
or text-dependent (TD) mode. The speakers in TI-SV systems have
the flexibility to speak any sentence or text during both the enroll-
ment and test phases. Whereas in TD-SV, speakers are constrained
to speak the predefined pass-phrases during both enrollment and test.
Since TD-SV maintains the matched phonetic condition between the
enrollment and test phases, it gives low error rates in SV using short
utterances. This makes TD attractive for real-world applications.

In the literature, many techniques have been proposed for the
improvement of TD-SV. Model domain methods include Gaussian
mixture model- universal background model (GMM-UBM) [1], i-
vector or total variability modeling [2] and x-vector [3], and in the
feature domain cepstral Mel-frequency cepstral coefficients (MFCC)
and bottleneck (BN) [4, 5] feature-based techniques are commonly
used. Though the x-vector systems give promising results in TI-SV,
they are not successful so far in TD-SV possibly due to the limited
training data [6]. All those techniques require a large amount of
audio-data for training its speaker-independent (SI) model param-
eters. Generally, the SI hyper-parameters in those modeling tech-
niques, (e.g., GMM-UBM or total variability space) are trained us-
ing the data/pass-phrase sets which are different from the evaluation
set. This is done due to the lack/unavailability of a large amount
of data (pass-phrases) matched to the evaluation set and is an open
problem to the TD-SV research communities.

Recently, several data augmentation techniques have been pro-
posed in the literature for creating additional data under low resource
applications: vocal tract length perturbation [7], SpecAugment (de-
formation of log Mel spectrogram with frequency masking) [8], ran-
dom image warping [9] on image processing, mixing noise or other
speech files with the given raw speech signal [10, 11], and applying
impulse (IR) response (of hall room, classroom) on the given raw
speech signal [12]. The effectiveness of data augmentation has been
proven in various studies including speech recognition [8], speaker
recognition [5, 6] and image processing [13].

In the context of speaker verification, augmented data in form of
added noise with existing training data are conventionally used
for training the SI model parameters in TI-SV, e.g., GMM-UBM
[14, 15], DNNs [8], total variability space in i-vector [5], and in post-
processing/scoring step, e.g., probabilistic linear discriminate anal-
ysis (PLDA) [3, 16]. However, none of these deals with data aug-
mentation for speaker enrollment and test phases. A limited num-
ber of studies are made where the noisy version of training speech
utterances/speaker enrollment data has been included in the enroll-
ment phase for building a noise-robust model for spoofing detection
[17] and TI-SV recognition [14]. These works mostly use multi-
conditional training, which is a classic approach for improving noise
robustness. However, to the best of our knowledge, there is no study
on generating auxiliary data for enrollment and verification in TD-
SV.

This motivates us to investigate deep neural network (DNN) for
generating additional data for TD-SV. First, we train pass-phrase
specific autoencoder referred to here as pass-phrase specific DNN
(PP-DNN) using the utterances of the particular pass-phrase. Then
audio-data for enrollment and test are processed with the PP-DNNs
and the output of PP-DNNs are used as auxiliary data for developing
TD-SD system. The proposed method can be viewed as the pro-
cess of mapping a speech utterance onto the evaluation pass-phrase
specific DNN space using non-linear transformation. This allows
generating several copies of the data-sets by processing the utter-
ances with PP-DNNs. The transformation of evaluation pass-phrase
through different PP-DNNs can be considered as the capturing of
cross-pass-phrase information relevant for the TD-SV. The generated data with the proposed method is then used to build a TD-SV per evaluation pass-phrase, i.e., PP-DNN with the standard TD-SV methods such as GMM-UBM or i-vector. Finally, the scores of the sub-systems based on different PP-DNN generated data are fused for decision making.

For training the PP-DNNs, two techniques are considered: (i) PP-DNNs are derived from a pre-trained DNN with transfer learning [18, 19, 20, 21, 22]. In the second method, PP-DNNs are trained from scratch. We demonstrate that the proposed method outperforms the conventional systems based on cepstral and BN features with GMM-UBM and i-vector techniques.

The paper is organized as follows: Sec. 2 describes the TD-SV techniques. The proposed method and experimental setup are presented in Secs. 3 & 4 respectively. Results and discussions are described in Sec 5. Finally, the paper is concluded in Sec 6.

2. TEXT-DEPENDENT SPEAKER VERIFICATION

The TD-SV system uses a frame-level acoustic feature followed by a speaker modeling technique. In this work, we use MFCC. In addition, we also extract frame-level bottleneck (BN) features. For extracting the BN, a DNN is trained which discriminates the speakers at the output layers with cross-entropy based objective function,

$$L(\theta) = \frac{1}{N} \sum_{t=1}^{N} y_t \log p(x_t, \theta)$$  \hspace{1cm} (1)

where $L, \theta, y_t, x_t$ and $p(.)$ denote the loss, parameters of DNN, the class label of the $t$-th input feature vector and speaker posterior at the DNN output layer, respectively. Next, the output from a particular hidden layer of the DNN is projected onto a low dimensional space to extract the BN. Next, we use the GMM-UBM and i-vector methods for speaker modeling and scoring.

2.1. GMM-UBM

In the GMM-UBM method, speaker dependent models are derived from a GMM-UBM using the enrollment data for the particular speaker with maximum-a-posteriori (MAP) adaptation. During test, the feature vectors of the test utterance $X = \{x_1, x_2, \ldots, x_k\}$ is scored against the claimant $\lambda_c$ (obtained in the enrollment phase) and GMM-UBM $\lambda_{ubm}$ models, respectively. Finally, the log-likelihood ratio, $\Lambda(X) = \sum_{l=1}^{n} \left[ \log p(X|\lambda_c) - \log p(X|\lambda_{ubm}) \right]$ is calculated using scores between the claimant and UBM models for decision making.

2.2. i-vector

In the i-vector method, the i-vector of a given speech utterance for a speaker is obtained by decomposing the speaker and channel-dependent GMM super-vector $M$ as $M = m + Tw$ where $m$ denotes the speaker-independent GMM super-vector and $w$ is called an i-vector. Here $T$ is the total variability space on a subspace of $m$, where speaker and channel information is assumed to be dense. During the training phase, each target is represented by an average i-vector computed over all of its enrollment i-vectors. During the test, the i-vector of the test utterance is scored against the claimant-specific i-vector by PLDA [24].

3. PROPOSED METHOD FOR DATA GENERATION

In the conventional/baseline TD-SV system, the speakers are enrolled with speech phrases from multiple sessions available in the evaluation set as per the evaluation plan. Here we propose a method for phrase-specific transformation using PP-DNN where features of a speech utterance are transformed at frame-level for generating multiple sets for training systems in an identical manner.

3.1. Pass-phrase-dependent DNN auto-encoder

At the first step, the PP-DNNs are trained using only limited utterances of particular pass-phrases used for the evaluation. The objective is to reconstruct the given input at the output layer and the objective function to be minimized is the reconstruction loss (e.g., mean squared error) plus $l2$ regularization. It can be defined as,

$$\text{loss} = \frac{1}{N} \sum_{t=1}^{N} \| x_t - \hat{x}_t \|^2 + l2$$  \hspace{1cm} (2)

where $x_t, \hat{x}_t$ denote, respectively, the $t$-th input frame and corresponding reconstructed input at the output layer of the DNN. Two strategies are considered for training PP-DNNs: (i) Transfer learning: PP-DNNs are derived from a pre-trained DNN with transfer learning concept (ii) Learning from scratch: PP-DNNs are trained from scratch with limited audio-data for specific pass-phrases. The two approaches will reflect the impact of an apriori knowledge on PP-DNNs modeling and so on the performance of TD-SV specially when a very limited amount of pass-phrase-wise data is available for training the systems.

3.2. Creation of new data

In the second step, the feature vectors for a given utterance is fed to the PP-DNNs and the frame-wise output from each PP-DNN is considered as the generated new features. This transformation is applied to the entire data set, including training, development and evaluation (both enrolment and test) data. The proposed system is illustrated in Fig. 1. Based on the number of PP-DNNs (say $n$, i.e., the number of pass-phrases in the evaluation database), the proposed approach generates $n$ sets of different features and they are separately used for

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*Fig. 1: Illustration of data generation using pass-phrase specific DNN with transfer learning for TD-SV.*
the system development, i.e., for training GMM-UBM, T-space, and PLDA. It can be expressed as,

\[ \hat{x}_i = f_{ppdnn}(x), \quad i = 1, \ldots, n \]  

(3)

where \( \hat{x}_i \) denotes the generated feature vectors using the \( i \)-th PP-DNN from a utterance \( x \). A TD-SV system is built using the generated data (feature vectors) from a particular PP-DNN. Finally, the scores of the PP-DNN systems are averaged with equal importance,

\[ f_{score} = \frac{1}{n} \sum_{j=1}^{n} s_{yy}^{j} \]  

(4)

We consider the MFCC and BN features and hence we develop two feature-based systems called PP-DNN MFCC and PP-DNN BN, respectively. Note that PP-DNN MFCC features are used for extracting the PP-DNN BN.

### 4. EXPERIMENTAL SETUP

Experiments are performed on male speakers in RedDots challenge 2016 database (task m-part-01) as per protocols in [28]. There are three enrollment sessions to train the particular pass-phrase-wise target speaker model. The utterances are of very short duration on an average of 2-3s per speech signal and recorded over 10 pass-phrases. A disjoint set of nine speakers’ data (approximately 148 files per pass-phrase, excluded from the evaluation) are considered as a development set. The remaining speakers are considered for the evaluation [27]. This gives 248 target models. The pass-phrases available in the speaker enrollment and development sets are used for the PP-DNN training (≈ 223 speech files per model) and give total of 10 PP-DNNs. Table 1 shows the number of different trials available for the system evaluation.

| # of Genuine trials | # of trials in non-target type |
|---------------------|-------------------------------|
| Target              | Impostor                      |
| -wrong (TW)         | -correct (IC)                |
| 2119                | 19071                         |
| 62008               | 557882                        |

Table 1: Number of trials for system evaluation.

57-dimensional MFCC feature vectors (19 static and their \( \Delta, \Delta \Delta \)) are extracted from speech signals using a 20ms Hamming window and a 10ms frame-shift with RASTA filtering [28]. An open-source robust voice activity detection (rVAD) [29] is applied to discard the speech frames with lower energies. The selected frames are processed with utterance-level cepstral mean and variance normalization (CMVN). A GMM-UBM with 512 mixture components and diagonal co-variance matrices is trained using 6300 speech files from the TIMIT database consisting of 630 speakers. The same data set is also used for training PCA projection matrix during BN features extraction. During MAP adaptation, we consider three iterations and relevance factor of 10.

For T-space, pre-trained DNN, PLDA, and DNN for the BN feature extraction, 72764 utterances (out of which 1000 utterances are left out for validation) over 27 pass-phrases (excluding the pass-phrases common in RedDots database) from the RSR2015 database [30] consisting of 157 male and 143 female speakers are used. The PP-DNN auto-encoder consists of hidden layers with 512 neurons, ReLU activation function and one linear output layer [31]. We experiment with various numbers of hidden layers. The learning rate, dropout, batch size, and the number of the epoch are considered, respectively 0.001, 0.01, 1024, and 50. In transfer learning and from scratch cases, 30 epochs are followed as the validation loss was decaying very slowly (as very limited data is available for training PP-DNNs).

For the BN extraction, DNN consists of a seven-layer feed-forward network, 1024 neurons per hidden layer, sigmoid activation function and 300 nodes at the output (number of speakers in the DNN training dataset). The input layer considers the context window of 11 frames (i.e. 5 frames left, current frame, 5 frames right). Each hidden layer consists of 1024 neurons. The frame-level output from the fourth hidden layer of DNNs for BNs is projected using PCA onto 57 dimensional space. The dimension is set to 57 for a fair comparison with MFCC as per [32]. We use TensorFlow toolkit for training the DNNs [24].

The i-vector (400 dimensional) system and PLDA scoring (with default parameters) are developed using the Kaldi toolkit [33]. In PLDA, the utterances of the same pass-phrase from a particular speaker are treated as an individual class and this gives 8100 classes (4239 males and 3861 females) in PLDA. System performance is measured in terms of equal error rate (EER) and minimum detection cost function (minDCF) as per the 2008 SRE [24].

### 5. RESULTS AND DISCUSSION

In this section, we first analyze the performance of TD-SV with the data generated by the PP-DNNs for two different training methods and the different number of hidden layers. The results are shown in Table 2 on part 1 of RedDots database. We observe that the performance of TD-SV (in terms of average EER) for different PP-DNNs based data is very close irrespective of the number of layers in their DNNs and training methodology. The fusion of the PP-DNNs system with baseline gives a marginal reduction in the error rate.

![Fig. 2: Upper penal: performance comparison of TD-SV with data created using different PP-DNNs (for 3 Hidden layers) methods; lower penal: number of frames available per pass-phrase during training.](image)

To look at the behaviors of the PP-DNNs trained with different methods, we compare the performance of TD-SV for each PP-DNN (3 hidden layers) generated data in Fig. 2. From Fig. 2, it can be noticed that the performances of the TD-SV systems are very different for each PP-DNN based data/feature. However, the average
EER values of the systems (after score fusion using Eq.(4)) are very close as in Table 2. This indicates that both the transfer-learning and scratch method based PP-DNNs are able to capture similar speaker relevant information for the TD-SV at the end. For simplicity, in the rest of the paper, we focus on the TD-SV with transfer-learning based PP-DNN data in further analysis and for comparison with baseline.

To further investigate the behaviours of PP-DNN based systems, we compare the performance of TD-SV for each pass-phrase in the evaluation set using the PP-DNN (with transfer-learning) based systems and the baseline system as shown in Fig. 3. It can be observed from Fig. 3 that the performance of TD-SV (in terms of average EER) quite differs across the systems. This shows that each PP-DNN generated data impact differently on the TD-SV, i.e., PP-DNNs are different though a very small amount of data is available for their training. Moreover, the performance of the PP-DNN feature-based systems is similar to that of the baseline MFCC and at the same time shows some variation, which is a positive observation as it indicates different characteristics of these systems and the potential to combine them to improve the overall performance as already shown in Table 2.

5.1. Impact of bottleneck features

Table 3 compares the performance of TD-SV for the proposed method with baseline using i-vector-PLDA technique on the RedDots (m-part-01 task). We observe that the proposed method shows a more relative reduction in EER compared to the improvement obtained with GMM-UBM system in the previous subsection.

6. CONCLUSION

In this paper, we introduced PP-DNN based auto-encoders for creating additional data for TD-SV, where PP-DNNs are trained using utterance of pass-phrases used for the evaluation of TD-SV. The utterances were processed at frame-level by the PP-DNNs and the output from each PP-DNN is considered as the set of generated new data for TD-SV. We also studied the impact of transfer learning while training the PP-DNNs. Our TD-SV experiments on RedDots corpus with generated data demonstrate consistent improvement over original data. Our method is simple but effective in reducing the EERs with generated data demonstrate consistent improvement over original data. Our method is simple but effective in reducing the EERs with generated data demonstrate consistent improvement over original data.
7. REFERENCES

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