EXPLORING UNIVERSAL SPEECH ATTRIBUTES FOR SPEAKER VERIFICATION WITH AN IMPROVED CROSS-STITCH NETWORK

Jiajun Qi, Wu Guo, Jingjing Shi, Yafeng Chen, Tan Liu

1National Engineering Laboratory for Speech and Language Information Processing, University of Science and Technology of China, Hefei, China
2HeFei XinLu Primary School, HeFei, China

ABSTRACT

The universal speech attributes for x-vector based speaker verification (SV) are addressed in this paper. The manner and place of articulation form the fundamental speech attribute unit (SAU), and then new speech attribute (NSA) units for acoustic modeling are generated by tied tri-SAU states. An improved cross-stitch network is adopted as a multitask learning (MTL) framework for integrating these universal speech attributes into the x-vector network training process. Experiments are conducted on common condition 5 (CC5) of the core-core and the 10 s-10 s tests of the NIST SRE10 evaluation set, and the proposed algorithm can achieve consistent improvements over the baseline x-vector on both these tasks.

Index Terms— Speaker verification, multitask learning, articulatory information, universal speech attributes

1. INTRODUCTION

Speaker verification is used to verify a person’s claimed identity based on the characteristics of their voice. During the last decade, the combination of the i-vector [1] algorithm with a probabilistic linear discriminant analysis (PLDA) [2] backend for similarity scoring has become very popular due to its good performance and ability to compensate for within-speaker variations [3, 4].

In recent years, this paradigm has been improved by incorporating deep neural networks (DNNs) in the process of extracting speaker embeddings, which are named the x-vector [5, 6] or d-vector [7] in the SV field. The DNN-based extraction of speaker embeddings outperforms the conventional method and achieves state-of-the-art performance in many cases, especially under conditions of short-duration speaker verification [8, 9].

Speech signals contain much information, such as content, speaker identity, emotion and environmental noise. However, in most SV embedding extraction systems, only the speaker identity is used as a training target, while other information hidden in acoustic features is ignored. To incorporate phonetic information in speaker embedding extraction, [10, 11] proposed using a phonetically aware DNN trained for senone (the tied-triphone states) recognition to guide conventional i-vector speaker modeling. In DNN-based speaker verification frameworks, phonetic information is integrated into speaker embedding extraction in a multitask learning framework by the auxiliary task of phoneme classification [12].

One limitation of the phoneme-related framework is that it is language dependent. The improvement of these SV systems is negligible when the language used in the SV system is different from that of the phoneme recognition system. To address this issue, language-independent articulatory features (AFs), such as the manner and place of articulation, which represent the way that humans produce speech, are introduced to provide auxiliary information for speaker embedding extraction. In [13], a two-step automatic clustering method was proposed to generate attribute units for acoustic modeling that are used in the DNN/i-vector embedding extraction process. Hong et al. proposed concatenating speakers and AFs embeddings to produce new embeddings with complementary information [14].

We also explore the effect of universal speech attributes on x-vector extraction using the MTL framework in this study. The place and manner of articulation form the fundamental speech attribute unit, and then new speech attribute (NSA) units, which are similar to senones in speech recognition, are generated by tree-based state tying [15]. Highly discriminative speaker embeddings can be obtained by integrating the classification of NSA units as an auxiliary task under the MTL framework. Different from the conventional MTL framework, an improved cross-stitch network is used to combine the shared representations of related tasks. Experiments on the NIST SRE10 evaluation dataset [16] show that our proposed MTL framework with articulatory information achieves better performance than previous frameworks.

Section 2 briefly introduces the baseline x-vector system. Section 3 presents the generation of NSA units as well as the proposed improved cross-stitch network for MTL. Section 4 presents the experimental setup and the results. In section 5, we summarize our work and discuss future work.
2. BASELINE X-VECTOR ARCHITECTURE

In this paper, we use the x-vector system as our baseline. The network architecture is the same as that presented in \[6\].

The x-vector network consists of frame-level layers, segment-level layers and a statistic pooling layer that serves as the connection between layers of different levels. Five TDNN layers are stacked as the frame-level feature extractor, and the final output vectors of the whole variable-length utterance are aggregated into a fixed utterance-level vector through the statistics pooling. The mean and standard deviation are calculated and then concatenated together as the output of the pooling layer. Then two additional fully connected layers are used to obtain a low-dimensional speaker representation after the pooling layer and finally passed to the softmax output layer.

The x-vector network consists of frame-level layers, segment-level layers and a statistic pooling layer that serves as the connection between layers of different levels. Five TDNN layers are stacked as the frame-level feature extractor, and the final output vectors of the whole variable-length utterance are aggregated into a fixed utterance-level vector through the statistics pooling. The mean and standard deviation are calculated and then concatenated together as the output of the pooling layer. Then two additional fully connected layers are used to obtain a low-dimensional speaker representation after the pooling layer and finally passed to the softmax output layer.

![Network architecture of the proposed MTL framework](image)

Fig. 1: Network architecture of the proposed MTL framework

3. MULTITASK LEARNING WITH UNIVERSAL SPEECH ATTRIBUTES

In this section, we describe the generation of the NSA units and the improved cross-stitch network for multitask learning, as depicted in Fig. 1. The left part of Fig. 1 is the same as the conventional x-vector architecture, and the classification of the identity of the speaker is the main task. The right part of Fig. 1 is the auxiliary network used to classify the NSA units. An improved cross-stitch network is used to combine the shared representations of related tasks.

3.1. Generation of the NSA units

The set of universal speech attributes used in this work is listed in Table 1, including the place and manner of articulation. Compared with the phoneme set (numbering approximately 40-50 units in English) in conventional speech recognition, the numbers of manners and places of articulation are much fewer, with only 11 and 10 units, respectively. Even when the context-dependent models are used, the numbers of these attribute units are not high enough to achieve good performance. For this reason, the place and manner of articulation are combined to increase the number of attribute units and to take advantage of both when representing the pronunciation habits of speakers. We propose a process for generating attribute units with the following two steps: first, combining the place and manner of articulation directly and second, generating speech attribute units by tree-based state tying.

| manner | affricate, fricative, nasal, vowel, voice-stop, unvoiced-stop, glide, liquid, diphthong, sibilant |
| place  | alveolar, alveo-palatal, dental, glottal, high, bilabial, labio-dental, low, mid, palatal, velar |

The place and manner of articulation are combined in a simple way, which is the same as the first step presented in \[13\]. Because there is a direct mapping between phonemes and attribute units, we use phonemes to generate attribute units. Looking up the corresponding place and manner of articulation of a phoneme, if they are different from those of other phonemes, we define a new attribute unit. For example, the manner and place of phoneme /m/ are /nasal/ and /bilabial/, respectively, so a new attributes unit is defined as /bilabial_nasal/. We call these new units SAUs. English phoneme-attribute mapping is used in our experiments, and 23 SAUs are obtained by combination.

In the second step, these SAUs are treated as monophones in the conventional speech recognition system. The tri-SAUs are used in content-dependent acoustic modeling, and tied tri-SAUs states are obtained by using decision trees with Kaldi toolkits \[17\]. We define these tied tri-SAUs states as new speech attribute (NSA) units. Once the NSA units are generated, the training procedure of the NSA-based acoustic model is identical to that of the conventional phoneme-based system.

After training the acoustic model with the NSA set, the speech data are aligned into the corresponding NSA units using a Viterbi decoder. In this work, the auxiliary task of the proposed MTL network in Fig. 1 is to estimate the NSA posteriors for providing articulatory information.

3.2. Multitask learning with cross-stitch units

We propose a soft parameter sharing-based multitask network for integrating articulatory information into speaker embedding extraction by using improved cross-stitch units. As depicted in Fig. 1, the left branch is a conventional x-vector network that targets speaker classification. The right branch is a TDNN-based framewise NSA recognizer.
**4. EXPERIMENTS**

**4.1. Experimental setup**

*4.1.1. Training data and evaluation metric*

The experiments are conducted on common condition 5 (CC5) of the core-core and 10 s-10 s tests of the NIST SRE10 evaluation set. NIST SRE 2004-2008 telephone excerpts, Switchboard Phase II Part 1/2/β and Cellular Part 1/2 are used as the training set for the speaker classification task. There are approximately 65,000 recordings for 6,500 speakers in total, and only speaker labels are available. To introduce articulatory information in the MTL framework, the 300-hour out-of-domain Switchboard-I Release 2 dataset is used for NSA task training.

We evaluate the results on the male and female pooled trials. The performance is evaluated in terms of the equal error rate (EER) and the minimal detection cost function (minDCF) with \( P_{\text{target}} = 0.001 \).

**4.1.2. Input features**

The input acoustic features in our experiments are 30-dimensional MFCCs with frame lengths of 25 ms that are mean-normalized over a sliding window of up to 3 s. An energy-based VAD is employed to filter out the nonspeech frames.

**4.1.3. X-vector baseline system configuration**

The baseline x-vector system is implemented with the TensorFlow toolkit [19]. Each of the bottom four frame-level layers has 512 nodes, and there are 1536 hidden nodes in the fifth layer. The dilation factors of these five layers are 1, 2, 3, 1 and 1. Both fully-connected layers after the statistic pooling layer have 512 nodes. Batch normalization is used on all layers except the statistic pooling layer. To prevent overfitting, L2-weight decay is employed. The network is trained on 2-4 s chunks. We utilize the Adam optimizer to train the network with batch sizes of 64 for 3 epochs. The initial learning rate is 0.001, and it is decayed to a final learning rate of 0.0001.

**4.1.4. MTL with NSA classification as an auxiliary task**

In our experiments, we generate NSA units to provide articulatory information for speaker embedding extraction. The NSA transcriptions are obtained by GMM-HMM forced alignment using the Kaldi toolkit [17]. In the proposed MTL framework, the speaker branch is the same as the x-vector network. The NSA branch consists of four TDNN layers, a framewise fully-connected layer with 128 nodes and a softmax output layer. The first four layers of both branches have the same TDNN architecture. Cross-stitch units are placed at the first two layers of the networks, and the initial values of \( \alpha_{NS}, \alpha_{SN} \) are set to 0.1 in Fig. 2. The network is trained with the same configuration as the x-vector network. When the MTL model is trained, speaker embeddings are extracted from the first fully-connected layer of the speaker branch with 512 dimensions. The speaker embedding dimension is reduced to 70 by LDA at first, and then a standard PLDA is used to calculate the verification scores between embeddings.

**4.2. Result**

*4.2.1. Comparison of senones and NSA units*

To investigate the effect of introducing different complementary information into the proposed MTL framework, we compare the performances of systems using senones and NSA
The numbers of both senones and NSA units are optimal so that both systems achieve the best performance. As shown in Table 2, both the MTL frameworks with senones and NSA units achieve better results than those of the baseline x-vector, and the MT-NSA can obtain the best performance on most evaluation metrics except for EER on CC5 of the core-core test. On the 10 s-10 s test, the MT-NSA provides a 15.3% and 7.6% relative improvement in terms of EER and minDCF over the baseline x-vector, respectively. On core-core test, the MT-NSA can obtain a 17.8% minDCF reduction compared with that of the baseline x-vector.

### Table 2: Results on NIST SRE 2010. MT-SEN denotes the MTL network with senones. MT-NSA denotes the MTL network with NSA units.

| System      | 10 s-10 s | core-core |
|-------------|-----------|-----------|
|             | EER%      | minDCF    | EER%      | minDCF    |
| x-vector    | 8.42      | 0.923     | 2.40      | 0.484     |
| MT-SEN      | 7.69      | 0.877     | 2.12      | 0.453     |
| MT-NSA      | 7.14      | **0.853** | 2.37      | **0.398** |

4.2.2. Comparison of different numbers of NSA units

The number of NSA units affects the granularity of articulatory information. Table 3 presents the performances of MT-NSA systems with 80, 400 and 1248 units. It can be observed that the proposed MT-NSA systems with 80 and 400 NSA units outperform the x-vector baseline system, while the performance of the system with 1248 units is similar to that of the x-vector.

### Table 3: Results on NIST SRE 2010. MT-NSAn denotes the MTL network with an NSA set of n units.

| System      | 10 s-10 s | core-core |
|-------------|-----------|-----------|
|             | EER%      | minDCF    | EER%      | minDCF    |
| x-vector    | 8.42      | 0.923     | 2.40      | 0.484     |
| MT-NSA80    | 7.69      | 0.886     | 2.26      | 0.462     |
| MT-NSA400   | **7.14**  | **0.853** | 2.37      | **0.398** |
| MT-NSA1248  | 8.41      | 0.911     | 2.42      | 0.482     |

4.2.3. Comparison of different numbers of shared layers

Except for the number of NSA units, the sharing of different layers in the cross-stitch network can also affect system performance. Table 4 illustrates the results of sharing different layers. We can observe that the best performance is obtained by sharing the first two layers. As the number of shared layers increases, the performance of the MTL system improves at first and then decreases slightly. A reasonable explanation for this is that the characteristics of the higher layers are more task-specific in both branches, and these characteristics may not benefit the other task as much as those in the bottom layers.

### Table 4: Results on NIST SRE 2010. MT-NSAn denotes the MTL network with an NSA set of n units.

| System      | 10 s-10 s | core-core |
|-------------|-----------|-----------|
|             | EER%      | minDCF    | EER%      | minDCF    |
| x-vector    | 8.42      | 0.923     | 2.40      | 0.484     |
| MT-NSA     | 7.14      | **0.853** | 2.37      | **0.398** |
| MT1-NSA    | 7.88      | 0.876     | 2.54      | 0.537     |
| MT2-NSA    | **7.14**  | **0.853** | 2.37      | **0.398** |
| MT3-NSA    | 7.69      | 0.895     | 2.54      | 0.458     |
| MT4-NSA    | 8.05      | 0.904     | **2.11**  | 0.474     |

4.2.4. Comparison among different MTL frameworks

In the following experiments, we compare the proposed MTL with other MTL frameworks to demonstrate its efficiency. The classification of the NSA is the auxiliary task in all these MTL frameworks. The results are reported in Table 5, where MT-shared refers to the MTL framework with shared layers proposed in [14], and MT-Ori-CS denotes the MTL network using the original cross-stitch unit [18]. The numbers of NSA units and shared layers are tuned to achieve the best performance among all these systems. Both the MT-shared and MT-Ori-CS systems can only achieve marginal improvements over the baseline x-vector, and they sometimes perform worse than the baseline x-vector. The MT-Ori-CS dynamically updates $\alpha_{SS}, \alpha_{NN}$ of Eq. 1 in the model training process, while the proposed MT-NSA fixes $\alpha_{SS}, \alpha_{NN}$ to 1, and this minor modification can enhance the task-specific representation. We can see from the experimental results that this modification can extract more discriminative speaker embeddings than the baseline x-vector.

### Table 5: Results of different MTL frameworks.

| System      | 10 s-10 s | core-core |
|-------------|-----------|-----------|
|             | EER%      | minDCF    | EER%      | minDCF    |
| x-vector    | 8.42      | 0.923     | 2.40      | 0.484     |
| MT-shared   | 8.05      | 0.898     | 2.39      | 0.469     |
| MT-Ori-CS   | 8.42      | 0.947     | 2.68      | 0.471     |
| MT2-NSA     | **7.14**  | **0.853** | **2.37**  | **0.398** |

5. CONCLUSION

In this paper, we propose combining speaker embedding extraction with universal speech attributes through an improved multitask learning framework for text-independent speaker verification. In the network training process, the improved cross-stitch units are used to learn the optimal linear combination of shared representations of the speaker and NSA task. The deep speaker embeddings can benefit from the complement of articulatory information in the proposed MTL framework. The experimental results demonstrate the effectiveness of our proposed strategy.

In future work, we will continue to focus on the use of universal speech attributes and investigate other useful multitask learning strategies for text-independent speaker verification.
6. REFERENCES

[1] Najim Dehak, Patrick J Kenny, Réda Dehak, Pierre Dumouchel, and Pierre Ouellet, “Front-end factor analysis for speaker verification,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 19, no. 4, pp. 788–798, 2010.

[2] Sergey Ioffe, “Probabilistic linear discriminant analysis,” in European Conference on Computer Vision. Springer, 2006, pp. 531–542.

[3] Patrick Kenny, “Bayesian speaker verification with heavy-tailed priors.,” in Odyssey, 2010, vol. 14.

[4] Daniel Garcia-Romero and Carol Y Espy-Wilson, “Analysis of i-vector length normalization in speaker recognition systems,” in Twelfth annual conference of the international speech communication association, 2011.

[5] David Snyder, Daniel Garcia-Romero, Daniel Povey, and Sanjeev Khudanpur, “Deep neural network embeddings for text-independent speaker verification.,” in Interspeech, 2017, pp. 999–1003.

[6] David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur, “X-vectors: Robust dnn embeddings for speaker recognition.,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5329–5333.

[7] Ehsan Variani, Xin Lei, Erik McDermott, Ignacio Lopez Moreno, and Javier Gonzalez-Dominguez, “Deep neural networks for small footprint text-dependent speaker verification.” in 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2014, pp. 4052–4056.

[8] Gautam Bhattacharya, Md Jahangir Alam, and Patrick Kenny, “Deep speaker embeddings for short-duration speaker verification,” in Interspeech, 2017, pp. 1517–1521.

[9] Chunlei Zhang and Kazuhiro Koishida, “End-to-end text-independent speaker verification with triplet loss on short utterances.,” in Interspeech, 2017, pp. 1487–1491.

[10] Patrick Kenny, Themis Stafylakis, Pierre Ouellet, Vishwa Gupta, and Md Jahangir Alam, “Deep neural networks for extracting baum-welch statistics for speaker recognition.,” in Odyssey, 2014, vol. 2014, pp. 293–298.

[11] Yun Lei, Nicolas Scheffer, Luciana Ferrer, and Mitchell McLaren, “A novel scheme for speaker recognition using a phonetically-aware deep neural network,” in 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2014, pp. 1695–1699.

[12] Yi Liu, Liang He, Jia Liu, and Michael T Johnson, “Speaker embedding extraction with phonetic information,” arXiv preprint arXiv:1804.04862, 2018.

[13] Sheng Zhang, Wu Guo, and Guoping Hu, “Exploring universal speech attributes for speaker verification,” in 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2017, pp. 5355–5359.

[14] Qian-Bei Hong, Chung-Hsien Wu, Hsin-Min Wang, and Chien-Lin Huang, “Combining deep embeddings of acoustic and articulatory features for speaker identification,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 7589–7593.

[15] Steve J Young, Julian J Odell, and Phil C Woodland, “Tree-based state tying for high accuracy modelling.” in HUMAN LANGUAGE TECHNOLOGY: Proceedings of a Workshop held at Plainsboro, New Jersey, March 8-11, 1994, 1994.

[16] Alvin F Martin and Craig S Greenberg, “The nist 2010 speaker recognition evaluation,” in Eleventh Annual Conference of the International Speech Communication Association, 2010.

[17] Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Lukas Burget, Ondrej Glembek, Nagendra Goel, Mirko Hannemann, Petr Motlicek, Yanmin Qian, Petr Schwarz, et al., “The kaldi speech recognition toolkit,” in IEEE 2011 workshop on automatic speech recognition and understanding. IEEE Signal Processing Society, 2011, number CONF.

[18] Ishan Misra, Abhinav Shrivastava, Abhinav Gupta, and Martial Hebert, “Cross-stitch networks for multi-task learning,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 3994–4003.

[19] Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al., “Tensorflow: A system for large-scale machine learning,” in 12th {USENIX} symposium on operating systems design and implementation ({{OSDI} } 16), 2016, pp. 265–283.