Lightweight Speaker Verification for Online Identification of New Speakers with Short Segments

Ivette Vélez\textsuperscript{a}, Caleb Rascon\textsuperscript{a,}\textsuperscript{*}, Gibrán Fuentes-Pineda\textsuperscript{a}

\textsuperscript{a} Instituto de Investigaciones en Matemáticas Aplicadas y en Sistemas (IIMAS), Universidad Nacional Autónoma de México (UNAM), Circuito Escolar 3000, 04510, Mexico

Abstract

Verifying if two audio segments belong to the same speaker has been recently put forward as a flexible way to carry out speaker identification, since it does not require to be re-trained when new speakers appear on the auditory scene. However, many of the current techniques employ a considerably high amount of memory, and require a specific minimum audio segment length to obtain good performances. This limits the applicability in areas such as service robots, internet of things and virtual assistants. In this work we propose a BLSTM-based model that reaches a level of performance comparable to the current state of the art when using short input audio segments, while requiring a considerably less amount of memory. Further, as far as we know, a complete speaker identification system has not been reported using this verification paradigm. Thus, we present a complete online speaker identifier, based on a simple voting system that shows that the proposed BLSTM-based model and the current state of the art are similarly accurate at identifying speakers online.

Keywords: speaker identification, generic verification, low resources

1. Introduction

It is of great interest that computer systems interact with humans in a similar manner as a human would. Thus, there is a growing need to correctly identify
the speaker by their voice alone [1], and there has been recent important progress in terms of performance in the wild [2]. This progress has been largely based on the use of deep neural networks [3], which tend to occupy a considerable amount of computational resources, since the number of parameters used to obtain such a high performance is usually relatively high [2]. Additionally, several of these techniques tend to require a sizeable segment of time with which to identify the user to obtain these high performances [4]. These two requirements limit the application scenarios in which these high-performing speaker identification techniques can be used, such as service robots [5], internet of things [6], and virtual assistants [7]. In these scenarios, users speak in small spurts of time [8], requiring that the identification is carried out only using short segments of audio. Additionally, other processes are usually carried out in parallel (such as natural language processing, face recognition, action planning, etc.) and it is of interest that all functionalities are run on-site (in case of network outages). This limits the amount of memory and computational resources that can be used for speaker identification.

Although there has been an increasing amount of speaker identification techniques based on Convolutional Neural Networks (CNN), Bi-directional Long Short-Term Memory networks (BLSTM) have rarely been used for this purpose, while they have provided good results in other audio applications, such as voice conversion [9], sound source separation [10] and speech recognition [11]. An important aspect of BLSTM is their re-use of weights in their inner processes for modeling temporal data, which results in a small amount of parameters. Additionally, because of their recurrent nature, as well as their use of memory, they are well suited for finding temporal patterns. Both of these features in conjunction make them a viable candidate to explore for carrying out lightweight speaker verification.

In typical human-human interaction, new users are often introduced in the environment, such as when a new customer enters a restaurant or when a new house guest uses a device. Classical identification techniques rely either on a classification model, that has an output for every known speaker, or on a series
of verification models, each trained to identify a known speaker [12]. Recently, there has been a shift away from this approach [13] towards what we will refer to “generic verification”, where a model is trained to compare two text-independent audio segments to establish if they are from the user or not. This generality makes the solution space much more complex, but provides the benefit that, with an additional selection scheme, the two-input verification model can be used for speaker identification. It is important to state that, although the ultimate aim for generic verification is to carry out speaker identification, as far as we know there has not been reported a complete speaker identification system based on this paradigm.

In this work, we propose a BLSTM-based model to carry out generic speaker verification that requires a relatively small amount of parameters and short segments of audio. It is important to state that our proposal does not aim to outperform the current state of the art of speaker verification. It aims to offer a reasonable trade-off between performance and portability. Meaning, we believe that the differential of the computational and segment-length requirements between the proposed model and the current state-of-the-art heavily outweighs their performance differential. Additionally, we propose to use this model alongside a simple voting system, to provide a complete online speaker identifier that does not require to be re-trained when new speakers are encountered.

To facilitate the adoption of our proposal, the source code and trained weights of the complete system can be freely downloaded from:

https://github.com/julik43/blstm_speaker_id

The remainder of this paper is organized as follows: a summary of works related to ours is presented in Section 2; in Section 3 the proposed BLSTM-based model is described; in Section 4 the proposed BLSTM-model is evaluated and compared against the state of the art in terms of performance and memory usage; in Section 5 a complete online speaker identifier is summarized, and is evaluated using the proposed BLSTM-based model and the state of the art; and, we conclude our work in Section 6.
2. Related Work

Speaker identification for a considerable amount of time has long been carried out by either classification or verification [12]. However, recently there has been an important shift towards techniques that transform the input signal to a “speaker domain”, where the speaker is represented by an embedding vector calculated from the input signal, and then compared against the embeddings of other known speakers. A popular approach is based on i-vectors [13], but more recently the use of deep learning techniques have been more prominent for embedding calculation [15]. Convolutional Neural Networks (CNN) have been the more popular choice, since they have been well tested for feature extraction in computer vision. They have been used to generate new types of features which are then fed into different statistical methods [15, 16, 17, 18, 19]. Moreover, CNNs have also been used with raw audio [20] to extract the relevant information to be used with an ad-hoc verifier generated for every speaker. They have also been extensively employed in a Siamese-fashion for biometric-based human identification for several years, e.g. in signature verification [21], fingerprint recognition [22], face verification (in conjunction with a similarity metric) [23], and gait recognition [24]. These applications are compatible with Siamese networks since they can be used to verify if two input signals are from the same source (in these cases, from the same user).

To this effect, speaker identification is now being approached by ways of what we in this work refer to “generic verification”: where a model is trained that establishes if two audio segments belong to the same speaker or not. In fact, the recent 2019 VoxCeleb Speaker Recognition Challenge (VoxSRC) [13] established the goal of the contestants for this specific task. An example of this approach is that of [25, 26], where speaker identification is carried out by comparing a measure of similarity between the audio of a speaker and patterns previously generated for known speakers.

Another representative example of this type of approach is the work of Nagrani et. al. [27], where the authors describe the VoxCeleb1 database and
trained a Siamese CNN for generic verification of speakers. They use the cosine distance between two signals as a measure of similarity. For the identification process they report an accuracy of 80.5% and 92.1% for top-1 and top-5 respectively. Although the authors also report an identification, they did not use the generic verification paradigm to carry this out; they used a traditional classification approach. This work was extended to use a “thin” ResNet, with a NetVLAD-based time feature aggregator, that is able to estimate such embeddings from input segments with a variable length [28].

Interestingly, the vast majority of these works are based on the use of CNNs for embedding calculation. A rare exception is [29], where speaker verification is carried out by using a Siamese model of two Long Short-Term Memory (LSTM) networks, and a contrastive loss function used for verification. However, this approach involves the training of a verification model for each speaker, which is more akin to the classical verification approach. The authors reported an Equal Error Rate (EER) of 22.9% and 22.1% in their tests. As mentioned previously, since BLSTMs re-use weights in there inner processes for temporal modeling, they tend to employ a small amount of parameters.

Furthermore, even though the vast majority of the recent embedding-based techniques report impressive verification performances, they do not aim for “lightweightedness”. Meaning, the amount of parameters they employ are usually quite high, limiting their applicability in scenarios such as service robotics, internet of things and virtual assistants. As for the length of audio segments, several seconds of information are required to obtain these high performances. A notable exception to this is the work of [4], where sub-1-second segments were tested with an EER below 7% and memory usage was of 268 MB.

It is then of interest to have a speaker verification system that provides a trade-off between performance and computational and segment-length requirements.

It is important to note that, even though the aim of embedding-based verification is to be ultimately used for speaker identification, as far as we know, there has not been a report of a full speaker identification system based on this
approach. To this effect, the work of [30] approaches the task of classification of written characters by using embedding-based verification in conjunction with a simple voting-based selection scheme, and obtained good results. The same can be employed for speaker identification; and, as such, this approach is also explored in this work.

3. Proposed BLSTM-Based Model

As described earlier, a recently popular approach for speaker identification is to train a system that establishes if two audio segments belong to the same speaker or not. This is carried out by calculating the embedding of the audio segments (to transform them into the “speaker domain”) and then measuring their similarity. To calculate these embeddings, we propose a model based on a Bi-directional Long Short-Term Memory network (BLSTM), because of the relatively few amount of parameters that are employed to find temporal patterns. The aim is then to obtain a relatively good performance, using a relatively small amount of parameters and small input lengths.

To train this model, we first establish a simple classification scenario, in which all but the last layer of the trained model is used for embedding calculation, as shown in Figure 1.

![Figure 1: Proposed architecture for embedding calculation.](image)

The last layer is a fully connected layer that carries out the classification
from the embedding. This layer is then removed, and the rest of the network is then used for embedding calculation of incoming input segments. The resulting network architecture is comprised of the three BLSTM layers with 256 units, and outputs an embedding of size 512, twice the number of units.

The Frobenius Inner Product is then used to calculate the similarity between the normalized embeddings, as described in Equation (1)

\[ d_{[f_1,f_2]} = \sum_{i=1}^{N} \left( \frac{f_1[i]}{\|f_1\|_2} \ast \frac{f_2[i]}{\|f_2\|_2} \right) \] (1)

where \( f_1 \) and \( f_2 \) are the calculated embeddings of the two input segments; \( N \) is the embedding vector length; \( i \) is the vector index; \( \| \cdot \|_2 \) the L2 norm operator; and \( d_{[f_1,f_2]} \) is the Frobenius Inner Product between \( f_1 \) and \( f_2 \). Because of the normalization of the embeddings, the possible values of \( d \) range between \([-1,1]\], with values close to 1 representing high similarity. It is important to point out that the L2-normalization is actually carried out in the last layer of the proposed embedding-calculation architecture (shown in Figure 1). This means that the calculated embeddings are already L2-normalized, and, thus, during testing the Frobenius distance is calculated by just summing up the point-to-point multiplication of \( f_1 \) and \( f_2 \). It is only included in Equation (1) for completeness sake.

For pre-processing, we employed the Voice Activity Detection technique based on [31], which employs a 20 dB threshold to discriminate between silent and active windows. In terms of the input segment length, the model was trained with segments of 0.25, 0.5, 1.0, 1.5 and 2.0 seconds.

In terms of employed features, we propose to explore different types of spectrograms, such that the input of the model is a matrix in which one dimension is time. In the other dimension, we extracted the following features to explore:

- Spectral magnitude in a linear scale. Referred here as SpecMag.
- Spectral magnitude in a decibel scale. The result is a type of frequency selector, since it tends to amplify frequency bins with high energy, while
reducing ones with low energy. Referred here as SpecdB.

- Spectral density, estimated by the square of the linearly-scaled magnitude. The result provides an estimate of the energy distribution throughout the spectral range. Referred here as Spec.

- Spectral magnitude in a linear scale after filtering the input audio with a simple pre-emphasis filter, which avoids distortion in high frequencies while reducing variability in the extracted spectra [32]. Referred here as EmphSpec.

- The previous feature, but in a decibel scale. Referred here as EmphSpecdB.

- The Mel-Frequency Cepstral Coefficient (MFCC) spectrum, built with 40 logarithmically spaced triangular filters. Referred here as MFCC.

The time dimension of all the employed spectrograms were calculated by using either a Hamming window (for Spec, EmphSpec, EmphSpecdB and MFCC) or a Hann window (for SpecMag and SpecdB) of 32 ms, with an overlap of 16 ms. Given that the recordings used for training and validation (described in the following section) are sampled at 16 kHz, the length of the window is of 512 samples. An interesting note here is that, regardless of the input segment length, the embedding dimension will ultimately be of 512, which could be argued provides consistency in the embedding-domain search space during training.

3.1. Training, Validation, and Testing Methodology

The VoxCeleb2 database [33] was used for training the classification network, from which the speaker embedding is calculated. For each training epoch, 1000000 randomly-selected recordings from the 5000 speakers of the “dev” subset of the corpus were used for training. Each model was trained for 30 epochs using the Adam optimizer [34], a cross-entropy loss function, a learning rate of 0.0001 and a batch size of 100. After each training epoch, a validation stage
was carried out with 8000 randomly-selected entries to determine its classification performance during training. The amount of epochs was determined by previous tests that showed that the resulting embeddings provided the same or worse verification performance.

As mentioned before, a VAD system (which is based on [31]) is used to extract time segments of vocal activity from the corpus audio files.

For testing the trained model for generic verification, the trained network was evaluated with the VoxCeleb1 verification test list, released by the VGG group\(^1\) composed of 37720 balanced data pairs of the VoxCeleb1 dataset. In this stage, for each audio in the test list, an embedding was generated using the trained model, then the Frobenius Inner product was calculated between the pairs listed determining if both were from the same speaker or not. This was carried out by using a threshold in the mid-point of \([-1, 1]\) range of possible values of the Frobenius Inner product.

4. Results

In Table 1, the number of employed parameters, memory usage (in MB) and the equal error rate (EER) of the verification of each of the models trained with every possible combination of segment lengths (0.25, 0.5, 1.5 and 2 s) and of explored input features (SpecdB, Spec, SpecMag, EmphSpec, EmphSpecdB and MFCC).

As it can be seen, the SpecdB feature (a spectrogram with spectral magnitude in a decibel scale) consistently outperformed the other features in each possible segment length. Because of this reason, all of the following comparisons were carried out using this feature as part of the proposed BLSTM-based model.

To fully evaluate our system we compare the BLSTM-based model to relevant state of the art models with varying degrees of input segment lengths, as well as memory usage.

\(^1\)Obtained from its GitHub repository in [https://github.com/WeidiXie/VGG-Speaker-Recognition](https://github.com/WeidiXie/VGG-Speaker-Recognition)
### Table 1: Results of the evaluation of all trained models.

| Input Feat. | Length (s) | EER (%) | Memory Usage (MB) |
|-------------|------------|---------|-------------------|
| SpecdB      | 2.00       | 13.61   | 16.80             |
| Spec        | 2.00       | 18.84   | 16.80             |
| SpecMag     | 2.00       | 14.22   | 16.80             |
| EmphSpec    | 2.00       | 14.11   | 16.80             |
| EmphSpecdB  | 2.00       | 13.53   | 16.80             |
| MFCC        | 2.00       | 13.63   | 15.03             |
| SpecdB      | 1.50       | 14.81   | 16.80             |
| Spec        | 1.50       | 20.79   | 16.80             |
| SpecMag     | 1.50       | 16.09   | 16.80             |
| EmphSpec    | 1.50       | 16.36   | 16.80             |
| EmphSpecdB  | 1.50       | 15.43   | 16.80             |
| MFCC        | 1.50       | 15.62   | 15.03             |
| SpecdB      | 1.00       | 17.54   | 16.80             |
| Spec        | 1.00       | 22.90   | 16.80             |
| SpecMag     | 1.00       | 19.09   | 16.80             |
| EmphSpec    | 1.00       | 19.03   | 16.80             |
| EmphSpecdB  | 1.00       | 18.61   | 16.80             |
| MFCC        | 1.00       | 18.07   | 15.03             |
| SpecdB      | 0.50       | 24.84   | 16.80             |
| Spec        | 0.50       | 29.41   | 16.80             |
| SpecMag     | 0.50       | 25.76   | 16.80             |
| EmphSpec    | 0.50       | 26.20   | 16.80             |
| EmphSpecdB  | 0.50       | 25.07   | 16.80             |
| MFCC        | 0.50       | 24.88   | 15.03             |
| SpecdB      | 0.25       | 29.92   | 16.80             |
| Spec        | 0.25       | 33.31   | 16.80             |
| SpecMag     | 0.25       | 30.96   | 16.80             |
| EmphSpec    | 0.25       | 31.64   | 16.80             |
| EmphSpecdB  | 0.25       | 30.00   | 16.80             |
| MFCC        | 0.25       | 29.79   | 15.03             |

4.1. EER vs Input Segment Length

In terms of what other embedding-based verification techniques with which to compare our system, i-vectors [14], x-vectors [35] and ResNet50-based [36], as far as we know, have not been evaluated with small input segment lengths and are not publicly available. Thus, a direct comparison cannot be made. Thus, we chose the aforementioned work of [28], where the authors employed a “thin” ResNet with a NetVLAD-based aggregator to calculate embeddings, here referred to VGG. It was chosen given that the model was publicly available, and is directly compatible with the comparison, since it supports input
segments with variable time lengths without requiring to be re-trained. Additionally, it has shown good results with input lengths of 2 seconds and above. Its architecture is shown in Figure 2.

Figure 2: The network architecture presented in [28], referred here as VGG.

The VoxCeleb1 corpus [27] was used for evaluation, and the input pairs were selected in the same manner as described in [28]. To ensure that our evaluation process does not deviate from previously reported results, we re-created the evaluation procedure used in [28] and re-evaluated VGG, and confirmed it reported the same results. Then, both VGG and the BLSTM-based model were evaluated using segments with lengths of 0.25, 0.5, 1, 1.5 and 2 s, the results of which are shown in Figure 3.

Figure 3: EER vs input time length using VoxCeleb1, with VGG and the BLSTM-based model.
It is clear that VGG provides lower EER than our system when using longer input segment lengths (≥ 1 s). However, both systems perform comparably with shorter segments.

It is also of interest to evaluate the consistency of the evaluated systems across different data sets. To this effect, the VoxCeleb2 corpus [33] was used to evaluate them both, using the same number of pairs (37720) of input segments, randomly selected from the “test” subset. These results are shown in Figure 4 along with the results from Figure 3 for comparison (as dashed lines).

As it can be seen, when tested with VoxCeleb2, our system also performs comparably to VGG with segments that are 1 s long. Additionally, while VGG performs differently when tested with VoxCeleb1 and with shorter input segments (≤ 0.5 s), our system performs more consistently when being tested with both datasets across all evaluated segment lengths.

4.2. EER vs Memory Usage

It is also of interest to inspect the amount of memory used by the BLSTM-based model, and see if the loss in performance is a reasonable trade-off for
lighter computational requirements and shorter input segment lengths. This comparison is shown in Figure 5, where for simplicity, the EER reported is the one obtained when using an input length 0.5 s, when being evaluated with the VoxCeleb1 corpus. This input length was chosen because it has been found that in cases of interaction that have a high grade of back-and-forth between the human and the automatic conversational system, shorter utterances (between 0.5 and 1 s) are spoken more frequently by the human [8].

![Figure 5: EER (input length of 0.5 s) vs memory usage with VGG and the BLSTM-based model.](image)

As it can be seen, even though the EER performance differential is less than 3 percentile points, the BLSTM-based model only uses nearly half the memory employed by VGG.

For completeness sake, it is important to mention the work of UtterIdNet [4], which has achieved very low EER with input segments of 0.5 s length, as shown in Table 2. However, as it can also be seen, the amount of memory required to run UtterIdNet is substantial, with it being an order of magnitude greater to the one required by the proposed BLSTM-model. To this effect, we believe that in applications such as service robots [5], internet of things [6], and virtual assistants [7], the memory differential heavily outweighs the EER differential
with shorter segments.

| Input Feat. | Length (s) | EER (%) | Memory Usage (MB) |
|-------------|------------|---------|-------------------|
| SpecdB      | 0.5        | 24.84   | 16.8              |
| VGG         | 0.5        | 22.01   | 31.1              |
| UtterIdNet  | 0.5        | 6.46    | 268               |

Table 2: Comparison between the BLSTM-based model (SpecdB), VGG and UtterIdNet (as reported in [4]) for an input segment length of 0.5 s.

5. Online Classification via a Voting System

To further compare the BLSTM-based model to current state of the art, we propose a complete online speaker identifier, based on a simple voting system. It is important to note that this proposal mainly serves as the basis of comparison between the two systems, and that more sophisticated voting systems may be applicable. However, we believe that it is important to report the results of an online speaker identifier (albeit a naive one) based on generic verification, so as to provide an initial baseline to the speaker identification community.

The voting system is a selection scheme based on verifying the current audio input with each of the audio entries of an external database, each belonging to a known speaker, and storing it. The speaker that has uttered the audio input is then selected from the stored verification results. A diagram of the whole identification process is shown in Figure 6.

![Diagram summarizing the complete online speaker identifier.](image-url)
To select the speaker to whom the audio input belongs to, the following steps are carried out:

1. Let \( r_c \) be the average of the verification results of all the audio entries belonging to the known speaker (or “class”) with index \( c \).
2. Calculate the \( r_c \) of all known speakers \([1, C]\), where \( C \) is the number of known speakers, and store them in \( R \).
3. Apply (2) to select the known speaker:

\[
o = \begin{cases} unknown, & \text{if } \forall r_c < 0 \\ \arg\max(R), & \text{otherwise,} \end{cases}
\]  

(2)

Since the value of a verification result ranges between \([-1, 1]\), the threshold of 0 in Equation (2) is the mid-point of that range and, thus, provides a reasonable threshold to discern if the audio input belongs to a known user or not. If the maximum value of \( R \) does not surpass this threshold, the user that uttered the audio input is deemed unknown. If this is the case, a simple speech/keyboard interaction can be carried out to ask for the speaker’s name, and subsequently add the embedding calculated from the audio input as an entry to the external database for their new class. If the speaker is deemed known, the embedding is added to the external database as an additional entry for their class.

It is then of interest to evaluate this simple online speaker identifier when using the BLSTM-based model as well as VGG as its generic verifier. To this effect, an accuracy heatmap was created for each, where each cell in the heatmap represents a test configuration between a specific number of known speakers and a specific number of audio entries per speaker in the external database. Figure 7 shows both accuracy heatmaps.

As it can be seen, there is very little difference between both heatmaps, and the difference that does show relates to the BLSTM-based model slightly outperforming VGG.
6. Conclusions

There has recently been a shift towards embedding-based generic speaker verification, with which online speaker identification can be carried out without requiring re-training when new speakers appear in the auditory scene. Impressive performances have been achieved by using CNN-based models, but they usually work well with large input segment lengths (\( \geq 2 \text{ s.} \)) and have considerably high computational requirements.

In this work, we proposed the use of a BLSTM-based model to calculate the embedding of the inputs, which provided performances comparable to the state of the art with shorter input segments, while requiring considerably less memory to achieve them.

Further, a complete online speaker identifier is presented, based on a simple voting scheme that uses generic verification to carry out speaker identification without requiring to be re-trained with new speakers. The identifier was evaluated with the BLSTM-based model and the state of the art, and different testing configurations were carried with both, in which different amounts of known speakers were tested with different amounts of entries per known speaker. The accuracy was very similar throughout all of the different testing configurations.
when using a short input segments (0.5 s), while only using half of the memory that the state of the art employs.

For future work, more sophisticated voting systems will be employed to increase the accuracy of the online speaker identification system and stricter rules will be tested for database management to increase robustness while maintaining low response times.

Acknowledgements

This work was supported by CONACYT grant [251319], and PAPIIT grants [IA100129] and [IA104016]. The authors would also like to thank Alejandro Maldonado for his support in code reviewing.

Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The code of the complete system, as well as the trained weights, can be found in https://github.com/julik43/blstm_speaker_id.

References

References

[1] K. Youssef, S. Argentieri, J. Zarader, Binaural speaker recognition for humanoid robots, in: 2010 11th International Conference on Control Automation Robotics Vision, 2010, pp. 2295–2300. doi:10.1109/ICARCV.2010.5707878

[2] A. Nagrani, J. S. Chung, W. Xie, A. Zisserman, Voxceleb: Large-scale speaker verification in the wild, Computer Speech and Language 60 (2020) 101027. doi:https://doi.org/10.1016/j.csl.2019.101027
[3] A. Irum, A. Salman, Speaker verification using deep neural networks: A review, International Journal of Machine Learning and Computing 9 (1).

[4] A. Hajavi, A. Etemad, A Deep Neural Network for Short-Segment Speaker Recognition, in: Proc. Interspeech 2019, 2019, pp. 2878–2882. doi:10.21437/Interspeech.2019-2240

[5] F. Grondin, F. Michaud, Wiss, a speaker identification system for mobile robots, in: 2012 IEEE International Conference on Robotics and Automation, 2012, pp. 1817–1822. doi:10.1109/ICRA.2012.6224729

[6] D. Shin, M. Jun, Home iot device certification through speaker recognition, in: 2015 17th International Conference on Advanced Communication Technology (ICACT), 2015, pp. 600–603. doi:10.1109/ICACT.2015.7224867

[7] V. Tiwari, M. F. Hashmi, A. Keskar, N. Shivaprakash, Virtual home assistant for voice based controlling and scheduling with short speech speaker identification, Multimedia Tools and Applications (2018) 1–26.

[8] C. Yu, M. Scheutz, P. Schermerhorn, Investigating multimodal real-time patterns of joint attention in an hri word learning task, in: 2010 5th ACM/IEEE International Conference on Human-Robot Interaction (HRI), 2010, pp. 309–316. doi:10.1109/HRI.2010.5453181

[9] X. Miao, X. Zhang, M. Sun, C. Zheng, T. Cao, A blstm and wavenet-based voice conversion method with waveform collapse suppression by post-processing, IEEE Access 7 (2019) 54321–54329. doi:10.1109/ACCESS.2019.2912926

[10] Z.-Q. Wang, J. Le Roux, J. R. Hershey, Alternative objective functions for deep clustering, in: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 2018, pp. 686–690.

[11] D. Wang, X. Wang, S. Lv, End-to-end mandarin speech recognition combining cnn and blstm, Symmetry 11 (5). doi:10.3390/sym11050644
[12] J. P. Campbell, Speaker recognition: a tutorial, Proceedings of the IEEE 85 (9) (1997) 1437–1462. doi:10.1109/5.628714

[13] J. S. Chung, A. Nagrani, E. Coto, W. Xie, M. McLaren, D. A. Reynolds, A. Zisserman, Voxsrc 2019: The first voxceleb speaker recognition challenge (2019). arXiv:1912.02522

[14] N. Dehak, P. J. Kenny, R. Dehak, P. Dumouchel, P. Ouellet, Front-end factor analysis for speaker verification, IEEE Transactions on Audio, Speech, and Language Processing 19 (4) (2011) 788–798. doi:10.1109/TASL.2010.2064307

[15] D. Snyder, D. Garcia-Romero, D. Povey, S. Khudanpur, Deep neural network embeddings for text-independent speaker verification, in: Proc. Interspeech 2017, 2017, pp. 999–1003. doi:10.21437/Interspeech.2017-620
URL http://dx.doi.org/10.21437/Interspeech.2017-620

[16] D. Snyder, P. Ghahremani, D. Povey, D. Garcia-Romero, Y. Carmiel, S. Khudanpur, Deep neural network-based speaker embeddings for end-to-end speaker verification, in: 2016 IEEE Spoken Language Technology Workshop (SLT), 2016, pp. 165–170. doi:10.1109/SLT.2016.7846260

[17] E. Variani, X. Lei, E. McDermott, I. L. Moreno, J. Gonzalez-Dominguez, Deep neural networks for small footprint text-dependent speaker verification, in: 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2014, pp. 4052–4056. doi:10.1109/ICASSP.2014.6854363

[18] G. Bhattacharya, J. Alam, P. Kenny, Deep speaker embeddings for short-duration speaker verification, in: Proc. Interspeech 2017, 2017, pp. 1517–1521. doi:10.21437/Interspeech.2017-1575
URL http://dx.doi.org/10.21437/Interspeech.2017-1575

[19] G. Heigold, I. Moreno, S. Bengio, N. Shazeer, End-to-end text-dependent speaker verification, in: 2016 IEEE International Conference on Acoustics,
[20] H. Muckenhirn, M. Magimai.-Doss, S. Marcell, Towards directly modeling raw speech signal for speaker verification using cnns, in: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018, pp. 4884–4888. doi:10.1109/ICASSP.2018.8462165

[21] J. Bromley, I. Guyon, Y. LeCun, E. Säckinger, R. Shah, Signature verification using a "siamese" time delay neural network, in: Advances in neural information processing systems, 1994, pp. 737–744.

[22] P. Baldi, Y. Chauvin, Neural networks for fingerprint recognition, Neural Computation 5 (1993) 402–418. doi:10.1162/neco.1993.5.3.402

[23] S. Chopra, R. Hadsell, Y. LeCun, Learning a similarity metric discriminatively, with application to face verification, in: 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), Vol. 1, 2005, pp. 539–546. doi:10.1109/CVPR.2005.202

[24] C. Zhang, W. Liu, H. Ma, H. Fu, Siamese neural network based gait recognition for human identification, in: 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2016, pp. 2832–2836. doi:10.1109/ICASSP.2016.7472194

[25] K. Daqrouq, Wavelet entropy and neural network for text-independent speaker identification, Engineering Applications of Artificial Intelligence 24 (5) (2011) 796 – 802. doi:https://doi.org/10.1016/j.engappai.2011.01.001

URL http://www.sciencedirect.com/science/article/pii/S095219761100011X

[26] K. Daqrouq, T. A. Tutunji, Speaker identification using vowels features through a combined method of formants, wavelets, and neural network classifiers, Applied Soft Computing 27 (2015) 231 – 239.
[27] A. Nagrani, J. S. Chung, A. Zisserman, Voxceleb: A large-scale speaker identification dataset, in: Proc. Interspeech 2017, 2017, pp. 2616–2620. doi:10.21437/Interspeech.2017-950
URL http://dx.doi.org/10.21437/Interspeech.2017-950

[28] W. Xie, A. Nagrani, J. S. Chung, A. Zisserman, Utterance-level aggregation for speaker recognition in the wild, in: ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019, pp. 5791–5795. doi:10.1109/ICASSP.2019.8683120

[29] A. Mobiny, Text-independent speaker verification using long short-term memory networks, ArXiv abs/1805.00604.

[30] G. Koch, R. Zemel, R. Salakhutdinov, Siamese neural networks for one-shot image recognition, in: IMCL, Deep Learning Workshop, 2015, pp. 1–8.

[31] catedrago, Audio split, https://github.com/catedrago/split_audio_VAD (2018).

[32] R. Vergin, D. O'Shaughnessy, Pre-emphasis and speech recognition, in: Proceedings 1995 Canadian Conference on Electrical and Computer Engineering, Vol. 2, 1995, pp. 1062–1065 vol.2. doi:10.1109/CCECE.1995.526613

[33] J. S. Chung, A. Nagrani, A. Zisserman, Voxceleb2: Deep speaker recognition, in: Proc. Interspeech 2018, 2018, pp. 1086–1090. doi:10.21437/Interspeech.2018-1929
URL http://dx.doi.org/10.21437/Interspeech.2018-1929

[34] D. P. Kingma, J. Ba, Adam: A method for stochastic optimization, arXiv preprint arXiv:1412.6980.
[35] K. Okabe, T. Koshinaka, K. Shinoda, Attentive statistics pooling for deep speaker embedding, Proc. Interspeech 2018 (2018) 2252–2256. URL https://ci.nii.ac.jp/naid/120006705553/en/

[36] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778. doi:10.1109/CVPR.2016.90