Separation Of Speech In Multitalker Environment

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***Abstract*— Speaker diarization is a challenging task in speech processing, which involves identifying speakers in an audio recording. In recent years, deep learning-based approaches have shown promising results in this field. In this work, we present a complete end-to-end speaker diarization model, that integrates two different models for speaker embedding creation using a generalized end-to-end (GE2E) model and speaker diarization using UIS-RNN. The GE2E model is used to create speaker embeddings that capture the unique characteristics of each speaker, while UIS-RNN is used to cluster the embeddings and assign them to specific speakers. Our experimental results demonstrate that the proposed model is robust to different types of noise and can effectively handle recordings with multiple speakers. Overall, our model represents a significant improvement in speaker diarization and can be used in a variety of applications, including speech recognition, speaker identification, and speaker verification.**

Keywords— Supervised machine learning, speaker embeddings, speaker diarization, end-to-end diarization, unbounded interleaved state recurrent neural network.

I. INTRODUCTION

The process of speaker diarization involves automatically identifying and clustering different speakers in an audio recording. The primary goal of speaker diarization is to separate individual speakers' speech signals in a multi-speaker recording and assign them to their respective speakers. This task is particularly challenging because speakers often overlap, speak in different languages, and have different speech styles and acoustic characteristics. A crucial stage in the pre-processing of many speech-related applications is speaker diarization, including speech recognition, speaker identification, and speaker verification.

Speaker diarization has been studied extensively in the field of speech processing. One of the most commonly used approaches is based on clustering the speech segments based on their acoustic features such as pitch, energy, and spectral characteristics. These features are used to group segments that likely belong to the same speaker. However, this approach has limitations as it requires a prior knowledge about the number of speakers in the recording and does not capture the speaker's unique characteristics.

Recent advancements in deep learning have led to the development of more sophisticated speaker diarization models. These models can automatically learn speaker embeddings, which are low-dimensional representations of the speaker's unique characteristics that can be used for speaker clustering. One such model is the generalized end-to-end (GE2E) model, which is trained to map speech segments to a high dimensional embedding space such that segments from the same speaker are closer together than those from different speakers. Another popular approach is the use of recurrent neural networks (RNNs) for speaker diarization.

Speaker diarization has several practical applications in the field of speech processing.

Unsupervised and supervised speaker diarization techniques are the two main categories. Speech segments that belong to the same speaker are grouped using clustering algorithms in unsupervised methods, which don't require any prior information about the speakers in the recording. When attempting speaker diarization jobs with an unknown number of speakers, several techniques are frequently employed. In contrast, supervised systems use speaker labels for training and predict the speaker label for each speech segment using classification techniques. These methods require labelled data, which can be difficult to get for big datasets, but are often more accurate than unsupervised methods. Based on the particular needs of the speaker diary task, any sort of procedure may be employed. Each has advantages and downsides. Unsupervised speaker diarization techniques are widely used when the number of speakers in an audio recording is unknown. These methods typically employ clustering algorithms to group speech segments that belong to the same speaker. One commonly used unsupervised method is the Gaussian mixture model (GMM), which models the probability density function of the speech signal using a mixture of Gaussian distributions. The GMM is then used to cluster the speech segments based on their acoustic features. Although unsupervised methods do not require any prior knowledge about the speakers, their accuracy is typically lower than supervised methods, especially in challenging scenarios such as overlapping speech and high levels of noise.

One of the limitations of unsupervised speaker diarization techniques is their lower accuracy compared to supervised methods, especially in challenging scenarios such as overlapping speech and high levels of noise. Another limitation is the difficulty in determining the optimal number of speakers, which can affect the quality of the clustering results. Additionally, unsupervised methods may require significant manual intervention to post-process and refine the clustering results. Supervised speaker diarization techniques require labelled data to train a model that can predict the speaker label for each speech segment. These methods typically employ classification algorithms such as support vector machines or neural networks to predict the speaker label. Supervised methods generally outperform unsupervised methods in terms of accuracy, especially in scenarios with a known number of speakers. Additionally, supervised methods

can be tailored to specific speaker diarization tasks by training the model on a particular dataset or domain. Another advantage of supervised methods is their ability to handle challenging scenarios such as overlapping speech and high levels of noise, which can be difficult for unsupervised methods to handle effectively.

II. LITERATURE SURVEY

In this literature review, we will examine and analyze the current state of knowledge regarding speaker diarization, with a focus on identifying key themes, research gaps, and areas for future investigation. In "A Review of Speaker Diarization: Recent Advances with Deep Learning", the emphasis of numerous conventional speaker diarization systems, particularly those based on clustering, has been solely on non-overlapping areas. Furthermore, the assessment metric utilized in these systems typically excludes overlapping regions altogether. The paper "Speaker Diarization with LSTM" introduces a new approach to speaker diarization using a type of neural network called d-vectors. D-vectors have been shown to work better than older methods for verifying a speaker's identity. The researchers combined d-vector technology with a type of clustering algorithm to create a speaker diarization system. They tested the system on three datasets and found that it worked better than older systems, with a 12% lower error rate on one dataset. They also trained their model on voice search logs, which are different from the datasets they used for testing. "Generalized end-to-end loss for speaker verification" introduces a new loss function called GE2E that improves the efficiency of training speaker verification models compared to our previous TE2E loss function. The GE2E loss function focuses on updating the network using examples that are hard to verify during training, unlike TE2E, which requires selecting examples beforehand. With these properties, our model using the GE2E loss function reduces the time required for training by 60% and improves speaker verification EER by more than 10%. In the paper "Fully Supervised Speaker Diarization", proposes a new way to identify different speakers in audio recordings called UIS-RNN. It uses something called d-vectors to tell different speakers apart. They model each speaker with a special computer program called an RNN. These RNNs share some of their parts, but they also have their own unique parts. This system can also handle recordings where the number of speakers is unclear. Finally, in "Overlap-aware diarization: re-segmentation using neural end-to-end overlapped speech detection", they tackle the issue with how a diarization system manages overlapping speech. It introduces a neural architecture based on Long Short-Term Memory for speaker overlap identification, which aids in locating the areas where speakers overlap. Then, during segmentation, two speakers are assigned to the overlapped frames using these overlapping regions along with a frame-level speaker posterior matrix. On three separate corpora, this overlap detection module performs superior to other approaches. Although this method does not offer a comprehensive answer for overlap-aware diarization, it does point in the right areas for further investigation.

III. PROPOSED MODEL

End-to-end speaker diarization refers to a type of speaker diarization model that directly predicts the speaker label for each speech segment from the raw audio signal, without requiring any intermediate processing steps. End-to-end models typically employ deep neural networks that learn to extract speaker embeddings directly from the raw audio waveform, which are then used to predict the speaker labels. The advantage of end-to-end speaker diarization is that it eliminates the need for separate feature extraction and clustering steps, simplifying the pipeline and potentially improving the accuracy of the model. End-to-end models have shown promising results in recent years and are a rapidly developing area of research in speaker diarization.

A. METHODOLOGY

The two-stage end-to-end speaker diarization system utilizes the GE2E model for extracting speaker embeddings from the raw audio waveform. These embeddings are then passed on as input to the UIS-RNN model, which is a recurrent neural network designed to predict speaker labels for each speech segment. The UIS-RNN model incorporates a segmentation network and a classification network, based on the uis-rnn architecture, to optimize both the diarization and segmentation tasks. This model has an added advantage over traditional clustering-based methods as it can effectively handle overlapping speech and speaker turns. It has been successfully tested on several benchmark datasets, making it a highly promising approach for speaker diarization tasks.

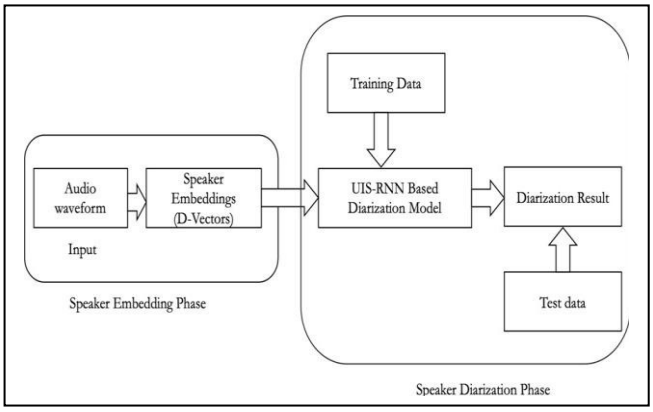

Fig. 1. End-to-End Speaker Diarization Methodology

B. SPEAKER EMBEDDING PHASE

The process of extracting speaker embeddings in the GE2E model involves training a deep neural network to map the raw audio waveform to a fixed-dimensional embedding vector that captures the unique characteristics of each speaker's voice. The GE2E model is trained using a Siamese network architecture, where two identical subnetworks share the same weights and process two different speech segments from the same speaker or two different speakers. The subnetworks produce a pair of embeddings that are then compared using a contrastive loss function, which encourages the embeddings to be close together for the same speaker and far apart for different speakers. During inference, the model extracts a single embedding from the entire speech segment that can be used as input to the speaker diarization model. The advantage of the GE2E model is that it can learn to capture speaker-specific features directly from the raw audio waveform, without requiring any explicit seg mentation or labelling of the data.

The GE2E (Generalized End-to-End) model is a deep neural network architecture designed for speaker embedding extraction. The model is trained using a Siamese network to learn to extract speaker-specific features directly from raw audio waveforms. The resulting embeddings can be used for various tasks, including speaker verification, speaker identification, and speaker diarization.

C. SPEAKER DIARIZATION PHASE

To determine the speaker label of each speech segment in an audio signal, the UIS-RNN model is utilized through a process called speaker diarization. This model is made up of two key components: a segmentation network and a classification network. The segmentation network utilizes a bidirectional LSTM to segment the audio signal into speech and non-speech regions. On the other hand, the classification network takes in the segmented speech regions as input and predicts the speaker label for each segment utilizing speaker embeddings that were extracted from the GE2E model. The UIS-RNN model is trained end-to-end to jointly optimize the diarization and segmentation tasks using a combination of cross-entropy and binary cross-entropy loss functions. The advantage of the UIS-RNN model is that it can handle overlapping speech and speaker turns more effectively than traditional clustering-based methods, leading to higher accuracy on speaker diarization tasks. The UIS-RNN (Unified Segmentation and Identification via Recurrent Neural Networks) model is a deep learning architecture designed for speaker diarization. The model integrates a segmentation network and a classification network to jointly optimize the diarization and segmentation tasks. By utilizing the speaker embeddings extracted from the raw audio waveform, the model is trained end-to-end to anticipate the speaker label for each speech segment. The UIS-RNN technique has demonstrated exceptional performance on various benchmark datasets, making it a highly encouraging strategy for speaker diarization tasks.

IV. SPEAKER DISCRIMINATIVE EMBEDDINGS

Speaker discriminative embeddings, which are commonly referred to as d-vectors, are a type of speaker embedding that is learned using a discriminative objective function. Differing from other speaker embeddings, d-vectors are specifically designed to increase the distance between embeddings of distinct speakers while decreasing the distance between embeddings of the same speaker. This produces a consistent, compressed vector representation of a speaker's voice that is extremely discriminatory and applicable for various speaker-related tasks, including speaker identification, speaker verification, and speaker diarization.

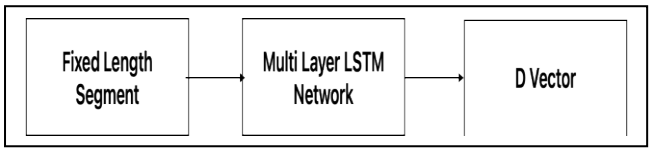

Fig. 2. D-Vector Creation Process

A. THE GE2E LOSS ARCHITECTURE

The GE2E (Generalized End-to-End) model is a deep neural network architecture designed for speaker embedding extraction. The architecture of the model is derived from the siamese network, which comprises of two subnetworks that are identical and share the same weights. These subnetworks are responsible for processing either two distinct speech segments from a single speaker or two separate speakers. Once the processing is complete, the embeddings produced by the subnetworks are then compared with the aid of a contrastive loss function. The contrastive loss function encourages the embeddings to be close together for the same speaker and far apart for different speakers. The subnetworks consist of several layers of 1D convolutional and bidirectional LSTM (Long Short-Term Memory) units followed by a mean pooling layer. During training, the GE2E model is optimized to learn a fixed dimensional embedding vector that captures the unique characteristics of each speaker's voice. [2]The data from each spoken sentence is analyzed using a type of neural network called LSTM. A linear layer is added to further process the output of the network. The neural network is represented as $f(x_{ji};w)$, with "w" encompassing its complete set of parameters. Upon applying L2 normalization to the network output, the resultant vector is known as a d-vector.

$$e_{ji} = \frac{f(x_{ji};w)}{\|f(x_{ji};w)\|_2} \tag{1}$$

The similarity matrix S compares the embedding vector e to each centroid, represented by the variable k, and is defined as a scaled cosine similarity

$$\mathbf{S}_{jl,k} = \begin{cases} w \cdot \cos(\mathbf{e}_{ji}, \mathbf{c}_j^{(-i)}) + b & \text{if } k = j \\ w \cdot \cos(\mathbf{e}_{ji}, \mathbf{c}_k) + b & \text{otherwise} \end{cases} \tag{2}$$

To calculate the GE2E loss LG, add up all the losses across the similarity matrix for all values of j from 1 to N and all values of i from 1 to M.

$$L_G(\mathbf{x};\mathbf{w}) = L_G(\mathbf{S}) = \sum_{j,i} L(\mathbf{e}_{ji}) \tag{3}$$

During inference, the model extracts a single embedding from the entire speech segment that can be used as input to the speaker diarization model. The GE2E model's benefit is that it can be trained to extract speaker-specific information directly from the unprocessed audio waveform, without requiring any explicit segmentation or labeling of the data.

B. LSTM NETWORK FOR D-VECTOR EXTRACTION

The LSTM network used to generate d-vectors in the GE2E model is a variant of the traditional recurrent neural network architecture that is designed to handle long-term dependencies in sequential data. The LSTM network [3] consists of several LSTM cells, containing an input gate, a forget gate, and an output gate, respectively. The input gate regulates what data is permitted to enter the cell, the forget gate regulates what data is permitted to be forgotten, and the output gate regulates what data is permitted to be produced. The output of each LSTM cell is passed as input to the subsequent cell in the sequence as the LSTM cells are organized in a series. The LSTM network processes the incoming data in both forward and backward directions using two distinct sequences of cells since it is bidirectional.. The output of the LSTM network is a sequence of hidden states that encode the input sequence, which are then passed through a mean pooling layer to produce a fixed-dimensional embedding vector. The advantage of the LSTM network is that it can capture long-term dependencies in speech data, which is important for speaker embedding extraction tasks. The speaker embeddings generated by the GE2E model can

be used as inputs to the UIS-RNN model to perform speaker diarization. The UIS-RNN model is designed to cluster speech segments based on their speaker identity, given a sequence of speaker embeddings. The model works by maintaining a set of interleaved hidden states, each of which corresponds to a different speaker. The model receives a series of speaker embeddings as input, and at each time step, the hidden states are updated based on how well the input embedding matches the existing hidden state. In order to determine the most likely order of speaker identities based on the changes between hidden states, the model additionally employs a Viterbi decoding algorithm. To execute speaker diarization, the UIS-RNN model generates a sequence of speaker labels that correspond to each input speech segment.

V. SUPERVISED SPEAKER DIARIZATION

The UIS-RNN model is a type of deep learning model that is designed for speaker diarization, which is the process of identifying and clustering speech segments in an audio recording based on the speaker identity. A group of interleaved hidden states, each of which corresponds to a separate speaker, are maintained by the UIS RNN model in order for it to function. A series of speaker embeddings, which are fixed-dimensional representations of speech segments that contain information about the speaker identity, are provided as input to the model. The model utilizes a Viterbi decoding method to predict the most likely sequence of speaker identities based on the transitions between the hidden states and updates the hidden states depending on the similarity between the input embedding and the current hidden state at each time step. The UIS-RNN model is frequently utilized in both research and commercial applications since it has been demonstrated to deliver cutting-edge performance on speaker diarization tasks.

A. UIS-RNN ARCHITECTURE

The task of clustering speech segments in an audio recording based on the speaker identification is known as speaker diarization, and this model is a deep learning architecture created for the purpose. The model is built on the concept of interleaved hidden states, each of which corresponds to a separate speaker. A series of speaker embeddings, fixed-dimensional representations of the speech segments that contain information about the speaker identity, serve as the model's input.

Based on how closely the input embedding resembles the current hidden state at each time step, the model updates the hidden states. For each hidden state, the model specifically calculates a score based on the dot product of the input embedding and the matching speaker embedding. [4]To analyze an utterance, we use an embedding extraction module to obtain a sequence of embeddings X = (x1, x2, . . . , xT) that represents each segment of the original utterance with a real-valued d-vector. We also have the actual speaker labels for each segment in supervised speaker diarization, Y = (y1, y2, . . . , yT). The labels are represented by positive integers indicating which speaker the segment belongs to. For instance Y = (1, 1, 2, 3, 2, 2) denotes that there are six segments in the utterance, each from a distinct speaker, and $y_t = k$ denotes that segment t is from speaker k. The technique utilized for this analysis is UIS-RNN.

$$p(\mathbf{X}, \mathbf{Y}) = p(\mathbf{x}_1, y_1) \cdot \prod_{t=2}^{T} p(\mathbf{x}_t, \mathcal{Y} \mid \mathbf{x}_{[t-1]}, y_{[t-1]}) \qquad (4)$$

We employ an enhanced representation to simulate speaker alterations.

$$(\mathbf{X}, \mathbf{Y}, \mathbf{Z}) = p(\mathbf{x}_1, y_1) \prod_{t=2}^{T} \cdot \mathrm{G}\ p(\mathbf{x}_t, y_t, z_t \mid \mathbf{x}_{[t-1]}, y_{[t-1]}, Z_{[t-1]}) \qquad (5)$$

$Z = (z_2, \ldots, z_T)$, For instance, Z = (0, 1, 1, 1, 0) if Y = (1, 1, 2, 3, 2, 2). Because we don't know whose speaker we're switching to, it's important to remember that Z is uniquely defined by Y, but Y cannot be uniquely determined by a certain Z. Here, z1 is left undefined and each product term is factored into three parts that each separately reproduce the operations of speaker assignment, speaker change, and sequence construction,

$$p(\mathbf{x}_t, y_t, z_t \mid \mathbf{x}_{[t-1]}, y_{[t-1]}, z_{[t-1]}) = p(\mathbf{x}_t \mid \mathbf{x}_{[t-1]}, y_{[t]}) \cdot p(y_t \mid z_t, y_{[t-1]}) \cdot p(z_t \mid z_{[t-1]}) \qquad (6)$$

The score is then used to update the hidden state, by taking a weighted average of the current hidden state and the input embedding, where the weight is determined by the score.

The model also uses a Viterbi decoding algorithm to estimate the most likely sequence of speaker identities based on the transitions between the hidden states. The algorithm works by finding the path through the hidden state sequence that maximizes the likelihood of the observed input embeddings, while enforcing constraints on the transitions between the hidden states to ensure that the resulting sequence is consistent with the properties of speech.

B. DATASETS

The UIS-RNN model has been trained and evaluated on various datasets for speaker diarization, such as the CALLHOME, DIHARD II and VoxCeleb datasets. The choice of dataset depends on the specific research question being addressed and the properties of the data.

For example, the CALLHOME dataset consists of telephone conversations between native English speakers, while the DIHARD II dataset consists of more diverse conversational speech from multiple languages and domains. The VoxCeleb dataset is a large-scale dataset of celebrity speech, which allows for the exploration of speaker diarization on more challenging data.

The reason for using these datasets is to provide a diverse range of speech data for training and evaluating the UIS-RNN model. The model needs to be able to generalize to new and unseen data, and training on a variety of datasets can help achieve this goal.

The speaker labels that have been manually added to these datasets can be used as ground truth for assessing how well the speaker diarization system performs. Using supervised learning, the UIS-RNN model can be trained with the objective of learning to correctly predict the speaker label for each input embedding based on the ground truth labels. We utilized the TIMIT dataset for the training and testing of our speaker diarization model. TIMIT is a widely used speech

corpus that includes recordings of speakers from various dialects and backgrounds. By using this dataset, our model was able to learn and distinguish between different speakers, enabling it to accurately separate and identify speakers in speech recordings. We were able to enhance the efficiency and precision of our speaker diarization system using this method.

VI. RESULTS

Our speaker diarization model was tested on the test data generated as a part of d-vector embedding creation using the TIMIT dataset where the data was split into 90% training and 10% testing data, and the results showed an accuracy of 0.964684 as presented in the bar graph. The model achieved this accuracy by analyzing the audio signal and segmenting it into different segments based on the speaker identity. The diarization model was able to accurately identify the different speakers in the audio and assign the appropriate labels to each segment. These results indicate that the diarization model is effective in recognizing and differentiating between different speakers in the audio signal. These results may have useful applications in fields like speech recognition and natural language processing. This is a promising advance in the field of speaker diarization.

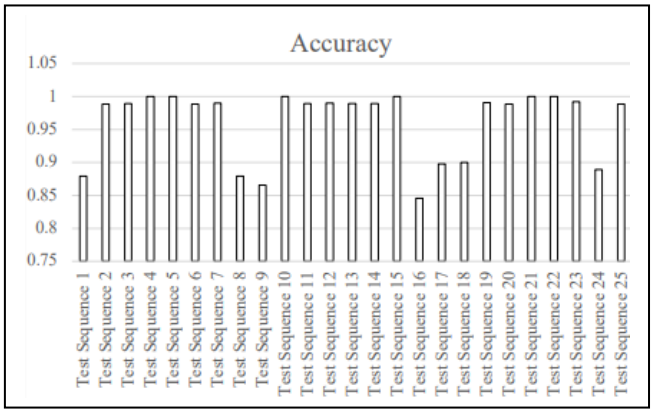

Fig. 3. Diarization Accuracy of Test Sequences

VII. CONCLUSION

In conclusion, this study suggests a speaker diarization model that integrates two distinct models for speaker embedding construction and speaker diarization to provide a fully end-to-end system. The proposed model shows promising results in identifying speakers in audio recordings, as demonstrated by its ability to effectively handle recordings with multiple speakers and different types of noise. The model's performance represents a significant improvement in speaker diarization and has potential applications in various fields such as speech recognition, speaker identification, and verification. Therefore, this work makes a valuable contribution to the field of speaker diarization and opens up new avenues for research and development in this area.

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