Using Active Speaker Faces for Diarization in TV shows

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Abstract

Speaker diarization is one of the critical components of computational media intelligence as it enables a character-level analysis of story portrayals and media content understanding. Automated audio-based speaker diarization of entertainment media poses challenges due to the diverse acoustic conditions present in media content, be it background music, overlapping speakers, or sound effects. At the same time, speaking faces in the visual modality can provide complementary information and not prone to the errors seen in the audio modality. In this paper, we address the problem of speaker diarization in TV shows using the active speaker faces. We perform face clustering on the active speaker faces and show superior speaker diarization performance compared to the state-of-the-art audio-based diarization methods. We additionally report a systematic analysis of the impact of active speaker face detection quality on the diarization performance. We also observe that a moderately well-performing active speaker system could outperform the audio-based diarization systems.

Index Terms: speaker diarization, face clustering, audio-visual, active speaker detection

1. Introduction

We use digital media in our daily lives to create, consume and experience stories in various forms: books, movies, TV shows, broadcast TV, etc. It impacts how we perceive, form, and communicate opinions and ideas. Recently there have been multiple efforts in the emerging field of computational media intelligence (CMI) to characterize and understand the impact of media portrayals on society. CMI focuses on developing computational tools to analyze media content to obtain a holistic understanding of the stories being told and their impact on the experiences and behavior of individuals [1].

One of the central components of CMI is understanding the portrayals of characters in media along with their representation among the dimensions of character attributes such as age, gender, race, and appearance. It also aims to analyze the interactions between the characters. To address these aspects of CMI, knowing who speaks when in the media session is crucial. In this work, we address the broad problem of speaker diarization in dialogues of TV shows: determining the active speaker leveraging visual information.

Speaker diarization refers to assigning all the speech segments in an audio session to their respective speakers, without using prior knowledge of the involved speakers, be their real identity or the number of participating speakers. There has been a plethora of work in diarization using the audio modality [2]. The conventional speaker diarization system involves voice activity detection and speaker turn detection to get speaker homogeneous speech segments, followed by clustering these segments in the speaker embedding space. Such solely audio-driven speaker diarization systems are prone to errors when applied to media content domain, consisting of narrative films, due to diverse and heterogeneous acoustic conditions and context: speech in background music, sound effects, overlapping speech, and wide variation in characters and their portrayals.

Unlike read-speech as in broadcast news, in media such as TV shows and movies, character interaction is more spontaneous, thus leading to more frequent turn change and smaller speech segments, making audio-based diarization systems further prone to errors. However, at the same time, the visual modality contains substantial clues for speaker identification, especially the dialogue deliveries in entertainment media. In this work, we investigate the applicability of active speaker face clustering for supporting speaker diarization in media content; our exemplary use case is TV shows.

We use a self-supervised framework followed by an audio-visual profile matching strategy, introduced in our previous works [3,5], to obtain active speaker faces in the videos from TV episodes (Friends show). We take advantage of established face verification [6], and speaker recognition [7] features to represent the active speaker faces and the corresponding speech segment. To obtain diarization results, we cluster the face features using DBSCAN [8] providing no information about the number of participating characters. In this work, we present experimental results on specific episodes of Friends, a part of Video Person Clustering Dataset (VPCD) [9]. We are interested in exploring the use of active speaker faces for diarization and in comparing them against the speaker embeddings derived from speech segments.

In this paper, our contributions are twofold: i) We show that active speaker face representations outperform state-of-the-art audio-based embeddings for the task of speaker diarization in TV shows. Face representations are coupled with a simple DBSCAN-based clustering, thus avoiding sophisticated refinement procedures explicitly designed in recently proposed speaker diarization clustering schemes [10]. ii) We report a systematic analysis on the impact of the quality of active speaker detection systems on speaker diarization performance. We show that even a moderately well-performing active speaker detection system (~60% accurate) can exceed the performance of audio-only systems.

2. Related Work

2.1. Active speaker detection

Earlier works on active speaker localization in visual frames focused on detecting activity in the lip regions of the appearing faces in the frames [11]. More recently, [12] released a large-scale dataset consisting of active speaker annotations for parts movies, which was followed by the introduction of a wide variety of fully-supervised methods for active speaker localization [13,15]. In parallel, there have been approaches posing the active speaker detection as a sound source localization task and proposed self-supervised systems trained for audio-visual synchrony in videos [16,18]. In our previous approaches, we
proposed a weakly supervised cross-modal system trained for the presence of speech in videos and used the class activation maps for active speaker localization [3]. We further proposed audio-visual character profile matching to improve the performance of active speaker localization [4].

2.2. Face and speaker recognition

**Face recognition:** Approaches in face recognition can be divided into 2 categories: i) Face verification task [19, 20] and ii) Face identification task [21–23]. A common approach to face recognition is metric learning [23], where a deep neural network [24] is trained for the task of face verification or identification [22, 25]. **Speaker Recognition:** Speaker recognition is a well-explored field with earlier approaches focused on learning speaker embeddings using variants of the softmax classification loss [26–30]. Recent efforts developing metric learning for speaker recognition [10, 27, 31].

2.3. Speaker diarization

Speaker diarization in audio modality has been extensively addressed, and an active area of research [2]. In general, diarization frameworks consist of multistage paradigms involving voice activity detection, speaker embedding extraction, and then clustering the speech regions in embedding space [10, 32, 33]. Recently there has been an increase in end-to-end neural speaker diarization systems [34]. Specific to diarization in TV shows, previous methods have used visual patterns among the shots [35], face clustering, and talking face detection [36, 37] to complement audio-driven speaker embeddings. Large-scale audio-visual diarization datasets around TV shows [37] and feature films [38] have also emerged, involving a semi-automatic annotation process.

3. Methodology

3.1. Problem formulation

Given a video segment, we acquire the set of speaker homogeneous speech segments \( \{s_n\} \) \( \forall n \in [1, N] \) and for each \( s_n \), the corresponding temporally overlapping set of face-tracks, \( \{f_n^c\} \), \( \forall k \in [1, K] \). We define active speaker detection (ASD) as the task of finding a source face-track (if any) for all speech segments \( s_n \) from their respective sets of overlapping face-tracks, \( \{f_n^c\} \). We formulate speaker diarization (SD) as a clustering task to cluster all the speech segments \( s_n \) into \( C \) clusters, \( \{s^c\} \), \( \forall n \in [1, L]\forall c \in [1, C] \), where \( L \) being the number of speech segments in the cluster \( c \) and \( C \) is the number of characters in the video, which in general is not known. We use oracle speaker homogeneous speech segments for all our experiments.

3.2. Active speaker detection (ASD)

We use a two-stage method for ASD. We first derive active speaker information from the visual cues using a weakly supervised cross-modal framework [3]. We next construct audio-visual character profiles and impose a constraint that for a given active speaker instance \( \{s_n, f_k\} \), source face-track \( f_k \) for the speech segment \( s_n \) belongs to the same character [4].

![Figure 1: Active speaker localization using HiCA architecture and GradCAMs](image)

3.2.1. Visual score

In our previous work, we proposed the Hierarchical Context Aware (HiCA) architecture [3], trained for the task of the presence of speech in a video segment, and showed that the system could localize active speakers in video frames. We used class activation maps (CAMs) to localize the salient regions. Formally, for a video segment \( v_i \), we compute a spatio-temporal (3D) feature map \( F^{m} \) at the last layer of the HiCA network, with \( m \) filters, and the softmax prediction score for the presence of speech, \( y_i \). We then compute the CAM, \( M \) following equation 1 with \( Z \) being the averaging factor. Overview of the system is shown in Figure 1.

\[
\alpha_m = \frac{1}{Z} \sum \Sigma_j \sum_k \frac{\partial y_i}{\partial F^{m}_{jk}} \quad M = ReLU(\sum_m \alpha_m F^{m}) \quad (1)
\]

For a face-track, \( f_k \), temporally overlapping with speech segment, \( s_n \), we compute a visual active speaker score, \( VAS_n \), by ROI pooling the relevant CAMs. We ROI pool the CAMs for each frame, \( t \), in the face-track that overlaps with \( s_n \) in time and compute an aggregate mean over the frames, with \( M_t \) denoting the CAMs for frame \( t \) and \( \{(x_1^t, y_1^t), (x_2^t, y_2^t)\} \) denotes the face bounding box in frame \( t \).

\[
VAS_n = \frac{1}{Z} \sum \Sigma_{x,y} M_t[x_1^t : y_1^t, x_2^t : y_2^t] \quad (2)
\]

3.2.2. Iterative profile matching

In [4] we introduced a strategy constructing audio-visual character profiles to complement the visual-only active speaker detection, which takes advantage of the fact that for a potential active speaker instance \( \{s_n, f_k\} \) if \( s_n \) is a speech of one character \( f_k \) should be the face of the same character. We initiate with a set of high confidence instances (HCI) of face-speech associations and cluster them to construct audio-visual character profiles \( \{P_c, S_c\} \). \( P_c \equiv \{f_k^c\} \) denotes the face instances clustered into character \( c \) (the real identity and number of characters are unknown), and \( S_c \equiv \{s_k^c\} \) denotes the corresponding speech instances for cluster \( c \).

Using the constructed audio-visual character profiles, we compute a profile matching score (PMS) [4] for all other instances as \( P(s_n \rightarrow f_k) \), signifying the confidence of speech segment \( s_n \) and face-track \( f_k \) belonging to the same character profile. We update the set of HCI with the high scored active speaker instances (computed using a combination of VAS and PMS) and repeat the process until no more instances scored high enough, to be added to HCI. At inference time we score any potential active speaker instance \( \{s_n, f_k\} \) as \( VAS_n + PMS_{n,k} \).
3.3. Speaker diarization

The diarization objective is to cluster all instances of speech segments \( s \) in the video such that speech segments coming from one character are grouped. Subsequent to active speaker detection, we have pairs of speech and associated face, \( \{s_n, f_n\} \) along with speech instances \( s_0 \) which have speakers in the background; thus, no face associated. For audio-based diarization baseline, we use all the speech instances \( s_n \cup s_0 \) and cluster them using spectral clustering, post applying a diarization specific refinement sequence and estimating the number of speakers as suggested in [10].

For vision-based clustering, we first filter the obtained set of speech-face associations \( \{s_n, f_n\} \) based on the confidence of the association to remove the noisy instances.

\[
A \equiv \{s_n, f_n\} : \text{VAS}_n + \text{PMS}_n > \tau \quad (3)
\]

We employ a density based clustering algorithm DBSCAN [8], which does not require knowledge of the number of clusters, to cluster all the face-track instances \( f_n \in A \) to obtain \( F_c \equiv \{f_c\} \quad c \in [1, C] \), where \( C \) is the number of clusters. DBSCAN also provides a list of points (no face clusters and marked as noisy samples). Next we form clusters among speech segments \( s_n \in \mathcal{A} \), using the available associations \( \{s_n, f_n\} \):

\[
S_c \equiv \{s_n^c\} : \exists \{s_n^c, f_n^c\} \in A \quad (4)
\]

In order to assign cluster labels to the remaining speech segments (no face segments, noisy speech-face association, marked noisy by DBSCAN), we compute their cosine distance in speaker embeddings space from all the clustered points. We assign a cluster label to each instance \( s_n \), the one that shows the least average distance, as shown in equation [5] where \{ \} represents dot product and \( ||.|| \) represents l2 norm.

\[
\arg \min_{S_c} \frac{1}{|S_c|} \sum_{n} \frac{s_n^c \cdot s_n}{||s_n|| \cdot ||s_n^c||} \quad (5)
\]

4. Experiments

We use a subset of VPCD [9], consisting of 7 episodes from season 3 of the Friends TV show, for evaluation purposes. VPCD provides all the face tracks appearing in the video frames and the character identities, and it also provides the speech segments for each character. It additionally consists of extracted face-embeddings for all the annotated faces and speaker embeddings for all the speech segments. We use the speaker homogeneous voices segments directly from the VPCD and use the provided face and speaker embeddings for our setup.

4.1. Active speaker detection performance

The employed active speaker detection system predicts a corresponding face to each ground truth speech segment. We compute the accuracy of this system as the ratio of the duration of the correctly predicted faces to the total duration of the available speech segments. For a CAMs-only system, for a speech segment we assign the face-track with a maximum VAS score, among all the temporally overlapping face-tracks, as an active speaker. When combined with the iterative profile matching strategy, we use VAS + PMS score as the criterion. In Table 1, we compare the performance under those two scenarios and show that the profile matching strategy consistently improved the ASD performance for all the videos.

### Table 1: Active speaker detection performance improvement with iterative profile matching strategy.

| Video/Name / Approach | 100% face-tracks | 75% face-tracks | 50% face-tracks | 25% face-tracks | 100% speech segments |
|------------------------|------------------|----------------|----------------|----------------|---------------------|
| Friends s03e17          | 0.69             | 0.76           | 0.71           | 0.70           | 0.78                |
| Friends s03e01          | 0.99             | 0.99           | 0.99           | 0.99           | 1.00                |
| Friends s03e02          | 0.95             | 0.95           | 0.95           | 0.95           | 1.00                |
| Friends s03e03          | 0.76             | 0.81           | 0.81           | 0.81           | 0.90                |
| Friends s03e04          | 0.77             | 0.81           | 0.81           | 0.81           | 0.90                |
| Friends s03e05          | 0.96             | 0.93           | 0.93           | 0.93           | 1.00                |
| Friends s03e06          | 0.77             | 0.84           | 0.84           | 0.84           | 0.91                |

4.2. Speaker diarization performance

As mentioned in section 3.3 before performing the face clustering for speaker diarization, we filter the obtained speech-face associations based on the confidence of the active speaker detection system. We present speaker diarization performance for four such filtered sets, containing top 25%, 50%, and 75% of all the instances, ranked based on ASD score (VAS + PMS) and one set containing all the samples (100%). We compare the performance against the audio-based speaker diarization [10]. We report the diarization error rate (DER) as the metric to compare the SD performance, tabulated in Table 2.

We observe that the face-clustering-based diarization outperforms the audio-based framework for all the videos, except when we use just 25% of samples for clustering. The relatively lower performance, in this case, can be attributed to the fact that 25% of samples may not have enough information for all the characters. Most of the videos perform relatively worse while using 100% of the samples than in the case with a lower number of high confidence points. This suggests that filtering of ASD results is a crucial step to remove noisy classifications before clustering them.

To further understand the effects and dynamics of filtering the ASD results, in Figure 2, we show the distance matrices for the selected speech-face associations (for episode 1, chosen arbitrarily), post-filtering, in the set \( A \) (as described in section 3.3) for different setups. We compute the distances in the face domain, using the cosine distances between the face-track embeddings. In Figure 2, we show the ideal case scenario, with perfect ASD output (obtained using the ground truth). For visualization purposes, we grouped the instances for each character (using ground truth identities for speech segments) and used the same grouping for rest of the cases for easier comparison. In Figure 2, we show the distance matrix for all the speech-face associations obtained from the ASD system. The incorrect predictions are evident in the form of visible noise in the distance matrix compared against the ideal case scenario in Figure 2.

In Figure 2, d,e we show the distance matrices of the filtered sets and observe that amount of noise decreases and the cluster patterns become more apparent. This results in improved SD performance with the filtered set, as shown in Table 2, for the majority of videos. Although in Figure 2, showing the dis-
Figure 2: Distance matrices for the speech-face associations, using cosine distance among face-track embeddings, for different sets of speech-face instances. Selecting all (b), top 75%(c), 50%(d) and 25%(e) samples in order of ASD scores.

Figure 3: Distance matrices for simulated ASD output. a) and c): Simulated output with all samples. b) and d): output with just the correct samples.

Table 3: Variation in speaker diarization performance (using face clustering) with the quality of active speaker detection.

| Video name / simulated accuracy | 100% | 90% | 80% | 70% | 60% | 50% |
|--------------------------------|------|-----|-----|-----|-----|-----|
| s03e17 (all samples)           | 0.06 | 0.13| 0.26| 0.43| 0.60| 0.71|
| s03e17 (correct samples)       | 0.06 | 0.06| 0.07| 0.08| 0.11| 0.16|
| s03e01 (all samples)           | 0.14 | 0.21| 0.33| 0.46| 0.61| 0.72|
| s03e01 (correct samples)       | 0.14 | 0.13| 0.15| 0.12| 0.15| 0.26|
| s03e02 (all samples)           | 0.16 | 0.23| 0.33| 0.46| 0.64| 0.72|
| s03e02 (correct samples)       | 0.16 | 0.15| 0.16| 0.15| 0.12| 0.17|

5. Conclusion

This work compared the use of active speaker faces for speaker diarization in media content against conventional audio-only methods. We used an off-the-shelf active speaker face detection system and performed DBSCAN clustering, not requiring information about the number of characters. We demonstrated that this system outperforms the state-of-the-art speaker embeddings based diarization system. We further performed a detailed analysis of the impact of active speaker detection quality on speaker diarization performance. We observed that even moderately performing (60% accurate) active speaker systems can have sufficient information to outperform speaker embeddings based clustering for speaker diarization. Future work will develop methods to effectively combine face and speech information from talking characters for diarization. Another critical step is further improving the active speaker detection systems since face clustering showed high potential for speaker diarization.
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