Cross-modal Speaker Verification and Recognition: A Multilingual Perspective

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Abstract. Recent years have seen a surge in finding association between faces and voices within a cross-modal biometric application along with speaker recognition. Inspired from this, we introduce a challenging task in establishing association between faces and voices across multiple languages spoken by the same set of persons. The aim of this paper is to answer two closely related questions: “Is face-voice association language independent?” and “Can a speaker be recognised irrespective of the spoken language?”. These two questions are very important to understand effectiveness and to boost development of multilingual biometric systems. To answer them, we collected a Multilingual Audio-Visual dataset, containing human speech clips of 154 identities with 3 language annotations extracted from various videos uploaded online. Extensive experiments on the three splits of the proposed dataset have been performed to investigate and answer these novel research questions that clearly point out the relevance of the multilingual problem.

Keywords: Multilingual Biometric Systems; Face and Voice Association; Cross-modal Verification; Multilingual Speaker Recognition

1 Introduction

Half of the world population is bilingual with people often switching between their first and second language while communicating[5]. Therefore it is essential to investigate the effect of multiple languages on computer vision and machine learning tasks. As introduced in Figure[1] this paper probes two closely related and relevant questions, which deal with the recent introduction of cross-modal biometric matching tasks in the wild:

[5] www.washingtonpost.com/local/education/half-the-world-is-bilingual-whats-our-problem/2019/04/24/129ec1c6-8f3f-11e9-a4b5-b39b90e0a879_story
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Multimodal data may provide enriched understanding to improve verification performance. Joaquin can wear make-up that makes visual identification challenging but voice can still bring enough cues to verify identity. In this work, we are interested to understand the effect of multilingual input when processed by audio-visual verification model (Q1) or just using the audio input (Q2). Joaquin is a perfect English-Spanish bilingual, would the system still be able to verify Joaquin when speaking Spanish even if the system was trained with English audio only?

Q1. Is face-voice association language independent?
Q2. Can a speaker be recognised irrespective of the spoken language?

Regarding the first question, a strong correlation has been recently found between face and voice of a person which has attracted significant research interest [20,26,32,33,34,46]. Though previous works have established a strong association between faces and voices, however none of these approaches investigate the effect of multiple languages on this task. In addition, existing dataset containing audio-visual information, VoxCeleb [1,22,31], FVCeleb [20], FVMatching [26] do not provide language level annotation. Therefore, we cannot deploy these dataset to analyse the effect of multiple languages on association between faces and voices.

Thus, in order to answer both questions, we create a new Multilingual Audio-Visual MAV-Celeb dataset comprising of video and audio recordings with a large number of celebrities speaking more than one language in the wild. The proposed dataset paves the way to analyze the impact of multiple languages on association between faces and voices. Then, we propose a cross-modal verification approach to answer Q1 by analyzing the effect of multiple languages on face-
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voice association. In addition, the audio part of the dataset supplies samples of 3 languages with annotations which serves as a foundation to answer Q2.

To summarise, the paper main contributions are listed as follow:

- We first propose a cross-modal verification approach to analyze the effect of multiple languages on face-voice association;
- Likewise, we perform an analysis that highlights the very same problem of multilingualism for speaker recognition;
- We propose the MAV-Celeb dataset, containing 2,182 human speech clips with language annotations with 41,674 utterances of 154 celebrities, extracted from videos uploaded online.

The rest of the paper is structured as follows: Section 2 explores the related literature on the two introduced questions. While Section 3 introduces the nature of proposed dataset followed by experimental evidence to answer both questions in Section 4 and 5. Finally, conclusions are presented in Section 6.

2 Related Work

We summarize previous work relevant to the two questions raised in the introduction. Q1 falls under cross-modal verification topic while Q2 deals with speaker recognition tasks.

2.1 Cross-modal Verification Between Faces and Voices

Last decade has witnessed an increasing use of multimodal data in challenging Computer Vision tasks including visual question and answering [3,4], image captioning [23,44], classification [19,25], cross-modal retrieval [35,45] and multimodal named entity recognition [6,50].

Typically, multimodal applications are built on image and text information, however recent years have seen an increased interest to leverage audio-visual information [21,37,42,65]. Previous works [21] capitalize on natural synchronization between audio and visual information to learn rich audio representation via cross-modal distillation. More recently, Nagrani et al. [33] leveraged audio and visual information to establish an association between faces and voices in a cross-modal biometric matching. Furthermore, recent works [26,32] introduced joint embedding to establish correspondences between faces and voices. These methods extract audio and face embedding to minimize the distance between embeddings of similar speakers while maximizing the distance among embeddings from different speakers. Similarly, Nawaz et al. [34] extracted audio and visual information with a single stream network to learn a shared deep latent space representation. Such framework used speaker identity information to eliminate the need of pairwise or triplet supervision [32,33]. Wen et al. [46] presents a disjoint mapping network to learn a shared representation for audio and visual information by mapping them individually to common covariates (gender, nationality, identity).
Our goal is similar to previous works \cite{26,32,33,35,46}, however, we investigate a novel problem: To understand if the association between faces and voices is language independent.

2.2 Speaker Recognition

Speaker recognition dates back to 1960s when Sandra et al. \cite{38} laid the groundwork for speaker recognition systems attempting to find a similarity measure between two speech signals by using filter banks and digital spectrograms. In the following we provide a brief overview of speaker recognition methods as clustered in two main classes: Traditional and deep learning methods.

**Traditional Methods** – For a long time, low dimensional short-term representation of audio input has been basis for speaker recognition tasks e.g. Mel Frequency Cepstrum Coefficients (MFCC) and Linear Predictive Coding (LPC) based features. These features are extracted using short overlapping segments of audio samples. Reynolds et al. \cite{39} introduced speaker verification method based on Gaussian Mixture Models using MFCCs. Differently, Joint Factor Analysis (JFA) models speaker and channel subspace separately \cite{24}. Najim et al. \cite{16} introduced i-vectors which combines both JFA and Support Vector Machines (SVM). Other works employed JFA as a feature extractor in order to train a SVM classifier. Furthermore, traditional methods have also been applied to analyze the effect of multiple languages on speaker recognition tasks \cite{7,25,30,28,30}. Though, traditional methods showed reasonable performance on speaker recognition task, however majority of these approaches suffer performance degradation in real-world scenarios.

**Deep Learning Methods** – Neural Networks have provided more efficient methods of speaker recognition. Therefore, the community has experienced a shift from hand-crafted features to deep neural networks. Ellis et al. \cite{17} introduced a system in which a classifier (Gaussian Mixture Model) is trained from embedding of hidden layers of a neural network. Salman et al. \cite{40} proposed a deep neural network which learn from speaker-specific characteristics from MFCC features for segmentation and clustering of speaker. Chen et.al. \cite{13} used a Siamese feed forward neural network which can discriminatively compare two voices based on MFCC features. Lei et al. \cite{27} introduced a deep neural model with i-vectors as input features for the task of automatic speaker recognition. More recently, Nagrani et al. \cite{31} proposed adapted convolutional neural network (VGG-Vox) with spectrogram for speaker recognition. This paper has similarities with the previous work i.e. speaker identification and verification, however the objective is different: We evaluate and provide an answer about the effect of multiple languages on speaker identification and verification strategies in the wild. To this end we propose a dataset instrumental for answering such questions.
Table 1. Comparison of our proposed dataset with existing multilingual datasets.

| Dataset                | Condition                  | Free | Language annotations |
|------------------------|----------------------------|------|----------------------|
| The Mixer Corpus [15]  | Telephone, Microphone      | ☒    | ✓                    |
| Vermobil [9]           | Telephone, Microphone      | ☒    | ✓                    |
| Common Voice [5]       | Microphone                 | ✓    | ✓                    |
| SITW [29]              | Multimedia                 | ✓    | ✓                    |
| VoxCeleb [1,22,31]     | Multimedia                 | ✓    | ✓                    |
| MAV-Celeb [proposed]   | Multimedia                 | ✓    | ✓                    |

2.3 Related Datasets

There are various existing datasets for multilingual speaker recognition task but they are not instrumental to answer Q1/Q2 due to at least one of the following reasons: i) they are obtained in constrained environment [15]; ii) they are manually annotated so limited in size; iii) not freely available [9]; iv) not audio-visual [15,15] v) missing language annotations [1,22,31]. A comparison of these dataset with our proposed MAV-Celeb dataset is given in Table 1.

3 Dataset Description

Multilingual Audio-Visual MAV-Celeb dataset provide data of 154 celebrities in 3 languages (English, Hindi, Urdu). These three languages have been selected because of several factors: i) They represent approximately 1.4 Billion bilingual/trilingual people; ii) The population is highly proficient in both or more languages; iii) There is a relevant corpus of different media that can be extracted from available online repositories (e.g. YouTube). The collected videos cover a wide range of ‘in the wild’, unconstrained, challenging multi-speaker environment including political debates, press conferences, outdoor interviews, quiet studio interviews, drama and movie clips.

It is also interesting to note that the visual data spans over a vast range of variations including poses, motion blur, background clutter, video quality, occlusions and lighting conditions. In addition, videos are degraded with real-world noise like background chatter, music, overlapping speech and compression artifacts. Fig. 2 shows some audio-visual samples while Table 2 shows statistics of the dataset. The dataset contains 3 splits English–Urdu (EU), English–Hindi (EH) and English–Hindi/Urdu) to analyze performance measure across multiple languages. The pipeline followed in creating the dataset is discussed in Appendix A.

4 Face-voice Association

We introduce a cross-modal verification approach to analyze face-voice association across multiple languages using MAV-Celeb dataset in order to answer the
Table 2. Dataset statistics. The dataset is divided into 3 splits (EU, EH, EHU) containing audio samples from 3 languages, English (E), Hindi (H) and Urdu (U).

| Dataset | EU | EH | EHU |
|---------|----|----|-----|
| Languages       | U/E/EU | H/E/EH | E/HU |
| # of Celebrities | 70 | 84 | 154 |
| # of male celebrities | 44 | 56 | 100 |
| # of female celebrities | 26 | 28 | 54 |
| # of videos | 560/407/967 | 546/669/1,215 | 2182 |
| # of hours | 59/32/91 | 48/60/109 | 200 |
| # of utterances | 11836/5551/17387 | 9975/13313/23288 | 41674 |
| Avg # of videos per celebrity | 8/6/14 | 6/8/14 | 14 |
| Avg # of utterances per celebrity | 169/79/248 | 119/158/277 | 270 |
| Avg length of utterances(s) | 17.9/17.8/17.8 | 17.4/16.5/16.9 | 17.3 |

For example, consider a model trained with faces and voice samples of one language. At inference time, the model is evaluated with faces and audio samples of both the same language and a completely unheard language. This experimental setup provides a foundation to analyze association between faces and voices across languages to answer Q1. Therefore, we extract face and voice embedding from two subnetworks trained on VGGFace2 [11] and voice samples from MAV-Celeb dataset respectively. Previous works showed that the faces and voices subnetworks can be trained jointly to bridge the gap between the two [26,32]. However, we built a shallow architecture on top of face and voice embedding to reduce the gap between them, inspired from the previous work on images and text [45].

The details of these subnetworks and shallow architecture are as follow:

**Face Subnetwork** – The face subnetwork must produce discriminative features for face verification task. However, CNNs trained with ‘softmax’ produce features which lack discriminative capabilities [10,47]. Therefore, we jointly trained a CNN with ‘softmax’ and ‘center loss’ [47] to extract discriminative embedding for faces. The network learns a center for embedding of each class and penalizes the distances between the embedding and their corresponding class centers. At inference time, the network produces discriminative embedding which is typically employed for face recognition tasks [10,47]. We trained the Inception ResNet-V1 network [43] with VGGFace2 [11] dataset together with ‘softmax’ and ‘center loss’.

**Voice Subnetwork** – Similarly, the audio network must also produce a discriminative embedding. Nagrani et al. [31] introduced VGG-Vox network to process audio information. The network is trained with ‘softmax’ loss function. In the
current work, we modify the last layer of the network to configure it with the center loss. After modification, VGG-Vox is jointly trained with ‘softmax’ and ‘center loss’ to produce discriminative embedding for verification task.

**Center Loss** – Suppose there are $n_c$ samples in $c$-th class representing an identity. During training, the geometric center $d_c$ of features is computed and the objective function consisting of the distance of each feature $f_i^c$ from the center is minimized using the center loss:

$$d_c = \sum_{i=1}^{n_c} \| f_i^c - \frac{1}{n_c} \sum_{j=1}^{n_c} f_j^c \|^2_2.$$  

(1)

The center loss simultaneously learns centers for all classes and minimizes the distances between each class center and features in a mini-batch. If there are $n$ classes and $m$ samples in a mini batch, the loss function is given by:

$$\mathcal{L}(\text{mini batch}) = -\sum_{i=1}^{m} \log \left( \sum_{c=1}^{n} e^{W_j^T f_i^c + b_c} \right) + \frac{\lambda}{2} \sum_{c=1}^{n} d_c,$$

(2)

where $f_i^c \in \mathbb{R}^d$ denotes the $i$th deep feature, belonging to the $y_i$th class and $d$ is the feature dimension. The vector $W_j \in \mathbb{R}^d$ denotes the $j$th column of the
weights $W \in \mathbb{R}^{d \times n}$ is the last fully connected layer and $b \in \mathbb{R}^n$ is the bias term. A scalar $\lambda$ is used for balancing the ‘softmax’ and center loss. The ‘softmax’ loss can be considered as a special case of this joint supervision, if $\lambda$ is set to 0 [47].

**Cross-modal verification** – Finally, we learn a face-voice association for cross-modal verification approach using a two stream neural network (we name it Two-Branch) with single layer of nonlinearities on top of the face and voice representations Fig. 3 shows the Two-Branch shallow architecture along with the pre-trained subnetworks. The shallow architecture consists indeed of two branches, each composed of fully connected layer with weight matrices $A_1$ and $V_1$ followed by Rectified Linear Unit (ReLU). At the end of each branch, we add $L2$ normalization.

**Loss Function** – Given a training face $f_i$, let $Y^+_{i}$ and $Y^-_{i}$ represent sets of positive and negative voice samples respectively. We impose the distance between $f_i$ and each positive voice sample $y_j$ to be smaller than the distance between $f_i$ and each negative voice sample $y_k$ with margin $m$:

$$d(f_i, y_j) + m < d(f_i, y_k) \quad \forall y_j \in Y^+_{i}, \forall y_k \in Y^-_{i}.$$  \hspace{1cm} (3)

Eq. (3) is modified for a voice $y_{i'}$:

$$d(f_{i'}, y_{i'}) + m < d(f_{i'}, y_{i'}) \quad \forall f_{i'} \in X^+_{i'}, \forall f_{i'} \in X^-_{i'},$$  \hspace{1cm} (4)

where $X^+_{i'}$ and $X^-_{i'}$ represents the sets of positive and negative face for $y_{i'}$.

Finally, constraints are converted to the training objective using hinge loss. The resulting adapted loss function is given by:
Fig. 4. Evaluation protocol to analyze the impact of multiple languages on association between faces and voices. Green and the red blocks represent training and testing strategies. At test time, the network is evaluated on unseen-unheard configuration from the same language (English) heard during training along with a completely unheard language (Urdu).

\[
L(X,Y) = \sum_{i,j,k} \max[0, m + d(f_i, y_j) - d(f_i, y_k)] \\
+ \lambda_1 \sum_{i',j',k'} \max[0, m + d(f_{i'}, y_{i'}) - d(f_{i'}, y_{k'})] \\
+ \lambda_2 \sum_{i,j,k} \max[0, m + d(f_i, x_j) - d(f_i, x_k)] \\
+ \lambda_3 \sum_{i',j',k'} \max[0, m + d(y_{i'}, y_{j'}) - d(y_{i'}, y_{k'})].
\]

The shallow architecture configured with the adapted loss function produce joint embedding of face and voice to study face-voice association across multiple languages using the proposed dataset.

4.1 Experimental Protocol

We propose an evaluation protocol in order to answer Q1 which deals face-association across multiple languages. The MAV-Celeb dataset is divided into train and test splits consisting of disjoint identities from the same language typically known as unseen-unheard configuration [32,33]. Fig. 4 shows evaluation protocol during training and testing stages. At inference time, the network is evaluated on a heard and completely unheard language. The protocol is more challenging than unseen-unheard configuration due to the presence of an unheard language in addition to disjoint identities. The dataset splits EU, EH, EHU contains 64–6, 78–6 and 142–12 identities for train and test respectively.

4.2 Results and Discussion

We evaluate cross-modal verification between faces and voices with the proposed model along with a previously introduced method, Deep Latent Space framework [34] to analyze similar performance measure across multiple languages.
Table 3. Cross-modal verification between face and voice across multiple language on various test configurations of MAV-Celeb dataset (lower is better).

| Method                  | Configuration  | Eng. test (EER) | Urdu test (EER) | Drop (%) |
|-------------------------|----------------|-----------------|-----------------|----------|
| EU                      |                |                 |                 |          |
| Two-Branch (Proposed)   | Eng. train     | 41.0            | 47.8            | 16.6     |
|                         | Urdu train     | 48.9            | 45.6            | 7.2      |
| Deep Latent Space       | Eng. train     | 39.4            | 46.9            | 19.1     |
|                         | Urdu train     | 45.9            | 33.4            | 12.1     |
| EH                      |                |                 |                 |          |
| Two-Branch (Proposed)   | English train  | 45.5            | 48.8            | 7.3      |
|                         | Hindi train    | 47.3            | 45.8            | 4.4      |
| Deep Latent Space       | Eng. train data| 34.5            | 41.1            | 19.3     |
|                         | Hindi train data| 42.7           | 38.1            | 12.0     |

The goal of cross-modal verification task is to verify if a voice segment and face image belong to the same identity or not. Table 3 shows the results of face-voice association with multiple languages using the proposed evaluation protocol. On average, 11.9%, 5.9% and 15.6%, 15.7% performance drop occurred on EU and EH splits with Two-Branch and Deep Latent Space methods respectively. These results clearly demonstrate that the association between faces and voices is not language independent. The performance degradation is due to different data distributions of the two languages, typically known as domain shift \[41\]. Moreover, the model does not generalize well to other \textit{unheard} languages. However the performance is still better than random verification, which is not trivial considering the challenging nature of the evaluation protocol.

Furthermore, it is clear that Deep Latent Space framework performance is superior than the proposed Two-Branch network because the former is trained from scratch and latter is trained on embedding extracted from pre-trained models. In any case, both approaches experience a performance drop when tested on \textit{unseen-unheard} identities along with completely \textit{unheard} language.

5 Speaker Recognition

This section investigates the performance of speaker recognition across multiple languages to answer the following question.

\textit{Q2. Can a speaker be recognised irrespective of the spoken language?}
For example, consider a model trained with voice samples of one language. At inference time, the model is evaluated with audio samples of the same language and a completely unheard language of the same identity. This experimental setup provides a foundation for speaker recognition across multiple languages to answer Q2. We developed following methodology for speaker recognition across multiple languages using MAV-Celeb dataset.

Input features – The signals are converted into single channel, 16-bit streams at a 16kHz sampling rate with sampling frequency in accordance to the frame rate. The encoded audio signals are short term magnitude spectrograms generated directly from raw audio of length 3 seconds. The approach provides spectrograms of size $512 \times 300$ for 3 seconds of speech segment using a hamming window of width 25ms and step size 10ms.

Architecture – Speaker identification under a closed set can be considered as a multi-class classification problem. Nagrani et al. [31] introduced VGG-Vox architecture by modifying VGG-M [12] model to adapt to the spectrogram input. Specifically, the fully connected $fc6$ layer of VGG-M is replaced by two layers a fully connected layer and an average pool layer.

Identification – Since identification task is considered as a multi-class classification problem, the last layer output of VGG-Vox is fed into a ‘softmax’ to produce a probability distribution over the total number of speakers in the dataset.

Verification – For verification, feature vectors can be obtained from the classification network (VGG-Vox) jointly trained with ‘softmax’ and center loss. The last layer ($fc8$) of the network is modified to produce 128 embedding size. Finally, euclidean distance is used to compare embedding for verification task.

5.1 Experimental Protocol

We proposed an evaluation protocol in order to analyze the impact of multiple languages on speaker recognition to answer Q2. The MAV-Celeb dataset is divided into typical classification scenario for speaker identification. However, different voice tracks of the same person are used for train, validation and test. The network is trained with one language and tested with the same language and a completely unheard language of same identities. Moreover, the dataset is split into disjoint identities for speaker verification [31]. Fig. 5 shows evaluation protocol for speaker recognition across multiple languages. The protocol is consistent with previous studies on human subjects for speaker identification [37].

5.2 Results and Discussion

We evaluate the performance of speaker recognition across multiple languages. Table 4 shows speaker identification performance on 3 splits (EU, EH, EHU) of MAV-Celeb dataset. We note that on average 18.7%, 34.7% and 15.3% performance drop occurred on a completely unheard language for EU, EH and EHU splits respectively. The speaker identification model (VGG-Vox) does not generalize well on unheard language and is overfitted on a particular language.
Fig. 5. Evaluation protocol to analyze the impact of multiple languages on speaker recognition. Green and the red blocks represent training and testing strategies respectively. At test time, the network is evaluated on the same language heard during training along with completely unheard language of the same identities.

Table 4. Speaker identification results across multiple languages on test configurations of MAV-Celeb dataset (higher is better).

|        | EU       |                      |                      |
|--------|----------|----------------------|----------------------|
|        | Configuration | Eng. test Top-1(%)  | Urdu test Top-1(%)  | Drop(%) |
|        |           |                      |                      |
|        | Eng. train | 54.7                 | 43.4                 | 26.0    |
|        | Urdu train | 47.5                 | 52.9                 | 11.4    |
|        |           |                      |                      |
|        | EH       |                      |                      |
|        |           | Eng. test Top-1(%)  | Hindi test Top-1(%)  |
|        |           |                      |                      |
|        | Eng. train | 65.7                 | 40.0                 | 64.3    |
|        | Hindi train | 49.9                 | 52.5                 | 5.2     |
|        |           |                      |                      |
|        | EHU      |                      |                      |
|        |           | Eng. test Top-1(%)  | Hindi/Urdu test Top-1(%)  |
|        |           |                      |                      |
|        | Eng. train | 60.1                 | 54.0                 | 11.3    |
|        | Hindi/Urdu train | 46.9                 | 56.0                 | 19.4    |

However, its performance is quantitatively better than random classification on unheard language. Based on these results, we conclude that speaker identification is a language dependent task. Furthermore, these results are inline with the previous studies which show that human’s speaker identification performance is higher on people speaking familiar language than people speaking unknown language [37].

Similarly, Table 5 shows speaker verification performance on 3 splits (EU, EH, EHU) of MAV-Celeb dataset. We note that on average 5.3%, 12.6% and 9.0% performance drop occurred on a completely unheard language for EU, EH and EHU respectively. Therefore, speaker verification is also not language independent.
Table 5. Speaker verification results across multiple languages on various test configurations of MAV-Celeb dataset (lower is better).

| Configuration | Eng. test (EER) | Urdu test (EER) | Drop (%) |
|---------------|----------------|----------------|----------|
| EU | | | |
| Eng. train | 36.7 | 38.7 | 5.4 |
| Urdu train | 37.6 | 35.6 | 5.6 |
| EH | | | |
| English train | 30.1 | 32.9 | 9.3 |
| Hindi train | 32.7 | 28.2 | 15.9 |
| EHU | | | |
| English train | 35.7 | 39.1 | 9.5 |
| Hindi/Urdu train | 34.5 | 31.8 | 8.5 |

6 Conclusion

In this work, effect of language is explored on cross-modal verification between faces and voices along with speaker recognition. A new audio-visual dataset consisting of 154 celebrities is presented with language level annotation. The dataset contains 3 splits having same set of identities speaking English/Urdu, English/Hindi and both. In the cross-modal verification experiment by changing training and test language, performance drop is observed indicating that face-association is not language independent. In case of speaker recognition, similar drop in performance is observed, thus concludes that speaker recognition is also language dependent task. The reason in performance is due to the domain shift caused by two different languages.

A Dataset Collection Pipeline

In this section we present a semi-automated pipeline inspired by Nagrani et al. [31] for collecting the proposed dataset. The pipeline is shown in Fig. 6 and various stages are discussed below.

Stage 1 – List of Persons of Interest: In this stage, candidate list of Persons of Interest (POIs) is generated by scraping Wikipedia. The POIs cover over a wide range of identities including sports persons, actors, actresses, politicians, entrepreneurs and singers.
Stage 2 – Collecting list of YouTube links. In this step we used crowdsourcing to collect lists of YouTube videos. Keywords like “Urdu interview”, “English Interview”, “public speech English”, “public speech Urdu” are appended to increase the likelihood that search results contain an instance of POI speaking. The links of search results are stored in text files. Videos are then automatically downloaded using the links from these text files.

Stage 3 – Face tracks. In this stage, we employed joint face detection and alignment using Multi-task Cascaded Convolutional Networks (MTCNN) for face detection and alignment [49]. MTCNN can detect faces in extreme conditions, and different poses. After face detection and alignment, shot boundaries are detected by comparing color histograms across consecutive frames. Based on key frames from shot boundaries and detected faces, face tracks are generated.

Stage 4 – Active speaker verification. The goal of this stage is to determine the visible speaking faces. We carried out this stage by using SyncNet which estimates the correlation between mouth motion and audio tracks [14]. Based on scores from this model, face tracks with no visible speaking faces, voice-over and background speech are rejected.

Stage 5 – Static Images. In this stage, static images are automatically downloaded using Google Custom Search API based on list of POIs obtained from stage 1. MTCNN is employed to detect and align static face images. A clustering mechanism based on a popular density-based clustering algorithm DBSCAN [18] is used to remove false positives from the detected and aligned faces. Interestingly, DBSCAN does not require a priori specification of the number of clusters in the data. Intuitively, the clustering algorithm groups faces of an identity that are closely packed together.

Stage 6 – Face tracks classification. In this stage, active speaker face tracks are classified if they belong to POI or not. We trained an Inception ResNet V1
network [43] on VGGFace2 dataset [11] with center loss [47] to extract discriminative embedding from face tracks and static images. A classifier is trained based on Support Vector Machine with static face embedding. Finally, classification is performed using a score with a threshold obtained from each face track.
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