Fusion and Orthogonal Projection for Improved Face-Voice Association

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Abstract—We study the problem of learning association between face and voice, which is gaining interest in the computer vision community lately. Prior works adopt pairwise or triplet loss formulations to learn an embedding space amenable for associated matching and verification tasks. Albeit showing some progress, such loss formulations are, however, restrictive due to dependency on distance-dependent margin parameter, poor run-time training complexity, and reliance on carefully crafted negative mining procedures. In this work, we hypothesize that enriched feature representation coupled with an effective yet efficient supervision is necessary in realizing a discriminative joint embedding space for improved face-voice association. To this end, we propose a light-weight, plug-and-play mechanism that exploits the complementary cues in both modalities to form enriched fused embeddings and clusters them based on their identity labels via orthogonality constraints. We coin our proposed mechanism as fusion and orthogonal projection (FOP) and instantiate in a two-stream pipeline. The overall resulting framework is evaluated on a large-scale VoxCeleb dataset with a multitude of tasks, including cross-modal verification and matching. Results show that our method performs favourably against the current state-of-the-art methods and our proposed supervision formulation is more effective and efficient than the ones employed by the contemporary methods.

Index Terms—Multimodal, Face-voice association, Cross-modal verification and matching

I. INTRODUCTION

It is a well-studied and understood fact that humans can associate voices and faces of people because the neuro-cognitive pathways for voices and faces share same structure [1], [2]. Recently, Nagrani et al. [3]–[5] introduced the face-voice association task into vision community with the creation of a large-scale audio-visual dataset, comprising faces and voices of 1,251 celebrities. Since then, the face-voice association task has gained significant research interest [3], [4], [6]–[10]. In addition, we are also witnessing creation of new audio-visual datasets to study this novel task. For example, Nawaz et al. [11] introduced a Multilingual Audio-Visual (MAV-Celeb) dataset to analyze the impact of language on face-voice association task; it comprises of video and audio recordings of different celebrities speaking more than one language.

Most existing works [3], [4], [7], [11] tackle face-voice association as a cross-modal biometric task. The two prominent challenges in developing an effective method for this task are learning of a common yet discriminative embedding space, where instances from two modalities are sufficiently aligned and instances of semantically similar identities are nearby. Often separate networks for face and voice modalities are leveraged to obtain the respective feature embeddings and contrastive or triplet loss formulations are employed to construct this embedding space. Although showing some effectiveness in this task, such loss formulations, however, are restrictive in following ways. First, they require tuning of a margin hyperparameter, which is hard as the distances between instances can alter significantly while training. Secondly, the run-time training complexity for contrastive and triplet losses are \( O(n^2) \) and \( O(n^3) \), respectively, where \( n \) is the number of available instances for a modality. Finally, to mitigate the high run-time training complexity challenge, different variants of carefully crafted negative mining strategies are used, which are both time-consuming and performance sensitive.

A few methods e.g., [3] have attempted to replace the contrastive/triplet loss formulations by utilizing auxiliary identity centroids [12]. The training process alternates between the following two steps: 1) clustering embeddings around their identity centroids and pushing embeddings away from all other identity centroids, and 2) updating these centroids using the mini-batch instances. Such centroid based losses are used with traditional classification loss (i.e. softmax cross-entropy (CE)). However, their co-existence is unintuitive and ineffective because the former promotes margins in Euclidean space whereas latter implicitly achieves separability in the angular domain.

In this work, we hypothesize that an enriched unified feature representation, encompassing complementary cues from both modalities, alongside an effective yet efficient supervision formulation is crucial towards realizing a discriminative joint embedding space for improved face-voice association. To this end, we propose a light-weight, plug-and-play mechanism that exploits the best in both modalities through fusion and semantically aligns fused embeddings with their identity labels via orthogonality constraints. We instantiate our proposed mechanism in the two-stream pipeline, which provides face and voice embeddings, and the resulting overall framework is an effective and efficient approach for face-voice matching and verification tasks.

We summarize our key contributions as follows. 1) We
propose to harness the complementary features from both modalities in forming enriched feature embeddings, that are consistent with semantics of identity, thereby allowing improved identity recognition. 2) We propose to impose orthogonality constraints on the fused embeddings. They are not only coherent with the angular characteristic of the commonly employed classification loss but are very efficient as they operate directly on mini-batches. 3) Experimental results on large-scale VoxCeleb [5] show the effectiveness of our method on both face-voice verification and matching tasks. Further, we note that our method performs favourably against the existing state-of-the-art methods. 4) We perform a thorough ablation study to analyze the impact of different components.

II. RELATED WORK

Face-voice Association. The work of Nagrani et al. [3] leveraged audio and visual information to establish an association between faces and voices in a cross-modal biometric matching task. Similarly, some recent work [4], [7], [9], [11] introduced joint embeddings to establish correlation between face and voice of an identity. These methods extract audio and face embeddings and then minimize the distance between embeddings of same identities while maximize the distance among embeddings from different ones. Wen et al. [10] presented a disjoint mapping network to learn a shared representation for audio and visual information by mapping them individually to common covariates (gender, nationality, identity) without needing to construct pairs or triplets at the input. Similarly, Nawaz et al. [8] extracted audio and visual information with a single stream network to learn a shared deep latent representation, leveraging identity centroids to eliminate the need of pairs or triplets [3], [4]. Both Wen et al. [10] and Nawaz et al. [8] show that effective face-voice representations can be learned without pairs or triplets formation.

Contrary to previous works, our method proposes to construct enriched embeddings via exploiting complementary cues from the embeddings of both modalities through a attention-based fusion. Further, it clusters the embeddings of same identity and separates embeddings of different identities via orthogonality constraints. The instantiation of both proposals in a two-stream pipeline results in an effective and efficient face-voice association framework.

III. OVERALL FRAMEWORK

To learn a discriminative joint face-voice embedding for F-V association tasks, we develop a new framework for cross-modal face-voice association (See Fig. 1) that is fundamentally a two-stream pipeline (sec. III-A) and features a light-weight module that exploits complementary cues from both face and voice embeddings and facilitates discriminative identity mapping via orthogonality constraints (sec. III-B).

A. Preliminaries

Problem Settings. Without the loss of generality, we consider cross-modal retrieval of bimodal data, i.e., for face and voice. Given that we have N instances of face-voice pairs, 

$$D = \{ (x_i^f, x_i^v) \}_{i=1}^N$$

where $$x_i^f$$ and $$x_i^v$$ are the face and voice examples of the ith instance, respectively. Each pair of an instance $$(x_i^f, x_i^v)$$ has an associated label $$y_i \in \{0, 1\}$$, where $$y_i = 1$$ if x_i^f and x_i^v belong to the same identity and $$y_i = 0$$ if x_i^f and x_i^v belong to a different identity. Both face and voice embeddings typically lie in different representation spaces owing to their different superficial statistics and are mostly unaligned semantically, rendering them incomparable for cross-modal tasks. Cross-modal learning aims at projecting both into a common yet discriminative representation space, where they are sufficiently aligned and instances from the same identity are nearby while from a different identity are far apart. Two-stream pipeline. We employ a two-stream pipeline [4] to obtain the respective feature embeddings of both face and voice inputs. The first stream corresponds to a pre-trained convolutional neural network (CNN) on image modality. We take the penultimate layer’s output, denoted as $$b_i$$, of this CNN as the feature embeddings for an input face image. Likewise, the second stream is a pre-trained audio encoding network that outputs a feature embedding, denoted as $$e_i$$, for an input audio signal (typically a short-term spectrogram). Existing approaches handling face-voice retrieval [4], [8], mostly resort to triplet and contrastive objectives with carefully crafted negative mining strategies, which significantly increases computational time and are performance-sensitive, to learn a discriminative embedding space. To this end, we introduce a light-weight mechanism that exploits complementary cues from both modality embeddings to form enriched fused embeddings and imposes orthogonal constraints on them for learning discriminative joint face-voice embeddings.

B. Learning Discriminative Joint Embedding

In this section, we first describe extracting complementary cues, via multimodal fusion, from both face and voice embeddings obtained through their respective pre-trained networks. We then discuss clustering fused embeddings belonging to the same identity and pushing away the ones with different identity via orthogonality constraints.

Prior to multimodality fusion, we project the face embeddings $$b_i \in \mathbb{R}^F$$ to a new d-dimensional embedding space $$u_i \in \mathbb{R}^d$$ with a fully-connected layer. Similarly, we project the voice embedding $$e_i \in \mathbb{R}^V$$ to a similar d-dimensional embedding space $$v_i \in \mathbb{R}^d$$ with another fully-connected layer. We then L2 normalize both $$u_i$$ and $$v_i$$ which can now be fused to get $$l_i$$, using the procedure described next. Multimodal fusion. We propose to extract complementary features from both modalities, some of which could be related to age, gender and nationality, to form an enriched unified feature representation which is crucial towards learning a discriminative joint embedding space. Inspired by [13], [14], we employ an attention mechanism to first compute the attention scores (affinity) between the embeddings of two modalities and then fuse these individual modality embeddings after recalibrating them with the attention scores (see Fig. 1).

We compute attention scores k between $$u_i$$ and $$v_i$$ as:

$$k = \sigma(F_{att}([u_i, v_i])),$$

where
logits corresponding to \( l \) classification loss with fused embeddings is computed as:

\[
W \text{denoted as } \ specifically, we use an identity linear classifier with weights \( A \). A popular choice to achieve this is softmax cross entropy whereas the ones with different identity labels are far away. Instances belonging to the same identity are placed nearby the identity labels with good accuracy. This is possible if the embeddings should be able to predict \( \sigma \). We want the supervision via orthogonality constraints. Formally, the constraints enforce fused embeddings of different identities to be orthogonal and the fused embeddings with the same identity to be similar:

\[
\langle l_i, l_j \rangle = \frac{1}{\|l_i\|_2 \|l_j\|_2}.
\]

Overall Training Objective. To train the proposed framework, we minimize the joint loss formulation, comprising of \( L_{CE} \) and \( L_{OC} \) as:

\[
L = L_{CE} + \alpha L_{OC},
\]

where \( \alpha \) balances the contribution of two terms in \( L \). We empirically set \( \alpha = 1.0 \) based on validation set performance. It is important to mention that CE loss operates in logit space and orthogonal constraints are imposed in the embedding space, however, both of them synergizes well with each other owing to their common angular domain characteristic.

IV. Experiments

Training Details and Dataset. We train our method on Quadro P5000 GPU for 50 epochs using a batch-size of 128 using Adam optimizer with exponentially decaying learning rate (initialised to \( 10^{-5} \)). We extract face and voice embeddings from VGGFace [20] and Utterance Level Aggregation [21]. Note that, we only backprop. through FOP module while the weights of face and voice subnetworks remains unaltered. We perform experiments on cross-modal verification and cross-modal matching tasks on the large-scale dataset of audio-visual human speech videos [5]. We follow the same train, validation and test split configurations as used in [4] to evaluate on seen-heard and unseen-unheard identities.

A. Results

Comparison with other F-V losses. We compare our (joint) loss formulation against various losses typically employed in F-V association methods, including center loss [8], [12], Git loss [17], Contrastive Loss [4] and Triplet Loss [3]. Table I reveals that our proposal performs better than other loss formulations across all configurations and both error metrics. Likewise, Table I shows that our (joint) loss formulation is...
superior than others in terms of both theoretical and empirical training efficiency.

We then validate the effectiveness of our (joint) loss formulation by examining the effect of Gender (G), Nationality (N), Age (A) and its combination (GNA) separately, which influence both face and voice verification (Table III). It achieves consistently better performance on G, N, A and the combination (GNA) in both seen-heard and unseen-unheard configurations than other loss formulations. Furthermore, we compare our (joint) loss formulation against aforementioned loss functions on a cross-modal matching task, 1 : 1, with \( n_c \) = 2, 4, 6, 8, 10 in Fig. 2(left). We see that it outperforms the counterpart loss formulations for all values of \( n_c \).

**TABLE III:** Cross-modal biometrics results under varying demographics for seen-heard and unseen-unheard configurations.

**Comparison with state-of-the-art.** Under unseen-unheard protocol, our method outperforms all competing approaches, including DIMNet [10], Learnable Pins [4], MAV-Celeb [11], Single Stream Network [8], and under seen-heard configuration, it achieves the second best performance (see Table IV). For cross-modal matching task, involving 1 : \( n_c \) matching tasks, our method outperforms [4] while achieves competitive performance against DIMNet [10] (Fig. 2(right)).

**Fig. 2:** Cross-modal matching results: (left) FOP vs other losses used in F-V methods. (right) Our method vs state-of-the-art methods.

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**TABLE IV:** Cross-modal verification results of our method and existing state-of-the-art methods.

**Ablation study and analysis.** Table V reveals that our method’s performance is mostly robust to the choice of \( \alpha \), which is a hyperparameter to balance the contribution of softmax CE and orthogonal constraints based loss in our joint formulation (Eq. 3). We also show that on replacing gated multimodal fusion with a much simpler linear fusion, the performance of our method significantly drops (Table VI). Finally, in Fig. 3, we find that the proposed OC with CE loss, in comparison to CE loss alone, enhances (overall) feature discriminability with orthogonality constraints, and enforces stronger intra-entity compactness and inter-entity separation in the joint F-V embedding space.

**Fig. 3:** (a) Feature Orthogonality (↓) (b) Similarity of same class features (↑) (c) Similarity of different class features (↓).

**V. CONCLUSION**

We presented a light-weight module (FOP) for F-V association task. It harnesses the best in both face and voice modalities through attention-based fusion and clusters the fused embeddings based on their identity-labels via orthogonality constraints. We instantiated this module in a two-stream pipeline, used for extracting face and voice embeddings, and the resulting overall framework is evaluated on a large-scale VoxCeleb dataset for F-V matching and verification tasks. Our method performs favourably against the existing state-of-the-art methods and proposed FOP outperforms competitors both in accuracy and efficiency.
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