Separating Sounds from a Single Image

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Abstract—Recently, visual information has been widely used to aid the sound source separation tasks. It aims at identifying sound components from a given sound mixture with the presence of visual information. Especially, the appearance cues play an important role on separating sounds. However, the capacity of how well the network processes each modality is often ignored. In this paper, we investigate the performance of appearance information, extracted from a single image, in the task of recovering the original component signals from a mixture audio. An efficient appearance attention module is introduced to improve the sound separation performance by enhancing the distinction of the predicted semantic representations, and to precisely locate sound sources without extra computation. Moreover, we utilize the ground category information to study the capacity of each sub-network. We compare the proposed methods with recent baselines on the MUSIC dataset. Project page: https://ly-zhu.github.io/separating-sounds-from-single-image.

I. INTRODUCTION

Human perceives a scene by looking, listening, and thinking, which requires different senses to capture multiple modalities and the ability of associating and understanding the received signals. Likewise, for developing deep networks, the performance of facilitating various tasks is highly relying on how well the models process and associate the correlated modalities. In recent years, researchers have developed diversified models to analyze different modalities from signals. Take visually guided learning as example, extensive effort has been focused on solving practical tasks, such as sound recognition [1], [2], [3], [4], cross-model retrieval [5], [6] and generation [7], [8], sound source separation [9], [10], [11], [12], [13], [14], [15], [16], [17], [18] and localization [19], [20], [18]. In this work, we are interested in the task of self-supervised audio-visual sound source separation, where our objective is to distinguish sound components via joint audio-appearance learning on unlabeled videos.

Recent researches [9], [10], [11], [12], [14], [15], [16], [17], [18] achieve decent results on various sound separation tasks by conditioning on associated appearance and motion knowledge. For the sounds that always occur with actions of physical world, the motion cues are extraordinarily important for synchronizing visual streams and sound tracks. However, impressively, recent work by [18] reports that with only appearance information can achieve decent sound separation performance. Sound features are split and separated by the semantic knowledge provided by the appearance information. In this paper, more specifically, we explore the performance of the sound source separation task conditioning on only appearance information (see e.g. Fig. 1).

Besides sound source separation, visualizing sound source locations is another classical audio processing problem. Early works e.g. [21] utilize microphone arrays to locate the sources. Recently, associating the audio and visual signals [19], [20] of a video has been used to determine the sound source locations. The unlabelled video with naturally aligned audio is more often available, which facilitates many self-supervised tasks.

This paper proposes a light yet efficient appearance attention module (Fig. 2) to improve the sound source separation performance. It enhances the distinction of the predicted semantic representations by predicting whether the learned appearance embedding and appearance feature maps are from the same source or not. This is an attention module adopted among input visual cues on the task of sound separation, which is not considered by previous works (e.g. [12], [13], [14], [15], [18]). We show that the appearance attention module can greatly improve the sound source separation performance compared to the baseline systems. Moreover, at the same time, the proposed appearance attention module can precisely locate the sound locations without extra computation (see e.g. Fig. 1).

The proposed appearance attention module is capable of enhancing the final sound source separation performance. We ask what is the upper bound of the sound separation system conditioning on only the appearance information? As
the category information of the MUSIC dataset is provided, we perform extensive experiments on evaluating the capacity of the proposed sound separation system with the ground category information in Sec. IV.

II. RELATED WORK

In this section, we briefly discuss the mainly related fields of audio-visual learning, audio-visual sound source separation, and sound source localization.

a) Audio-Visual Learning: Recent studies have shown promising prospect of learning audio-visual correspondences. Aytar et al. [1] bridged visual content with sound representations by minimizing the KL-divergence of their distributions. Owens et al. [22] provided sound supervision for visual learning. Arandjelovic et al. [2], [5] associated the learnt audio and visual embeddings by asking whether they belong to a same video. Nagrani et al. [3] identified which of a pair of faces possesses the same identity as the voice by face and audio matching. More recently, researchers developed different approaches to map monaural to binaural audio by leveraging visual features [16], implement audio-video deep clustering [23], generate talking faces [24], predict audio-driven 3D facial animation [25], and disentangle speech embeddings using the co-occurrence of faces in video [26].

b) Audio-Visual Sound Source Separation: Researchers have recently proposed various learning-based approaches to include the visual signal to the task of sound separation. Ephrat et al. [10] extracted face embeddings using a pre-trained face recognition model to facilitate speech separation. Similarly, Gao et al. [13] trained an object detector to localize objects in all video frames to improve the sound separation quality. Zhao et al. [12] learned to separate sounds by a linear combination of sounds and images. A subsequent work [14] introduced motion features and improvements to the output spectrogram prediction. Xu et al. [15] separated sounds by recursively removing the sounds with large energy from sounds mixture. Gan et al. [17] associated body and finger movements with audio signals by learning a keypoint-based structured representation from a Graph CNN. Zhu et al. [18] proposed a cascaded opponent filter to utilize visual features of all sources to look for incorrectly assigned sound components from opponent sources. The most impressive results were mostly based on the models with both appearance and motion information. However, the contribution of the pure appearance knowledge has not been completely analyzed. In this work, we explore the performance of sound separation conditioning only on appearance information that extracted from a single image.

c) Sound Source Localization: Localizing sound sources entails identifying the regions where the sound comes from. Effort had been put to explore the audio-visual synchrony [27], audio-visual subspace distribution [28], canonical correlations [29], and temporal coincidences [30]. Most recently, Arandjelovic et al. [5] visualized sound location by computing the similarity between the audio and all visual embeddings. [31], [11] applied the class activation map for localizing ambient sounds. [12], [14], [15] visualized sound sources by calculating the sound volume at each spatial location. Gao et al. [13] localized potential sound source regions via a separate object detector. Morgado et al. [32] displayed the sound areas by converting mono audio into spatial audio. Senocak et al. [33] learned to localize sound sources in visual scenes by transferring the sound-guided visual concepts to sound context vector. Zhu et al. [18] located sound sources by learning to identify a minimum set of input pixels to produce almost identical output as for the entire image. In contrast to these methods, we propose a self-supervised appearance attention module to localize sound sources.

III. ARCHITECTURE

This section describes the framework of the proposed appearance-aided sound source separation and localization system. The framework, illustrated as Fig. 2, consists of three components: appearance network, sound network, and appearance attention module. The input to the system consists of a mixture audio and a keyframe of each sequence video, each representing one component of the mixture. The objective of the system is to recover the audio component from sound mixture corresponding to each appearance information.

A. Appearance Network

To avoid the aid of motion cues, we import only a keyframe $I$ of a sequence video to the appearance network $A$. We choose Res-18 and Res-50 [34] as two alternative appearance networks. The appearance network converts the input image of size $3 \times H \times W$ to feature maps $A(I)$ of size $K \times H/16 \times W/16$. With a spatial max pooling, we get a compact visual representation $e$ of size $1 \times K$ ($K$ is the number of categories in the dataset). After a sigmoid operation, each element of the visual vector $e$ is within the range of $[0, 1]$, which indicates the possibilities of which sound category (e.g. violin) appears in the input image.

B. Sound Network

The sound network is implemented using U-Net [35] and DV3P (DeepLabV3+) [36] with mobilenetV2 [37] as backbone, we refer to it as DV3P). The input to the sound network is a mixture audio, which is represented as spectrograms that obtained from the audio stream using Short-time Fourier Transform (STFT). The sound network $S$ converts the input audio spectrogram $X$ of size $1 \times HS \times WS$ into a set of feature maps $S(X)$ of size $K \times HS \times WS$. The $K$ equals to the $K$ of the appearance representation from appearance network. The sound source separation is achieved by a linear combination between the learned appearance representation $e$ and the sound feature maps $S(X)$, as follows

$$b = th(\sigma(\sum_k e_k \odot S(X)_k))$$

where $e_k$ is the $k$-th element of the appearance representation, and $S(X)_k$ is the $k$-th sound network feature map for input spectrogram $X$. $\odot$ indicates scalar product. $\sigma$ denotes the sigmoid operation. We get the predicted binary mask $\hat{b}$ by setting a threshold of 0.5. 

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The framework of appearance-aided sound source separation and localization system. The appearance network $A$ converts the input image $I$ (a keyframe of a sequence video) to visual feature maps $A(I)$ and further, with a spacial pooling, to a compact representation $e$. The sound network $S$ splits the mixture spectrogram $X$ into a set of feature maps $S(X)$. A linear combination of appearance representation $e$ and sound features maps $S(X)$ produces a sound separation mask $\hat{b}$. The pixel-wise multiplication between the mask $\hat{b}$ and input mixture spectrogram $X$ determines the output component spectrogram, which recovers the final separated audio signal by following an inverse Short-time Fourier Transform (iSTFT). The appearance attention module is formed by a scalar product between the appearance representation $e$ and appearance feature maps $A(I)$. The appearance attention module produces a source location mask $\hat{p}$. The red and blue arrows represent the appearance attention module.

C. Appearance Attention Module

The performance of the appearance module might be limited because of the appearance similarity and existing noise within the video sequences. In order to enhance the distinction of the predicted semantic representations, we add an appearance attention branch with an auxiliary contrastive loss to the appearance network. The appearance attention module is depicted as red and blue arrows in Fig. 2.

In this paper, we discuss the appearance-aided sound source separation of the sounds from different categories (e.g. instruments). In other words, the corresponding input image to each appearance network as well as the sound sources of audio mixture are from different categories. As is shown in Fig. 2, the appearance attention module is optimized by predicting whether the appearance embedding $e$ and appearance feature maps $A(I)$ are from the same categories (positive pairs) or not (negative pairs). The red arrows (positive pairs) represent the scalar product between the appearance embedding (e.g. $e_2$) and feature maps (e.g. $A(I_2)$) from the same input image. With a sigmoid operation, it outputs a location mask which locate the sound sources. However, the blue arrows (negative pairs) show that the multiplication components are from different inputs (e.g. $e_2$ and $A(I_1)$). The scalar product between the appearance embedding and visual feature maps of same category (e.g. instrument) will locate the sound sources (e.g. $\hat{p}_2$), and of different categories will return a blank mask (e.g. $\hat{p}_1$). The output of the appearance attention module is described as below,

\[
\hat{p}_{pos} = \sigma\left(\sum_k e_{nk} \odot A(I_n)_k\right) \quad n, m \in [0, N-1], \quad m \neq n
\]

where $\hat{p}$ is the predicted location mask of the appearance attention module. $A(I_n)$ is the appearance feature maps of $n$-th video, $e_n$ is its corresponding appearance embedding that derived from $A(I_n)$ by a spatial pooling. $N$ is the number of sounds in sound mixture. $k$ is in $[0, K-1]$. $K$ is the number of elements in appearance representation $e$ as well as the channel number of feature maps $A(I)$.

D. Learning Objective

The learning objective of our system is to estimate a binary mask $\hat{b}$ (Eq. (1)) to separate the target sound from mixture. The binary ground truth mask $b$ of sound separation is calculated based on whether the target sound is the dominant component in the input sound mixture spectrogram $X$. The model parameters are optimised with respect to the Binary Cross Entropy (BCE) loss that is calculated between the predicted binary mask $\hat{b}$ and ground truth masks $b$. Moreover, we add an appearance attention module with an auxiliary contrastive loss to the appearance network. The ground truth $p$ of the appearance attention module is defined by whether the appearance embedding and appearance feature maps are from the same categories (1) or not (0). More specifically,

\[
\mathcal{L} = BCE(\hat{b}, b) + BCE(th(maxpool(\hat{p})), p)
\]
where $\hat{b}$ and $b$ are the predicted sound separation mask and ground truth mask respectively. $th(maxpool(\hat{p}))$ adds a maxpooling and threshold operation on the predicted location mask $\hat{p}$ of appearance attention module. $p$ is the ground truth of positive/negative pairs.

IV. EXPERIMENTS

We evaluate the proposed approach on the public dataset MUSIC [12]. The proposed model is trained using artificial examples, generated by adding audio signals from two training videos. The performance of the final sound source separation is measured in terms of standard metrics: Signal to Distortion Ratio (SDR), Signal to Interference Ratio (SIR), and Signal to Artifact Ratio (SAR). Higher is better for all metrics. It might be worth to note that SDR and SIR scores measure the separation accuracy, SAR captures only the absence of artifacts (and hence can be high even if separation is poor).

In the following, we first introduce the dataset and continue to investigate the contribution of proposed appearance attention module and the capacity of each model component with the presence of ground category embedding. Finally, we present the comparisons with recent state-of-the-art self-supervised audio-visual approaches.

A. Dataset

MUSIC [12] dataset is a high quality dataset of musical instruments. Most of the video frames are well aligned with the audio track and have little off-screen noise. It contains 714 untrimmed YouTube videos which span 11 instrumental categories, namely accordion, acoustic guitar, cello, clarinet, erhu, flute, saxophone, trumpet, tuba, violin, and xylophone. However, part of the original MUSIC dataset is no longer available in YouTube (10%) and its train/test splits are not published. Thus, we replaced the missing entries with similar YouTube videos and randomly split the dataset into 400 training videos, 100 validation videos, and 130 test videos.

We extract video frames at 8fps and adopt frame augmentation by random scaling, random horizontal flipping, and random cropping ($224 \times 224$) during training. We sub-sample each audio signals at 11kHz and randomly crop an audio clip of 6 seconds for training. A Time-Frequency (T-F) spectrogram of size $512 \times 256$ is obtained by applying Short-time Fourier Tranform (STFT), with a Hanning window size of 1022 and a hop length of 256, to the input sound clip. We further re-sample this spectrogram to a T-F representation of size $256 \times 256$ on a log-frequency scale. The final separated sound is achieved by adding an inverse Short-time Fourier Tranform (iSTFT) to the predicted component spectrogram.

B. Baselines

The appearance network learns an appearance representation of length K from a single RGB image. The predicted appearance representation will force the sound network to split and project the mixture spectrogram into feature maps of corresponding K channels. Finally, the appearance weighted summation of sound component features, with a sigmoid operation, will yield a sound separation mask. A multiplication between the mask $\hat{b}$ and the sound mixture spectrogram $X$, following an iSTFT, recovers the corresponding audio components from mixture. The above-mentioned processes form the baseline framework of audio-appearance sound separation system (without the red and blue arrows of Fig. 2). We combine the appearance network $A$ of Res-18 and Res-50 with sound network $S$ of U-Net and DV3P as four baseline models $A(Res-18) + S(U-Net), A(Res-18) + S(DV3P), A(Res-50) + S(U-Net)$, and $A(Res-50) + S(DV3P)$. We report the corresponding sound separation metric scores of SDR, SIR, and SAR in Tab. 1.

C. Sound Source Separation with Appearance Attention Module

As shown in the Tab. I, with the same appearance network, the higher capacity the sound network has, the better performance the system achieves, e.g. from $A(Res-18) + S(U-Net)$ to $A(Res-18) + S(DV3P)$, it achieves the improvement of e.g. 2.35dB in SDR scores. However, with the same sound network, having the appearance network of higher capacity does not achieve clearly large performance improvement, e.g. from $A(Res-18) + S(DV3P)$ to $A(Res-50) + S(DV3P)$, the improvement is only 0.22dB in SDR. The appearance network of current system, we hypothesize, does not reach its upper bound on the task of self-supervised sound source separation.

To study this, we introduce an efficient appearance attention module to emphasize the learned semantic distinction (appearance network), which enhances the predicted categorical possibility by predicting whether the appearance embedding and feature maps are from same sources or not. We assess the performance of the appearance attention module (denoted as $att$) for the sound separation task (sound source localization in Sec. IV-F) in Tab. II. The improvement, e.g. 1.49dB in SDR and 1.74dB in SIR scores of $A(Res-18, att) + S(DV3P)$ compared to its counterpart $A(Res-18) + S(DV3P)$, indicates

| Models                  | SDR   | SIR   | SAR   |
|-------------------------|-------|-------|-------|
| A(Res-18) + S(U-Net)    | 5.38  | 11.00 | 9.77  |
| A(Res-50) + S(U-Net)    | 5.88  | 11.09 | 10.73 |
| A(Res-18) + S(DV3P)     | 7.73  | 13.48 | 11.55 |
| A(Res-50) + S(DV3P)     | 7.95  | 13.66 | 12.16 |

Fig. 3. The framework of the appearance classifier aided sound source separation.

![Diagram of the framework of the appearance classifier aided sound source separation](image-url)
that the model with the proposed appearance attention module clearly outperforms the baselines.

### D. Sound Source Separation with Ground Category Embedding

Given a sound mixture and a video keyframe which contains the target sounding object, the objective of appearance guided sound source separation in this work is to use the appearance network to predict the sound category from visual image and further separate its corresponding sound components from the sound mixture. When providing the ground truth categories of dataset, we encode the category information of a keyframe into binary embedding. As an example, if the visual frame contains instrument e.g. accordion, the binary ground embedding is [1,0,0,...,0]. This binary ground embedding will be used as semantic cues on the sound separation results. How far can we push the appearance network prediction towards the upper bound, e.g. the scores as semantic cues on the sound separation results. How far can we push the appearance network prediction towards the upper bound, e.g. the scores.

At the training phase, we adopt the binary ground embedding as the appearance (semantic) cues to separate the target sound components from the sound mixture with the sound network. The category information helps to investigate the capacity of the sound networks. As is shown in Table. II, with the ground category embedding, the sound network U-Net [35] attains the performance of SDR: 8.55, SIR: 14.98 and SAR: 11.21, which tells the capacity of the chosen sound network in current system on the task of sound source separation. Moreover, we obtain a more powerful architecture DV3P [36] as the sound network. The system of binary ground embedding with DV3P achieves the performance to SDR: 10.74, SIR: 17.29 and SAR: 13.04. We conclude that with the ground category information, the system can separate sounds with high quality, which is the upper bound of the system, and the higher capacity of the chosen sound network the better performance the system can achieve.

### E. Sound Source Separation with Appearance Classifier

Results in Tab. II demonstrate that the proposed appearance attention module is capable of enhancing the semantic distinction. However, there is still a relatively large gap between using appearance network prediction as the ground categories and semantic cues on the sound separation results. How far can we push the appearance network prediction towards the upper bound, e.g. the scores as semantic cues on the sound separation results. How far can we push the appearance network prediction towards the upper bound, e.g. the scores.

We take the framework of A(Res-50) + S(DV3P) as an example to visualize the learned appearance embedding from the appearance network on different conditions (e.g. appearance attention, appearance classifier, and ground category embedding) with t-SNE [38] in Fig. 4. As we can see, the compactness of both the intra- and inter-class of Res-50 embedding is limited. From the Res-50 to Res-50 with appearance attention, the system pushes its sound separation performance further towards the upper bound, e.g. the scores of SDR: 10.59, SIR: 17.23, and SAR: 12.75 of A(Res-50, classifier) + S(DV3P).

![Fig. 4. Visualization of visual embedding of (a) Res-50 and (b) Res-50 with appearance attention, (c) Res-50 classifier, and (d) ground category embedding.](image-url)
Fig. 5. Visualizing sound source locations by the appearance attention module.

### TABLE III

| Models                          | SDR    | SIR    | SAR    |
|---------------------------------|--------|--------|--------|
| SoP [12]                        | 5.38   | 11.00  | 9.77   |
| SoM [14]                        | 4.83   | 11.04  | 8.67   |
| MP-Net [15]                     | 5.71   | 11.36  | 10.45  |
| Co-Separation [13]              | 7.38   | 13.7   | 10.8   |
| COF [18]                        | 10.07  | 16.69  | 13.02  |
| A(Res-50) + S(DV3P)             | 7.95   | 13.66  | 12.16  |
| A(Res-50, att) + S(DV3P)        | 9.41   | 15.56  | 12.66  |
| A(Res-50, classifier) + S(DV3P) | 10.59  | 17.23  | 12.75  |
| A(Ground Category Emb) + S(DV3P)| 10.74  | 17.29  | 13.04  |

**F. Sound Source Localization with Appearance Attention Module**

Given a sound mixture and a keyframe of a video, we use the spatial pooled appearance representation to give self attention to the appearance features to localize the sounding objects. It is shown as red arrows in Fig. 2. We visualize the sound source location examples in Fig. 5 by applying the appearance attention module, which precisely localizes sound sources with appearance information. We display the spatial location in heatmaps on input image during inference.

**G. Comparison with State-of-the-Art**

We compare our best appearance-based methods with recent approaches SoP [12], SoM [14], MP-Net [15], Co-Separation [13], and COF [18] on the task of visually guided sound source separation on MUSCI test set. The quantitative results are provided in Table III. Note that the compared approaches were either trained on multiple images or involved with motion information. However, our methods only have single keyframe of a video as the input to the appearance network. The quantitative results in Table III indicate that the model with appearance attention can greatly improve the performance, and the system with the ground category information outperforms recent approaches by a large margin.

**V. Conclusion**

In this paper, we proposed an efficient appearance attention module to enhance the semantic cues by predicting whether the appearance embedding and appearance feature maps are from same sources or not. The improvement of sound source separation performance on the discussed baseline models indicates that the appearance attention module can greatly improve the distinction of the learnt semantics from the appearance network. Moreover, at the same time, the proposed appearance attention module can precisely locate the sound locations without extra computation. Furthermore, with the ground category information presented in the dataset, we trained an appearance classifier and performed extensive experiments on evaluating the capacity of the proposed appearance aided sound source separation system.
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