How to Listen? Rethinking Visual Sound Localization

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Abstract

Localizing visual sounds consists of locating the position of objects that emit sound within an image. It is a growing research area with potential applications in monitoring natural and urban environments, such as wildlife migration and urban traffic. Previous works were usually evaluated with datasets having mostly a single dominant visible object, and their proposed models usually require the introduction of localization modules during training or dedicated sampling strategies, but it remains unclear how these design choices play a role in the adaptability of these methods in more challenging scenarios. In this work, we analyze various model choices for visual sound localization and discuss how their different components affect the model’s performance, namely the encoders’ architecture, the loss function and the localization strategy. Furthermore, we study the interaction between these decisions, the model performance, and the data, by digging into different evaluation datasets spanning different difficulties and characteristics, and discuss the implications of such decisions in the context of real-world applications. Our code and model weights are open-sourced and made available for further applications.

Index Terms: sound source localization, acoustic event detection, acoustic scene understanding, audio-visual scene understanding, explainability.

1. Introduction

Audio-visual information is fundamental for the understanding of real-world scenes, as the visual and acoustic characteristics of natural objects provide complementary information that allow us to make sense of them [1, 2, 3, 4]. Modelling the appearance and acoustics of objects not only can help machines understand them better, but also can help them be more efficient in doing so, as shown in recent works which exploit the intrinsic structure of audio-visual data to train models that localize sounding objects without manual labels (self-supervision) [5, 6, 7, 8]. Recently, these audio-visual self-supervised learning techniques became very popular as they improve their performance in common visual sound localization benchmarks [9, 10, 11, 12]. Most of these proposed approaches require training with carefully designed localization modules (e.g. attention, audio-visual fusion) [2, 10, 13, 14, 15, 16, 17], and/or dedicated sampling strategies (e.g. hard negative mining) [17, 18].

However, there is little understanding on the biases of the audio-visual dataset benchmarks used for visual sound source localization in both training and evaluation of these models, especially when it comes to generalizing to real-world scenarios. Given how challenging it is to annotate and curate such datasets, most of them have either a low number of object categories annotated in few frames and are not suitable for video modeling [10]; have mainly one-dominant object in the whole video [17] which is uncommon in most real-world scenes; or have very particular synthetic visual structure (e.g. objects divided in quadrants) [12]. To move forward in the localization of sound sources in realistic settings, we think that it is key that we understand better what these models are learning from the data, what design choices are important in these architectures, and what insights our evaluation benchmarks are providing.

Our main contributions are: 1. We analyze various model choices for visual sound localization and discuss how their different components affect the model’s performance both quantitatively and qualitatively in different datasets, in particular the encoder’s architecture, the loss function and the localization strategy. 2. We provide an extensive analysis of the characteristics of different dataset benchmarks, namely number, area and locations of bounding boxes, audio domains and scene complexity, and discuss their biases in the evaluation of visual sound source localization models. For reproducibility, we open source code and model weights\textsuperscript{1}.

2. Design choices for localization

The different models variations that we study are summarized in Table 1, along with their main modular design choices. All models exploit a ResNet audio encoder, but they differ on the different components that affect the model’s performance both quantitatively and qualitatively in different datasets, in particular the encoder’s architecture, the loss function and the localization strategy. Further, we study the interaction between these decisions, the model performance, and the data, by digging into different evaluation datasets spanning different difficulties and characteristics, and discuss the implications of such decisions in the context of real-world applications. Our code and model weights are open-sourced and made available for further applications.

\textbf{Table 1: Summary of models and the different design choices.}

<table>
<thead>
<tr>
<th>Models</th>
<th>Image Enc</th>
<th>Loss</th>
<th>Localization</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCGrad</td>
<td>ResNet</td>
<td>Contrastive</td>
<td>Grad-CAM [19]</td>
</tr>
<tr>
<td>CLIPsGradTran</td>
<td>ViT</td>
<td>Contrastive</td>
<td>Transf-MM [20]</td>
</tr>
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</table>

\textsuperscript{1}\texttt{github.com/hohsiangwu/rethinking-visual-sound-localization}

2.1. Audio-visual encoders

We use two sets of audio-visual encoders. The first one RC, inspired by LVS [17], consists of ResNet audio and image encoders, which we initialize randomly for the audio encoder and with ImageNet for the image encoder following [17]. We train this model using contrastive loss on VGGSound. We randomly sample 5-second videos from the training split, use the corresponding audio as input to the audio encoder, and randomly select one image frame from the video.

The second one CLIPAudio exploits the vision transformer (ViT) [21] from CLIP [22], which was trained with millions of image-text pairs from the internet, and the audio encoder from Vav2CLIP [23], also a ResNet distilled from CLIP via VGGSound with contrastive loss to project audio embeddings into...
the same space as CLIP’s text and image embeddings. We use the pre-trained models from CLIP\(^2\) and Wav2CLIP\(^3\).

2.2. Loss functions
All models use a specific type of contrastive learning, namely InfoNCE [24]. The main difference is that LVS [17] compares between audio and image sub-patches w/ hard negative mining for regions within an image [17], while the other models compare the entire audio and image samples.

2.3. Localization techniques
Cosine similarity with sub-patches: LVS is trained to localize the sound source within the image sub-patches, therefore, the model output consists of localization heatmaps computed using the cosine similarity between the audio and image patches, with interpolation from size 14x14 to actual image size [17].

Gradient-based (Grad-CAM [19]) (Grad): Grad-CAM directly considers the gradients of the loss with respect to the input of each layer, computed and aggregated through back-propagation, in order to generate heatmaps. We use the Grad-CAM implementation\(^4\), which we modify so instead of back-propagating the one-hot encoded class labels, we back-propagate the entire audio embedding as is. We follow the best performing results in [19] and select the output of the first normalization layer in the last block of the ResNet encoder as our target layer. For more detail information, please refer to the original paper [19].

Transformer-based (Transformer-MM [20]) (Tran): This approach is designed specifically for transformer models. It combines ideas from both relevancy and attention based explainability methods, by looking at self-attention layers in the encoders. These attention maps of each layer are aggregated recursively through back-propagation in order to generate relevancy maps. We use the implementation\(^5\) provided from the authors, and back-propagate both Wav2CLIP audio embeddings and CLIP text embeddings for our study on each modality.

We use the Gradient-based explainability technique with RC because neither encoder is a transformer, and the Transformer-based one with CLIPAudio since in preliminary experiments this technique greatly outperformed Grad-CAM when using ViT [20]. We call these models RCGrad and CLIPAudioTran respectively. To better understand the role of the ViT encoder in CLIPAudio and its match with the Wav2CLIP audio encoder, we include the results of localization using CLIP (CLIPText), i.e. using the image and text encoders for the datasets with available text labels.

3. Experimental design
3.1. Evaluation datasets
We focus our analysis in four different datasets for sound source localization, spanning different sound sources and localization difficulties, as depicted in Table 2.

**Flickr-SoundNet (FS)** [10] testset is a popular benchmark for visual sound source localization. It contains 250 image audio pairs with 20s audio with 3 annotation bounding boxes from different annotators. We follow the same pre-processing steps as [17] and take overlapped region agreed on from at least two annotators as ground-truth.

**VGGSS (VS)** [17] is a new dataset released with real-world urban traffic scenes, featuring vehicle labels including car, motorcycle, bus and truck. It is a video dataset of 10-second clips and stereo audio, with video annotations at 2fps with variety of bounding boxes number ranging from 1 to 25, along with sound events annotations in the audio. We sampled audio-image pairs of 1s audio with the image centered, and we only take those samples with labeled bounding boxes overlapping with audio annotations, resulting in 10802 image frames.

<table>
<thead>
<tr>
<th>Dataset</th>
<th># Frames</th>
<th># BBoxes</th>
<th>Audio Len</th>
<th>Domain</th>
<th>Labels</th>
</tr>
</thead>
<tbody>
<tr>
<td>FS [10]</td>
<td>250</td>
<td>1</td>
<td>20s</td>
<td>General</td>
<td>N</td>
</tr>
<tr>
<td>VS [17]</td>
<td>4436</td>
<td>1-5</td>
<td>10s</td>
<td>General</td>
<td>Y</td>
</tr>
<tr>
<td>MS [12]</td>
<td>455</td>
<td>2</td>
<td>1s</td>
<td>Music</td>
<td>N</td>
</tr>
<tr>
<td>US [25]</td>
<td>10802</td>
<td>1-25</td>
<td>1s</td>
<td>Vehicle</td>
<td>Y</td>
</tr>
</tbody>
</table>

Table 2: Evaluation datasets: Flickr-SoundNet (FS), VGGSS (VS), Music Synthesis (MS), and Urbansas (US).

With more than one bounding boxes per each image of 220 classes. We are able to acquire 4436 10-second videos from YouTube, and we use the center image frame as originally proposed in [17].

**Music Synthesis (MS)** [12] is a synthetic audio-visual music dataset. Each audio-visual pair is constructed by concatenating four music instrument frames and randomly selecting two out of four to be the ones producing sound, with corresponding 1s audio, resulting in 455 pairs.

**Urbansas (US)** [25] is a new dataset released with real-world urban traffic scenes, featuring vehicle labels including car, motorcycle, bus and truck. It is a video dataset of 10-second clips and stereo audio, with video annotations at 2fps with variety of bounding boxes number ranging from 1 to 25, along with sound events annotations in the audio. We sampled audio-image pairs of 1s audio with the image centered, and we only take those samples with labeled bounding boxes overlapping with audio annotations, resulting in 10802 image frames.

3.2. Baselines
Figure 2 shows the characteristics of each dataset, these statistics illustrate the type of scenes that compose the different datasets. Flickr-SoundNet and VGGSS have most of their bounding boxes located in the middle of the image and occupying a considerable portion of the image, with more than half of the frames covering over 30% of it. These two datasets are totally (FS) or mostly composed (89.3%, VS) of clips with a single bounding box (i.e. one sounding object at a time). Inspired by this, we think that a good naive baseline for these datasets would be one bounding box centered in the middle of the image covering at least 50% of it.

In contrast, all examples in Music Synthesis have at least two sources, and bounding boxes are considerably smaller than the previous two datasets, with most of them being less than 30% of the image, and their centers are very precisely located in one of four quadrants in the image. We hypothesize that a good baseline in this case would be to locate four boxes in four of those quadrants spanning 1/8 of the image, since it would consistently hit half of the ground-truth positions. Finally, Urbansas bounding boxes are also almost always smaller than 30% of the image, but their location is very difficult to predict naively, since the dataset comprises images of moving vehicles that constantly move from side to side of the image and thus the center of the bounding boxes not concentrated in any particular section. Urbansas also has different amounts of sounding vehicles per scenes, with the majority of the dataset having one or two. Given that there is no clear naive baseline for this dataset, we use a bounding box centered in the middle covering 50% of the image, which will cover most cases with multiple vehicles and their location in the scene.

The intuition behind these baselines is to help us understand the difficulties of each dataset as well as how much improvement the models get from the simplest things we could do with the data. Besides these baselines, we compare with the state-of-the-art (SOTA) models for Flickr-SoundNet and VG-

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\(^2\)https://github.com/openai/CLIP
\(^3\)https://github.com/descriptinc/lyrebird-wav2clip
\(^4\)https://github.com/jacobgil/pytorch-grad-cam
\(^5\)https://github.com/hila-chefer/Transformer-MM-Explainability
GSS [17] (LVS), trained with specific localization and hard negative mining, and for Music Synthesis [12] (DSOL), trained on music domain data specifically, and require object-level representations. We use the LVS model provided by the authors, pre-trained with VGGSound [26], an audio-visual YouTube video dataset containing ~200k 10-second clips (16kHz sample rate) labeled with 309 multi-classes, and follow [17] for the implementation to output localization heatmaps.

Figure 1: Examples of different models (LVS, RCGrad, CLIPAudioTran, CLIPTextTran) performance on VGGSS and Urbansas. GT is ground-truth. Top two rows are examples where models perform better on average, bottom two rows are worse on average.

Figure 2: Top row is the distribution (in percentage number of frames) of the bounding boxes' area (red dotted line) and predicted heatmap area (solid color for different models) percentage to the entire image. Middle row is the location distribution of each bounding box in the resized 224x224 images. Bottom row is the number of bounding boxes per frame in different datasets.

3.3. Evaluation metrics
Following [10, 17], we apply the same post-processing of output heatmap predictions by min-max normalization, outputting heatmaps with values between 0 and 1. For metrics, we compute the consensus intersection over union (cIoU), namely cIoU@0.5 for Flickr-SoundNet and VGGSS following previous works, meaning that we binarize the heatmap predictions with a threshold equal to 0.5. For Music Synthesis, we use cIoU@0.3 in order to compare with [10], and we also apply cIoU@0.3 for Urbansas. We report the area under curve (AUC) as well, to do so, we compute the IoU with different thresholds.

4. Results and discussion
Results are presented in Table 3. Note that the LVS results (FS and VS) in Table 3 are different from the original paper [17], which could be due to slightly different data.

4.1. Qualitative analysis: what are the models localizing?
Figure 1 shows some qualitative examples of the model predictions. We observe that LVS tends to predict big regions in the center of the image regardless of the scene, RCGrad tends to adapt better across scenes, and CLIPAudioTran tends to predict smaller heatmap regions than the others (top two rows), and predict larger regions when the scenes are challenging (bottom two rows). For instance, in the first two rows under VS, CLIPAudioTran seems to predict the actual sounding part (chimes in the clock, head of a bird) instead of the entire object, causing IoU to drop. This is an interesting observation that distillation from CLIP might actually attend to more granular sound sources.

The third row under US in Figure 1, shows an example where the models under-perform, this happens particularly when the objects are very small in the scene, and when there are other background noises interfering (e.g., wind or background crowds). In these challenging situations, both RCGrad and CLIPAudioTran tend to also focus on other regions of the image. We hypothesize that this could improve by pre-processing the audio to enhance differences between foreground versus background sounds [27]. An interesting example is depicted in the last row of Figure 1 under US. In this case, there are two vehicles in the scene, one is parked and the other one is moving, and the latter is producing sound and thus is the one annotated. Both RCGrad and CLIPAudioTran focus on the larger vehicle parked by the street, which would be a mistake in a monitoring system. This prediction makes sense since the models do not have any temporal context, and we will explore in future work relying on the sequence of images instead of independent frames, and combining with multi-channel audio in order to exploit phase differences indicative of the objects position and motion.
4.2. Looking deeper: baselines and datasets distributions

Looking at both the actual distribution of predicted heatmaps in Figure 3, and middle row of Figure 2, we can see that LVS always predict around 50% of area regardless of the datasets, which fits well with the bounding box area distribution from FS and VS, indicating also why we see good performance from our naive baseline models by predicting a box at the center with 50% of the image’s area. In the case of MS and US, the objects appear in smaller areas in the image, so the results of LVS are worse, even than the naive baselines as in Table 3.

Among all models, RCGrad is the one that adapts better to the different datasets, as can be seen by how the area of the predictions matches more closely the ground-truth in Figure 2 (middle row) and 3 for most cases, especially MS and US. That also is reflected in its performance in those datasets as in Table 3. CLIPAudioTran tends to produce predictions that cover big areas when it is uncertain, and though it seems to work well in FS and VS, there is a big gap in performance between this model and the rest as in Table 3, which suggests that the predictions are focusing on the actual sounding area when the model does well and are likely miss-placed when the model is uncertain, both causing IoU to drop.

4.3. How does the loss function affect the localization?

Comparing LVS with RCGrad in Table 3, we see that the performance of RCGrad is better in FS, relatively close to LVS in VS [17], and significantly better than the other models in MS and US. RCGrad’s consistent performance across datasets and the trends present in Figure 2 suggest that the hard-negative sampling and learn to localize modules (with size 14x14) might not be able to provide the granularity required for MS and US. For Music Synthesis, RCGrad outperforms SOTA [12], which is originally trained on a music dataset with extra object level representations, indicating that training with simple contrastive loss might be sufficient, and generalize better to different domains. An important outcome of our analysis is that the evaluation dataset considerably mediates the conclusions on the usefulness of the different modules of the system for the localization of visual sources, so it is critical to have a diverse set of datasets featuring different conditions and challenges to be able to properly understand them.

4.4. What is the impact of the encoder choice?

When comparing CLIPAudioTran with RCGrad, we are seeing a big gap in performance, especially for more challenging datasets, i.e. MS and US. This is to our surprise since ViT is a more powerful image encoder (w/ 87.8M parameters, compared to 11.7M for ResNet), and maintains spatial information better than ResNet [28]. Also, CLIP is trained with massive amounts of data, and Wav2CLIP shows pretty promising results in most audio classification tasks [23]. To understand this difference better, we look at CLIPTextTran, as shown in Table 3. CLIPTextTran performs well in both VS and US, even better than RCGrad. This result aligns with our intuition that the ViT encoder and the exposure to considerable amounts of data during training should make CLIP-based models more competitive. The fact that RCGrad does better than CLIPAudioTran potentially indicates that there might be semantic mismatch between image-text and image-audio for the distillation from CLIP to Wav2CLIP, which it might be better to train image-text and audio from scratch, or that the distillation from image and text to audio should be done using more data.

5. Conclusions

In this work, we discuss the impact of different design choices and dataset evaluation benchmarks in the adaptability and understanding of localization methods. Furthermore, we study the interaction between these decisions, the model performance, and the data, by digging into different evaluation datasets spanning different difficulties and characteristics, and discuss the implications of such decisions in the context of real-world applications. We also show that it is critical to have evaluation datasets featuring diverse conditions, including location of sources, number of sources and size. For future work, we would like to explore the use of pre-processing and de-noising techniques to help boost the foreground objects versus the background noises in the audio, include temporal context via sequences of images, and include spatial information from multi-channel audio to further distinguish moving from still objects.
6. References


