LISA: Localized Image Stylization with Audio
via Implicit Neural Representation

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Abstract

We present a novel framework, Localized Image Stylization with Audio (LISA) which performs audio-driven localized image stylization. Sound often provides information about the specific context of the scene and is closely related to a certain part of the scene or object. However, existing image stylization works have focused on stylizing the entire image using an image or text input. Stylizing a particular part of the image based on audio input is natural but challenging. In this work, we propose a framework that a user provides an audio input to localize the sound source in the input image and another for locally stylizing the target object or scene. LISA first produces a delicate localization map with an audio-visual localization network by leveraging CLIP embedding space. We then utilize implicit neural representation (INR) along with the predicted localization map to stylize the target object or scene based on sound information. The proposed INR can manipulate the localized pixel values to be semantically consistent with the provided audio input. Through a series of experiments, we show that the proposed framework outperforms the other audio-guided stylization methods. Moreover, LISA constructs concise localization maps and naturally manipulates the target object or scene in accordance with the given audio input.

1. Introduction

Audio-guided image stylization transfers the style from sound to an image without changing the content of the original image. While recent audio-guided image stylization works show promising results by learning the audio-visual...
relationship [21–23], they modify the entire image’s style, which makes the output unrealistic if the image content does not match with the target style. Also, these approaches are unsuitable for the image editing application since users cannot select the desired content to stylize.

To alleviate these issues, early approaches leverage a segmentation map to localize the stylizing area after changing the style of the entire image [4, 19, 39, 42]. As these segmentation maps are often obtained by a pre-trained supervised semantic segmentation network, the segmentation area is limited by the pre-defined object categories. Moreover, previous approaches directly copy the background part from the source image to the stylized image using a binary mask, thus the final results look unnatural with rough object boundaries.

As sound is typically associated with a specific part of the scene or an object, this information can be used to localize the area. Recent studies [5, 27] show that the model can learn to localize sound source objects by aligning audio and visual features without any ground-truth data. However, these approaches use a class-specific activation map or a heatmap learned by audio-visual features to locate the sound source object. Therefore, the localization is not pixel-level accurate which affects the quality of stylization. In this work, we introduce a pixel-level localization based on input sound which is used for stylizing the image locally.

Furthermore, many image stylization approaches [11, 16, 18, 20, 25] use convolution neural network (CNN) architecture as a backbone to stylize the image. These methods often produce boundary artifacts, as shown in Fig. 8, since they do not support direct pixel-wise mapping. To reduce the artifacts, we design stylizing network as Implicit Neural Representation (INR) [40] to generate per-pixel values based on audio input given corresponding pixel coordinates.

The proposed framework consists of two stages. First, we design an audio-visual localizer to localize sounding objects or scenes in an image. Specifically, we train the audio-visual localizer to predict segmentation maps with pseudo ground-truth by zero-shot text-based segmentation networks in a weakly supervised manner. Second, the localized object or scene is stylized based on the semantics of the input sound via INR which maps each RGB pixel value from the coordinate that corresponds to the semantic meaning of the input sound. Finally, given the localization map as the probability mask predicted by the audio-visual localizer, the style of the source image is manipulated to match the semantics of the audio by leveraging the multi-modal shared embedding space.

In our extensive experiments, our method outperforms other localized [19], text-guided [20] and sound-guided [22, 23] state-of-the-art methods. As shown in Fig. 1, given the Engine sound input and source image named “Howl’s Moving Castle”, the castle is localized. Then a style of burning castle is produced with the fire crackling sound with a subsequent audio input. We demonstrate various examples in the supplemental material and project website. In this study, our main contributions are listed as follows:

- We propose a novel audio-guided image localized stylization. In particular, our method is able to perform partial stylization without manually producing a segmentation mask by using sound source localization.
- We carefully design implicit neural representation for style transfer to achieve naturalness. We demonstrate that this structure is effective in removing boundary artifacts. With INR, our method can stylize the source image at any arbitrary resolution.
- We achieve state-of-the-art performance compared with the existing sound source visual localization methods. Using a pseudo-ground-truth segmentation mask from images and text joint representation, we improve the quality of the audio-visual source localization that generates concise object or scene boundaries.

2. Related Work

Audio-Driven Image Stylization. Audio-driven image manipulation approaches have demonstrated the usefulness of sound for manipulating the style and appearance of objects in an image. A few works show promising visual synthesis results with sound [9, 38]. A typical task to generate from a speech sound is a neural talking head [7, 45, 46, 48], which aims to synchronize sound and head with various priors related to the face, such as keypoints and head pose. Lee et al. manipulates the image to be suitable with the semantics of the sound, such as fire crackling by leveraging pre-trained CLIP-based [33] audio embedding space in StyleGAN latent space [22]. Li et al. shows successful audio-guided image stylization [23] in an unsupervised manner. However, those works are not able to perform localized image editing. Instead, we can edit the images with the sound semantics and sound source localization using the audio-visual localizer.

Localized Image Style Transfer. Localized image style transfer is defined as stylizing specific parts of the source image instead of the whole image. Gatys et al. [12] utilize the predefined binary mask for spatial control of stylization. Alegre et al. [2] proposed a framework to stylize the source image using facial semantic segmentation. Castillo et al. [4] and Virtusio et al. [42] present a method that smoothly merges the extracted stylized object with the background. Xia et al. [43] also propose the mask enhancement network to smooth the edge of the mask. Despite the promising results, the methods above are highly dependent on the class-based pre-trained models, which do not consider how to obtain the mask in the real world. Text2LIVE [3] is the first to adopt the mask-free approach for localized image editing by text
In this paper, we propose a novel audio-guided localized image stylization method. As shown in Fig. 2, our model consists of two main parts: (i) Audio-Visual Localizer, which outputs a pixel-level localization mask conditioned on an audio input (e.g., given a sound of engine noise input, our model localizes a train from the source image, producing a probability mask) and (ii) Audio-Guided INR Stylizer, which outputs stylized images by taking pixel locations as input and producing RGB pixel values as output. Conditioned on a new user-provided sound input (e.g., splashing plastic bag), our model is optimized with multi-scale PatchCLIP loss to generate an audio-guided “locally” stylized image. We also use Foreground Regularization Loss to make the stylized image and a source image perceptually look similar.

Figure 2. An overview of our proposed method called Localized Image Stylization with Audio (LISA). Our model consists of two main parts: (i) Audio-Visual Localizer, which outputs a pixel-level localization mask conditioned on an audio input (e.g., given a sound of engine noise input, our model localizes a train from the source image, producing a probability mask) and (ii) Audio-Guided INR Stylizer, which outputs stylized images by taking pixel locations as input and producing RGB pixel values as output. Conditioned on a new user-provided sound input (e.g., splashing plastic bag), our model is optimized with multi-scale PatchCLIP loss to generate an audio-guided “locally” stylized image. We also use Foreground Regularization Loss to make the stylized image and a source image perceptually look similar.

Audio-Visual Sound Source Localization. A few works demonstrate that audio-visual localization can localize the region of the image where the sound comes from without ground truth [5, 27, 41]. LVS [5] proposes a mechanism that mines hard negative samples to formulate contrastive learning with a differentiable threshold. EZ-VSL [27] introduces multiple instances contrastive learning to focus on the most aligned regions in audio-visual representation. However, those works have a limitation in that they cannot create a delicate audio-visual source localization map because they learn to produce a localization map without any supervision. Zhou et al. [47] proposed the pixel-level segmentation of the sounding object in a supervised manner. To overcome the class-limited problem, we propose a weakly supervised audio-visual source localization by leveraging a powerful knowledge of zero-shot text-based segmentation [26].

Implicit Neural Representations (INRs). Neural implicit networks are defined as fields parameterized by multi-layer perceptrons and have the advantage of being able to encode a continuous signal at an arbitrary resolution [44]. INRs recently have shown that neural fields can be represented successfully for various domains with coordinates as input [13, 14, 32, 36]. This approach can capture high-frequency signals, which conventional convolutional neural networks cannot. In addition, implicit neural representations have the advantage of fast optimization speed and a small number of parameters. Following the powerful novel view synthesis capabilities of neural radiance fields, many style transfer studies focus on producing a stylized novel view [8, 15, 17, 28]. Inspired by these works, we propose implicit neural representations for audio-guided localized stylization.

3. Method

In this paper, we propose a novel audio-guided localized image stylization method. As shown in Fig. 2, our model has two main components: (i) Audio-Visual Localizer (Sec. 3.1) and (ii) Audio-guided INR Stylizer (Sec. 3.2). Our Audio-visual Localizer predicts a pixel-level localization mask given a sound input (e.g., given a sound of “engine noise,” our model localizes a train from a source image). Conditioned on this localization map, our Audio-guided INR Stylizer outputs a “locally” stylized image according to the semantics of the new user-provided audio sources (e.g., given a sound of “a splashing plastic bag,” our model stylizes a train from a source image accordingly).

3.1. Audio-Visual Localizer

As shown in Fig. 3, our audio-visual localizer produces a pixel-level probability mask given a sound input. This module is implemented based on a general encoder-decoder architecture. Our audio encoder is pre-trained jointly with the image-text CLIP embedding space (Sec. 3.1.1), producing $d$-dimensional latent representation $\mathbf{z}_a \in \mathbb{R}^d$. Given this $\mathbf{z}_a$ and a latent representation for a source image $\mathbf{z}_v$, our Transformer-based Audio-Visual Decoder is trained to produce a binary segmentation mask (Sec. 3.1.2).

3.1.1 Pre-training Audio Encoder

Inspired by Lee et al. [22], we first map the audio embeddings to the image-text CLIP embedding space via contrastive learning. We adopt the InfoNCE loss [1] to map the same scene with different modalities close to each other while that of different scenes are far away in the CLIP em-
Figure 3. An overview of our Audio-visual Localizer, which identifies an image region corresponding to the sound input (e.g., localizing a train based on a sound of engine noise), producing a probability mask as an output. Due to the lack of data to supervise, we leverage the existing text-guided zero-shot segmentation model [26], using its output as a pseudo label.

bedding space [33]. Furthermore, Lee et al. apply contrastive learning between audio latent representations as well as cross-modal. To generalize this technique, we interpolate the latent representations \( z_{av} \in \mathbb{R}^d \) linearly between audio embedding \( z_a \in \mathbb{R}^d \) and visual embedding \( z_v \in \mathbb{R}^d \) as

\[
\hat{z}_{av} = \alpha \cdot z_a + (1 - \alpha) \cdot z_v, \quad (1)
\]

where \( \alpha \) is randomly sampled from \([0, 1]\). We employ the augmented audio input and image to obtain diverse latent representations \( \hat{z}_a, \hat{z}_v \in \mathbb{R}^d \). In the same way, we obtain \( \hat{z}_{av} \in \mathbb{R}^d \) with \( z_a \) and \( z_v \).

Given mini-batches of size \( N \) of interpolated latent representations, we minimize the InfoNCE loss with the interpolated latent representation pairs \( \{z_{av}^i, \hat{z}_{av}^i\} \) for \( i \in \{1, 2, ..., N\} \) as follows:

\[
\mathcal{L}_{\text{ctr}}(i) = - \log \frac{\exp (\hat{z}_{av}^i \cdot \hat{z}_{av}^i / \tau)}{\sum_{k=1}^{N} \exp (\hat{z}_{av}^i \cdot \hat{z}_{av}^k / \tau)}, \quad (2)
\]

where \( \tau \) is the temperature scale and \( \cdot \) denotes the cosine similarity. Note that those latent representations are \( l_2 \)-normalized. Then, we minimize the following loss term \( \mathcal{L}_{\text{ctr}} \), defined in Eq. 3, for all positive latent representation pairs in each mini-batch.

\[
\mathcal{L}_{\text{ctr}} = \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}_{\text{ctr}}(i). \quad (3)
\]

For audio augmentation, we adopt the SpecAugment [31] that generates augmented Mel-spectrogram acoustic features. This augmentation strategy randomly warps the features and masks blocks in frequency channels.

### 3.1.2 Audio-Visual Decoder

**Weakly-Supervised Learning.** After pre-training the audio encoder, our audio-visual decoder learns to produce a pixel-level sound source location probability mask conditioned on the audio latent representation. Given audio, randomly sampled middle frame, and text descriptions \( x_a, x_v, x_t \) from the video, we obtain \( l_2 \)-normalized vector \( z_a, z_t, z_v \). With the pre-trained audio encoder and CLIP image, text encoder. Then, we generate the pseudo ground-truth mask using text-based zero-shot segmentation, CLIPSeg [26]. Given the input image of width \( W \) and height \( H \), we compute the pseudo-segmentation mask \( M_{\text{pseudo}} \in \mathbb{R}^{1 \times W \times H} \) as follows:

\[
M_{\text{pseudo}} = \begin{cases} 
1 & \sigma(F_v(x_v, z_i)) > \text{threshold}, \\
0 & \text{otherwise}, 
\end{cases} \quad (4)
\]

where \( \sigma \) denotes the sigmoid function. CLIPSeg decoder \( F_v \) predicts the segmentation map \( M_{\text{pseudo}} \) with text latent representation \( z_i \) and the input image \( x_v \). In the same way, audio-visual decoder \( F_a(\cdot, \cdot) \) outputs \( M_{\text{pred}} \in \mathbb{R}^{1 \times W \times H} \) by \( F_a(x_v, z_a) \) conditioned on the input image \( x_v \) and audio latent representation \( z_a \) as follows:

\[
M_{\text{pred}} = \sigma(F_a(x_v, z_a)). \quad (5)
\]

**Loss Function.** We minimize pixel-wise binary cross entropy loss between \( M_{\text{pseudo}} \) and the predicted segmentation mask \( M_{\text{pred}} \) as follows:

\[
\mathcal{L}_{\text{bce}} = \frac{1}{W \cdot H} \sum_{i} \sum_{j} M_{\text{pred}}^{(i,j)} \cdot \log M_{\text{pred}}^{(i,j)} + (1 - M_{\text{pred}}^{(i,j)}) \cdot \log M_{\text{pred}}^{(i,j)},
\]

where \( W, H \) denotes the width and height of the output probability mask and the pseudo mask.

### 3.2 Audio-Guided INR Stylizer

To locally stylize an image based on the audio input, we introduce an audio-guided INR stylizer. It consists of three modules: mask generator, INR, and multi-scale patching, shown in Fig. 2. First, our mask generation process outputs the probability mask to determine the degree of style within the segmentation area of the sounding object using the pre-trained audio-visual localizer. Using the probability mask, the INR module predicts pixel-level continuous neural fields of style via multi-layer perceptron (MLP). We also introduce the multi-scale patch sampling in CLIP embedding space to make the stylized image more realistic and dynamic.

**Mask Generation Process.** Given audio input \( x_a \) and the source image \( I_x \in \mathbb{R}^{3 \times W \times H} \), we first create a mask to stylize only a specific part of the source image. Audio latent representation \( z_a \) is obtained by the pre-trained audio encoder. Then, we use the pre-trained audio-visual localizer \( F_a \) to generate the probability mask \( M \in \mathbb{R}^{1 \times W \times H} \) for sounding object or scene in the source image. \( M \) is formulated as follows:

\[
M = \sigma(F_a(I_x, z_a)), \quad (7)
\]
which enhances high-frequency details \[40\].

The goal of INR is to stylize the specific object or scene in the source image by using the predicted probability mask from the mask generator. Given the source image \(I_x\), the implicit neural network \(f_\theta : \mathbb{R}^2 \rightarrow \mathbb{R}^d\) is optimized with parameters \(\theta\) by mapping the pixel location \((i,j)\) in \(I_y\) into RGB pixel values \((r, g, b)\). Formally, the stylized image \(I_y\) is composited by the output of implicit neural representation \(f_\theta\) and the pixel value of the source image as follows:

\[
I_y(i, j) = M(i, j) \cdot f_\theta(\gamma(i, j)) + (1 - M(i, j)) \cdot I_x(i, j).
\]

(8)

Fourier feature mapping function \(\gamma\) encodes the pixel coordinate to higher dimension space before feeding into MLP, which enhances high-frequency details \[40\].

**Multi-Scale Patch Sampling.** Given the source image and the INR output. We split the foreground \(M(i, j) \cdot f_\theta(\gamma(i, j))\) and background \((1 - M(i, j)) \cdot I_x(i, j)\). The foreground is then used for multi-scale patching, and the background is copied to obtain the final stylized image. We crop the foreground into \(K\) number of patches denoted by \(P_k\) for \(k \in \{1, ..., K\}\) where the pixel location of the patch center is in the segmentation mask with the predicted probability mask. The scale of each patch is selected randomly and each patch of the foreground is obtained by random augmentation strategy. We use these patches instead of the whole image to compute the similarity between audio and image embeddings in CLIP embedding space. This multi-scale patch sampling helps to produce more dynamic and realistic style patterns as shown in the experiment section (Fig. 9).

### 3.2.1 Training

For training, we use two losses: multi-scale PatchCLIP loss and foreground regularization loss. To stylize the source image with the audio input, we minimize the cosine distance in CLIP embedding space \[33\] between the latent representation of audio and the multi-scale patches from the output of INR. Furthermore, we propose a foreground regularization loss to preserve the content of the source image by minimizing the pre-trained VGG feature distance between the source image and the stylized image.

**Multi-Scale PatchCLIP Loss** \(L_{CLIP}\): Following Kwon et al. \[20\], we adopt the PatchCLIP loss to minimize cosine distance between randomly cropped patches and target audio in the CLIP embedding space. Given stylized patches \(P_k\) and audio, we employ a CLIP-based visual and audio encoder to obtain visual and audio latent representation \(v_k, a \in \mathbb{R}^d\). We minimize multi-scale PatchCLIP loss as follows:

\[
L_{CLIP} = \frac{1}{K} \sum_{k=1}^{K} (1 - \langle \Delta v_k, a \rangle),
\]

(9)

where \(K\) denotes the number of sampled patches. The visual direction \(\Delta v\) is computed by subtracting the embedding of the \(k\)-th cropped patch \(v_k\) and the visual embedding of the source image. \(\langle \Delta v_k, a \rangle\) represents the cosine similarity, i.e. \(\Delta v_k, a = \Delta v_k \cdot a / ||\Delta v_k|| ||a||\). Online hard example mining (OHEM) \[35\] is also applied to select a small number of hard examples, which avoids stylizing only the easy patches during optimization. Instead of minimizing the average of the cosine distances for each patch, we arrange the patches in the order of the largest cosine distance and then minimize the number of patches with large distances.

**Foreground Regularization Loss** \(L_{reg}\): Preserving the source image is crucial for local stylization. To obtain a perceptually reasonable stylized image, we apply perceptual loss \[18\] to the entire image as follows:

\[
L_{reg} = \sum_{k=0}^{K} |G_k(\mathcal{I}_y) - G_k(\mathcal{I}_x)|,
\]

(10)

where \(G_k^\phi\) denotes the gram matrix of \(k\)-th layer’s respective feature maps from the pre-trained VGG-16 network. We
minimize the $L_1$ loss between the gram matrix of the source image and that of the stylized image.

**Total Loss.** Ultimately, we minimize the following loss function $L_{\text{total}}$:

$$L_{\text{total}} = \lambda_{\text{CLIP}} L_{\text{CLIP}} + \lambda_{\text{reg}} L_{\text{reg}} + \lambda_{c} L_{c},$$  \hspace{1cm} (11)

where $\lambda_{\text{CLIP}}$, $\lambda_{\text{reg}}$, and $\lambda_{c}$ are hyperparameters to tune the strength of each term. We also apply content loss function $L_{c}$ following Johnson et al. [11], which helps preserve the visual properties of the source image by minimizing the mean squared error between the features of the source and the output images with the pre-trained VGG-19 [10].

### 4. Experiments

#### 4.1. Implementation Details

**Datasets.** We composite two different dataset for pre-training audio encoder and decoder: Greatest Hits [30] and VGG-Sound [6] for mapping CLIP embedding space [33] with audio latent representation. VGG-Sound contains large-scale audio-visual pairs. The number of audio-visual pairs in the VGG-Sound dataset is over 200K. However, we collect 155,040 videos for training due to missing video clips on YouTube. The Greatest Hits dataset includes various audios of hitting and scratching various objects with a drumstick. The number of the Greatest Hits training dataset is 733 videos in total. Note that there is no ground-truth for the segmentation mask in the composited dataset.

**Training Details of Audio-Visual Localizer.** To represent the audio latent vector, we adopt Swin-S [24] architecture as the audio encoder backbone and the output dimension of the audio encoder is 512. Audio-visual decoder follows the CLIPSeg [26] architecture. We employ the (ViT-B/16) CLIP transformer-based decoder [33]. The input image size is fixed as $352 \times 352$ for training the audio-visual decoder for 20 epochs with Adam optimizer. We choose the cosine cyclic learning rate scheduler. The batch size for training is determined as 160.

**INR Architecture.** We follow the basic structure of implicit neural representation instead of the conventional U-Net-based approach. Based on Tancik et al. [40], we replace ReLU activation with SIREN [36]. The parameters of MLP (8 layers, 256 channels, SIREN activation) are trained with Fourier feature mappings.

**Hyperparameter Setup.** We use $512 \times 512$ resolution for training. For localized style transfer, we remove the global CLIP loss which is defined in CLIPStyler [20]. The loss weight $\lambda_{\text{CLIP}}$, $\lambda_{\text{reg}}$, $\lambda_{c}$ is set to 35, 0.2, 2. We randomly select the multi-scale patch sizes in the range $[64, 256]$.

#### 4.2. Comparision to Baselines

To the best of our knowledge, our work is the first to attempt audio-driven localized stylization of sounding objects from the wild image. We compare our method to several state-of-the-art image stylization methods carefully.

**Localized Style Transfer.** To compare our method to a mask-based style transfer model, we choose CBStyling [19] as a baseline. Fig. 4 shows the qualitative comparison of our method to the previous approach. To obtain mask, our method uses the audio input as a condition and generates the mask using audio-visual localizer. However, CBStyling requires reference style image and mask with full class supervision. For fairness, we report the CBStyling result with the same sound source localization map. We observe that our proposed model produces more realistic stylized image.
than CBStyling on the edge of the predicted mask. This is because the previous blending approaches simply crop the result of the stylization using mask and paste it into the source image. However, our INR-based method jointly optimizes the stylization loss and foreground regularization loss.

**Audio-Guided Image Stylization.** We compare our model to the existing audio-driven image stylization methods. We select two baselines: Lee et al. [22] and AVStyle [23]. As Fig. 5 shows, none of the existing audio-guided image stylization methods perform localized image stylization. Although Lee et al. changes specific parts of scenes with semantic cues from audio, the area of stylization is not controllable (see 2nd row, 3rd column). Furthermore, Lee et al. fails to maintain some geometric features, such as the shape of tree branches (see 1st row, 3rd column). Note that Lee et al. cannot manipulate diverse wild image domains because their work needs the mapping function of the input image to the latent space of the pre-trained generative model. AVStyle fails to stylize the image with out-of-domain audio (e.g., explosion), which is not included in the audio-visual training dataset. In contrast, our method can cover various audio by leveraging CLIP embedding space [33].

**Interactive Stylization with Audio & Text.** We compare our style transfer model to state-of-the-art text-driven image editing models, CLIPStyler [20] and Text2LIVE [3]. Note that our model can perform image stylization under various audio and text conditions because our audio latent representation shares with CLIP embedding space. Fig. 6 demonstrates that our model produces more reasonable stylization results at the object boundary than Text2LIVE. This is because our method explicitly provides the predicted probability mask as a condition. We further show more examples in the supplementary material.

### 4.3. Audio-Visual Localizer

**Qualitative Analysis.** In qualitative comparisons, we visualize the localization with a state-of-the-art audio-visual source localization model, LVS [5] which is pre-trained with the full VGG-Sound [6] dataset. We sample images from the Flickr SoundNet sound localization dataset [34] to qualitatively evaluate audio-visual source localization. We qualitatively demonstrate our audio-visual localization method by visualizing the heatmap in Fig. 7. We observe that our model has the capability of producing a more precise audio-visual source localization performance compared to other baselines.

**Quantitative Evaluation.** In Table. 1, we quantitatively compare our audio-visual source localization with existing audio-visual source localization methods. We choose LVS [5] and EZ-VSL [27] as baselines for audio-visual source localization. Baseline models have trained in an unsupervised manner with the full VGG-Sound [6] dataset.

![Figure 7. Localization quality comparison with existing state-of-the-art sound-based visual localization methods, including LVS [5] and EZ-VSL [27]. For each method, we visualize a predicted heatmap of sound-based localization.](image)

| Model       | SSL Metric | CIoU (%) | AUC (%) |
|-------------|------------|----------|---------|
| LVS [5]     | 73.59 %    | 59.00 %  |
| EZ-VSL [27] | 83.94 %    | 63.60 %  |
| Ours        | 85.94 %    | 66.70 %  |

We choose the Flickr SoundNet testset [34] for quantitative evaluation. We measure the two metrics for sound source localization, Consensus Interaction over Union (CIoU), and the Area Under Curve (AUC). We set a CIoU threshold as 0.5 for all baselines.

### 4.4. Ablation Study

**Effect of INR in Style Transfer.** Fig. 8 demonstrates that implicit neural representations are effective in artifact removal for local stylization. The first row is the result of stylization with audio Thunderstorm, and the second row is the airplane image stylized with text condition Desert. The downscaling and upscaling operation with zero-padding in the U-Net-based style transfer [20] loses fine-level visual details and generates line-shaped border artifacts [29] at the edge of the stylized image. On the contrary, our styled result produces a clean image without any disturbance of the perceptual naturalness since our INR maps $(x, y)$ coordinate directly into an RGB pixel value without affecting neighboring pixels.

**Multi-Scale PatchCLIP Loss.** Fig. 9 shows the stylization results according to multi-scale PatchCLIP loss. We compare
Figure 8. Stylization quality comparison between conventional U-Net-based [20] vs. INR-based approach (ours). Note that the former suffers from artifacts near borders, while the INR-based approach generates clearer images.

Figure 9. Effect of our Multi-scale PatchCLIP loss compared to a model with Single-scale PatchCLIP loss given a fixed patch size. By increasing the patch size as follows: 64×64, 256×256, and multi-scale patches. We observe that a larger patch size results in a larger stylization area in the source image. By using multi-scale patches, we can produce more dynamic and realistic style patterns.

The Number of SIREN Layers. We perform the ablation study about the number of fully-connected SIREN [36] layers. We compare the stylization results by increasing the number of SIREN layers to 2, 8, 14, and 20. As the number of layers increases, the style change becomes finer, and more iterations are required for convergence, which results in more time consumption (see the supplemental material).

4.5. User Study

We gather 100 participants from Amazon Mechanical Turk to assess whether our proposed method is realistic from a human perspective. Participants are asked 20 questions with binary choices to validate our proposed method. We investigate two factors, including Naturalness and Attribute Consistency. Participants are required to answer binary choice questions to assess our method against the other method directly.

Since AVStyle [23] and Lee et al. [22] do not have localization capability, we stylize the global region of the source image. For a fair comparison, we give CBStyling [19] the same sound source localization map as our model because CBStyling uses a different segmentation network from ours. Fig. 10 shows that our method excels the other state-of-the-art methods in terms of stylization naturalness (69.83% in average) and attribute consistency (84.47% in average).

5. Discussion

Limitation. The implicit function offers fast training time compared to existing CNN-based models. However, since the CLIP loss is a bottleneck, the overall optimization speed is similar to that of the CLIPStyler.

Broader Impact. We can stylize user-desired parts of the source image with the audio input. Since our model stylizes images solely on user intention, the images that the user stylized can raise ethical concerns or may apply a style that is opposite to the intention of the original image creator.

6. Conclusion

In this work, we propose a novel framework for audio-guided local image stylization, named LISA. Audio-visual sound source localizer provides a delicate localization map by leveraging the CLIP embedding space in a weakly supervised manner. Using this localization map, the coordinate-based implicit neural representation effectively produces more realistic and vivid stylization results than cut-and-paste approaches. We also observe that our network helps to remove line-shaped border artifacts that existed in CNN-style mapping structures. Moreover, our method is able to perform text-driven local and semantic stylization as well as audio because our audio latent representation shares CLIP embedding space.
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Supplementary Material

Overview. In this supplementary material, we provide implementation details including the training setting and evaluation protocol (Section A). Next, this supplementary material also provides an additional ablation study with a different set of hyperparameters to see their effects on the quality of audio-guided localized image stylization (Section B). Lastly, in Section C, we provide more qualititative results with a variety of sound sources.

A. Implementation Details

A.1. Audio-Visual Localizer

Training Details of Audio-Visual Encoder. For training the audio encoder, we use the composited dataset as mentioned in the main paper. Each audio in the dataset is a 10-second log and sampled at frequencies of 44.1 kHz. Given a raw audio input, we preprocess audio inputs to produce Mel-spectrogram acoustic features. For each video clip, we randomly sample the middle frame and employ it as an input image (30fps). We resize the middle frame to the image with resolution of 224×224. We use Adam optimizer with the cosine cyclic learning rate scheduler [37]. We set the learning rate to 10^{-4} with the momentum 0.9 and weight decay 10^{-4}. We use a batch size of 320. We adopt SpecAugment [31] for audio augmentation with the frequency mask ratio of 0.15 and time masking ratio of 0.15.

Training Details of Audio-Visual Decoder. We use the same composited dataset as the audio encoder is trained. We also preprocess audio inputs to produce Mel-spectrogram acoustic features. To generate a pseudo-segmentation mask, the corresponding text prompts are extracted from the short text descriptions (e.g. people giggling). We adopt the following decoder architecture as CLIPSeg [26], a zero-shot text-based segmentation model. Given the input image 352×352, the pre-trained CLIP [33] visual transformer projects activations of the internal layer to the 64 visual token embedding with patch size 16. The audio-visual decoder outputs the binary segmentation with a linear projection on the transformer’s visual tokens at the last layer.

Evaluation Details. We compare our method to other sound source localization baselines. At the evaluation stage, the localization maps are resized to 224×224. For audio preprocessing, we extract the Mel-spectrograms and resize the audio input to 128×512.

A.2. Audio-Guided INR Stylizer

Training Details of INR. We train our INR by using Multi-Layer Perceptron (MLP) with 8 layers and 256 channels. Each MLP layer uses SIREN [36] activation, except the output layer. We use 3 channels for the output layer without an activation function. Following Tan-ck et al. [40], we use Gaussian mapping γ for Fourier feature mapping function, which is computed as \( \gamma(v) = [\cos(2\pi 10 B v), \sin(2\pi 10 B v)]^T \), where \( v \) denotes the pixel coordinate and each \( B \in \mathbb{R}^{m \times d} \) is sampled from \( \mathcal{N}(0, \sigma^2) \). We set \( m \) as 256 and \( d \) as 2, respectively. \( \sigma \) is set to 1. We use Adam optimizer with a learning rate of 10^{-4}. Stylizing one source image of size 512×512 with our audio-guided INR stylizer takes one minute to train on a single GPU (NVIDIA RTX 3090) for a total of 200 iterations.

B. Ablation Study

Effect of Foreground Regularization Loss. To show the effect of foreground regularization loss, we conduct an ablation study. We use two different settings for the ablation study: training the INR without \( \mathcal{L}_{\text{reg}} \), without \( \mathcal{L}_{\text{c}} \). Fig. 14 demonstrates that the stylized image can maintain the content of the source image by applying \( \mathcal{L}_{\text{c}}, \mathcal{L}_{\text{reg}} \).

Effect of Audio-Visual Localizer. We conduct an ablation study on applying different audio-visual localization maps to our localized style transfer (see Fig. 11). We choose LVS [5] and EZ-VSL [27] as the baselines. Then, we show that our localization map helps create the locally stylized images. In particular, our method prevents rough stylization at the boundary of the object.

Effect of INR Optimization for Local Area. We compare our method to a naïve approach that attaches globally stylized images to the source images. As Fig. 15 shows, we observe that optimizing the INR over the localized area helps...
the semantics of the audio to appear in the foreground. For
example, given the pond image, and the target sound “Grass
Scratching”, we stylize an image over the entire area (see
Fig. 15 (a)) and then multiply the localization map for the
sound of “Water” (see Fig. 15 (b)). As shown in Fig. 15 (c),
the foreground of the stylized image is more highly associ-
ated with this audio semantic.

C. Qualitative and Quantitative Results

The Number of SIREN Layers. As mentioned in the pa-
ter, we analyze the effect according to the number of fully-
connected SIREN [36] layers. As Fig. 12 shows, we compare
the stylization results by increasing the number of SIREN
layers to 2, 8, 14, and 20. When the number of layers is two,
INR cannot represent the style in the foreground. However,
when the number of layers is increased to 8, the style in the
foreground becomes more realistic. As the number of layers
increases, more iterations are required for convergence, re-
sulting in more time consumption. Specifically, the required
time to optimize the INR is 37, 48, 61, and 72 seconds, as
the number of layers is 2, 8, 14, and 20, respectively.

Stylizing High-Resolution Image. As Fig. 16 shows, we
also perform localized image stylization with high-resolution
input images. We compare the stylization results of CLIP-
styler [20] and our method. We observe that our stylized
image is more realistic than the CLIPstyler. There are two
reasons: multi-scale patching and INR. While CLIPstyler
uses too small patches for the given high-resolution image,
our method adjusts the patch size for stylization. Moreover,
our approach can capture high-frequency details using INR,
which can stylize the source image even in high resolution.

Additional Qualitative and Quantitative Examples. Fig 17
shows interactive stylization results with different
types of condition modality using multi-modal joint em-
bedding space. We provide the stylization results for four
combinations of audio and text as follows:

- Audio-localized & text-guided image stylization.
- Text-localized & audio-guided image stylization.
- Text-localized & text-guided image stylization.

Furthermore, we compare our method with text-driven lo-
calized image stylization, Text2LIVE [3]. Since audio and
text and image share the CLIP embedding space, our method
can also stylize the image with the user-provided text de-
scriptions. First, we create a probability mask with CLIPSeg,
a zero-shot text-based segmentation. Then, we perform lo-
calized image stylization with our INR-based optimization.
As shown in Fig 18, we observe that Text2LIVE shows dis-
torted structures on the outside of the target area, whereas
our method produces a natural image without disturbing
background areas.

Additional User Study. We conduct an additional user
study to compare our method with Text2LIVE [3]. As men-
tioned in the paper, we assemble 100 participants from Amaz-
on Mechanical Turk (AMT). For a fair comparison, we
perform text-localized image stylization. Fig 13 shows that
our method is competitive to text-localized image stylization.

User Study Details. Our user study contains two parts for
the evaluation of naturalness and attribute consistency. Each
section consists of 20 random binary choice questions that
compare our method to one of the baselines (AVStyle [23]
and Lee et al [22] and CBStyling [19]). We emphasize
that our user study is anonymous and does not collect any
personally identifiable data.
Figure 14. Effect of our Foreground Regularization loss. $L_c, L_{reg}$ preserve the visual properties of the source image. The yellow box denotes the localization map conditioned by *Car Sound* and "church" respectively from top to bottom. The red box denotes a magnified image of the border area in each stylized image.

Figure 15. Effect of INR optimization for the local area. (a), (b), and (c) refers to sound-guided global stylization, an image pasted into the source image by cutting the mask area from (a), and our local area optimization approach, respectively. While (b) fails to stylize the local area, our method (c) stylizes the semantics of the audio to be well-matched to the local area.
Figure 16. Comparison of stylizing high-resolution image (1536 × 1024) using CLIPstyler [20] and ours. Unlike CLIPstyler, our method can generate a realistic style even for a high-resolution image.
Figure 17. Interactive stylization results with different types of condition modality. The first to second rows use audio as a localization condition, and from the third to last rows localization is conditioned by text prompt. For stylization conditions, from second to fourth columns are conditioned by audio, and from fifth to the final column is conditioned by text prompts. The red box at each source image indicates a predicted sound source localization map, respectively.
Figure 18. Additional comparison between Text2LIVE [3] and Ours. Text2LIVE shows distorted structures on the outside of the target area. However, our approach stylizes the foreground of the source image per-pixel with maintaining the background.