# Separate Anything You Describe

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https://audio-agi.github.io/Separate-Anything-You-Describe

***Abstract*—Language-queried audio source separation (LASS) is a new paradigm for computational auditory scene analysis (CASA). LASS aims to separate a target sound from an audio mixture given a natural language query, which provides a natural and scalable interface for digital audio applications. Recent works on LASS, despite attaining promising separation performance on specific sources (e.g., musical instruments, limited classes of audio events), are unable to separate audio concepts in the open domain. In this work, we introduce AudioSep, a foundation model for open-domain audio source separation with natural language queries. We train AudioSep on large-scale multimodal datasets and extensively evaluate its capabilities on numerous tasks including audio event separation, musical instrument separation, and speech enhancement. AudioSep demonstrates strong separation performance and impressive zero-shot generalization ability using audio captions or text labels as queries, substantially outperforming previous audio-queried and language-queried sound separation models. For reproducibility of this work, we will release the source code, evaluation benchmark and pre-trained model at: https://github.com/Audio-AGI/AudioSep.**

***Index Terms*—sound separation, language-queried audio source separation (LASS), natural language processing.**

## I. Introduction

COMPUTATIONAL auditory scene analysis (CASA) [1] aims to design machine listening systems that perceive complex sound environments in a similar way as the human auditory system does. Sound separation is a fundamental research task for CASA, which aims to separate real-world sound recordings into individual source tracks, also known as the "cocktail party problem" [2]. Sound separation has a wide range of applications, including audio event separation [3], [4], music source separation [5], and speech enhancement [6], [7].

Many previous works on sound separation mainly focus on separating one or a few sources such as speech enhancement [6], [7], speech separation [8], [9], and music source separation [5]. Recently, universal sound separation (USS) [4] has attracted a lot of research interest. USS aims to separate arbitrary sounds in real-world sound recordings. Separating every sound source from a mixture is challenging due to the vast variety of sound sources existing in the world. As an alternative, query-based sound separation (QSS) has been addressed which aims to separate specific sound sources conditioned on a piece of query information. QSS allows users to extract desired audio sources which could be useful in many applications such as automatic audio editing [10] and multimedia content retrieval [11]. Using the query of different modalities such as vision [12]–[14], audio [15]–[18] or label [19]–[22] for sound separation has been investigated in the literature.

Recently, a new paradigm of QSS has been proposed, known as language-queried audio source separation (LASS) [3]. LASS is the task of separating arbitrary sound sources using natural language descriptions of the desired source. LASS provides a potentially useful tool for future digital audio applications, allowing users to extract desired audio sources via natural language instructions. Compared with previous vision-queried [12]–[14] or audio-queried [15]–[18] methods, utilization of natural language queries offers significant advantages, such as flexible and convenient acquisition of query information. Compared with label-queried [19]–[22] methods that usually pre-define a fixed set of label categories, LASS does not limit the scope of input queries and can be seamlessly generalized to open domain.

The challenge of learning a LASS system is associated with the complexity and variability of natural language expressions. The text query description could range from sophisticated descriptions of multiple sound sources, such as "*people speaking followed by music playing with a rhythmic beat*" to simple and compact phrases such as "*speech, music*". In addition, the same audio source can be delivered with diverse language expressions, such as "*music is being played with a rhythmic beat*" or "*an upbeat music melody is playing over and over again*". LASS not only requires these phrases and their relationships to be captured in the language description but also one or more sound sources that match the language query should be separated from the audio mixture.

The original approach [3] for LASS relies on supervised learning with labeled audio-text paired data, however, such annotated audio-text data is limited in size. To overcome the data scarcity issue, recent advancements have investigated training LASS with multimodal supervision [23]–[25]. The key idea behind this approach is to leverage multimodal contrastive pre-training models such as the contrastive language-image pretraining (CLIP) model, as the query encoder. As contrastive learning is capable of aligning text embedding with other modalities (e.g., vision), it enables the training of the LASS system using data-rich modalities and facilitates inference with text in a zero-shot mode. However, existing LASS methods leverage small-scale data for training and focus on separating restricted source types, such as musical instruments and a limited set of sound events. The potential of generalizing LASS to open-domain scenarios such as hundreds of real-world sound sources has not been fully explored. Furthermore,

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previous works on LASS evaluate model performance on each domain-specific test set, which makes future comparison and reproduction inconvenient and inconsistent.

In this work, our goal is to establish a foundation model for sound separation with natural language descriptions. Our focus is on the development of a pre-trained sound separation model, leveraging large-scale datasets, to enable robust generalization in open-domain scenarios. With this model, we aim to holistically address the separation of a diverse range of sound sources. This work is an extension of our original work on LASS [3]. The contribution of this work includes:

- We introduce AudioSep, a foundation model for open-domain, universal sound separation with natural language queries. AudioSep is trained with large-scale audio datasets and has shown strong separation performance and impressive zero-shot generalization capabilities.
- We extensively evaluate AudioSep. We constructed a comprehensive evaluation benchmark for LASS research, involving numerous sound separation tasks such as audio event separation, musical instrument separation, and speech enhancement. AudioSep substantially outperforms off-the-shelf audio-queried sound separation and state-of-the-art LASS models.
- Additionally, we conduct in-depth ablation studies to investigate the impact of scaling up AudioSep using large-scale multimodal supervision [23]–[25]. Our findings provide valuable insights for future direction.
- We will release the code, benchmark, and pre-trained model at: https://github.com/Audio-AGI/AudioSep to promote research in this area.

## II. Related Work

### A. Universal sound separation

Sound separation is a fundamental research task in CASA, which aims to separate real-world sound recordings into individual source tracks. A substantial amount of previous research has been concentrated on domain-specific sound separation, focusing primarily on areas such as speech [8], [9] or music [5]. Universal sound separation (USS) [4] aims to separate a mixture of arbitrary sound sources in terms of their classes. The challenge inherent in USS is the vast diversity of sound classes in real-world scenarios, which increases the difficulty of separating all of these sound sources with a single sound separation system. The work in [4] reported promising results on separating arbitrary sounds using permutation invariant training (PIT) [26], a supervised method initially designed for speech separation. The PIT method uses synthetic training mixtures simulated from single-source ground truth, performing sub-optimally due to a mismatch in the distribution between these synthetic mixtures and real-world sound recordings. Furthermore, it is not feasible to record a large database of single sources for PIT, as such sound recordings are often tainted by cross-talk. An unsupervised method called mixture invariant training (MixIT) [27] is proposed for sound separation using noisy audio mixtures. MixIT has achieved competitive performance compared to supervised methods (e.g., PIT), showing substantial improvements in reverberant sound separation performance. Both [4], [27] methods need a post-selection process to classify separated sources into specific sound classes.

### B. Query-based sound separation

Query-based sound separation (QSS) also known as target source extraction, aims to separate a specific source from an audio mixture given query information. Existing QSS approaches could be divided into three categories: the vision-queried method, the audio-queried method, and the label-queried method. We will introduce each one below.

*1) Vision-queried sound separation:* In the computer vision community, there has been active research focusing on utilizing visual information as queries to extract target sounds in speech [28], [29], music [12], and acoustic events [13]. AudioScope [14] has been recently proposed to perform on-screen sound separation based on the MixIT method. Such vision-queried approaches are beneficial for automatically decomposing sound sources from audio-visual video data. However, their performance is subject to the dynamic visibility conditions of visual objects, such as occlusion or low-light conditions. In addition, video data often contains off-screen sounds, learning from noisy audio-visual data is a key challenge for vision-queried sound separation systems [14], [23].

*2) Audio-queried sound separation:* Another line of research leverages the audio modality as a query to separate acoustically similar sounds. Studies by [17], [18] have addressed the problem of using one or few examples of a target source as the query to separate a particular sound source, which is known as one-shot or few-shot sound separation. These methods separate the target sound conditioned on the average audio embedding of a few audio examples of the target source, which requires labeled single sources for training. The work in [15], [16] proposes to train the audio-queried sound separation system with large-scale weakly labeled data (e.g., AudioSet [30]), which is achieved by first using a sound event detection model [31] to detect the anchor segment of sound events which are further used to constitute the artificial mixtures for the training of audio-queried sound separation models. These audio-queried sound separation approaches have shown great potential in the separation of unseen sound sources. However, during the test time, the preparation of reference audio samples for the desired sound is often a time-consuming process.

*3) Label-queried sound separation:* The most intuitive way to query a specific sound source is to use the label of its sound class, as studied in the [19]–[22]. Although acquiring a label query is effortless compared to the audio or visual query, the label set is often pre-defined and adheres to a finite set of source categories. This imposes a challenge when attempting to generalize the separation system into an open-domain scenario, which often requires re-training the sound separation model or using complicated methods such as continual learning [20], [32]. In addition, label information lacks the capability to describe the relationship between multiple sound events such as their spatial relation and temporal order. This poses a challenge when the user intends to separate an entire soundscape rather than isolate a single sound event.

### C. Language-queried audio source separation

Language-queried audio source separation (LASS) is a recently proposed new paradigm of QSS. LASS uses the natural language description of the target source to separate an arbitrary target source from an audio mixture. Such natural language descriptions can include auxiliary information for describing the target source such as spatial and temporal relationships of sound events, such as "*dog barks in the background*" or "*people applaud followed by a woman speaking*". LASS systems could seamlessly generalize into open-domain scenarios due to the unrestricted scope and flexible nature of language descriptions.

LASS-Net [3] is the first attempt that performs end-to-end language-queried sound separation. LASS-Net consists of a language query encoder and a separation model. The separation model performs target source separation in the frequency domain and the target waveform is reconstructed using the noisy phase and inverse short-time Fourier transform (STFT). LASS-Net is trained on a subset ($\sim$17.3 hours, 33 sound categories) of the AudioCaps [33] dataset and has shown great success in separating universal sounds using audio caption queries. Similar to the architecture of LASS-Net, Kilgour et al. [24] proposed a model that accepts audio or text queries in a hybrid manner. Tzinis et al. [34] propose an optimal condition training (OCT) strategy for LASS. OCT performs greedy optimization toward the highest-performing condition among multiple conditions associated with a given target source, which improves the separation performance.

Above LASS methods [3], [24], [34] require labeled text-audio paired data for supervised training, while such labeled data is often limited in practice. Recent work [23], [25] has investigated the potential of the self-supervised approach for LASS, particularly, these approaches leverage the visual modality as a bridge to learn the desired audio-textual correspondence. Instead of using a uni-modal text encoder (e.g., BERT [35]) [3], Dong et al. [23] use the contrastive language-image pretraining (CLIP) [36] model as the query encoder and train the LASS model conditioned on the visual context of unlabeled noisy videos. Thanks to the aligned embedding space learned by the CLIP model, at the inference time, the separation model can be queried with text inputs in a zero-shot setting. The experimental results show that combining text and image conditions for hybrid training leads to better text-queried sound separation performance on musical instrument separation. In summary, although preliminary studies have been undertaken into LASS, existing approaches work under the constraints of limited-source scenarios, such as musical instruments and a restricted set of universal sound classes. As such, these approaches have not met the expectation of LASS for zero-shot, open-domain sound separation.

### D. Multimodal audio-language learning

Recently, the field of audio and language has emerged as an important research area in audio signal processing and natural language processing. Multi-modal audio-language tasks hold immense potential in various application scenarios. For instance, automatic audio captioning [37]–[44] aims to provide meaningful language descriptions of audio content, benefiting the hearing-impaired in comprehending environmental sounds. Language-based audio retrieval [45]–[49] facilitates efficient multimedia content retrieval and sound analysis for security surveillance. Text-to-audio generation [50]–[58] aims to synthesize audio content based on language descriptions, serving as sound synthesis tools for filmmaking, game design, virtual reality, and digital media, and aiding text understanding for the visually impaired. Contrastive language-audio pre-training (CLAP) [59] aims to learn an aligned audio-text embedding space via contrastive learning, which facilitates downstream audio-text multimodal tasks (e.g., zero-shot audio classification) [60], [61]. In this work, we focus on the cross-field of audio source separation and natural language processing, which is a valuable and promising field for CASA research but less explored.

## III. AudioSep

We next describe AudioSep, a foundation model for open-domain sound separation with natural language queries. AudioSep has two key components: a text encoder and a separation model, as illustrated in Figure 1. We will introduce the details of each component below.

### A. Text encoder

We use the text encoder of the contrastive language-image pre-training model (CLIP) [36] or contrastive language-audio pre-training model (CLAP) [59] to extract the text embedding of the natural language query. The input text query is denoted as $q = \{q_n\}_{n=1}^{N}$, consisting of a sequence of $N$ tokens, which is processed by the text encoder to obtain the text embedding for the input language query. The text encoder encodes the input text tokens via a stack of transformer blocks. After passing through the transformer layers, the output representations are aggregated, resulting in a fixed-length $D$-dimensional vector representation, where $D$ corresponds to the latent dimension of the CLIP or CLAP. The text encoder is frozen during training.

CLIP is pre-trained on large-scale image-text paired data via contrastive learning, its text encoder learns to map textual descriptions to the same semantic space as the visual representations. The advantage of using the text encoder of CLIP in our task is, we are able to train or scale up the LASS model from large-scale unlabeled audio-visual data [23], by using visual embedding as an alternative. CLIP enables the training of LASS models without the need for annotated audio-text paired data [23], [25]. Similar to CLIP, CLAP connects language and audio by using an audio encoder and a text encoder via a contrastive learning objective, bringing audio and text descriptions into a joint audio-text latent space. The text encoder of CLAP represents the text descriptions aligned to the audio context, which may be more suitable for the LASS task. However, in the literature, it remains uncertain which of the text encoders in CLIP and CLAP is more suitable for LASS, particularly with large-scale multimodal supervision, in open-domain scenarios. In this work, we benchmark the performance of CLIP and CLAP and show our observation in the experiments section.

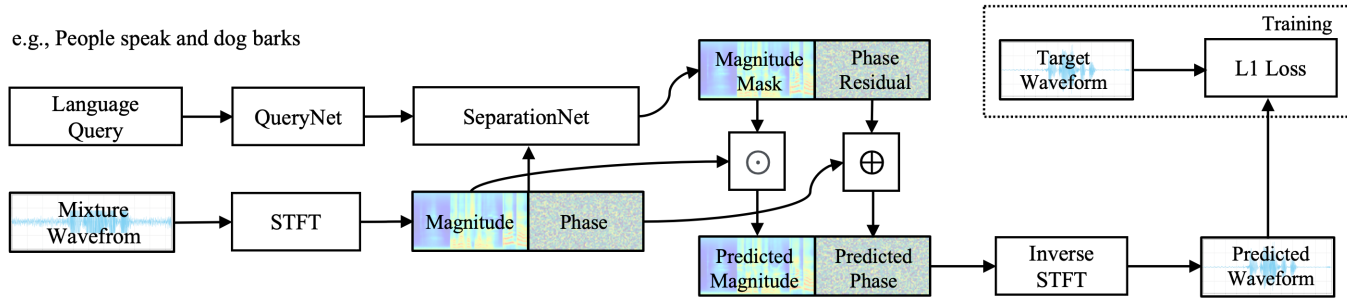


Fig. 1. Framework of AudioSep.

### *B. Separation model*

We apply the frequency-domain ResUNet model [5], [15] as the separation backbone. The input to the ResUNet model is a mixture of audio clips. First, we apply a short-time Fourier transform (STFT) on the waveform to extract the complex spectrogram $X \in \mathbb{C}^{T \times F}$, the magnitude spectrogram and phase of $X$ are denoted as $|X|$ and $e^{j\angle X}$, where $X = |X|e^{j\angle X}$. Then, we follow the same setting of [15], and we construct an encoder-decoder network to process the magnitude spectrogram. The ResUNet encoder-decoder comprises 6 encoder blocks, 4 bottleneck blocks, and 6 decoder blocks. In each encoder block, the spectrogram is downsampled into a bottleneck feature using 4 residual convolutional blocks, while each decoder block utilizes 4 residual deconvolutional blocks to upsample the feature and obtain the separation components. A skip connection is established between each encoder block and the corresponding decoder block, operating at the same downsampling/upsampling rate. The residual block consists of 2 CNN layers, 2 batch normalization layers, and 2 Leaky-ReLU activation layers. Furthermore, we introduce an additional residual shortcut connecting the input and output of each residual block. The ResUNet model inputs the complex spectrogram $X$ and outputs the magnitude mask $|M|$ and the phase residual $\angle M$ conditioned on the text embedding $e_q$. $|M|$ controls how much the magnitude of $|X|$ should be scaled, and the angle $\angle M$ controls how much the angle of $\angle X$ should be rotated. The separated complex spectrogram can be obtained by multiplying the STFT of the mixture and the predicted magnitude mask $|M|$ and phase residual $\angle X$:

$$\hat{S} = |M| \odot |X|e^{j(\angle X + \angle M)}, \tag{1}$$

where $\odot$ is the Hadamard product.

To bridge the text encoder and the separation model, we use the Feature-wise Linearly modulated (FiLm) layer [62] after each ConvBlock deployed in the ResUNet. Specifically, let $H^{(l)} \in \mathbb{R}^{m \times h \times w}$ denote the output feature map produced by ConvBlock $l$ with $m$ channels, here $h$ and $w$ are the height and width of the feature map $H^{(l)}$, respectively. The modulation parameters are applied per feature map $H_i^{(l)}$ with the FiLm layer as follows:

$$\mathrm{FiLM}(H_i^{(l)}|\gamma_i^{(l)}, \beta_i^{(l)}) = \gamma_i^{(l)} H_i^{(l)} + \beta_i^{(l)}, \tag{2}$$

where $H_i^{(l)} \in \mathbb{R}^{h \times w}$, and $\gamma^{(l)}, \beta^{(l)} \in \mathbb{R}^m$ are the modulation parameters from $g(.)$, i.e., $(\gamma, \beta) = g(e_q)$, such that $g(.)$ is a neural network and $e_q$ is the text embedding obtained from the text encoder. In this work, we model $g(\cdot)$ with two fully connected layers followed by ReLU activation, which is jointly trained with the ResUNet separation model.

### *C. Loss and training*

During training, we use the loudness augmentation method proposed in [15]. When constituting the mixture $x$ with $s_1$ and $s_2$, we first calculate the energy of $s_1$ and $s_2$ as $E_1$ and $E_2$ by $E = \|s\|_2^2$. We then apply a scaling factor $\alpha = \sqrt{E_1/E_2}$ to $s_2$ so that the $s_1$ and $s_2$ have the same energy:

$$x = s_1 + \alpha s_2. \tag{3}$$

We train AudioSep end-to-end using an L1 loss function between the predicted and ground truth waveforms. As waveform-based L1 loss is simple to implement and has shown good performance on universal sound separation tasks [15].

$$l = \|s - \hat{s}\|_1 , \tag{4}$$

where $l$ is the loss function, the lower loss value indicates the separated signal $\hat{s}$ is closer to the ground truth signal $s$.

## IV. Datasets and Evaluation Benchmark

In this section, we provide a detailed description of the training dataset used for AudioSep, along with the established evaluation benchmark. The statistics of the dataset are presented in Tables I and II.

### *A. Training datasets*

*1) AudioSet:* AudioSet [30] is a large-scale, weakly-labelled audio dataset with 2 million 10-second audio snippets sourced from YouTube. Each clip in the collection is categorised by the presence or absence of sound classes, without the specificity of knowing the timing of sound events. AudioSet includes a broad ontology[1] of 527 distinct sound classes, such as “Human sounds”, “Music”, “Natural Sounds”, among others. The training set comprises 2 063 839 clips, which also includes a balanced subset of 22 160 audio clips. For each sound class in the balanced training set, there are at least 50 audio clips. After accounting for unavailable YouTube links, we were able to download 1 934 187 audio clips with

[1] https://research.google.com/audioset/ontology/index.html

their corresponding video streams, equating to 94% of the complete training set. All the clips are either padded with silence or cut short to a duration of 10 seconds. All audio clips are padded with silence or truncated into 10 seconds. Due to the fact that a large amount of YouTube audio recordings have a sampling rate below 32 kHz, we have converted all audio recordings to a mono format and resampled them at 32 kHz. All audio clips within the training set are used as training data.

*2) VGGSound:* VGGSound [63] is a large-scale audio-visual dataset sourced from YouTube. VGGSound contains nearly 200 000 video clips of length 10 seconds, annotated across 309 sound classes consisting of human actions, sound-emitting objects, and human-object interactions. The creation process of VGGSound has ensured that the object producing each sound is also discernible in the corresponding video clip. We utilize the original version of the VGGSound dataset, which includes 183 727 audio-visual clips for training and 15 449 for testing. We resample all audio clips at 32 kHz. All data within the training split are used for our training process.

*3) AudioCaps:* AudioCaps [33] is the largest publicly available audio captioning dataset with 50 725 10-second audio clips sourced from AudioSet. AudioCaps is divided into three splits: training, validation, and testing sets. The audio clips are annotated by humans with natural language descriptions through the Amazon Mechanical Turk crowd-sourced platform. Each audio clip in the training sets has a single human-annotated caption, while each clip in the validation and test set has five ground-truth captions. We retrieved AudioCaps based on the AudioSet we downloaded. Our retrieved AudioCaps dataset contains 49 274/49 837 audio clips in the training set, 494/495 clips in the validation set, and 957/975 clips in the test set. All audio clips within the training and validation sets are used for our training process.

*4) Clotho v2:* Clotho v2 [64] is an audio captioning dataset that comprises sound clips obtained from the FreeSound platform[2]. Each audio clip in Clotho has been annotated via the Amazon Mechanical Turk crowd-sourced platform. Particular attention was paid to fostering diversity in the captions during the annotation process. In this work, we use Clotho v2 which was released for Task 6 of the DCASE 2021 Challenge[3]. Clotho v2 contains 3839, 1045, and 1045 audio clips for the development, validation, and evaluation split respectively. The sampling rate of all audio clips in the Clotho dataset is 44 100 Hz, each with five captions. Audio clips are of 15 to 30 seconds in duration and captions are 8 to 20 words long. We merge the development and validation split, forming a new training set with 4884 audio clips. All audio clips within the new training set and evaluation set are resampled at 32 kHz.

*5) WavCaps:* WavCaps [65] is a recently released large-scale weakly-labeled audio captioning dataset, comprising 403 050 audio clips with paired captions, totaling approximately 7568 hours. The audio clips constituting WacCaps originate from diverse sources, including FreeSound, BBC Sound Effects[4], SoundBible[5], and AudioSet. The audio captions are filtered and generated using the assistance of ChatGPT[6] based on the online-harvested raw audio descriptions. The average duration of audio clips is 67.59 seconds and the average text length of captions is 7.8 words. We resampled all audio clips within WavCaps at 32 kHz for training.

TABLE I
AUDIOSEP TRAINING DATASETS.

| | Caption | Label | Video | Num. clips | Hours |
|---|---|---|---|---|---|
| AudioSet | × | ✓ | ✓ | 2 063 839 | 5800 |
| VGGSound | × | ✓ | ✓ | 183 727 | 550 |
| AudioCaps | ✓ | ✓ | ✓ | 49 768 | 145 |
| Clotho v2 | ✓ | × | × | 4884 | 37 |
| WavCaps | ✓ | × | × | 40 350 | 7568 |

### B. Evaluation benchmark

*1) AudioSet:* The evaluation set of AudioSet [30] contains 20 317 audio clips with 527 sound classes. We downloaded 18 887 audio clips from the evaluation set (93%) out of 20 317 audio clips. Source separation on AudioSet presents a considerable challenge given that AudioSet encapsulates a vast and diverse range of sounds within a hierarchical ontology. To create evaluation data, we adopt the pipeline proposed in [15], which uses a sound event detection system [31] to each 10-second audio clip to pinpoint anchor segments. Subsequently, two anchor segments from different sound classes are selected and combined to form a mixture with a signal-to-noise ratio (SNR) at 0 dB. We generate 100 mixtures for each sound class, leading to 52 700 mixtures for all 527 sound classes in total.

*2) VGGSound:* Similar to [23], we manually curated 100 clean samples that each contain a distinct target sound event from the VGGSound test set, which we refer to as VGGSound-Clean. For each audio sample from VGGSound-Clean, we randomly selected 10 audio samples from the remaining VGGSound test set to construct mixtures. Specifically, following [66], we first uniformly sampled the loudness of the two audio samples between -35 dB and -25 dB LUFS (Loudness Units Full Scale); then we mixed the signals together. The mixtures were scaled to 0.9 if clipping occurred. Finally, we constructed an evaluation set with 1000 samples. The average SNR of the evaluation set is around 0 dB.

*3) AudioCaps:* Our downloaded test set of the AudioCaps dataset [33] includes 957 audio clips, each annotated with five captions. To generate audio mixtures, we initially select an audio clip from the test set to serve as the target source, followed by a random selection of another audio clip as the background source, ensuring that the sound event tag[7] of the background source does not coincide with that of the target source. For the test mixtures, each test audio is mixed with five randomly chosen background sources with an SNR at 0 dB. Each mixture is assigned one of the five audio captions of the target source. Consequently, 4785 test mixtures are created.

[2]https://freesound.org/
[3]https://dcase.community/challenge2021
[4]https://sound-effects.bbcrewind.co.uk/
[5]https://soundbible.com/
[6]https://openai.com/blog/chatgpt
[7]The sound event tags of each audio clip in AudioCaps can be retrieved from its corresponding AudioSet annotations.

*4) Clotho v2:* The Clotho v2 [64] evaluation set includes 1045 audio clips, each provided with five human-annotated captions. The duration of audio clips varies between 15 and 30 seconds. For the creation of test mixtures, we designate each audio clip in the evaluation set as a target source. Subsequently, we select two audio clips at random from the evaluation set, concatenate them, and then truncate it to match the length of the target source, thereby producing the interference source. Applying this pipeline, each audio clip in the evaluation set is mixed with five audio clips at an SNR of 0 dB. Each created mixture is then assigned one of the five audio captions of the target source. This procedure culminates in a total of 5225 mixtures for evaluation.

*5) ESC-50:* The ESC-50 dataset [67] contains 2000 environmental audio recordings evenly arranged into 50 semantic classes including natural sounds, non-speech human sounds, domestic sounds, and urban noise. Each class contains 40 examples, with each audio clip having a duration of 5 seconds and with a sampling rate of 44.1 kHz. To make a consistent evaluation, we first downsample all audio clips at 32 kHz. Then, we randomly mix two audio clips from different sound classes with an SNR at 0 dB to form a pair. We constitute 40 mixtures for each sound class. This leads to a total of 2000 evaluation pairs, which are used to evaluate the zero-shot performance of our model on environmental sound separation.

*6) MUSIC:* The MUSIC dataset [12] is a collection of 536 video recordings of people playing a musical instrument out of 11 instrument classes such as accordion, acoustic guitar, and cello. These video clips are crawled from YouTube and are relatively clean. Following the previous work [23], we downloaded the 46 video recordings in the test split. We further segment all test videos into non-overlapping 10-second clips and resampled them at 32 kHz. For each video segment, we randomly select one segment from each of the other instrument classes to create a mixture with an SNR at 0 dB, resulting in a total of 5004 evaluation pairs, which are used to evaluate the zero-shot performance of our model on musical instrument separation.

*7) Voicebank-Demand:* The Voicebank-Demand dataset [68] integrates the Voicebank dataset [68], which includes clean speech, and the Demand [69] dataset, which encompasses a variety of background sounds that are used to create noisy speech. The noisy utterances are created by mixing the Voicebank dataset and the Demand dataset under signal-to-noise ratios of 15, 10, 5, and 0 dB. The test set of the Voicebank-Demand dataset includes a total of 824 utterances, which is used to evaluate the zero-shot performance of our model on speech enhancement. To make a fair comparison with previous speech enhancement systems [6], [7], [70], [71], we resample all audio clips at 16 kHz. We use "Speech" as the input text query to perform speech enhancement.

### C. Evaluation metrics

We utilize signal-to-distortion ratio improvement (SDRi) [15], [20] and scale-invariant SDR (SI-SDR) [72] to evaluate the performance of sound separation tasks. For the speech enhancement task, following previous works [6], [7], [70], [71], we apply the Perceptual evaluation of speech quality (PESQ) [73], Mean opinion score (MOS) predictor of signal distortion (CSIG), MOS predictor of background-noise intrusiveness (CBAK), MOS predictor of overall signal quality (COVL) [74] and segmental signal-to-ratio noise (SSNR) [75] for evaluation. For each evaluation metric, higher values indicate better performance.

TABLE II
THE EVALUATION BENCHMARK FOR OPEN-DOMAIN SOUND SEPARATION WITH NATURAL LANGUAGE QUERIES.

| | Num. mixtures | Sr (Hz) | Query Type |
|---|---|---|---|
| AudioSet | 52 700 | 32 k | text label |
| VGGSound | 1000 | 32 k | text label |
| AudioCaps | 4785 | 32 k | caption |
| Clotho v2 | 5225 | 32 k | caption |
| ESC-50 | 2000 | 32 k | text label |
| MUSIC | 5004 | 32 k | text label |
| Voicebank-Demand | 824 | 16 k | text label |

## V. EXPERIMENTS

### A. Training Details

We randomly sample two audio segments from two audio clips from the training set and mix them together to constitute a training mixture. The length of the audio segment is 5 seconds. We extract the complex spectrogram from the waveform signal with a Hann window size of 1024 and a hop size of 320. We use the text encoder of CLIP [36] or CLAP [59] to extract the text embedding. For the CLIP model, we use the 'ViT-B-32' checkpoint. For the CLAP model, we use the publicly-available state-of-the-art checkpoint 'music_speech_audioset_epoch_15_esc_89.98.pt', which is trained on music, and speech datasets in addition to the original LAION-Audio-630k dataset [59]. The default configuration of AudioSep is using text supervision only. For processing video data, we uniformly extract frames with one-second intervals and compute their averaged CLIP embedding as the query embedding. For the separation model, we use a 30-layer ResUNet consisting of 6 encoder and 6 decoder blocks, which is the same as the previous work [15] on universal sound separation. Each encoder block consists of two convolutional layers with kernel sizes of $3 \times 3$. The number of output feature maps of the encoder blocks is 32, 64, 128, 256, 512, and 1024, respectively. The decoder blocks are symmetric to the encoder blocks. We apply an Adam optimizer with a learning rate of $1 \times 10^{-3}$ to train the AudioSep with the batch size of 96. We train the AudioSep model for 1M steps on 8 Tesla V100 GPU cards.

### B. Baseline systems

*1) LASS models:* We employ two state-of-the-art publicly available LASS models as the baseline system. The first one is LASS-Net [3], which uses a pre-trained BERT and ResUNet as the text query encoder and the separation model, respectively. LASS-Net is trained on a subset (~17.3 hours) of AudioCaps including universal sounds of categories such as human sounds, animal, sounds of things, natural sounds, and environmental sounds. The second one is CLIPSep, which uses

TABLE III
BENCHAMRK EVALUATION RESULTS OF AUDIOSEP AND COMPARISON WITH BASELINE SYSTEMS.

| | **AudioSet** | | **VGGSound** | | **AudioCaps** | | **Clotho** | | **MUSIC** | | **ESC-50** | | **VoicebankDemand** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SI-SDR | SDRi | SI-SDR | SDRi | SI-SDR | SDRi | SI-SDR | SDRi | SI-SDR | SDRi | SI-SDR | SDRi | PESQ | SSNR |
| USS-ResUNet30 [15] | - | 5.57 | - | - | - | - | - | - | - | - | - | - | 2.18 | 9.00 |
| USS-ResUNet60 [15] | - | 5.70 | - | - | - | - | - | - | - | - | - | - | 2.40 | **9.35** |
| LASSNet [3] | -3.64 | 1.47 | -4.50 | 1.17 | -0.96 | 3.32 | -3.42 | 2.24 | -13.55 | 0.13 | -2.11 | 3.69 | 1.39 | 0.98 |
| CLIPSep [23] | -0.19 | 2.55 | 1.22 | 3.18 | -0.09 | 2.95 | -1.48 | 2.36 | -0.37 | 2.50 | -0.68 | 2.64 | 2.13 | 1.56 |
| AudioSep-CLIP | **6.60** | **7.37** | 7.24 | 7.50 | 5.95 | 7.45 | 4.54 | 6.28 | **9.14** | **10.45** | 8.90 | 10.03 | 2.40 | 8.09 |
| AudioSep-CLAP | 6.58 | 7.30 | **7.38** | **7.55** | **6.45** | **7.68** | **4.84** | **6.51** | 8.45 | 9.75 | **9.16** | **10.24** | **2.41** | 8.95 |

CLIP [36] as the query encoder and Sound-of-Pixels (SOP) [12] based model for separation. CLIPSep [23] is trained with noisy audio-visual videos (∼500 hours) from VGGSound [63] dataset using hybrid vision and text supervision signal. In addition, CLIPSep employs a novel training strategy called noise invariant training (NIT), which enables robust learning from noisy video data. As the CLIPSep model is trained with 16 kHz sampling rate, we downsample the audio mixtures and corresponding ground truth signal to 16 kHz for evaluation. Both LASS-Net and CLIPSep are frequency domain separation models, the noisy phase is used to reconstruct the waveform in the test time.

*2) Audio-queried sound separation models:* We set audio-queried separation models as baseline systems. Kong et al. [15] proposed a universal sound separation system trained on the large-scale weakly labeled AudioSet, which can separate hundreds of sound classes using a single model. This system performs query-based sound separation by using the average audio embedding calculated from query examples from the training set as the condition. Empirical studies [15] conducted by Kong et al. have assessed the effectiveness of various sound separation systems such as ConvTasNet [9], UNet [76], and ResUNet [5], along with different audio embedding extractors such as PANNs [31] and HTSAT [77]. The conclusion indicates that the system combining PANNs and ResUNet achieved the best performance. As a result, we adopt the PANN-ResUNet separation model with 30 and 60 layers of the ResUNet as the baseline systems, denoted as USS-ResUNet30 and USS-ResUNet60, respectively.

*3) Speech enhancement models:* Following [7], we adopt four off-the-shelf speech enhancement models as the baseline system including Wiener [70], SEGAN [6], AudioSet-UNet [7], and Wave-U-Net [71]. Wiener [70] is a speech enhancement model based on signal processing methods. SEGAN is designed with the generative adversarial network [78]. AudioSet-UNet is a frequency-domain UNet-based model trained with weakly labeled AudioSet [30] data. Wave-U-Net is a time-domain UNet-based speech enhancement model.

### C. Evaluation results on seen datasets

We first assess the performance of AudioSep on seen datasets during training including AudioSet, VGGSound, AudioCaps, and Clotho, as shown in Table III. The AudioSep model with CLIP and CLAP text encoders are referred to as AudioSep-CLIP and Sound-CLAP, respectively. AudioSep has shown strong sound separation performance using text labels or audio captions as input queries. On the AudioSet, AudioSep-CLIP achieves an SI-SDR and SDRi of 6.6 dB and 7.37 dB across 527 hierarchy audio event classes, respectively. Comparatively, the AudioSep-CLAP achieved an SI-SDR of 6.58 dB and an SDRi of 7.3 dB. For the VGGSound dataset, the AudioSep-CLAP model demonstrated an SI-SDR of 7.38 dB and an SDRi of 7.55 dB. On the AudioCaps and Clotho datasets, the AudioSep-CLAP model achieved an SI-SDR of 6.45 dB and 4.84 dB, respectively, along with SDRi values of 7.68 dB and 6.51 dB, respectively. Overall, AudioSep-CLIP model under-performs AudioSep-CLAP on VGGSound, AudioCaps, and Clotho datasets, suggesting that the CLAP text embedding outperforms CLIP text embedding for universal sound separation.

TABLE IV
SPEECH ENHANCEMENT RESULTS ON VOICEBANK-DEMAND DATASET.

| | PESQ | CSIG | CBAK | COVL | SSNR |
|---|---|---|---|---|---|
| Noisy | 1.97 | 3.35 | 2.44 | 2.63 | 1.68 |
| Wiener [70] | 2.22 | 3.23 | 2.68 | 2.67 | 5.07 |
| SEGAN [6] | 2.16 | 3.48 | 2.94 | 2.80 | 7.73 |
| AudioSet-UNet [7] | 2.28 | 2.43 | 2.96 | 2.30 | 8.75 |
| Wave-U-Net [71] | 2.40 | **3.52** | **3.24** | **2.96** | **9.97** |
| AudioSep-CLIP | 2.40 | 3.37 | 3.09 | 2.88 | 8.09 |
| AudioSep-CLAP | **2.41** | 3.30 | 3.15 | 2.84 | 8.95 |

Two state-of-the-art LASS models LASS-Net and CLIPSep did not perform well on separating target sounds on our established benchmark. As they are trained using audio data with limited concepts, as a result, they are inadequate for extending their performance to open-domain scenarios. Audio-queried sound separation baseline systems USS-ResUNet30 and USS-ResUNet60 have achieved an SDRi of 5.57 dB and 5.7 dB, respectively, which substantially underperform when compared to AudioSep. Notably, in the inference stage, AudioSep only requires the text description of the target source, which is more convenient to acquire compared with the audio-queried methods. Evaluation results on seen datasets indicate the superior performance of AudioSep compared with previous state-of-the-art LASS models and off-the-shelf audio-queried sound separation models.

### D. Evaluation results on unseen datasets

We conducted further evaluations to assess the zero-shot separation performance of AudioSep on unseen datasets, including MUSIC, ESC-50, and Voicebank-Demand. AudioSep has achieved impressive zero-shot separation performance on

TABLE V
ABLATION STUDY OF SCALING UP AUDIOSEP WITH MULTIMODAL SUPERVISION.

| | **AudioSet** | | **VGGSound** | | **AudioCaps** | | **Clotho** | | **MUSIC** | | **ESC-50** | | **VoicebankDemand** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SI-SDR | SDRi | SI-SDR | SDRi | SI-SDR | SDRi | SI-SDR | SDRi | SI-SDR | SDRi | SI-SDR | SDRi | PESQ | SSNR |
| AudioSep-CLIP-TR0.0 | 0.45 | 2.91 | -3.84 | 0.78 | -0.02 | 3.29 | -1.50 | 2.42 | -0.21 | 2.97 | -0.24 | 3.67 | 2.27 | 6.67 |
| AudioSep-CLIP-TR0.5 | 6.48 | 7.28 | 7.01 | 7.27 | 5.84 | 7.25 | 4.32 | 6.10 | 7.40 | 9.05 | 8.74 | 9.97 | 2.37 | **9.07** |
| AudioSep-CLIP-TR0.75 | 6.52 | 7.31 | **7.46** | **7.67** | **5.98** | 7.41 | 4.38 | 6.16 | 8.00 | 9.35 | **8.92** | **10.10** | **2.40** | 8.83 |
| AudioSep-CLIP-TR1.0 | **6.60** | **7.37** | 7.24 | 7.50 | 5.95 | **7.45** | **4.54** | **6.28** | **9.14** | **10.45** | 8.90 | 10.03 | **2.40** | 8.09 |
| AudioSep-CLAP-TR0.0 | 0.95 | 3.35 | -3.01 | 0.88 | -1.10 | 2.57 | -1.45 | 2.31 | -1.36 | 2.36 | -1.95 | 2.74 | 2.32 | 6.42 |
| AudioSep-CLAP-TR0.5 | 5.52 | 6.46 | 5.40 | 5.93 | 5.43 | 6.89 | 3.98 | 5.84 | 6.80 | 8.47 | 6.77 | 8.42 | 2.40 | 8.82 |
| AudioSep-CLAP-TR0.75 | 6.13 | 6.96 | 6.88 | 7.07 | 6.02 | 7.35 | 4.55 | 6.27 | 7.80 | 9.24 | 8.48 | 9.69 | 2.45 | 8.30 |
| AudioSep-CLAP-TR1.0 | **6.58** | **7.30** | **7.38** | **7.55** | **6.45** | **7.68** | **4.84** | **6.51** | **8.45** | **9.75** | **9.16** | **10.24** | **2.41** | **8.95** |

MUSIC musical instrument separation and ESC-50 sound effects separation, as shown in Table IV. Particularly, on MUSIC, AudioSep-CLIP achieved an SI-SDR of 9.14 dB and an SDRi of 10.45 dB, considerably outperforming AudioSep-CLAP which achieved an SI-SDR of 8.45 dB and an SDRi of 9.75 dB. The experimental results indicate that the CLIP text embedding captures the difference between musical instruments better than the CLAP text embedding. For ESC-50, AudioSep CLAP achieved an SI-SDR of 9.16 dB and an SDRi of 10.24 dB, which slightly outperforms the AudioSep-CLIP which achieved an SI-SDR of 8.9 dB and an SDRi of 10.03 dB. Although CLIPSep could successfully separate musical instruments from background noise [23], its performance degrades when faced with musical instrument mixtures. Neither CLIPSep nor LASS-Net performs well in these evaluation datasets.

Table V shows the results of Voicebank-Demand speech enhancement. Noisy speech without enhancement has PESQ, CSIG, CBAK, COVL, and SSNR of 1.97, 3.35, 2.44, 2.63 and 1.68 dB respectively. AudioSep-CLIP results of PESQ, CSIG, CBAK, COVL, and SSNR values of 2.40, 3.37, 3.09, 2.88 and 8.09 dB respectively. AudioSep-CLAP achieves PESQ, CSIG, CBAK, COVL, and SSNR of 2.41, 3.30, 3.15, 2.84 and 8.95 dB respectively. AudioSep-CLAP surpasses all the speech enhancement baselines in the PESQ metric. In addition, both AudioSep-CLIP and AudioSep-CLAP outperform the Wiener [70] and AudioSet-UNet [7] method across all metrics, showing the good speech enhancement capability of the AudioSep model. On the other hand, AudioSep performs less effectively than the SEGAN [6] method in the CSIG metric, indicating that AudioSep may lose certain speech details, particularly in the high-frequency component. This discrepancy could potentially be due to the presence of large-scale narrow-band signals in the training data, such as those found in AudioSet [30].

Experimental results on the unseen datasets indicate the powerful zero-shot generalization performance of AudioSep. With AudioSep, we can perform sound separation tasks on new data distributions.

### *E. Leveraging multimodal supervision for AudioSep*

Recent research has explored the potential of utilizing multimodal supervision [23]–[25] to enhance the scalability of training LASS models. However, these works mainly focused on small-scale training sets. In this section, we present in-depth ablation studies to investigate the efficacy of utilizing large-scale multimodal supervision with CLIP and CLAP models for scaling up AudioSep. We aim to gain insights into the applicability and performance of leveraging large-scale multimodal supervision for LASS.

For the CLIP model, we utilize hybrid vision-language supervision for AudioSep with varying text ratios (TR). Specifically, we experiment with text ratios of 0%, 50%, 75%, and 100%. The resulting AudioSep models are referred to as AudioSep-CLIP-TR0.0, AudioSep-CLIP-TR0.5, AudioSep-CLIP-TR0.75, and AudioSep-CLIP-TR1.0, respectively. The hybrid supervision approach is exclusively adopted for the training process using AudioSet [30] and VGGSound [63] datasets that have video stream information. For datasets that solely consist of audio and text, such as WavCaps [65], we continue to utilize text supervision. This training configuration allows us to effectively leverage the available modalities and tailor the supervision approach to suit the specific characteristics of each dataset. Experimental results are shown in the upper part of Table V. When training AudioSep-CLIP0.0 without text supervision using the AudioSet and VGGsound datasets, the performance is clearly inadequate across all evaluation datasets. As large-scale video data often contain irrelevant audio contexts, this experimental result highlights the key role of text supervision from audio event labels provided by AudioSet and VGGSound in effectively training AudioSep. When training AudioSep using text ratios of 50% and 75%, the overall performance is comparable to AudioSep-CLIP-TR1.0 trained exclusively with text supervision. This observation suggests that incorporating additional supervision from the visual modality does not enhance the separation performance in large-scale training settings, which can potentially be attributed to the inherent noise within video data at scale.

For the CLAP setting, similar to CLIP, we employ a hybrid audio-text supervision approach for AudioSep. We conduct experiments with text ratios of 0%, 50%, 75%, and 100%. The resultant AudioSep models are denoted as AudioSep-CLAP-TR0.0, AudioSep-CLAP-TR0.5, AudioSep-CLAP-TR0.75, and AudioSep-CLAP-TR1.0, correspondingly. Experimental results are shown in the bottom part of Table V. In contrast to the findings in the CLIP setting, utilizing hybrid audio-text supervision for training results in a decrease in separation performance. Specifically, we observed that the inclusion of more audio supervision leads to lower

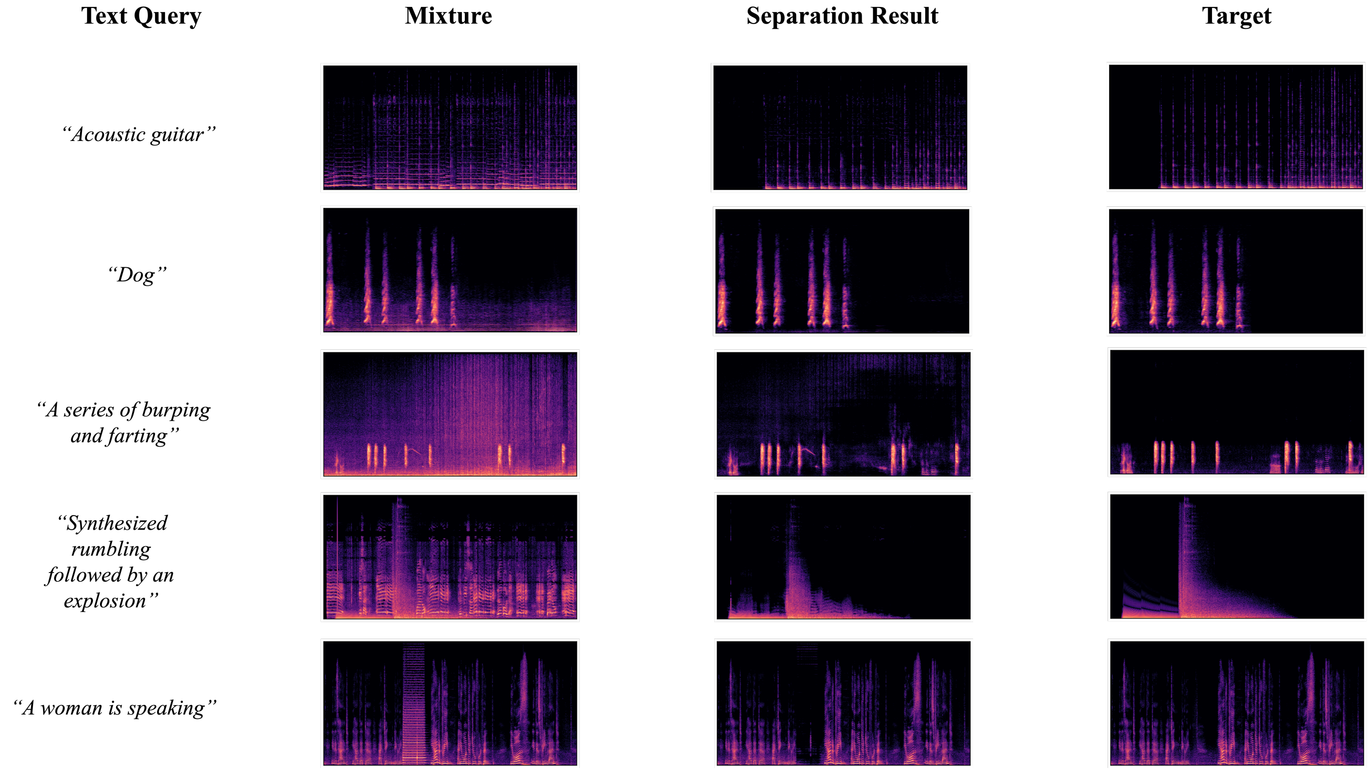


Fig. 2. Visualization of separation results obtained by the AudioSep-CLAP model.

separation performance. Given the substantial difference in training data size, with CLIP trained on a dataset of around 400M image-text pairs and CLAP on approximately 630K audio-text pairs, we analyze the reason could be due to the audio-text latent spaces of CLAP not being aligned well. Consequently, AudioSep tends to overfit the audio latent when a large amount of audio supervision is utilized, which further results in performance degradation using text queries in the inference stage.

### *F. Visualization of separation results*

We performed visualizations of spectrograms for audio mixtures, and ground-truth target audio sources, and separated sources using text queries of diverse sound sources (e.g., musical instrument, audio event, speech) with the AudioSep-CLAP model, as shown in Figure 2. We observe that the spectrogram pattern of the separated source is close to the ground truth source, which is consistent with our objective experimental results. More audio separation samples are available on our project page[8].

### *G. Comparison of various text queries*

In practice, human descriptions of an audio source are often personalized. For this purpose, we randomly selected 50 audio clips from the test set of the AudioCaps dataset. We engaged four language experts to individually annotate the selected clips. Each expert provided a single description per audio clip without any specific hints or restrictions. Consequently, we obtained a set of six descriptions for each audio clip. This set included one caption sourced from AudioCaps, four captions provided by the recruited annotators, and the AudioSet audio event text labels. To create test mixtures, each audio clip was mixed with ten background sources randomly selected with an SNR at 0 dB, ensuring that the sound event labels of the background source do not overlap with that of the target source. We denote this test dataset as AudioCaps-Mini.

We evaluate the performance of AudioSep-CLIP and AudioSep-CLAP on AudioCaps-Mini. To investigate the effects of various text queries, we utilize the retrieved AudioSet event labels, the original AudioCaps audio captions, and our re-annotated natural language descriptions, which are referred to as the "text label" "original caption" and "re-annotated caption", respectively. An example of AudioCaps-Mini can be found in Table VI. Experimental results are shown in Table VII. For both the AudioSep-CLIP and AudioSep-CLAP models, we have observed a considerable performance improvement when utilizing the "original caption" as text queries instead of using the "text label". This can be attributed to the fact that human-annotated captions provide more comprehensive and accurate descriptions of the source of interest compared to audio event labels. Despite the personalized nature and different word distribution of our re-annotated captions, the results obtained using the "re-annotated caption" are slightly worse than those using the "original caption", while still marginally outperforming the results obtained with the "text label". These experimental findings demonstrate the promising generalization performance and robustness of AudioSep in

[8] https://audio-agi.github.io/Separate-Anything-You-Describe

real-world cases with diverse language queries.

TABLE VI
AN EXAMPLE FROM AUDIOCAPS-MINI.

| | Text Description |
|---|---|
| Text label | "Vibration" |
| Original caption | "Clicking followed by vibrations" |
| Re-annotated caption1 | "Gear change, moving vehicle" |
| Re-annotated caption2 | "The distant engine sound" |
| Re-annotated caption3 | "The engine is running in distant" |
| Re-annotated caption4 | "The engine is starting" |

TABLE VII
EXPERIMENTAL RESULTS OF COMPARISON OF DIFFERENT TEXT QUERIES ON AUDIOCAPS-MINI DATASET.

| | SI-SDR | SDRi |
|---|---|---|
| AudioSep-CLIP (text label) | 6.39 | 7.70 |
| AudioSep-CLIP (original caption) | 7.27 | 8.25 |
| AudioSep-CLIP (re-annotated caption) | 6.44 | 7.75 |
| AudioSep-CLAP (text label) | 6.32 | 7.65 |
| AudioSep-CLAP (original caption) | 7.73 | 8.47 |
| AudioSep-CLAP (re-annotated caption) | 6.59 | 7.80 |

### *H. Comparison to Interspeech work*

Since this work constitutes an extension of our previous research, as presented in the Interspeech 2022 [3], we highlight the contribution of this work here. First, we introduced AudioSep, a foundation model for open-domain sound separation with natural language queries, while the LASS-Net presented in the Interspeech work did not perform well in open-domain scenarios. In addition, we established a comprehensive evaluation benchmark for LASS, including tasks of musical instrument separation, audio event separation, and speech enhancement. Furthermore, we conducted extensive experiments to evaluate the performance of AudioSep and performed ablation studies about scaling up LASS with large-scale multimodal supervision. The state-of-the-art results we achieved and the empirical observations further demonstrate the contributions we made in this work.

## VI. CONCLUSION AND FUTURE WORK

In this work, we presented AudioSep, a foundation model for open-domain universal sound separation with natural language descriptions. AudioSep can perform zero-shot separation seamlessly using text labels or audio captions as queries. We presented a comprehensive evaluation benchmark for LASS including numerous sound separation tasks such as audio event separation, musical instrument separation, and speech enhancement. AudioSep significantly outperforms state-of-the-art text-queried separation systems and off-the-shelf audio-queried sound separation models. We show that AudioSep is a promising approach to flexibly address the CASA problem with strong sound separation performance. In the future, we will improve the separation performance of AudioSep via unsupervised learning techniques [14], [27] and extend AudioSep to support vision-queried separation, audio-queried separation, and speaker separation tasks.


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