SPEECHCLIP: INTEGRATING SPEECH WITH PRE-TRAINED VISION AND LANGUAGE MODEL

Yi-Jen Shih1, Hsuan-Fu Wang1, Heng-Jui Chang1,2, Layne Berry3, Hung-yi Lee1, David Harwath3

1National Taiwan University
2MIT CSAIL
3The University of Texas at Austin

ABSTRACT

Data-driven speech processing models usually perform well with a large amount of text supervision, but collecting transcribed speech data is costly. Therefore, we propose SpeechCLIP, a novel framework bridging speech and text through images to enhance speech models without transcriptions. We leverage state-of-the-art pre-trained HuBERT and CLIP, aligning them via paired images and spoken captions with minimal fine-tuning. SpeechCLIP outperforms prior state-of-the-art on image-speech retrieval and performs zero-shot speech-text retrieval without direct supervision from transcriptions. Moreover, SpeechCLIP can directly retrieve semantically related keywords from speech.

Index Terms—Visual grounding, vision and language, self-supervised learning

1. INTRODUCTION

Conventionally, speech processing tasks like speech recognition need transcribed speech data for machine learning. They usually require large labeled datasets to perform well, but transcribing an enormous amount of speech is expensive. Therefore, recent studies exploit unlabeled speech to pre-train models with self-supervised learning (SSL) [1]. Models learn to predict pseudo targets generated from raw data in SSL pre-training. Some typical speech SSL methods include masked reconstruction [2–6], contrastive learning [7–11], classification [12–14], multi-task learning [15], and knowledge distillation [16–18]. These methods succeed in a wide range of speech processing problems [19–21].

Besides SSL methods focusing on a single modality, researchers propose using data from other modalities to boost machine performance on a specific modality. E.g., pairing images with semantically related text or spoken captions is a typical method since collecting parallel image-text or image-speech data is fast and inexpensive [22]. Specifically, paired image-text data can be obtained by crawling images and captions from the internet. Paired image-speech data can be collected by uttering text captions or describing images in speech. This paper uses paired image-speech data and an image-text pre-trained model to enhance speech SSL models.

Much effort was put into using paired images and spoken captions to help speech processing [24], and they are usually called visually grounded speech models (VGS). VGS models benefit many applications like speech recognition [25], word discovery [26], speech generation [27], cross-modal alignment [22, 28, 29], and multilingual spoken language processing [30–33]. Most studies pre-train and evaluate VGS models on image-speech retrieval, showing the capabilities of capturing the correspondence between images and speech [34, 35]. E.g., the recent Fast-Slow Transformer for Visually Grounding Speech (FaST-VGS and FaST-VGS+) succeeds in many speech processing tasks by utilizing transformers and cross-modal attention mechanisms to perform image-speech retrieval and semantic tasks [36,37]. Moreover, VGS models trained with retrieval objectives can extract semantic and word-level information from speech [38], which is difficult to achieve by training solely with speech [39].

While many studies obtain semantic information from speech without transcriptions, some extent of assistance from text could be helpful for some tasks. E.g., recent unsupervised ASR methods rely on nonparallel text data and a pronunciation lexicon [40,41]. To circumvent transcriptions or lexicons, we propose to bridge speech and text domains with pre-trained vision and language models.
via images, i.e., taking advantage of paired image-speech and image-text data. Thus, this paper introduces SpeechCLIP, a novel framework to integrate speech SSL models with a pre-trained vision and language model as depicted in Fig. 1. We use Contrastive Language-Image Pre-training (CLIP), a powerful model pre-trained to align parallel image-text data [23]. Then, a speech encoder initialized by a pre-trained speech SSL model is enhanced by aligning with CLIP using paired image-speech data. By aligning a speech encoder’s and CLIP’s image embedding spaces, the speech encoder is implicitly aligned with CLIP’s text encoder, forcing it to capture more textual content.

We propose two SpeechCLIP architectures: parallel and cascaded. The parallel model is similar to WAV2CLIP [42]. However, our speech encoder uses a pre-trained speech SSL model and focuses on capturing local and global spoken contents. Meanwhile, WAV2CLIP extracts global features in general audio for classification and retrieval. Furthermore, AudioCLIP is an extension of WAV2CLIP since it is trained with paired image, audio, and text data [43]. The cascaded SpeechCLIP cascades CLIP’s text encoder on top of the speech encoder, forcing the model to output subword embeddings. Eventually, the cascaded model captures spoken words in speech signals.

In this paper, the proposed SpeechCLIP models achieve state-of-the-art image-speech retrieval on two standard spoken caption datasets with minimal fine-tuning. Moreover, we demonstrate SpeechCLIP’s capability of performing zero-shot speech-text retrieval and capturing keywords directly from speech. We also make our code available on Github1.

1https://github.com/atosystem/SpeechCLIP

2. METHOD

2.1. Preliminaries

We briefly explain pre-trained models used in SpeechCLIP. **Contrastive Language-Image Pre-training (CLIP)** [23]. CLIP uses contrastive learning to pre-train visual models from natural language supervision on an enormous scale, where the supervision comes from paired image-text data. Composing two encoders processing image and text separately, CLIP aims to align semantically similar images and text captions. CLIP can easily transfer across various computer vision tasks with little supervision.

**Hidden-unit BERT (HuBERT)** [12]. HuBERT is a speech SSL method similar to masked language modeling, predicting labels generated by clustered acoustic features. HuBERT comprises a CNN feature extractor followed by a transformer encoder [44] and offers good initialization for many speech processing tasks [19, 21].

In SpeechCLIP, pre-trained CLIP and HuBERT models are frozen and serve as feature extractors, as shown in Fig. 2. The CLIP model extracts image and sentence embeddings to supervise SpeechCLIP. Following SUPERB [19], HuBERT’s CNN output and transformer encoder’s hidden representations are weighted and summed by a set of learnable weights. The weights automatically assign importance to each hidden layer to minimize the overall objective function. Only the newly added components excluding HuBERT and CLIP are learnable during training, reducing the computational cost significantly, thus enabling a larger batch size for contrastive pre-training. In the following sections, we introduce two SpeechCLIP architectures: parallel and cascaded.
2.2. Parallel SpeechCLIP

Parallel SpeechCLIP is similar to CLIP, which aligns semantically related images and spoken captions, as shown in Fig. 2a. Since the weighted sum of HuBERT’s output is a sequence of frame-level features, we add a learnable CLS token at the beginning of each sequence. The sequence is passed through a transformer encoder layer to obtain an utterance-level representation [44]. The representation is used to compute the cosine similarity with image embeddings in a mini-batch for calculating the contrastive loss. Cosine similarity scores are also used for retrieving speech and image samples. Following CLIP, the loss function has a learnable temperature for scaling the similarity scores.

By aligning speech and CLIP image encoders, parallel SpeechCLIP implicitly bridges speech and text representations since CLIP’s image and text encoders are well-aligned. Therefore, it can perform both image-speech and speech-text retrieval. Still, this method is limited to summarizing utterances because it has no explicit constraints to capture word-level content. Thus, the following section introduces a novel method addressing this issue.

2.3. Cascaded SpeechCLIP

To force the speech encoder to capture semantic information from speech, we propose cascaded SpeechCLIP by cascading speech encoder with CLIP’s text encoder as shown in Fig. 2b. Following parallel SpeechCLIP, the cascaded model is trained with contrastive loss, but the difference lies in the summarization process of utterances.

First, we add $K$ learnable CLS tokens at the beginning of an audio feature sequence, where $K$ is a hyper-parameter for the number of keywords obtained from an utterance. The sequence is fed into a transformer encoder and projected to the CLIP input embedding dimension. Next, the projected CLS tokens are batch-normalized to match the mean and variance of CLIP’s subword embeddings. We apply vector quantization (VQ) to map the $K$ normalized embeddings to CLIP’s $V$ subword embeddings. This operation produces keywords indicating the essential concepts in each utterance.

The VQ process is described as follows. We first compute the cosine similarity between the $k^{th}$ normalized CLS embedding ($z_k$) and the $v^{th}$ subword embedding ($e_v$) as

$$s_{kv} = \cos(z_k, e_v). \tag{1}$$

Next, we choose the subword embedding with the highest similarity from the vocabulary, which can be expressed as

$$e_{v^*}, \text{ where } v^* = \arg\max_{1 \leq v \leq V} s_{kv}. \tag{2}$$

Since $e_{v^*}$ is not differentiable, we compute another embedding by weighted summing all $V$ subword embeddings as

$$\overline{h}_k = [e_1 \ldots e_V] \text{softmax} \left( \frac{[s_{k1} \ldots s_{kV}]^\top}{\tau} \right), \tag{3}$$

where each embedding $e_v$ is a column vector and $\tau$ is a hyper-parameter ($\tau = 0.1$). Combining Eqs. 2 and 3, we apply straight-through gradient estimator [45] to obtain quantized keywords

$$h_k = e_{v^*} + \overline{h}_k - \text{sgn}(\overline{h}_k), \tag{4}$$

where $\text{sgn}(x) = x$ and $\frac{dx}{dx} \text{sgn}(x) = 0$ is the stop gradient operator. The $K$ keywords are then fed into the CLIP text encoder for computing the contrastive objective.

Overall, the cascaded SpeechCLIP encourages the speech encoder to extract subwords because of the supervision from the CLIP text encoder. Hence, it is expected to capture more semantic and content information from speech.

3. EXPERIMENT

3.1. Setup

Dataset. SpeechCLIP is pre-trained and evaluated with retrieval on Flickr8k Audio Captions Corpus [26] and SpokenCOCO dataset [27]. Each image in both datasets is paired with five spoken captions produced by humans uttering text captions. Flickr8k consists of 8k images and 46 hours of speech, while SpokenCOCO has 123k images and 742 hours of speech. Following FaST-VGS, we use the Karpathy split for SpokenCOCO [46].

Model. We implemented SpeechCLIP in two sizes: Base and Large, a detailed comparison is shown in Table 1. Note that we omit the Base notation in the following sections. The hidden dimension of the transformer encoder is the same as that of the audio encoder. The feed-forward network in the cascaded model’s transformer encoder is removed for better performance. Parallel and cascaded models have respectively eight and one attention head. We set $K$ to 8 in all experiments. All models are trained with Adam optimizer with a weight decay of $10^{-6}$, batch size of 256, and 50k steps in total. The learning rate linearly increases to $10^{-4}$ in the first 5k steps and linearly decreases to $10^{-8}$ afterward. All experiments are conducted on a 32GB V100 GPU except for pre-training on SpokenCOCO, which uses two. The largest model’s pre-training lasts approximately two days.

3.2. Image-Speech Retrieval

In this section, we evaluate SpeechCLIP on the image-speech retrieval task, showing how well models can align speech
Table 2: Recall scores for image-speech retrieval on Flickr8k and SpokenCOCO testing sets.

| Method | Speech → Image | Image → Speech |
|--------|----------------|----------------|
|        | R@1   | R@5   | R@10 | R@1 | R@5 | R@10 |
| Flickr8k |       |       |       |      |      |      |
| FaST-VGS_{CD} [36] | 26.6  | 56.4  | 68.8  | 36.2 | 66.1 | 76.5  |
| FaST-VGS_{CL} [36] | 29.3  | 58.6  | 71.0  | 37.9 | 68.5 | 79.9  |
| MILAN [35]  | 33.2  | 62.7  | 73.9  | 49.6 | 79.2 | 87.5  |
| Parallel   | 26.7  | 57.1  | 70.0  | 41.3 | 73.9 | 84.2  |
| Cascaded   | 8.2   | 25.7  | 37.2  | 14.1 | 34.5 | 49.2  |
| Parallel Large | 39.1  | 72.0  | 83.0  | 54.5 | 84.5 | 93.2  |
| Cascaded Large | 14.7  | 41.2  | 55.1  | 21.8 | 52.0 | 67.7  |
| SpokenCOCO |       |       |       |      |      |      |
| ResDAVEnet [25] | 17.3  | 41.9  | 55.0  | 22.0 | 50.6 | 65.2  |
| FaST-VGS_{CD} [36] | 31.8  | 62.5  | 75.0  | 42.5 | 73.7 | 84.9  |
| FaST-VGS_{CL} [36] | **35.9** | 66.3  | 77.9  | 48.8 | 78.2 | 87.0  |
| Parallel Large | 35.8  | **66.5** | **78.0** | **50.6** | **80.9** | **89.1** |
| Cascaded Large | 6.4   | 20.7  | 31.0  | 9.6  | 27.7 | 39.7  |

Table 3: Recall for speech-text retrieval on Flickr8k and SpokenCOCO. ‘Sup.’ indicates the supervised version of parallel SpeechCLIP by replacing the image encoder with CLIP text encoder in parallel SpeechCLIP.

| Method | Speech → Text | Text → Speech |
|--------|---------------|---------------|
|        | R@1   | R@5   | R@10 | R@1 | R@5 | R@10 |
| Flickr8k |       |       |       |      |      |      |
| Random | 0.10  | 0.50  | 0.99  | 0.10 | 0.50 | 0.99  |
| Parallel Large | 19.56 | 44.06 | 58.46 | 22.50 | 44.14 | 54.54 |
| Parallel Large (Sup.) | 97.06 | 99.24 | 99.46 | 97.88 | 99.76 | 99.90 |
| SpokenCOCO |       |       |       |      |      |      |
| Random | 0.02  | 0.10  | 0.20  | 0.02 | 0.10 | 0.20  |
| Parallel Large | 60.32 | 81.81 | 88.18 | 65.45 | 85.82 | 91.27 |
| Parallel Large (Sup.) | 95.02 | 99.46 | 99.78 | 95.35 | 99.68 | 99.93 |

Table 4: Keyword hit rates for cascaded SpeechCLIP. Avg denotes averaged hit rate. † and ‡ respectively denote models trained on Flickr8k and SpokenCOCO.

| Model | kw1 | kw2 | kw3 | kw4 | kw5 | kw6 | kw7 | kw8 | Avg |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Base† | 57.0 | 25.6 | 20.2 | 5.0 | 20.0 | 26.5 | 10.5 | 16.6 | 22.7 |
| Large† | 56.5 | 19.6 | 20.5 | 37.5 | 21.7 | 34.6 | 26.4 | 44.7 | 32.7 |
| Large‡ | 27.5 | 22.4 | 35.8 | 61.0 | 21.6 | 54.2 | 60.1 | 22.9 | 38.2 |

3.3. Zero-shot Speech-Text Retrieval

This section highlights parallel SpeechCLIP’s capability to perform zero-shot speech-text retrieval. Speech and text representations are respectively computed from a pre-trained parallel SpeechCLIP’s speech encoder and a CLIP text encoder. The representations are then used to calculate cosine similarity scores for retrieval. Although this problem has been studied for a while, prior studies require either paired speech-text training data [47, 48] or pretrained image tagger [49].

Additionally, two supervised parallel SpeechCLIP models respectively trained with paired spoken and text captions in Flickr8k and SpokenCOCO are considered as toplines. These models’ CLIP image encoders are replaced with CLIP text encoders to align speech and text explicitly. When computing recall, we regard retrieving speech and text captions related to the same image as successful. Therefore, results only show whether models retrieve semantically related samples, not exact matching of speech and transcriptions.

According to Table 3, proposed SpeechCLIP models yield considerably better performance than random retrieval, showing that speech and text embedding spaces are well aligned. Specifically, parallel SpeechCLIP performs better on this task when trained on a larger dataset like SpokenCOCO. Although the performance gap between the proposed methods and the supervised toplines remains, we show that bridging speech and text with image is possible and promising.

We demonstrate that parallel SpeechCLIP retrieves noisy transcriptions for speech signals. These transcriptions can then be used for supervised or semi-supervised speech recognition model training. Furthermore, by replacing CLIP with Multilingual-CLIP2, we can retrieve noisy transcriptions of different languages, thus performing speech translation.

3.4. Keyword Retrieval with Cascaded SpeechCLIP

Due to the unique design of cascaded SpeechCLIP, we investigate what and how well the speech encoder extracts keywords. For each encoded and normalized CLS token $z_k$, keywords are retrieved by finding subwords with the highest cosine similarities between $z_k$ and the corresponding subword embeddings. Notice that previous works [49, 50] are also capable of retrieving semantically related keywords from speech. Nonetheless, they required pretrained image tagger and the size of keywords set is very limited. For SpeechCLIP, we can apply the same method to other pretrained language models’ vocabulary, technically. Also, our setting is quite dif-
different from [51], where the 8 keywords are discovered from speech utterance without any text query in our work. Namely, SpeechCLIP can automatically summarize the speech by selecting 8 keywords. We offer quantitative and qualitative analyses in the following paragraphs.

We inspect how well keywords are retrieved from speech signals for the quantitative analysis. The evaluation metric is hit rate, which is the percentage of successful top-1 keyword retrieval of any word in the caption averaged over all testing samples. In Table 4, some CLS tokens frequently retrieve words in the ground truth captions, showing that the cascaded architecture can directly capture words from speech. Moreover, the first keyword’s hit rate for models trained on Flickr8k is relatively high compared to other keywords. Probably because the first word in a sentence has a higher chance to be “a”, which is also the top-1 commonly retrieved subword from the first keyword in Flickr8k. Another finding is that the Large model obtains a higher averaged keyword hit rate than the Base model on Flickr8k, which is consistent with the trend in Table 2. Hence, retrieving correct keywords is related to retrieving between speech and image samples. Although some CLS tokens obtain reasonable hit rates, one might question whether the retrieved words are meaningful instead of stopwords. Hence, we next analyze the results qualitatively to address this concern.

For the qualitative analysis, we offer two samples from the SpokenCOCO testing set in Fig. 3, showing their attention maps in the transformer encoder and retrieved words for each CLS token. In the first example, although only a few retrieved keywords are in the ground truth caption, some semantically related words are found. For instance, attention maps of keywords 1, 2, and 6 focus on segments uttering “tie” and “suit.” Meanwhile, they retrieve words related to clothes and appearance, e.g., “dapper”, “tuxedo”, and “scarf.” A similar trend can be found in the second sample, showing that the cascaded objective makes the speech encoder captures semantic information. Moreover, looking at both examples, each keyword seems to have a particular purpose, e.g., the 8th keyword tends to retrieve specific nouns from utterances while the 7th retrieves prepositions. This observation leads us to investigate the properties of each keyword.

In Table 5, we list the top 10 successfully retrieved subwords for each keyword on SpokenCOCO test set using the cascaded Large model. The subwords are sorted in decreasing occurrence.

| kw1   | kw2  | kw3   | kw4    | kw5    | kw6    | kw7   | kw8   |
|-------|------|-------|--------|--------|--------|-------|-------|
| a     | a    | a     | a      | street | in     | train |
| pizza | cat  | bathroom | a    | a      | street | in     | train |
| the   | room | in     | with   | kitchen| to     | cake  |
| giraffe | sheep | horse | man  | eating | train  | from  | clock |
| bathroom | frisbee | elephant | woman | and    | beach | for    | is    |
| skateboard | skis | motorcycle | dog  | playing | bed    | a      | bus   |
| living | bird | kitchen | train | the    | bus    | on     | truck |
| gira | skateboard | clock | with    | flying | grass | at    | car   |
| sheep | surf | tower  | is      | sitting | road   | the    | of    |
| an   | kite | bear  | to      | walking | room  | –      | signs |

Fig. 3: Demonstration of a cascaded SpeechCLIP Large model retrieving words using its CLS tokens’ outputs. The two utterances are from the SpokenCOCO test set. For each keyword in each sample, we show the transformer encoder’s attention map over the whole sequence and the retrieved subwords on the right and sorted in decreasing cosine similarity. Subwords in boldface indicate they exist in the ground truth caption.
3.5. Layer Importance in SpeechCLIP Speech Encoder

In this section, we show which HuBERT hidden layers are crucial for SpeechCLIP to perform well in various tasks discussed earlier. Hence, we visualize the learned weights in the weighted sum mechanism mentioned in Sec. 2.1 in Fig. 4. Both parallel and cascaded SpeechCLIP utilize the roughly the 8th to the 10th layers in HuBERT, inferring that HuBERT’s top layers capture rich content and semantic information. This result is consistent with prior works investigating the importance of different hidden layers in speech SSL models [16, 39, 40], i.e., the top hidden layers contain word meaning and content information. However, the cascaded model’s weights distribute more evenly over the layers than parallel SpeechCLIP, showing that the model architecture design affects the utilization of HuBERT’s layers.

3.6. Ablation Studies

3.6.1. Batch Normalization in Cascaded SpeechCLIP

Here, we demonstrate the importance of batch normalization in the cascaded SpeechCLIP. We compare cascaded SpeechCLIP with its variant without using batch normalization, as shown in the first two rows of Table 6. Removing batch normalization degrades retrieval performance significantly, showing the significance of mean and variance matching described in Sec. 2.3.

3.6.2. Number of Keywords in Cascaded SpeechCLIP

This section discusses the impact of the number of keywords in cascaded SpeechCLIP. We report retrieval results on Flickr8k using different amounts of keywords in Table 6. Results show that reducing keywords degrades retrieval performance, indicating that using fewer keywords is incapable of passing information from the speech encoder to the CLIP text encoder. Furthermore, the number of subword tokens in a Flickr8k utterance is 11.3 ± 4.1, and some tokens carry less information like stopwords. Therefore, we suggest 8 is a reasonable number for $K$ to obtain good performance with cascaded SpeechCLIP. Although dynamically assigning $K$ for utterances of different lengths is more appropriate, we leave this approach for future investigation.

4. CONCLUSION

This paper introduces SpeechCLIP, a novel framework integrating CLIP into visually grounded speech models. We demonstrate significant improvements in image-speech retrieval with CLIP’s supervision. Moreover, the proposed methods can perform zero-shot speech-text retrieval and capture semantically related keywords in speech signals. Results indicate that bridging speech and text domains with CLIP’s supervision is possible and promising. Overall, SpeechCLIP opens a new research direction of indirectly supervising speech models with text via other modalities. We suggest some topics in SpeechCLIP are worth investigating in the future, including integrating parallel and cascaded in the same model and cascaded structure with variable length prediction aiming for unsupervised ASR. Furthermore, extending SpeechCLIP to a multilingual model is possible using spoken captions from other languages or Multilingual-CLIP models. Finally, we wish to inspect how CLIP can enhance speech SSL models’ performance on downstream problems like speech recognition and intent classification.

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