CLAP-S: Support Set-Based Adaption for Fiber-Optic Acoustic Recognition

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***Abstract*—Fiber-optic-based acoustic recognition plays an important role in environmental sensing and has many critical applications. Contrastive language-audio pretraining (CLAP) models have demonstrated unprecedented performance in various acoustic downstream tasks. Adapting CLAP for fiber-optic acoustic recognition has become an active research area. As a non-conventional acoustic sensor, fiber-optic acoustic recognition presents a challenging, domain-specific, low-shot deployment environment with significant domain shifts due to unique frequency response and noise characteristics. To address these challenges, we propose a support-based adaptation method, CLAP-S, which linearly interpolates a CLAP Adapter with the Support Set, leveraging both implicit knowledge through fine-tuning and explicit knowledge retrieved from memory for cross-domain generalization. Experimental results show that our method delivers competitive performance on both laboratory-recorded fiber-optic ESC-50 datasets and a real-world dataset collected from field trials over existing telecommunication cables.**

***Index Terms*—Fiber-optic acoustic recognition, pre-trained model adaptation, sound event classification, transfer learning**

I. Introduction

Distributed acoustic sensing (DAS) [1] is a powerful technology that captures acoustic disturbances by measuring phase changes in the backscattered optical signal caused by vibrations. DAS interrogator connecting to one end of the optical fiber (spanning kilometers) transforms the cable into equally spaced sensing elements with meter-scale spatial resolution, enabling new fiber-based acoustic applications. In particular, DAS is advantageous for harsh environments such as outdoor or underwater settings, where power supply and data transmission pose challenges. Conventional sound recording device such as microphones is considered as *point sensor*, each of which only monitors one small area. In contrast, DAS can utilize long optical fibers as *linear sensors* for wide-area monitoring over vast distances without the need for numerous individual sensors and battery installation. This technology has been successfully applied to pipeline leak detection [2], rail crack detection [3], drone detection [4], utility pole localization [5], [6], seismic monitoring [7], insect activity monitoring [8], whale call detection [9], and underwater surveillance [10].

Despite high prospects in a wide range of industrial applications, developing fiber-optic acoustic recognition systems still faces some challenges: First, field data collection and annotation are labor-intensive and time-consuming. As a result, obtaining sufficient labeled data from DAS for supervised learning is often more difficult than from microphones, especially for rare classes in the long tail. Second, the characteristics of sensing data are influenced by multiple factors including sensor configuration, propagation media, signal source, and optical factors [11], [12], causing severe domain gaps. Third, users may be interested in recognizing events of new classes that are unseen during training, which leads to an open-set recognition problem. Moreover, certain event types may be challenging to accurately describe through language (e.g., gunshot vs. cannon fireworks).

Recently, contrastive language-audio pre-training (CLAP) models [13], [14] pre-trained on large-scale audio-text data, have demonstrated strong zero-shot performance in multiple downstream domains including sound, music, and speech. Encouraged by this success, we explore the possibility of adapting CLAP to the fiber-optic acoustic domain of interest. Due to severe domain shifts, directly using CLAP pre-trained on microphone-recorded audio data to recognize fiber-optic acoustic events results in very low zero-shot classification accuracy, e.g., less than 30% on a 50-class environmental sound dataset recorded from a fiber coil, as shown in Table II.

Existing approaches, such as Prompt Tuning [15] and Adapter [16], enable efficient cross-domain knowledge transfer by updating a small portion of model parameters. However, they are not always effective across diverse downstream tasks. Prompt Tuning works better in scenarios where the target data distribution closely matches the pertained domain but struggles to retain new knowledge when facing significant domain gaps. Adapter methods, on the other hand, tend to overfit when training on small datasets due to their reliance on large supervised data. Data-centric adaptation methods, such as Tip-Adapter [17] and Treff [18], effectively inject explicit knowledge using external support set in a training-free manner, but their design heavily depends on the pre-trained knowledge embedded in the pre-trained model.

In this paper, we investigate the adaptation method of the CLAP model to the fiber acoustic domain, focusing on how the pre-trained knowledge, domain shift, and limited labels will affect our adaptation process. To systematically study this problem, we create a fiber-optic version of the ESC-50 dataset [19] by replaying and recording it under various data acquisition settings in the lab. We also consider real-world gunshot vs. firework classification dataset collected from existing telecommunication cables in the field [20]. This task is particularly challenging due to differences in the recording device, the complex outdoor environment, and the sound characteristics of the unseen and new classes.

We evaluate the effectiveness of several model adaptation approaches, including prompt tuning [15], [21], inserted adapter [16], Tip-Adapter [17] and Treff [18]. Different from existing methods, to maximize the use of labeled data, we propose fine-tuning and augmenting CLAP models with the same support set, which facilitates cross-domain generalization based on both implicit knowledge memorized in model parameters and explicit knowledge stored in the support set. The proposed approach consistently improves performance on both lab-collected data and field data across different recording devices.

II. Method

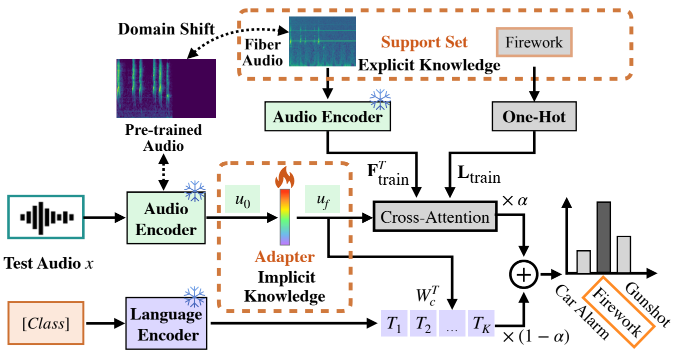

Fig. 1. **The pipeline of our proposed method.** A test sample is sent to the frozen pre-trained audio encoder and fine-tuned adapter to obtain the embedding, which is then used to perform cross-attention with the keys from the support audio samples. The attention weights are further multiplied by the values of the support set to serve as **Explicit Knowledge**. The final prediction is obtained by Linear interpolation with the Explicit Knowledge and the **Implicit Knowledge** captured by a fine-tuned Adapter .

Given a pre-trained CLAP model and a downstream dataset, we assume K-shot N-class training samples for fine-tuning. For all NK training audios X_K, the audio embeddings are represented as $F_{\text{train}} = \text{AudioEncoder}(X_K)$, where $F_{\text{train}} \in \mathbb{R}^{NK\times C}$, where C is the hidden dimension of the audio encoder. The label vectors are represented as $L_{\text{train}} = \text{OneHot}(L_N)$, where $L_{\text{train}} \in \mathbb{R}^{NK\times N}$. The audio embeddings and label vectors form the keys and values of the **Support Set**, respectively. The Support Set stores all new knowledge extracted from the training set.

For a given test audio sample x, the normalized audio embedding $u \in \mathbb{R}^{1\times C}$ is obtained by feeding the sample into the audio encoder. The audio embedding u serves as a **query**, while the stored audio embeddings F_{train} serve as **keys**. Cross-attention is applied between the query and keys. The attention weights are multiplied by the **values** L^T_{train} to obtain the similarity-based prediction.

Complimentary Mechanisms of Generalization. We propose to utilize supervised information in the support set twice, for both the fine-tuning adapter and the key-value support set. Our approach uses a Linear interpolation between both implicit knowledge from model fine-tuning and explicit knowledge from the support set and seeks a balance. The final prediction is derived by

$$p_{\text{final}}(y|x) = (1-\alpha)p_{\text{clap}}(y|x,u) + \alpha p_{\text{support}}(y|x,u) \quad (1)$$

where p_{clap} is the class distribution from the fine-tuned CLAP model and p_{support} is the class distribution from the support-set-based class distribution. They are defined as follows:

$$p_{\text{clap}}(y|x,u) = uW_c^T,$$
$$p_{\text{support}}(y|x,u) = e^{-\beta\left(1-uF^T_{\text{train}}\right)}L^T_{\text{train}}.$$

Here, $\alpha \in [0,1]$ is a tuned parameter balancing the contribution from the implicit knowledge and explicit knowledge from the support set, and β is the sharpness parameter. Here u has two different representations, one is the text-aligned audio representation u_0, and the other one is the task-aligned audio representation u_{f}, they obtained by the following equation:

$$u_{\text{f}} = \text{Adapter}(u_0), \quad u_0 = \text{AudioEncoder}(x) \quad (2)$$

The Adapter is a two-layer MLP. u_0 is obtained by feeding the test audio sample x into the audio encoder, which is aligned with the text embedding during pretraining. And u_{f} is derived by passing u_0 through the two-layer MLP Adapter, while u_{f} is aligned with the task during fine-tuning.

By combining u_0 and u_{f}, we can derive many variants from Equation 1: (1) combine u_0 for p_{clap} and u_{f} for p_{support}. (2) combine u_{f} for p_{clap} and u_0 for p_{support}. (3) combine u_{f} for p_{clap} and u_{f} for p_{support}. **These combinations allow us to explore whether text-aligned or task-aligned embeddings are more effective for fiber acoustic recognition.** We empirically find that combination (3) proves to be the most effective for our task and we summarize our method two variants:

CLAP-S: Here u=u_0 and $\alpha = 1$, our final prediction relies solely on generalization through memorization via p_{support}, completely removing the influence of zero-shot or fine-tuning knowledge.

CLAP-S$^+$: Here u=u_{f} and $0 < \alpha < 1$, $p_{\text{clap-s}}$ is obtained by linearly interpolating between the knowledge in p_{clap} and the explicit knowledge p_{support} from the support set. This method uses task-aligned embeddings for both classification and retrieval. The pipeline of CLAP-S$^+$ is shown in Figure 1.

TABLE I
Implicit & Explicit Generalization Combination.

p_{clap}	p_{support}	Combination	Method	ZS
u_0		ZS (α=0)	ZS-CLAP	Yes
	u_0	Support set (α=1)	**CLAP-S**	No
u_0	u_0	ZS + Support set	Tip-Adapter	Yes
u_0	u_{f}	ZS + Support set^F	Tip-Adapter-F	Yes
u_{f}	u_{f}	Adapter + Support Set$^+$	**CLAP-S$^+$**	No

Relation with Existing works. The difference between our method and existing method is shown in Table I. Compared to Tip-Adapter [17] and Treff [18], which treats the keys in the whole support as the task-aligned embedding, our CLAP-S$^+$ take a more natural approach using embedding from the fine-tuned adapter for both query and key. This leads to stronger generalization in practice (see Table II and V).

TABLE II
ZERO-SHOT & FULL-SHOT ADAPTION ON THE FIBER-OPTIC ACOUSTIC SENSING DATASET.

	Method	Shot	Laboratory Task			Real Task		Average
			ECM	FM	FC	FMO	FCO	
Trainin-Free	[class]	zero	71.8	35.2	22.1	18.0	14.0	32.2
	this is [class]	zero	79.9	42.9	27.4	20.0	10.0	36.0
	this is an audio of [class]	zero	80.7	44.3	27.2	17.0	10.0	35.8
	i can hear the sound of [class]	zero	77.5	40.6	27.9	16.0	16.0	35.6
	Tip-Adapter [17]	full	$87.0_{\pm 0.1}$	$59.0_{\pm 0.1}$	$39.0_{\pm 0.1}$	$78.8_{\pm 1.5}$	$82.2_{\pm 1.0}$	69.2
	CLAP-S (ours)	full	$92.0_{\pm 0.1}$	$61.4_{\pm 0.8}$	$43.0_{\pm 0.0}$	$79_{\pm 0.1}$	$83_{\pm 0.1}$	71.6
	△		**+5.0 ↑**	**+2.4 ↑**	**+ 4 ↑**	**+ 0.2 ↑**	**+0.8 ↑**	**+2.4 ↑**
Training-Required	Prompt Tuning [15]	full	$87.3_{\pm 1.7}$	$46.3_{\pm 1.8}$	$30.2_{\pm 1.2}$	$4.0_{\pm 4.0}$	$5.0_{\pm 5.2}$	34.6
	Adapter [16]	full	$92.9_{\pm 1.1}$	$68.8_{\pm 1.0}$	$48.8_{\pm 1.7}$	$81.4_{\pm 0.9}$	$90.2_{\pm 0.7}$	76.4
	Treff [18]	full	$90.3_{\pm 0.8}$	$67.5_{\pm 0.9}$	$46.8_{\pm 1.0}$	$84.2_{\pm 1.3}$	$90.1_{\pm 1.7}$	75.8
	Tip-Adapter-F [17]	full	$91.0_{\pm 0.7}$	$68.6_{\pm 1.0}$	$47.4_{\pm 0.8}$	$84.6_{\pm 1.2}$	$90.8_{\pm 0.7}$	76.5
	CLAP-S$^+$ (ours)	full	$94.0_{\pm 1.2}$	$70.0_{\pm 0.8}$	$51.0_{\pm 1.2}$	$87.0_{\pm 1.9}$	$92.0_{\pm 1.7}$	78.8
	△		**+2.8 ↑**	**+1.4 ↑**	**+3.0 ↑**	**+2.4 ↑**	**+1.2 ↑**	**+2.3 ↑**

TABLE III
DATASET COMPARISON.

	Dataset Name	Classes	Train	Val	Test	Total
Lab Task	Electric Microphone (ECM)	50	1400	400	200	2000
	Fiber Mandrel (FM)	50	1400	400	200	2000
	Fiber Coil (FC)	50	1400	400	200	2000
Real Task	Fiber Mandrel Outdoor (FMO)	8	647	167	421	1235
	Fiber Coil Outdoor (FCO)	8	406	106	263	775

III. EXPERIMENTAL RESULTS

We use the CLAP model from 2023 as the pre-trained model. In all subsequent experiments, each dataset is run five times, and reported the average and standard deviation in the tables. We use the AdamW optimizer with a learning rate of 1e-5, batch size of 64, and trained for 20 epochs. All experiments were conducted on an RTX A6000.

A. Datasets

Laboratory-Recorded Fiber-Optic ESC-50 Dataset To study the effects of different device domains (and recording environment), we record data using two fiber-optic sensors: (1) a Fiber Mandrel (FM) with a cylinder wrapped in single-mode bare fiber [22], (2) a Fiber Coil (FC), and (3) an Electric Condenser Microphone (ECM8000) as a reference. We utilize a DAS system to record the ESC-50 dataset [19], a public benchmark dataset that includes 2000 samples from 50 categories of environment sounds.

Field Fiber-Optic Acoustic Event Classification Dataset To further evaluate the ability to distinguish fine-grained event classes and generalize to real-world environments, we consider the field fiber-optic acoustic event classification dataset [20]. It contains 8 types of real-life sound events: gunshots, crackers, cannons, fountain cannons, high-altitude fireworks, vehicle door slamming, vehicle alarms, and background noise. This dataset was collected from pre-deployed telecom networks using two types of DAS sensors in the outdoor environment: Fiber Mandrel Outdoor (FMO) and Fiber Coil Outdoor (CO). The datasets split and comparison are shown in Table III.

B. Zero-shot & Full-shot Adaptation

Zero-shot Adaptation. This scenario tests the performance of the pre-trained model when we do not have any labeled data for fine-tuning. **The results show that the domain shift on the real-world task is higher than the laboratory-recorded task.** The laboratory datasets, based on ESC-50, include typical environmental sounds (e.g., dog, engine, rain) frequently found in the pretraining data in the CLAP model under test. In contrast, the real-world dataset features uncommon categories (e.g., 'fountain cannon", a label for the firework event) and larger background noise (e.g., wind), which is considered to contribute to poor zero-shot recognition, with accuracy dropping below 20%. Besides, we also found **the domain shift in the fiber mandrel is also larger than the fiber coil** as FM achieved a higher accuracy (44.3%) than the FC (27.9%), even though they share the same label space.

Full-shot Adaptation. Once we have enough labeled data, we can inject the new knowledge from these data into the model. If the computing resource is not available, then the train-free framework is a good way. Tip-Adapter is a strong baseline in the training-free methods, significantly improving the average by 33.6 percentage points without any parameter update. However, Tip-Adapter relies on the CLAP pre-trained model, which may not help our fiber acoustic data, as a significant domain shift exists. As shown in the table, **our proposed CLAP-S, which relies solely on external knowledge retrieval from the support set, achieves better results than Tip-Adapter**. When training resources are available, fine-tuning the model can further improve the adaptation performance. **Our method, CLAP-S-$^+$, achieves the highest accuracy among all the baseline methods,** including Prompt Tuning, Adapter, Treff, and Tip-Adapter-F. CLAP-S-$^+$ utilizes task-aligned embedding to repeated use of feature knowledge and thus further improves accuracy over the Tip-Adapter-F. Prompt Tuning performed poorly on our real-world dataset, with an accuracy of only 4-5%. We hypothesize that this is due to Prompt Tuning being designed to maximize the use of pre-trained knowledge, which is less effective for tasks completely unseen by the pre-trained model.

TABLE IV
EFFICIENCY COMPARISON

Method	Acc	Training	Parameters	Time	Inference
Prompt Tuning	34.6	Required	6.14k	30min	266ms
Tip-Adapter	69.2	Free	0.0	5min	55ms
CLAP-S (ours)	71.6	Free	0.0	4min	45ms
Adapter	76.4	Required	0.52M	15min	96ms
Tip-Adapter-F	76.5	Required	1.43M	10mins	70ms
CLAP-S$^+$ (ours)	78.8	Required	0.52M	7mins	56ms

C. *Few-Shot Adaptation*

Adaption in Limited Data This scenario applies when we aim to minimize labeling cost and only limited data are available. We conducted few-shot experiments ranging from 2-shot to 24-shot, as shown in Figure 2. The results demonstrate that both **CLAP-S and CLAP-S$^+$ consistently improve accuracy across the four datasets and perform competitively against baseline methods.**

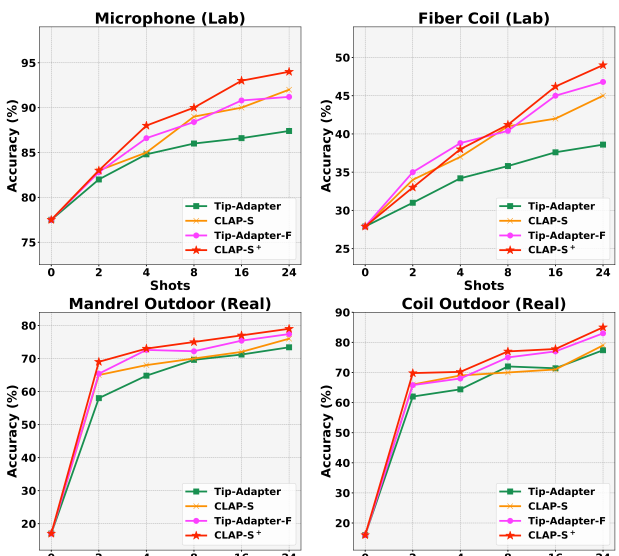

Fig. 2. The Few-Shot Adaptation Results.

D. *Efficiency Comparison*

We also compared the efficiency of our method with other baselines, as shown in Table IV. **CLAP-S demonstrated the best efficiency, requiring no training or additional parameter storage, with the lowest training and inference time.** However, this comes at the cost of sub-optimal performance. In contrast, our training-required version of CLAP-S$^+$ achieves the highest average accuracy across five datasets, with only slightly higher training and inference time than CLAP-S.

E. *Ablation Study*

1: Does Zero-shot knowledge always contribute positively? The result in Table V shows that by adding the zero-shot ('ZS' in the table) knowledge, the performance of the Support Set model and the Adapter model both drops. Thus, **in our fiber acoustic domain, the zero-shot knowledge is not helpful**. This could be due to the misalignment of the text-audio representation caused by domain gaps and the deficiency of the language encoder in handling new acoustic concepts. This conclusion applies only to the specific domain considered, yet one can see that when significant domain gaps exist and acoustic events are difficult to describe with language, the zero-shot transfer may have unintended negative effects.

TABLE V
ABLATION STUDY

Methods	ECM	FM	FC	FMO	FCO	Avg
Support Set	92.0$_{\pm 0.1}$	61.4$_{\pm 0.8}$	43.0$_{\pm 0.0}$	79$_{\pm 0.1}$	83$_{\pm 0.1}$	71.6
ZS + Support Set	87.0$_{\pm 0.1}$	59.0$_{\pm 0.1}$	39.0$_{\pm 0.1}$	78.8$_{\pm 1.5}$	82.2$_{\pm 1.0}$	69.2
ZS + Support Set$^+$	91.8$_{\pm 1.0}$	58.6$_{\pm 1.0}$	39.2$_{\pm 1.8}$	25.0$_{\pm 0.1}$	20.0$_{\pm 0.1}$	46.9
Adapter	92.9$_{\pm 1.1}$	68.8$_{\pm 1.0}$	48.8$_{\pm 1.7}$	81.4$_{\pm 0.9}$	90.2$_{\pm 0.7}$	76.4
Adapter + ZS	94$_{\pm 1.1}$	68.6$_{\pm 0.5}$	48$_{\pm 1.1}$	82.2$_{\pm 1.3}$	85.8$_{\pm 2.1}$	75.7
Adapter + Support Set	93.4$_{\pm 1.4}$	71.6$_{\pm 1.0}$	50.6$_{\pm 1.0}$	84.0$_{\pm 1.5}$	88.3 $_{\pm 1.3}$	77.6
Adapter + Support Set$^+$	**94.0**$_{\pm 1.2}$	**70.0**$_{\pm 0.8}$	**51.0**$_{\pm 1.2}$	**87.0**$_{\pm 1.9}$	**92.0**$_{\pm 1.7}$	**78.8**

2: Which representation is more effective for retrieval in the support set — text-aligned or task-aligned? The text-aligned embedding for the Support Set is represented as 'Support Set', while the task-aligned embedding for the Support Set is represented as 'Support Set$^+$' in Table V. The results indicate that, for the same ZS or Adapter, adding 'Support Set$^+$' consistently yields better performance than adding the 'Support Set'. **Thus the task-aligned representation is more effective for key-value retrieval** than text-aligned representation. This is due to the larger domain gaps encountered in the fiber-optic acoustic domain than the conventional microphone domain [18].

3: Fine-tuning jointly or separately? In scenarios with data collected from multiple devices or neighboring channels, should we fine-tune one model or individual models separately? We conducted experiments with all the datasets. Perhaps surprisingly, **the model trained jointly on all the datasets outperformed the models trained independently** on each individual dataset (results shown in Table VI). The reason is that joint training with the same ground truth dataset serves as a form of data augmentation, where increased data improves performance on individual tasks.

TABLE VI
JOINTLY TRAINING VS INDEPENDENTLY TRAINING

Methods	ECM	FM	FC	FMO	FCO	Avg
Adapter-Independently	92.9$_{\pm 1.1}$	68.8$_{\pm 1.0}$	48.8$_{\pm 1.7}$	81.4$_{\pm 0.9}$	90.2$_{\pm 0.7}$	76.4
Adapter-Jointly	**93.4**$_{\pm 0.9}$	**70.8**$_{\pm 1.5}$	**50.2**$_{\pm 1.6}$	**81.9**$_{\pm 0.7}$	**90.9**$_{\pm 0.5}$	**77.4**

IV. CONCLUSION

In this paper, we explored efficient model adaptation methods for the challenging fiber-optic acoustic domain with two complimentary generalization mechanism from the support set. Specifically, our experiments demonstrate that the support set adaptation method significantly outperforms existing baselines in both few-shot and full-shot scenarios. Our approach also showed strong fine-grained classification accuracy in real-world fiber-optic sound recognition tasks.

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