

INTERACTIVE DUAL ATTENTION CONFORMER WITH SCENE-BASED MASK FOR SOFT SOUND EVENT DETECTION

Han Yin¹, Jisheng Bai¹, Mou Wang², Dongyuan Shi³, Woon-Seng Gan³, Jianfeng Chen¹

¹ Joint Laboratory of Environmental Sound Sensing
School of Marine Science and Technology, Northwestern Polytechnical University, Xi'an, China

² Institute of Acoustics, Chinese Academy of Sciences, Beijing, China

³ School of Electrical & Electronic Engineering, Nanyang Technological University, Singapore

ABSTRACT

The emergence of soft-labeled data for sound event detection (SED) effectively overcomes the lack of traditional strong-labeled data. However, the performance of present SED systems based on such soft labels is still unsatisfactory. In this work, we introduce a dual-branch SED model designed to leverage the information within soft labels. Four variations of the interacted convolutional module are presented to investigate the effective mechanism for information interaction. Furthermore, we incorporate the scene-based mask generated by an estimator to directly apply to the prediction of SED models. Experimental results show that the mask estimator can achieve comparable or even better performance than the manually-designed mask and significantly improve the performance of SED. The proposed approach achieved the top ranking in the DCASE 2023 Task4B Challenge.

Index Terms— Sound event detection, soft labels, information interaction, scene-based mask, DCASE

1. INTRODUCTION

Sound event detection (SED) involves automatically identifying specific sound events and providing their temporal locations from acoustic signals. Recently, SED tasks have been addressed as frame-level multi-label classification problems.

Many neural network-based methods are proposed, such as convolutional neural network (CNN) [1], recurrent neural network (RNN) [2] and convolutional recurrent neural network (CRNN) [3]. Recently, transformer-based models are studied to handle longer sequences [4, 5]. And some variants from transformer, such as the convolution-augmented transformer (Conformer), has been widely employed for more accurate SED [6, 7]. The conformer integrates CNNs with transformers to effectively capture both local and global dependencies while maintaining parameter efficiency.

However, the effectiveness of SED models is significantly hindered by the absence of strongly-annotated data. There are usually two measures to address this problem. One option is the utilization of alternative annotation methods. Recently, a novel annotation workflow is developed that utilizes the effectiveness of crowdsourcing weak labels and involves a substantial number of annotators to produce dependable and unbiased strong labels [8]. In contrast to traditional binary strong labels, the obtained labels, called *soft labels*, encompass not only textual information and temporal boundaries of the target sound occurrences but also incorporate their corresponding probability of occurrence.

Improving the performance of SED with soft labels is challenged. A CRNN model is employed to demonstrate the beneficial information contained within soft labels[9]. The pre-trained model, audio spectrogram transformer, is applied as a feature extractor to generate frame-wise embeddings to improve SED based on soft labels [10]. Furthermore, the spectro-temporal receptive field is incorporated in convolutional layers to build a human auditory soft SED system [11]. However, the fine-grained information within non-binary soft labels is not effectively utilized in above methods.

Using additional information to facilitate SED tasks is another method to overcome the lack of strongly-annotated data. Acoustic environment analysis can be conducted based on the relationship between sound events and scenes [12]. Different scenes exhibit distinct sound event characteristics, implying that certain events have a low probability of occurring in specific scenes. The prevalent method is to jointly analyze sound scenes and events using multitask learning [13]. When only focusing on SED, scenarios can be utilized as the prior knowledge to enhance performance. For example, scene-based contexts are used as priors that are converted into embeddings for neural networks to achieve more accurate SED [14]. However, the semantic information of these embeddings is unclear and challenging to interpret.

This study introduces a novel dual-branch model for SED that incorporates soft labels. We presents four variations of the interacted convolutional module (ICM) in order to inves-

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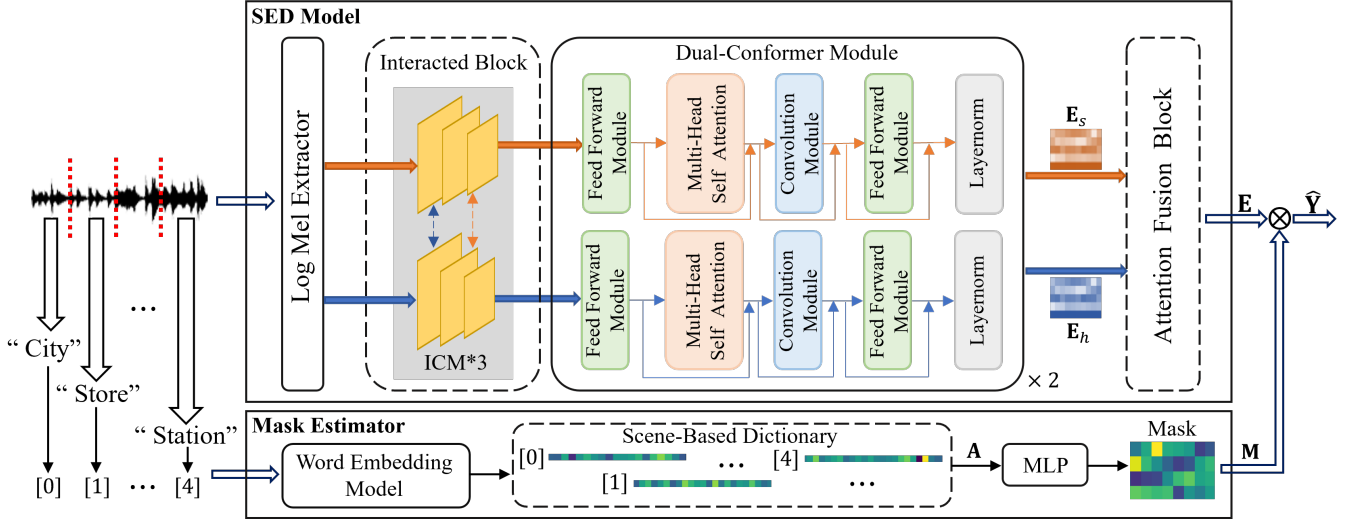


Fig. 1. The overview of proposed interacted dual attention conformer with scene-based mask for sound event detection

tigate the best mechanism for information interaction. One noteworthy addition to our work is the integration of an interpretable scene-based mask, generated by an estimator, into the prediction process of SED models. This integration leads to a notable enhancement in the performance of SED. Compared with our submission report [15] for DCASE 2023, this paper presents a more comprehensive description of the proposed system and conducts various ablation experiments to explore the effectiveness of different methods.

2. METHODS

2.1. Overview

Fig. 1 shows overview of the proposed system. In order to fully exploit the fine-grained information from soft labels \mathbf{Y}_s , we use a fixed threshold (set to 0.5) to convert \mathbf{Y}_s into coarse-grained binary *hard labels* \mathbf{Y}_h . The subscripts s and h stand for *soft* and *hard*, respectively. Therefore, a dual-branch model is applied to exploit the information at different scales from \mathbf{Y}_s and \mathbf{Y}_h simultaneously.

The log mel spectrogram $\mathbf{X} \in \mathbb{R}^{T \times F}$ is extracted, where T and F represent the number of frames and filters, respectively. \mathbf{X} is passed through the SED model to estimate frame-level sound event probability matrices $\mathbf{E}_s \in \mathbb{R}^{T \times K}$ and $\mathbf{E}_h \in \mathbb{R}^{T \times K}$, where K is the number of target event categories. An attention fusion block is employed to perform the back-end fusion of \mathbf{E}_s and \mathbf{E}_h , which produces the final output denoted as $\mathbf{E} \in \mathbb{R}^{T \times K}$.

Meanwhile, we use a mask estimator to produce a frame-level mask $\mathbf{M} \in \mathbb{R}^{T \times K}$ based on acoustic scene priors. The final prediction $\hat{\mathbf{Y}} \in \mathbb{R}^{T \times K}$ can be calculated as:

$$\hat{\mathbf{Y}} = \mathbf{E} \odot \mathbf{M} \quad (1)$$

where \odot is the element-wise multiplication. The loss function can be formulated as:

$$\begin{aligned} Loss = & \alpha \cdot [f(\mathbf{E}_s, \mathbf{Y}_s) + g(\mathbf{E}_h, \mathbf{Y}_h)] \\ & + \beta \cdot [f(\hat{\mathbf{Y}}, \mathbf{Y}_s) + g(\hat{\mathbf{Y}}, \mathbf{Y}_h)] \end{aligned} \quad (2)$$

where α and β denote hyperparameters, $f(\cdot)$ and $g(\cdot)$ represent the mean square error and binary cross-entropy loss functions, respectively.

2.2. SED Model

As depicted in Fig. 1, the SED model is composed of an interacted block, two dual-conformer modules and an attention fusion block. The dual-conformer module is utilized to extract both local features and global dynamic information contained in the embeddings generated by the interacted block, where each branch is composed of a conformer block with the same configuration described in [6].

2.2.1. Interacted Block

The interacted block is applied to transfer information from different branches, which consists of three sequentially connected ICMs. To demonstrate the most beneficial information interaction mechanism, we propose four different structures of ICM shown in Fig. 2.

(1) NI (No Interacted). This structure without any interaction can help us to observe the influence introduced by the other three mechanisms.

(2) PS (Parameter Shared). Parameter sharing is applied in many works [16]. Different components of the network share identical weights, facilitating both branches to learn from similar features during the training process.

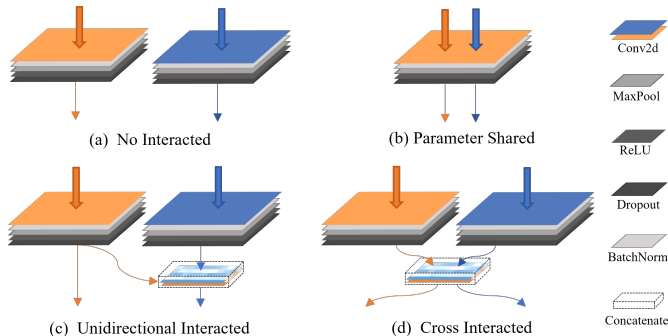


Fig. 2. Different architectures of the interacted convolution module

(3) UI (Unidirectional Interacted). This approach can incorporate fine-grained features from one branch into another branch to capture higher-level semantic features.

(4) CI (Cross Interacted). In the proposed SED model, different branches capture the characteristics of sound events from different scales. This mechanism can achieve multi-scale feature fusion of different branches.

2.2.2. Attention Fusion Block

The proposed attention fusion block is exploited for attentional back-end fusion of results produced by different branches of the SED model, which can be formulated as:

$$f(\mathbf{E}_s, \mathbf{E}_h) = \mathbf{E}_s(i, j) \cdot \mu(j) + \mathbf{E}_h(i, j) \cdot [1 - \mu(j)] \quad (3)$$

where $i = 1, 2, \dots, T - 1$, $j = 1, 2, \dots, K - 1$, and $\mu \in \mathbb{R}^K$ is the learnable attention vector with values from 0 to 1.

Through this attention mechanism, the probability matrices \mathbf{E}_s and \mathbf{E}_h estimated by different branches can be attentionally weighted based on the categories of sound events, and only K attention factors need to be learned. This mechanism is adaptable to audio of varying durations, making it more computationally convenient during inference.

2.3. Mask Estimator

As shown in Fig. 1, the scene-based mask is directly applied to the prediction of the SED model. The mask can reduce the probability of certain events based on the relationship of scene and sound events, and therefore improve the performance. Specifically, a word embedding model is applied to generate the \mathbf{H} -dimensional scene-based dictionary and get the frame-level acoustic scene embedding $\mathbf{A} \in \mathbb{R}^{T \times H}$. Then, we use a MLP to build non-linear projections from the dictionary to the mask $\mathbf{M} \in \mathbb{R}^{T \times K}$. Specifically, we use *Pytorch.nn.Embedding*¹ as the word embedding model. The MLP consists of two linear layers and a LeakyReLU

activation function [17], where the hidden size is set to half of the input dimension ($H/2$).

The scene-based mask can also be designed manually. We firstly calculate the occurrence probabilities of different sound events in each scene based on the entire training set, and then design the mask directly according to the statistical results. This is a time-consuming process, but this artificial mask should be very high quality.

3. EXPERIMENTS

3.1. Dataset and Evaluation Metrics

All experiments are conducted on the dataset provided by the DCASE 2023 Task4B Challenge². The dataset consists of real recordings from 5 scenes, and the evaluation is performed on 11 categories of sound events. F1 score (F1) and error rate (ER) are used as basic indicators [18], based on different decision thresholds and statistical calculation methods [19], the four evaluation metrics are as follows:

$F1_{MI}$. Micro-average F1 with a threshold of 0.5.

ER_{MI} . Micro-average ER with a threshold of 0.5.

$F1_{MA}$. Macro-average F1 with a threshold of 0.5.

$F1_{MO}$. Macro-average F1 with optimum threshold per class.

3.2. Experimental Setup

Mixup [20] is used to alleviate the problem of data imbalance. 128-dimensional log-mel spectrogram is extracted with a window size of 500 ms and a hop size of 250 ms. During training, we feed audio with a fixed duration of 25 s to the model, and therefore the shape of the log-mel spectrogram is 100×128 ($T = 100$, $F = 128$). The hyperparameters α , β in the loss function are set to 0.2 and 0.8, respectively. Dropout rate is set to 0.1.

We develop our systems with the same 5-fold cross-validation setup as the official baseline³. The Adam optimizer is employed to update weights and the batch size is set to 32. The learning rate is initialized to 0.001, which is automatically halved when there is no performance improvement on the validation set for 10 consecutive epochs. Training stops when the learning rate drops 5 consecutive times.

3.3. Main Result

As presented in Table 1, results on the blind test set demonstrate the superiority of the proposed system over other state-of-the-art (SOTA) systems. Our method achieves the best performance on all metrics and outperforms other systems at least by 8.71% and 10.82% on the most important metric $F1_{MO}$ for ensemble and single-mode results, respectively.

²Dataset available at <https://zenodo.org/record/7244360>

³Available at <https://dcase.community/challenge2023/task-sound-event-detection-with-soft-labels>

¹Online available at <https://pytorch.org/docs/stable/generated/torch.nn.Embedding.html>

Table 1. Results of the proposed system and other SOTA systems on the blind test set. All trained using a cross-validation setup.

System	Single-Model				Ensemble			
	$F1_{MI}$	ER_{MI}	$F1_{MA}$	$F1_{MO}$	$F1_{MI}$	ER_{MI}	$F1_{MA}$	$F1_{MO}$
CRNN ³	74.13%	0.484	35.28%	43.44%	-	-	-	-
H. Zhang et al.[21]	77.86%	0.367	35.71%	43.60%	77.96%	0.376	36.45%	43.58%
T. D. Nhan et al. [22]	-	-	-	-	-	-	-	47.17%
M. Chen et al. [10]	75.95%	0.419	31.03%	44.69%	80.89%	0.320	31.74%	52.03%
X. Xu et al. [23]	78.05%	0.371	32.29%	46.13%	80.80%	0.329	35.58%	51.13%
D. Min et al. [11]	78.05%	0.361	29.19%	48.95%	78.27%	0.351	28.68%	48.72%
Proposed	80.04%	0.325	40.29%	59.77%	81.01%	0.320	37.33%	60.74%

Table 2. Results on the validation set based on the proposed system with different interaction mechanisms in ICM.

ICM	$F1_{MI}$	ER_{MI}	$F1_{MA}$	$F1_{MO}$
NI	75.31%	0.402	44.06%	51.16%
PS	75.29%	0.391	43.92%	51.92%
OI	76.18%	0.387	45.83%	53.71%
CI	77.90%	0.384	46.69%	54.49%

3.4. Ablation Study

3.4.1. Interaction Mechanisms in ICM

In order to explore the effective information interaction mechanism for ICM, we obtain the experimental results in Table 2 based on the proposed system. The dimension of the word embedding model is set to 1024. According to Table 2, the ICM with CI structure performs the best. The mechanism effectively fuses embeddings of different scales learned from soft and hard labels, suggesting that a high-accuracy SED system requires adequately granular information for learning. Labels that are too fine-grained, such as soft labels, are tend to generate ambiguous predictions. In contrast, too coarse-grained binary labels can lead the SED system disregard the low-probability sound events more easily.

3.4.2. How Scene-based Mask assists SED

As described in Sec. 2.3, the scene-based mask is learned with a word embedding model and a MLP for more accurate SED. The key to this approach is selecting an appropriate word embedding dimension. Therefore, we use masks generated by the word embedding model with different dimensions and obtain the following results.

As depicted in Fig. 3, the efficacy of the mask steadily enhances and eventually surpasses that of the high-quality artificial mask as the dimensionality of the word embedding model increases. The rationale for this assertion is an increase in

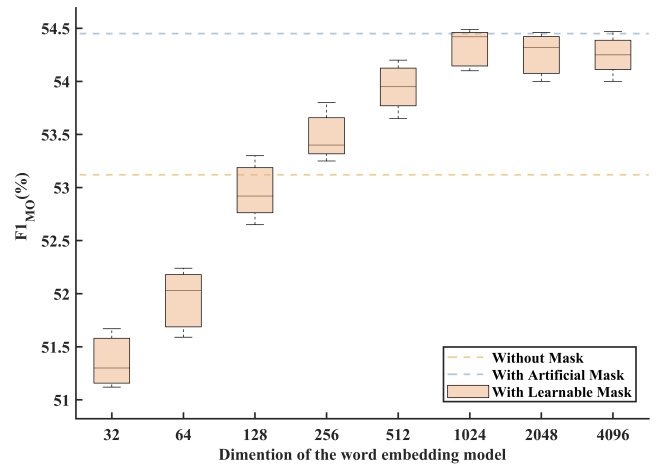


Fig. 3. Results on the validation set based on the proposed system with different mask settings

dimensionality facilitates a greater number of non-linear projections, thereby enhancing the capacity to discern the intricate associations between sound events and their corresponding scenes. Excessive dimensionality, in contrast, might result in a decline in performance. A 1024-dimensional word embedding model is a suitable choice.

4. CONCLUSION

This study introduced a dual-branch model with the scene-based mask generated by an estimator for soft sound event detection (SED). The proposed model achieved the top ranking in the DCASE 2023 Task4B Challenge. The information at various scales is effectively utilized through the dual-branch architecture, and we provide evidence that the cross-interaction mechanism exhibits superior performance in the suggested interacted convolutional module. Furthermore, the efficacy of the scene-based mask produced by the proposed estimator is confirmed to be on par with or even surpass that of the manually built mask. This improvement in performance has a substantial impact on SED.

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