GUIDED MULTI-BRANCH LEARNING SYSTEMS FOR DCASE 2020 TASK 4

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ABSTRACT

In this paper, we describe in detail our systems for DCASE 2020 Task 4. The systems are based on the 1st-place system of DCASE 2019 Task 4, which adopts weakly-supervised framework with an attention-based embedding-level multiple instance learning pooling module and a semi-supervised learning approach named Guided learning (GL). This year, we incorporate Multiple branch learning (MBL) into the original system to further improve its performance. MBL makes different branches with different pooling strategies (including instance-level and embedding-level strategies) and different pooling modules (including attention pooling, global max pooling or global average pooling modules) share the same feature encoder of the model. Therefore, multiple branches pursuing different purposes and focusing on different characteristics of the data can help the feature encoder model the feature space better and avoid overfitting. To better exploit the strongly-labeled synthetic data, inspired by multi-task learning, we also employ a sound event detection branch (SEDB). To combine sound separation (SS) with sound event detection (SED), we fuse the results of SED systems with SS-SED systems which are trained using separated sources output by an SS system. The experimental results prove that MBL can improve the model performance and using SS has great potential to improve the performance of SED ensemble system.

Index Terms— Sound event detection, multi-task learning, weakly-supervised learning, source separation, semi-supervised learning

1. INTRODUCTION

DCASE 2020 task 4 \([1]\) is the follow-up to DCASE 2019 task 4 \([2]\). While DCASE 2019 task 4 targets on exploring the usage of weakly labeled data, unlabeled data and synthetic data in sound event detection (SED), DCASE 2020 task 4 encourages participants to combine sound separation with SED in addition to the same task in DCASE 2019. There are three subtasks in DCASE 2020 task 4: SED without sound separation, SED with sound separation and sound separation (using the SED baseline system). We participated in the first two subtasks. However, for the second subtask, we just use the baseline system for sound separation provided by the challenge organizer and focus on combination of sound separation and SED.

In this paper, we describe in detail our systems for the two subtasks we participated in DCASE2020 task 4. The systems are based on the first-place system of DCASE 2019 task 4 developed by Institute of Computing Technology (ICT), Chinese Academy of Sciences (CAS) \([3]\), which adopts the multiple instance learning (MIL) framework with embedding-level attention pooling \([4]\) and a semi-supervised learning approach named Guided learning \([5]\). The multi-learning branch learning approach \([6]\) is then incorporated into the system to further improve the performance. Multiple branches with different pooling strategies (embedding-level or instance-level) and different pooling modules (attention pooling, global max pooling or global average pooling) are used and shares the same feature encoder. To better exploit the synthetic data with strong labels, inspired by multi-task learning \([7]\), a sound event detection branch (SEDB) is also added. Therefore, multiple branches pursuing different purposes and focusing on different characteristics of the data can help the feature encoder model the feature space better and avoid overfitting. To incorporate sound separation into SED, we train models using output of the baseline system of sound separation and fuse the event detection results of models with of without sound separation.

2. THE DCASE 2019 TASK 4 SYSTEM BY ICT

Our systems for DCASE 2020 task 4 follows the framework of the DCASE 2019 task 4 system by ICT \([3]\), which won the 1st place and the reproducible system award in the DCASE 2019 task 4 challenge. The system utilizes convolutional neural network (CNN) with embedding-level attention pooling module for weakly-supervised SED and uses disentangled features to solve the problem of unbalanced data with co-occurrences of sound events \([4]\). To better use the unlabeled data jointly with weakly-labeled data, the system adopts a semi-supervised learning method named Guided Learning \([5]\), which uses different models for the teacher model and student model to achieve different purposes implied in weakly-supervised SED. For the synthetic data, the system regards them as weakly annotated training set and the time stamps of sound events in the strong labels are not used. The system is trained by the DCASE 2019 training data, including weakly-labeled data, synthetic data and unlabeled data without data augmentation. The system won the 1st place in DCASE 2019 task 4 were the ensemble system of 6 systems with the same model architecture, and the ensemble method is averaging all the probabilities output by the systems.
3. METHOD

3.1. Guided learning for semi-supervised SED

We use the guided learning method as our basic model framework. The guided learning method is composed of two parts: a professional teacher model (PT model) and a promising student model (PS model). The PT-model is designed to predict reliable audio tagging. As a result, The instance-level feature generated by the PT-model has large receptive field.

The PS-model is designed to detect the sound event, of which the audio tagging and the event boundary are both needed to predict. Since the PS-model is not focused on the audio tagging predicting, the instance-level feature generated by the PT-model has small receptive field.

During training, the PT-model and PS-model use the same input data. For the data with weak labels in a batch of input data, the PT-model and PS-model both use the label as their training target. For event category $c$, the loss function is calculated as:

$$\text{Loss}_{\text{labeled}} = \sum_{c} \text{cross-entropy}(y_c, \hat{P}(y_c|x))$$  \hspace{1cm} (1)

where $y_c$ is the ground truth.

For the unlabeled data, the PS-model uses the pseudo labels generated by the PT-model as the training target and the PT-model does not have any training target. The pseudo label generated by the PT model is obtained as:

$$\psi^{PT}_c = \begin{cases} 1, & \hat{P}(y^c_{PT}|x) \geq 0.5 \\ 0, & \text{otherwise} \end{cases}$$  \hspace{1cm} (2)

where $\hat{P}(y^c_{PT}|x)$ denotes the probability of audio tagging output by the PT-model. Then the loss function of the unlabeled data is:

$$\text{Loss}_{\text{unlabeled}}^{PS} = \sum_{c} \text{cross-entropy}(\psi^{PT}_c, \hat{P}(y^c_{PS}|x))$$  \hspace{1cm} (3)

where $\hat{P}(y^c_{PS}|x)$ denotes the probability of audio tagging output by the PS-model. After $s$ training epochs, the PS-model is able to achieve reliable audio tagging. Then, the audio tagging pseudo labels of unlabeled data output by the PS-model is also used as the training target of the PT-model. The loss function is calculated as:

$$\text{Loss}_{\text{unlabeled}}^{PS} = \alpha \sum_{c} \text{cross-entropy}(\psi^{PS}_c, \hat{P}(y^c_{PT}|x))$$  \hspace{1cm} (4)

where $\alpha$ is the hyperparameter to adjust the loss weight. In our experiments, we set $\alpha = 1 - 0.99^{\text{epoch} - s}$.

3.2. Multi-branch learning for semi-supervised SED

To further improve the performance, the multi-branch learning approach\cite{6} is incorporated into the guided learning system (MBL-GL). Multiple branches with different pooling strategies such as embedding-level pooling and instance-level pooling and different pooling modules such as attention pooling (ATP), global max pooling (GMP) and global average pooling (GAP), are used and shares the same feature encoder. As shown in Figure 1, one branch is set as the main branch which takes part in training and detection and another branch is set as the auxiliary branch which is only used for training. In our system, we apply the MBL into PS-model. We choose the embedding-level ATP as the main branch and instance-level GMP or instance-level GAP as the auxiliary branch. The loss function is calculated as:

$$\text{Loss}_{\text{total}}^{PS} = \alpha \text{Loss}_{\text{main}}^{PS} + \beta \text{Loss}_{\text{auxiliary}}^{PS}$$  \hspace{1cm} (5)

The reason why we apply the MBL method in PS-model is that the PS-model outputs the final results of sound event detection while the PT-model only outputs the audio tagging which is only used in the training process of PS-model. In our early study, we find that the improvement of MBL for audio tagging is limited than the sound event detection.

By using multi-branches, in addition to better train the feature encoder, we can also fuse the results of both branches to obtain better result. In this paper, if the auxiliary branch is instance-level GAP, we ensemble the detection results of the main branch and auxiliary branch by taking the average results of instance-level probabilities.

$$\hat{P}_{\text{fusion}}(y_c|x_i) = \alpha \hat{P}_{\text{GAP}}(y_c|x_i) + (1 - \alpha) \hat{P}_{\text{ATP}}(y_c|x_i)$$  \hspace{1cm} (6)

We set $\alpha = 0.5$ in our experiments.

In\cite{6}, the MBL approach is proposed only for weakly-labeled data. However, in this work, we need to use the unlabeled data to train our model. In our early experiments, we found that while using the original data ratio between the weakly-labeled and unlabeled data, which is about $1:9$ in mini-batches, the MBL-GL is hard to achieve good performance. The reason for this phenomenon is that for MBL, although more branches can make the common feature be fit for various learning purposes so that reduce the risk of overfitting, if the training data contains much noise, more branches can increase the risk that the common feature can not fit for any learning purpose. For the Guided learning framework, the training targets of the unlabeled data for PS-model are produced by the PT-model, which contains some noise. As a result, we increase the ratio between labeled data and unlabeled data to reduce the noise in training data. Besides, different from\cite{6}, we only use one auxiliary branch since we find that using two auxiliary branches can decrease the model performance of MBL-GL for the same reason that in guided learning, the training data for the PS-model contains noise and may increase the difficulty to train multiple branches.

3.3. The detection branch for synthetic data

In previous study, the multi-task learning of SED in which the detection of sound event boundary and the existence of the sound event are considered as two tasks are proved to be a good method to improve the performance of SED. However, this method needs strong label for training. In this work, only the synthetic data has strong label. To better exploit the synthetic data with strong labels, inspired by multi-task learning, a sound event detection branch (SEDB) is
also added. As shown in Figure 1 all training data, only the synthetic data are used for training the SEDB and the output of the SEDB is the probability of each instance. Then the loss function is calculated as:

$$\text{Loss}_{\text{SEDB}} = \sum_o \sum_t \text{cross}\text{-}\text{entropy}(y_{ct}, \hat{P}(y_{ct}|x_t)) \quad (7)$$

where $c$ denotes event category, $t$ denotes frame number. $\hat{P}(y_{ct}|x_t)$ is the instance-level probability output by the SED and the $y_{ct}$ is the instance-level ground truth.

While using the strong labels of the synthetic data to train the SEDB, we also use the weak label of synthetic data to train other branches of the MBL-GL model. In our method, we only apply the SEDB in PS model because the PS-model is mainly used to detect the sound event.

### 3.4. Data augmentation

Data augmentation is applied in the training process. For all training data, including weakly-labeled data, unlabeled data and synthetic data, we use time-shifting and frequency-shifting to generate augmented data. For time-shifting, all frames (500) are shifted for 90 steps. For frequency-shifting, all frequencies (64) are shifted for 8 steps. We set the ratio between the original data and the augmentation data to be 8:1.

### 3.5. System ensemble

For system ensemble, we choose different kinds of systems to construct the ensemble system. We take 3 systems with instance-level GAP as auxiliary branch and 3 systems with instance-level GMP as auxiliary branch to construct the SED-Ensemble system. To make the difference between systems large enough, 2 of the 3 systems with instance-level GMP auxiliary branch are with sound event detection branch. To construct the SS-SED-Ensemble system, besides 6 systems in the SED-Ensemble system, we add 3 other systems which are trained by source separated data and has instance-level GAP auxiliary branch. We take the weighted sum of all the system outputs as the final results. The function is:

$$\hat{P}_{\text{ensemble}}(y_{ct}|x_t) = \sum_i w_i \hat{P}^{\text{single-system}}_i(y_{ct}|x_t) \quad (8)$$

where $\sum_i w_i = 1$. The default $w_i = 1/\text{number of systems}$ and the values can be tuned based on the performance of the validation set.

### 3.6. Combination of sound separation and SED

To incorporate sound separation into sound event detection, we train the SED models by the separated data output from the baseline system of sound separation. We use the MBL-GL model with instance-level GAP auxiliary branch (no sound event detection branch) as the SS-SED model. We also generate augmented data based on the separated data and set the ratio between the original data and the augmented data to be 8:1. Then, we fuse the sound event detection results of models trained by real data and separated data to get the final SS-SED-Ensemble system result. $\sum_i w_i + \sum_j w_j = 1$.

$$\hat{P}^{\text{SS-SED-Ensemble}}(y_{ct}|x_t) = \sum_i w_i \hat{P}^{\text{SS-SED}}_i(y_{ct}|x_t) + \sum_j w_j \hat{P}^{\text{SS-SED}}_j(y_{ct}|x_t) \quad (9)$$

### 4. SYSTEM

#### 4.1. Model architecture

For the PS-model, the feature encoder consists of 3 CNN blocks, each of which contains a convolution layer, a batch normalization layer, a max pooling layer and a ReLU activation layer. For the PT-model, the feature encoder consists of 8 CNN blocks with a dropout. The main branch of the PS-model and the PT-model uses embedding-level ATP. And the PS-model has an auxiliary branch which uses instance-level GMP or GAP. The sound event detection branch is optional and is add to the PS-model in some systems.

#### 4.2. Model training

We use the Adam optimizer with learning rate 0.0018 to train the model. The learning rate is reduced by 20% for every 10 epochs. The mini-batch size is set to be 64. For a mini-batch of data, we set the ratio of the weakly-labeled data: synthetic data: unlabeled data to be 3:1:12 (It means that there are 12 weakly-labeled data, 4 synthetic data and 48 unlabeled data in a mini-batch).

#### 4.3. The competition systems

We participated in 2 subtasks which are SED without sound separation and SED with sound separation (SS-SED). We submitted 4 systems for each subtask and the best system for subtask 1 an event-based F1 score of 44.6% and the best system for subtask 2 achieves an event-based F1 score of 44.7%. For our best system of subtask 1, we use 6 systems to make the ensemble system. For our best system of subtask 2, besides the 6 systems in subtask 1, we use 3 systems trained by source separated data to make the ensemble system.

### 5. EXPERIMENT

#### 5.1. Experimental setup

The training set of our SED system contains a weakly-labeled training set (1578 clips), an unlabeled training set (14412 clips), and a synthetic strongly labeled set (2584 clips). The validation set contains 1168 strongly-labeled clips. The public test set contains 692 strongly-labeled clips. For the SS-SED system, we use the baseline system of source separation to separate the training set of the SED. The separated data is used to train the SS-SED system. We report the event-based marco F1 score [3]. All the experiments are repeated 20 times with random initiation and we report both the average result and the best result of each model.

#### 5.2. Experimental results

Experimental results are shown in Table 1, Table 2 and Table 3. The Table 1 shows the results of individual systems which are used for system ensembling, and Table 2 and Table 3 show the average and the best result of each kind of system and the results of ensemble systems. For all the experiments, we do not change the PT model and only change the PS model. In the table, E-* denotes the embedding-level approach and I-* denotes the instance-level approach. SS-* denotes the system uses the source separated data. For the baseline system E-ATP, we use the MBL-GL model structure. The only difference between the baseline system and other two kinds of system (E-ATP + I-GAP, E-ATP + I-GMP) is that the baseline system dose not have any auxiliary branch. As shown in Table 2 and Table 3.
we find that adding auxiliary branch such as I-GMP or I-GAP can have a beneficial effect. For the ensemble system, we use 3 E-ATP + I-GMP and 3 E-ATP + I-GAP systems to construct it. Besides, to make the difference between models larger, 2 of the 3 E-ATP + I-GMP models use SEDB. The ensemble system achieves an F1 score of 0.497 on the public test set and 0.467 on the validation set. Compared to only using systems without the SEDB, using some systems with the SEDB has potential to improve the performance of the ensemble system. We use the 3 E-ATP + I-GAP and 3 E-ATP + I-GMP systems (2 of the 3 systems which use SEDB are replaced by E-ATP + I-GMP-4 and E-ATP + I-GMP-5 ) without SEDB to construct ensemble system which is named SED-Ensemble_6 systems. It achieves F1 scores of 0.495 on public test set and 0.463 on the validation set, which are not as good as the ensemble system using SED-B, i.e., SED-Ensemble (submit).

For the SS-SED-Ensemble system, besides the 6 models used in SED-Ensemble, 3 E-ATP + I-GAP models which are trained by separated data are used and the SS-SED ensemble system achieves F1 scores of 0.495 on the public test set and 0.463 on the validation set. We use 3 other E-ATP+I-GAP systems (E-ATP + I-GAP-4, E-ATP + I-GAP-5, E-ATP + I-GAP-6) trained by real data to replace the SS-SED systems in the SS-SED-Ensemble system. The ensemble system which is named SED-Ensemble_9 systems achieves F1 scores of 0.485 on the public test set and 0.463 on validation set, which are lower than the SS-SED-ensemble system. Although the performances of the 3 E-ATP + I-GAP systems trained by real data are better than the SS-E-ATP + I-GAP systems, they can not improve the system performance while the SS-E-ATP + I-GAP can improve the performance. It proves that adding SS-SED systems to construct the ensemble system can achieve a better performance since the SS-SED systems may have some feature that SED systems do not have. If the performance of the SS-SED system can be further improved, it is expected to further improve the performance of the ensemble system.

6. CONCLUSIONS

This paper presents the details of our systems for DCASE 2020 task 4. The systems are based on the first-place system of DCASE 2019 task 4, which adopts the multiple instance learning (MIL) framework with embedding-level attention pooling and a semi-supervised learning approach called guided learning. The multi-branch learning approach is then incorporated into the system to further improve the performance. Multiple branches with different pooling strategies and different pooling modules are used and shares the same feature encoder. To better exploit the synthetic data with strong labels, inspired by multi-task learning, a sound event detection branch (SED-B) is also added. Therefore, multiple branches pursuing different purposes and focusing on different characteristics of the data can help the feature encoder model the feature space better and avoid over-fitting. The source separation method is also used and we find that combining the source separation method to make the ensemble system has great potential to improve the system performance.

### Table 1: The event-based F1 of individual systems

| Model                  | Average F1 | Best F1 |
|------------------------|------------|---------|
| E-ATP                  | 0.42 ± 0.0115 | 0.444   |
| E-ATP + I-GMP          | 0.430 ± 0.0088 | 0.445   |
| E-ATP + I-GAP          | 0.431 ± 0.0156 | 0.451   |
| SED-Ensemble (submit)  | -          | 0.467   |
| SED-Ensemble_6 systems | -          | 0.463   |
| SS-SED-Ensemble (submit) | - | 0.472 |
| SS-SED-Ensemble_9 systems | - | 0.463   |

### Table 2: The event-based F1 scores on the validation set

| Model                  | Average F1 | Best F1 |
|------------------------|------------|---------|
| E-ATP                  | 0.449 ± 0.0124 | 0.47    |
| E-ATP + I-GMP          | 0.468 ± 0.0125 | 0.478   |
| E-ATP + I-GAP          | 0.450 ± 0.0130 | 0.470   |
| SED-Ensemble (submit)  | -          | 0.497   |
| SED-Ensemble_6 systems | -          | 0.495   |
| SS-SED-Ensemble (submit) | - | 0.485   |
| SS-SED-Ensemble_9 systems | - | 0.485   |

### Table 3: The event-based F1 scores on the public test set
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