Soft-Median Choice: An Automatic Feature Smoothing Method for Sound Event Detection

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Abstract—In existing Sound Event Detection (SED) algorithms, the roughness of extracted feature causes decline of precision and recall. In order to solve this problem, a novel automatic feature smoothing algorithm based on Soft-Median Choice is proposed. Firstly, in the feature extractor of Convolutional Recurrent Neural Network (CRNN), 1-dimension (1-D) convolutional layers are added to extract more temporal information. Secondly, a novel module of the Median Choice is inserted into CRNN. It is consisted of median filters and a Linear Choice layer to automatically get the knowledge of the features with different smoothing levels. Thirdly, a Soft-Median function is designed to replace the median function. It uses all the data instead of one, so as to dredge the path of gradient flowing and make the network converge better. Finally, in the classifier, the Linear Softmax is utilized to avoid the unnecessary false positives caused by attention module. Through evaluations, we demonstrate that the proposed method obtains significantly better scores than the referential algorithms.

Index Terms—Convolutional Recurrent Neural Network (CRNN), Linear Softmax, Mean-teacher, Soft-Median Choice, Sound Event Detection (SED), Semi-supervised Learning

I. INTRODUCTION

Sound event detection (SED) is a task to recognize the presence of sound events, and also detect their onsets and offsets. As of 2013, the Challenge on Detection and Classification of Acoustic Scenes and Events (DCASE) competition has helped to raise attention in SED problems. In the preparation of the training dataset, the strongly labeled datasets with onsets and offsets annotated are labeled by humans, which costs much labor work. To save time and labor costs, in DCASE Task 4 of 2020, the weakly labeled and unlabeled data are used, where weak label means only labeling the presences or absences of sound events without onsets and offsets. The synthesized data are also used as strongly labeled data as they are easier to obtain than annotating real samples[1].

Reference [1] serves as the baseline and uses a CRNN model for classification, an attention method for aggregation and a mean-teacher[2] model for semi-supervised learning. Derived from this, some researchers use newer models, for example, Miyazaki[3][4] used the Transformer or Conformer frameworks in the place of RNN as they can solve the problem of long-term dependence. The Transformer or Conformer is more complex than RNN but results have shown that there has not been much improvement in the single model due to the lack of transparent long-term dependence in sound events. Capsule network is a model capable for recognizing overlapping figures which may work well in polyphonic SED[5]. Inspired by this, [6-8] use capsule layers for SED but the CNN and pooling layers being used goes against the original intention of inventing Capsule: to avoid the shortcomings of CNN. What is more, due to the incompatibility of dynamic routing with RNN, the RNN structure is abandoned in [6] and [7] whereas for highly time-connected sound events, it is necessary to take time dependencies into good account. In order to avoid over-fitting, mixup[9] and time-shifting[10] are used. For aggregation from strong predictions to weak predictions, [11] replaces the attention module with Linear Softmax and results show that it is the best approach among the 5 pooling methods.

The predictions of the sound events are not smooth, which inspired researchers to optimize the model. For example, Ebbers[12] designed a model with 1-D convolution layers to get more information in the time axis; Yao[13] used a multi-scale pooling layer to get the knowledge of larger scales. However, an average pooling is not robust to outliers, but the median filter is. Thus, the performance of the median-filter is presumably better than the average pooling. To solve the problem of roughness in the predictions, we use a linear combination of the smoothed values yielded by a series of median filters, which is called the Median Choice. But the training path is greatly blocked by the median function. To smooth the training process, we further design the Soft-median function. Our proposed Soft Median Choice method achieves much better event-based F1 Score (EBFS) and Polyphonic Sound Detection Score (PSDS) compared to the baseline system, which indicates higher precision and recall.

II. PROPOSED METHOD

Fig. 1 is an overview of the proposed method. During training process, the Mel Spectrum is first obtained through the input of an audio clip. For the first part of the model, the Mel Spectrum goes through the CRNN block to extract enough features for classification. The CNN is consisted of 7 layers of 2-D convolution and 3 layers of 1-D convolution conducted through the time axis. Between CNN and RNN, a novel structure named Soft-Median Choice is added to choose a linear combination of different smoothness levels of the feature. Each
channel of the smoothed feature is obtained by a Soft-Median filter of a different window length. The features go through an RNN block of 2 layers of Bidirectional Gated Recurrent Unit (BiGRU). The temporal structure of 1-D convolutions and RNN enables the model to grab more information through time, which is useful as sound signals are highly time-sequential. In the classifier, the strong prediction is obtained through a linear layer and a sigmoid function; the weak prediction is obtained from the strong prediction with a Linear Softmax function. In this way, the model can yield strong and weak predictions simultaneously. During evaluation, the strong prediction goes through a post-processing of thresholding and median-filtering resulting in one-hot strong prediction.

A. Improvements in the Feature Extractor of CRNN

The 2-D CNN used in baseline does not pay enough attention to the temporal connections. Inspired by [12], three 1-D convolutional layers are added after the seven 2-D convolutional layers, as seen in Fig. 1, in order to obtain more information through time.

B. Soft-median Choice

The roughness of the yielded predictions causes false negatives within a sound event and false positives in the middle of nothing, which produces wrong predictions. For smoothing methods, the median-filtering is more robust to outliers and is thus used by the baseline in post-processing to smooth the predictions. However, it is the roughness in the features that eventually causes the roughness in the predictions and none of the previous researchers has tried to smooth the features using median-filtering. Also, in the median-filtering post-processing, the length of the window is not learned but fixed by humans, which is also not optimal. To smooth the features with median-filtering and also without a fixed window length, we propose a novel structure of the Median Choice. It uses median filters within the feature extractor to smooth the features for the classifier to yield smoother predictions. The hyperparameter of the window length is not needed, rather, the results of a series of median filters with different lengths are provided for the model to choose by itself and the weight of the result of each median filter is learned automatically.

1) Median Choice

The Median Choice is designed for the purpose of getting the knowledge of feature smoothed to different extents simultaneously, as shown in Fig. 2.

The extracted feature is first processed by median filter layers of different window sizes, then a Linear Choice block integrates the information provided by the median filter layers, yielding a linear combination:

$$z = \sum_{i} w_i y_i + b$$  \hspace{1cm} (1)

where $y_i$ denotes the smoothed result of $i$-th median filter, $z$ is the output of the Linear Choice, $w_i$ is the weight of the $i$-th median filter and $b$ is the bias. The weights and bias are randomly initialized and learned by back-propagation.

The proposed Median Choice method can get the information of smoothed feature of median filters with different window lengths. The automatically smoothed feature can make the classifier yield more stable predictions.

2) Soft-Median

Although the Median Choice is presumably able to contribute to smoother predictions and improve performance, the model with this framework cannot converge well as expected. The reason lies in the median function used in the median filters. Like the max function, the median function only picks one value among multiple values. Thus, in the back-propagation of gradient, only the parameters related to the picked points can acquire a gradient, which greatly affects the training process and weakens the performance of the model. In order to solve this problem, we design a novel Soft-Median function in the place of the original median function to aggregate values to their median while using all the data simultaneously.

The process of designing Soft-Median is similar with that of Softmax. Fig. 3 shows the distributions of 3 existing functions and the expected distribution of Soft-Median to be designed. As shown in Fig. 3, the equation of Max can be denoted by:

$$W_i = \delta(x_i - x_{\max})$$  \hspace{1cm} (2)
where \( x \) is the symbol of data points, \( W \) denotes weight, \( k \) indicates the sequence number of the points within a window and \( \delta \) denotes the unit impulse function:

\[
\delta(x) = \begin{cases} 
1, & x = 0 \\
0, & others 
\end{cases}
\]  

(3)

The weights of Softmax are exponential. Softmax gives almost all the weights to the largest value and smaller weights to smaller values. The weights of Softmax are calculated by the function as follows:

\[
W_i = \frac{e^{x_i}}{\sum e^{x_i}}
\]  

(4)

Similarly, the median function is denoted by:

\[
W_k = \delta(x_k - \bar{x})
\]  

(5)

where "\( \bar{x} \)" means the median within a window.

The Soft-Median function must satisfy three conditions: a) The weight must be the largest at the median point. b) The longer the distance between the point and the median is, the smaller the weight is. c) The weight must decrease sharply to zero so the function can be still approximated as a median function.

Due to the aforementioned reasons, the weight function of Soft-Median is chosen to be \( x^2 \), but the weight of the median point itself cannot be 1, so we use a small \( \varepsilon \) to divide some weights to other points, circumventing the median point to get all the weight. The equation is denoted as follows:

\[
W_i = \frac{1}{\sum (x_k - \bar{x})^2 + \varepsilon}
\]  

(6)

It can be proved that when \( \varepsilon \rightarrow 0 \), (6) → (5). Note that each aggregated value is reached by a weighted sum:

\[
y_w = \sum_{i} W_i y_i x_i = \sum_{i} \frac{(x_k - x_0)^2 + \varepsilon}{\sum (x_k - \bar{x})^2 + \varepsilon} x_i
\]  

(7)

where \( j \) denotes the number of the points in the filtered result.

It should be mentioned that the denominator and numerator of the weights can be very large. For numerical stability, it is recommended that the weights are calculated first before multiplying \( x_i \). The Soft-Median function successfully accelerates the training process and helps the model to converge to a better point, which results in much better performance.

C. Improvement in the Classifier

The classifier is consisted of a linear layer with Sigmoid and an aggregation method. In the aggregation, the predicted strong prediction is assembled as a weak prediction. According to [11], the attention method focuses on frames with low probabilities, causing false positives. On the other hand, Linear Softmax shows reasonable behavior in gradient flow and reaches the best performance. Therefore, we replace the attention module to Linear Softmax. The equation of Linear Softmax is as follows:

\[
L_w = \sum_{i} L_{wi} L_{si}
\]  

(8)

where \( L \) means the label result, \( w \) and \( s \) means weak and strong respectively, and \( i \) is the sequence number.

D. Data Augmentation

To prevent the model from over-fitting, we use data augmentation methods of mix-up[9] and time-shifting[10]. The shift size is chosen from a normal distribution with a mean of 0 and a derivation of 90. The feature is shifted through the time axis, while the strong labels are shifted accordingly. The method of mix-up is denoted as follows:

\[
\tilde{d} = \lambda d_1 + (1 - \lambda) d_2
\]  

(9)

\[
\tilde{l} = \lambda l_1 + (1 - \lambda) l_2
\]  

(10)

Where the data points and the labels are \( d_1 \), \( d_2 \) and \( l_1 \), \( l_2 \), \( \tilde{d} \) and \( \tilde{l} \) are the mixed data and label respectively. \( \lambda \) is chosen randomly from a beta distribution Beta \((\alpha, \alpha)\), in which \( \alpha = 0.2 \). The data augmentation is done in the interiors of the 3 datasets, as the labels need to be in the same form.

III. EXPERIMENTS AND RESULTS

A. Training Configuration

The datasets are from DCASE Task 4[1]. The number of samples in the “weak-real”, “strong-synthetic” and “unlabeled-real” for training datasets are respectively 1578, 2584 and 14412; the number of validation and evaluation datasets are 1168 and 692. Each audio sample is of a length of 10 seconds. The models all use a mean-teacher method[2] for semi-supervised training. All of the other configurations follow the baseline. The implementation of differentiable median filters is derived from kornia, which is available at https://pytorch.org/project/kornia/.

B. Evaluation of Soft-Median Choice

The consequential bias in the Linear Choice is small and from -0.0470 to 0.0513, so we focus on the weight. Fig. 4 shows how the weights change during training. The upper picture uses a Soft-Median Choice (SMC) with the lengths of the filters from 1 to 60 (not including 60) with a gap of 2, which makes 30 Soft-Median filters; the lower uses the lengths from 1 to 60 (not including 60) with a gap of 4, which makes 15 Soft-Median filters. At the beginning of the training, the weights are randomly initialized. From about epoch 19 the weights begin to change rapidly; at about epoch 50, the weights are reallocated and appear to be relatively stable.

The result of the training process shows that at the beginning of the training, the feature extractor cannot yet yield distinct
feature for the presence/absence information of the classes. As a result, the model focus on training the modules in feature extractor and classifier. When the model is capable to yield the strong and weak predictions more accurately, the un-smoothness of the prediction reveals its harmfulness in the performance of the model. The model begins to automatically learn to reach an optimal combination of the features smoothed at different levels.

The relatively stable weights at epoch 200 are shown in Fig. 5. Regardless if the first weight is positive or negative, which also appears randomly, they are all of rather large absolute values, indicating the greater importance over all other filters. The other filters are of less importance but the weights are not zero, meaning that the model ensembles the information of highly smoothed features as well.

C. Evaluation of the Proposed Method

The performance indicators are EBFS[14] and PSDS[15]. They indicate a balanced level of precision and recall. All the indicators suggest better performance when they are larger. The settings of the indicators follow [1]. The best epochs are chosen according to the best EBFS in validation set without median-filter post-processing, and are further processed with a median filter of 0.45s in the validation set and the evaluation set for comparison.

Table I shows a comparison of the different models of different indicators and under different circumstances. CRNN and Classifier Improved (CCI) Model is an improvement to the baseline according to IIA and IIC. According to Group 1-2 in Table I, the CCI model shows much better EBFS and PSDS than the baseline. In Group 3, the scores of the baseline raise unexpectedly, resulting in about 1% better than the CCI model. That is because the size of the evaluation set is rather small, causing uncertainty, but the overall performance of the CCI model is still considered better. Compared with the baseline, the CCI model adds 1-D convolutional layers after the 2-D convolutional layers in CNN. The 1-D convolution is conducted in time axis to grab the time-dependency information. Thus, it can alleviate the problem of the instability in the prediction. According to [11], the back-propagation causes the attention to incorrectly focus on the points with low possibilities, which increases false positives. The CCI model also replaces the attention module with Linear Softmax. conducted in Despite the improvement, the model still cannot integrate the features of different smoothing levels. Based on CCI, we further add the proposed module of SMC. According to Table I, compared with CCI model, the models with SMC show better performance under all circumstances. As explained in IIIB, SMC can pull together the feature smoothed to different extents, thus it is robust against unexpected interference of outliers.

According to Table I, the proposed method of CCI+SMC shows much better performance compared with baseline. The reason lies in that the 1-D convolutional layers in CCI grab more knowledge in the time axis, the SMC method solve the problem of the roughness of the feature, and the Linear Softmax in CCI prevents unnecessary false positives.

The models of 15 or 30 filters show similar performances. While the one of 15 filters is less likely to overfit (showed in Group 2 of Table I), the one of 30 filters is better at generalization (shown in Group 3 of Table I). According to overall performance and the size of model, the CCI+SMC model with 15 filters is regarded as the best model.

IV. CONCLUSION

In this paper, we used 1-D convolutions and Linear Softmax to improve the SED model. We also proposed Median Filter Choice to obtain more information in the feature of different levels of smoothness. We further designed a novel Soft-Median function for the convenience of training. The proposed Soft-Median Choice can get the knowledge of the features smoothed in different levels and is more robust to the roughness of the feature. As a result, our proposed method showed better performance of EBFS and PSDS than referential algorithms.

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REFERENCES

[1] Turpault N, Serizel R. Training sound event detection on a heterogeneous dataset[J]. arXiv preprint arXiv:2007.03931, 2020.

[2] Tarvainen A, Valpola H. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results[C]//Advances in neural information processing systems. 2017: 1195-1204.

[3] Miyazaki K, Komatsu T, Hayashi T, et al. Weakly-Supervised Sound Event Detection with Self-Attention[C]//ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020: 66-70.

[4] Miyazaki K, Komatsu T, Hayashi T, et al. Convolution-Augmented Transformer for Semi-Supervised Sound Event Detection[R]. Tech. Rep. DCASE Challenge, 2020.

[5] Sabour S, Frosst N, Hinton G E. Dynamic routing between capsules[C]//Advances in neural information processing systems. 2017: 3856-3866.

[6] Vesperini F, Gabrielli L, Principi E, et al. Polyphonic sound event detection by using capsule neural networks[J]. IEEE Journal of Selected Topics in Signal Processing, 2019, 13(2): 310-322.

[7] Iqbal T, Xu Y, Kong Q, et al. Capsule routing for sound event detection[C]//2018 26th European Signal Processing Conference (EUSIPCO). IEEE, 2018: 2255-2259.

[8] Liu Y, Tang J, Song Y, et al. A capsule based approach for polyphonic sound event detection[C]//2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE, 2018: 1853-1857.

[9] Zhang H, Cisse M, Dauphin Y N, et al. mixup: Beyond empirical risk minimization[J]. arXiv preprint arXiv:1710.09412, 2017.

[10] Delphin-Poulat L, Plapous C. Mean teacher with data augmentation for dcase 2019 task 4[J]. Orange Labs Lannion, France, Tech. Rep, 2019.

[11] Wang Y, Li J, Metze F. A comparison of five multiple instance learning pooling functions for sound event detection with weak labeling[C]//ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019: 31-35.

[12] Ebbers J, Haeb-Umbach R. Convolutional Recurrent Neural Networks for Weakly Labeled Semi-supervised Sound Event Detection in Domestic Environments[J]. 2020

[13] Yao T, Shi C, Li H. Sound Event Detection in Domestic Environments Using Dense Recurrent Neural Network[J]. 2020

[14] Mesaros A, Heittola T, Virtanen T. Metrics for polyphonic sound event detection[J]. Applied Sciences, 2016, 6(6): 162.

[15] Bilen Ç, Ferroni G, Tuveri F, et al. A framework for the robust evaluation of sound event detection[C]//ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020: 61-65.