LEARNING DISCRIMINATIVE AND ROBUST TIME-FREQUENCY REPRESENTATIONS FOR ENVIRONMENTAL SOUND CLASSIFICATION

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\textbf{ABSTRACT}

Convolutional neural networks (CNN) are one of the best-performing neural network architectures for environmental sound classification (ESC). Recently, attention mechanisms have been used in CNN to capture the useful information from the audio signal for sound classification, especially for weakly labelled data where the timing information about the acoustic events is not available in the training data, apart from the availability of sound class labels. In these methods, however, the inherent time-frequency characteristics and variations are not explicitly exploited when obtaining the deep features. In this paper, we propose a new method, called time-frequency enhancement block (TFBlock), which temporal attention and frequency attention are employed to enhance the features from relevant frames and frequency bands. Compared with other attention mechanisms, in our method, parallel branches are constructed which allow the temporal and frequency features to be attended respectively in order to mitigate interference from the sections where no sound events happened in the acoustic environments. The experiments on three benchmark ESC datasets show that our method improves the classification performance and also exhibits robustness to noise.

\textbf{Index Terms}— environmental sound classification, convolutional neural networks, attention mechanism, sound event

\textbf{1. INTRODUCTION}

Environmental sound classification (ESC) is an important research area in human-computer interaction with a variety of potential applications such as audio surveillance \[\text{1}\] and smart room monitoring \[\text{2}\]. Due to the dynamic and unstructured nature of acoustic environments, it is a practical challenge to design appropriate features for environmental sound classification. In many existing ESC methods, the features are often designed based on prior knowledge of acoustic environments, and a classifier is then trained with the features to obtain the category probability of each environmental sound signal.

Among these methods, deep learning, which is facilitated by the availability of increased amount of training data and techniques of data augmentation, offers the state-of-the-art performance in ESC, including the convolutional neural networks (CNN) based methods, such as \[\text{3, 4}\], where spectrograms and mel-scale frequency cepstral coefficients (MFCC) have been used as features. Different from the images in visual recognition tasks, however, the time and frequency information represented by spectrograms will have different characteristics and degree of importance in sound recognition. Although translation in the time domain has little effect on the classification of sound events, the difference across frequency bands has significant impact on the performance on sound classification. To capture the information about which parts of the features are more relevant to the output classes, attention mechanisms have been proposed, including temporal attention and spatial attention \[\text{5, 6, 7, 8}\]. Temporal attention has been applied to obtain weights for combining feature vectors at different time steps, but does not consider the importance of different frequency bands. On the other hand, spatial attention focuses on global regions over the whole feature map and is prone to adverse effect by noise.

To address the above issues, we propose a frequency-selective attention method, which allows the networks to be aware of the variety of information in frequency channels, and to pay a different degree of attention to various frequency bands. Our idea is inspired by the study of frequency-selective attentional filter in human primary auditory cortex \[\text{9}\], which shows that the human brain facilitates selective listening to a frequency of interest in a scene by reinforcing the fine-grained activity pattern throughout the entire superior temporal cortex that would be evoked. In addition, we apply temporal attention to capture the certain frames where sound events happen. Our method pays attention to the temporal and frequency features with two different branches whose outputs are summed up with different weights to mitigate interference from the sections where no sound events happened in the acoustic environments. For example, the activation of noisy frequency bands can be weakened by temporal atten-
tion, which leads to improved robustness to frequency distortions. The proposed method is evaluated on three benchmark datasets: ESC-10 [10], ESC-50 [10] and UrbanSound8k [11]. Based on the experiments, the proposed method can achieve classification accuracy of 95.8%, 87.7% and 88.5%, for the three datasets respectively, which are 1.2%, 1.2%, and 0.5% higher, compared with the state-of-the-art results. Furthermore, we visualize our results to give a better understanding how our model helps capturing the subtle changes in the spectral and temporal structure of sound events in a complex and dynamic acoustic environment.

The remainder of this paper is organized as follows. Section 2 discusses related work. Section 3 gives our method and network architecture. In Section 4, we carry out experiments to show the effectiveness of our proposed method. Finally, Section 5 concludes this paper.

2. RELATED WORK

Environmental sound classification has received sustained attention. In recent years, many works have employed deep architecture to extract time-frequency representations that can automatically capture the sound events across the time and frequency axis of the spectrogram. Piczak [3] designed one of the first experiments to use convolutional neural networks on the ESC-50 dataset [10]. Deep CNN with data augmentation [12] was proposed to obtain a feature representation through stack convolutional layers. In [13], a CNN-LSTM based method is proposed to model spatial and temporal information in different stages, where CNN is used first to extract time-frequency features and then the Long Shot-Term Memory (LSTM) is used to model temporal information within the signal. In these methods, however, the local temporal relationship is not considered. To address this limitation, temporal attention [7] [14] is adopted to calculate the contribution of different frames to ESC and spatial attention [8] is applied to obtain weights over the whole feature map. However, temporal attention does not consider the difference across the frequency bands, while spatial attention is prone to the adverse effect of noise, so that these attention mechanisms cannot be effectively applied to the complex spectrograms generated by the environmental sounds. As a solution to the above problems, we present a new method, namely time-frequency enhancement block, which consists of parallel branches for exploiting the time-frequency information of environmental sound. In this way, our method can learn more discriminative and robust sound representations.

3. PROPOSED METHOD

In this paper, we propose a time-frequency enhancement block (TFBlock) for environmental sound classification, which can guide the network to pay different attention to the temporal and frequency characteristics of environmental sounds. Our model is called TFNet (neural network with TFBlocks) and its overall architecture is shown in Figure 1. Details about TFBlock is given in Section 3.1.

3.1. TFBlock

The structure of the time-frequency enhancement block is depicted in Figure 1. For the given input feature maps $X_1$ where $X_1 \in \mathbb{R}^{T \times F \times C}$, two convolutional layers of $3 \times 3 \times C$ are applied to obtain feature maps $U_1$ and $U_2$, both with a size of $T \times F \times C$. Batch normalization is applied between convolutional layers and we use PReLU as the activation function.

We apply two attention mechanisms, which are Temporal Attention and Frequency Attention, to enhance the features from certain frames and frequency bands. Our method uses convolutional layers to extract local information...
and uses fully-connected layers to integrate global information. Specifically, $1 \times 1 \times 1$ convolutional layers are applied to get a global feature map across channels, whose size is $T \times F \times 1$. The $1 \times 1$ filters are used to squeeze the number of channels to 1 and can learn more nonlinear information than average pooling between channels. After that, global temporal map and global frequency map are both extracted and then squeezed by global average pooling. Formally, the $t$-th element of the temporal vector $z_T \in R^T$ and the $f$-th element of the frequency vector $z_F \in R^F$ from a global feature map $u \in T \times F \times 1$ can be calculated by:

$$z_T(t) = \frac{1}{F} \sum_{i=1}^{F} u(t, i, 1) \quad (1)$$

$$z_F(f) = \frac{1}{T} \sum_{i=1}^{T} u(i, f, 1) \quad (2)$$

Here, $t \in [1, 2, ..., T]$, $f \in [1, 2, ..., F]$. In this way, local temporal vectors ($T \times 1 \times 1$) and local frequency vectors ($1 \times F \times 1$) have been obtained and then fed to fully-connected layers to get global temporal vectors and global frequency vectors. We also use tanh activation to restrict the values to a range of $(0, 1)$. We use the following formulas to realize this idea:

$$y_T(t) = \tanh(W * z_T(t) + b) \quad (3)$$

$$y_F(f) = \tanh(W * z_F(f) + b) \quad (4)$$

Global temporal vectors $y_T$ and global frequency vectors $y_F$ can be seen as scales and calculated with the feature maps $U_2$ using Hadamard product [15]. Therefore, we get the temporal-wise features $U_T$ and frequency-wise features $U_F$:

$$U_T = y_T * U_2 \quad (5)$$

$$U_F = y_F * U_2 \quad (6)$$

Finally, a summation of the three branches (Temporal Attention, Frequency Attention and shortcut) are applied to obtain time-frequency features. We set two summation modes: with same weights and with different learnable weights. From the experiments, the second mode performs better and can get more robust time-frequency feature representation. Given coefficient as $\alpha$, $\beta$, $\gamma$, three branches can be summed up by the following formulas:

$$X_2 = \alpha U_T + \beta U_F + \gamma U_2 \quad (7)$$

where $\alpha$, $\beta$, $\gamma$ are learnable parameters, and softmax function is applied to restrict them to meet a relationship of $\alpha + \beta + \gamma = 1$. $X_2$ is the time-frequency feature and $X_2'$ is the output from the average pooling layer, where $X_2' \in R^{T/2 \times F/2 \times C}$.

### 3.2. Implementation details

As shown in Figure 2, five different blocks were used in our experiments. Conv-block is a simple implementation consisting of a branch with two convolution layers. Each convolution layer is followed by batch normalization and PRelu activation. T-block and F-block are summed up with Temporal Attention and Frequency Attention respectively. While for the TF-block, three branches have been used which include two modes for summation: with same weights (TF-block-a) and with different learnable weights (TF-block-b). We adapt batch normalization after all the convolution layers which are followed by an average pooling layer.

### 3.3. Training

In the training phase, the Adam algorithm is employed as the optimizer with the default parameters. The model is trained end-to-end with the learning rate schedule strategy of the exponential decay, shown as Equation (8).

$$l_r = \alpha^{\text{iteration}/\text{step}} \times l_r^0 \quad (8)$$

where $l_r^0$ is the initial learning rate which is set to 0.01 and the exponential decay rate $\alpha$ is set to 0.98 with 5 iterations per step. Parameters of TFNet are learned using the categorical cross entropy loss. Batch size is set to 64 and training is terminated after 1000 iterations.
4. EXPERIMENTS

4.1. Datasets, Metrics and Preprocessing

Datasets. The ESC-50 dataset [10] which is a public labeled set of environmental recordings comprising 50 equally balanced classes of 2,000 samples, and each sample is a monaural 5s sound recorded with a sampling rate of 44.1 kHz. The 50 classes can be divided into 5 categories: animal sounds, natural soundscapes and water sounds, human (non-speech) sounds, interior/domestic sounds, and exterior/urban sounds. The ESC-10 dataset [10] is a selection of 10 classes from the ESC-50 dataset and the differences between the classes are much more pronounced than the ESC-50 dataset. ESC-10 and ESC-50 datasets have been prearranged into 5 folds for cross-validation. For a fair comparison, the same folds divisions are proposed in our evaluation, and we shuffle the audio data before training.

The UrbanSound8k dataset [11] consists of 8,732 audio clips summing up to 7.3 hours of audio recordings. The maximum duration of audio clips is four seconds and there are 10 unbalanced classes in the dataset. The original audio clips are recorded at different sample rates. We use the official 10 folds for a fair comparison and shuffle the audio data as well.

Metrics. For all the three datasets, we use the accuracy of classification as evaluation metric, which is the most commonly used metric for ESC [15].

Preprocessing. As the frequencies of the audio events in the environmental sounds are often in the range of 20Hz to 15,000Hz, we resample the raw audio to 44.1kHz which is a common sampling frequency [16]. All the audio data is fixed to a certain length by zero-padding or truncating. The length is set to 5s in ESC-10 and ESC-50, and 4s is set in UrbanSound8k. Then we extract the melspectrograms from the audio data with a window size of 1764 samples and a hop size of 882 samples, which equals to 40ms and 20ms. The number of Mel bands is set to 40 so that we get the feature vectors of size 250 × 40, 250 × 40 and 200 × 40 from ESC-10, ESC-50 and UrbanSound8k respectively.

4.2. Data augmentation

Mixup is a popular data augmentation method used to improve the performance for classification tasks [17], which creates a new training sample by mixing a pair of two training samples. We can create a new training sample \((X, y)\) from the data and label pair \((X_1, y_1), (X_2, y_2)\) by the following equation.

\[
X = \lambda X_1 + (1 - \lambda) X_2 \\
y = \lambda y_1 + (1 - \lambda) y_2
\]

where \(\lambda \in (0, 1)\) is acquired by sampling from the beta distribution \(B_\alpha(\alpha, \alpha)\), and \(\alpha\) is a hyper parameter. It is set to 0.3 according to our empirical tests.

In addition, we found out that the parameter \(\lambda\) is more effective while it is in the range of \((0, 0.35)\) and \((0.75, 1)\).

4.3. Comparison to state-of-the-art methods

We evaluate our method on three benchmark datasets (ESC-10, ESC-50 and UrbanSound8k) and compare the results to the recent state-of-the-art methods. Results are presented in Table 1. Among the previous methods, 2D CNN [10, 19] are often used to extract deep features just like the way in image classification tasks, but the time-frequency information may lose in the process. M18 [20] and WaveMsNet [21] attempt to model the temporal structure from raw audio using 1D CNN. However, spatial information will be ignored during the modeling process. Meanwhile, previous attention-based method [7, 14] also cannot capture the complex time-frequency relationships in the environmental sounds effectively. In contrast, our proposed method can make better use of the time-frequency information and obtain discriminative and robust sound representation, which achieves classification accuracy of 95.8%, 87.7% and 88.5% on the three ESC datasets. It is worth mentioning that we surpass the performance of human being on both the ESC-10 dataset and the ESC-50 dataset, and our method achieves the highest accuracy to the best of our known.

Table 1. Comparison of accuracy on ESC-10, ESC-50 and UrbanSound8k

| Model Block | ESC-10 | ESC-50 | UrbanSound8k |
|-------------|--------|--------|--------------|
| Conv-block  | 80.2%  | 75.2%  | 79.6%        |
| T-block     | 82.1%  | 79.1%  | 80.1%        |
| F-block     | 83.4%  | 81.8%  | 82.3%        |
| TF-block-a  | 90.1%  | 85.7%  | 86.9%        |
| TF-block-b  | 93.1%  | 86.2%  | 87.2%        |

For instance, if \(\lambda = 0.5\), two data is mixed on average and the label is difficult to ascertain. Therefore we limit the parameter \(\lambda\) to \((0, 0.35)\) and \((0.75, 1)\).

SpecAugment is another data augmentation method proposed by Daniel et al. [18], which has been proved to be suitable for automatic speech recognition. SpecAugment is based on the log-mel spectrogram, and the spectrogram is seen as image to be processed. There are three deformations, which are time warping, frequency masking and time masking. During experiments, we found SpecAugment works effectively.
4.4. Experiment analysis

In order to analyze the effectiveness of the proposed TF-Block, we carry out ablation experiments on the five blocks (as shown in Figure 2) and the data augmentation methods. The results are presented in Table 2. T-block and F-block both perform better than Conv-block, which reflects the effectiveness of Temporal Attention and Frequency Attention. Different sound events in the acoustic environments have different time-frequency characteristics, for the reason that both TF-blocks achieve high accuracy. By using learnable weights instead of the same weight, TF-block-b performs better than TF-block-a because different attention is paid to the time-aware characteristics and the frequency-aware characteristics.

We make a comparison of different data augmentation methods we use during training. The results are shown in Table 2. It is clear that both Mixup and SpecAugment can improve the performance of our model. However, it is hard to make a conclusion which method is better from our experiments. Therefore, we apply both methods to our network to get the best model.

In addition, we visualize the feature maps of the first TF-Block to explain the effectiveness of our method, and use Conv-block as a comparison. We can use TFNet and CNN to represent the two methods. As shown in Figure 3, the first row shows the four melspectrograms that are fed to TFNet and CNN. The second and the third row shows the feature maps of CNN and TFNet respectively. Figure 3(a) is the original audio from the ESC-50 dataset. We can see that TFNet focus more on the useful temporal frames and frequency bands, and weaken the useless information comparing with CNN.

To further test the robustness of TFNet, we add noises in three different regions to the original audio. Figure 3(b) and Figure 3(c) show the results of adding random noise in several temporal frames and frequency bands. CNN cannot deal with the noisy audio well and the feature maps are activated in the noisy sections. While for our TFNet, the feature maps in the noisy sections are much less activated. It is because we introduce attention modelling in two different branches so that computation for representation learning is focused on specific discriminative local regions rather than being spread evenly over the whole feature map, which leads to a better robustness when a single branch is disturbed by the sections where no sound events happened in the acoustic environments. Specifically, when random noise in several temporal frames is added, the Frequency Attention can mitigate the impact of the noisy sections by global average pooling in the time axis. Similarly, we can explain the performance of TFNet in noisy frequency bands.

Moreover, we add Gaussian noise to the whole audio, which is shown in Figure 3(d). The result is that the proposed TFNet can still obtain time-frequency representation of the sections that sound events happen. However, CNN can hardly get effective information and the feature map looks noisy.

5. CONCLUSION

In this paper, we propose a new time-frequency enhancement block (TFBlock), which adopts temporal attention and frequency attention in different branches to better capture the time-frequency characteristics of sound events. The experiments show that our method achieves the state-of-the-art on the ESC-10, ESC-50 and UrbanSound8K datasets. By visualizing the results, our method shows the powerful ability to learn more discriminative and robust sound representations under different noisy conditions. We will adopt our method to other tasks in the future.

Table 3. Comparison of different data augmentation methods for our TFNet

| Data Augmentation          | ESC-10 | ESC-50 | UrbanSound8K |
|----------------------------|--------|--------|--------------|
| TFNet                     | 93.1%  | 86.2%  | 87.2%        |
| TFNet+Mixup               | 94.8%  | 87.1%  | 88.2%        |
| TFNet+SpecAugment         | 94.1%  | 86.5%  | 88.3%        |
| TFNet+Mixup+SpecAugment   | 95.8%  | 87.7%  | 88.5%        |
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