A MULTI-CHANNEL TEMPORAL ATTENTION CONVOLUTIONAL NEURAL NETWORK MODEL FOR ENVIRONMENTAL SOUND CLASSIFICATION

You Wang, Chuyao Feng, David V. Anderson

Georgia Institute of Technology, School of Electrical and Computer Engineering, Atlanta, Georgia, USA

ABSTRACT

Recently, many attention-based deep neural networks have emerged and achieved state-of-the-art performance in environmental sound classification. The essence of attention mechanism is assigning contribution weights on different parts of features, namely channels, spectral or spatial contents, and temporal frames. In this paper, we propose an effective convolutional neural network structure with a multi-channel temporal attention (MCTA) block, which applies a temporal attention mechanism within each channel of the embedded features to extract channel-wise relevant temporal information. This multi-channel temporal attention structure will result in a distinct attention vector for each channel, which enables the network to fully exploit the relevant temporal information in different channels. The datasets used to test our model include ESC-50 and its subset ESC-10, along with development sets of DCASE 2018 and 2019. In our experiments, MCTA performed better than the single-channel temporal attention model and the non-attention model with the same number of parameters. Furthermore, we compared our model with some successful attention-based models and obtained competitive results with a relatively lighter network.

Index Terms— Environmental sound classification, convolutional neural network, temporal attention, multi-channel

1. INTRODUCTION

Environmental sound classification (ESC) is an important area of sound event detection and classification with applications in many areas including audio surveillance systems [1], hearing aids [2], smart rooms [3], and smart cars, etc. Traditional machine learning algorithms for audio pattern recognition include K-nearest neighbors, support vector machines, and Gaussian mixture models, etc. But with the support of more labelled datasets, neural networks based methods including convolutional neural networks [4,5], recurrent neural networks [6,7], and their combination [8,9], have achieved superior performance over the traditional approaches.

In recent years, an attention mechanism was introduced to emphasize certain parts of the feature set to further improve the performance. The concept of attention was first introduced in [10] for machine translation. Since then, attention-based neural networks have been widely used in computer vision [11], natural language processing [12] and speech recognition [13]. In audio classification, attention mechanisms are used to assign importance to channels, spectral or spatial content, and/or temporal frames. Because of the unique temporal structure of audio signals, temporal attention has been very widely used for audio classification. For general audio scene classification, this is particularly appropriate since salient characteristics of an acoustic scene may be only briefly present or may reside only in certain features. One goal of the many proposed attention mechanisms is to discover the best approach for identifying the salient regions or features. Yu et al. [14] proposed a multi-level attention model for weakly labelled audio classification that applies temporal attention to single-channel embedded feature maps. Li et al. [15] proposed a multi-stream network with temporal attention in which the structure is composed of three streams, each containing a single temporal attention vector. Zhang et al. [9] integrated temporal attention into its CRNN architecture and the same authors [16] proposed a model that combines channel attention and temporal attention together.

However, the above audio classification models either do not embed input feature maps into multiple channels or apply only one single temporal attention vector on feature maps of all channels. Therefore, these models fail to take advantage of the fact that feature maps in different channels actually have different temporal structures. To overcome this limitation, we propose a CNN model with a multi-channel temporal attention (MCTA) block that extracts different temporal attention vectors for different channels to more fully exploit channel-wise temporal information.

2. MULTI-CHANNEL TEMPORAL ATTENTION (MCTA) CNN MODEL

Typically, a CNN will apply convolution on the input with multiple filters to extract more high-level channel-wise features. These channels contain information from different aspects of the input, all of which will contribute to the final classification. Our proposed MCTA model provides each channel with a unique attention vector, better exploiting the different structures of channel-wise feature maps and different information associated with them.
The block diagram of our proposed multi-channel temporal attention model. The ⊗ sign stands for Hadamard product and the ⊕ sign represents summing over the time dimension and squeezing the frequency dimension.

### 2.1. Model Architecture

The architecture of our proposed model is shown in Fig. 1. The model takes multi-channel feature maps \( X \in \mathbb{R}^{C \times T \times F} \) as input where \( C \) is the number of channels, \( T \) is number of time frames and \( F \) is number of mel-frequency bins, and passes them through an embedding block that consists of several convolutional and max-pooling layers. For example, the feature map extracted from ESC-50 dataset has a size of \( 3 \times 431 \times 128 \). The embedding block will embed the input to a hidden number of channels and aggregate it along the frequency dimension, yielding a set of embedded feature vectors \( X' \in \mathbb{R}^{C' \times T' \times 1} \), where \( C' = 512 \) and \( T' = 52 \) in the ESC-50 case. These embedded vectors then enter the attention block where the network starts to bifurcate to generate the further embedded vectors \( X'_L \) and the attention vectors \( A \) respectively, and then the attended vectors \( X'_A \) are obtained by performing element-wise multiplication. Finally the time and frequency dimensions of \( X'_A \) are both squeezed to form a hidden vector \( H \in \mathbb{R}^{C' \times 1} \), which is then passed through a fully connected layer for the final classification.

### 2.2. The Embedding Block

Fig. 2 presents the details of the embedding block. Because of the size of the datasets used in our work, a relatively shallow CNN structure is used, having a total of 5 convolutional layers and 2 max-pooling layers. Inspired by the work of Kumar [17], our embedding block is designed to eventually aggregate the 128 mel bins to 1 and reduce the time dimension by max pooling to extract useful segment-level temporal information. After each convolutional layer, batch normalization (BN in the figure) is performed and ELU (Exponential Linear Unit) is used as activation. The numbers in the brackets after “Conv. block” indicate the numbers of filters of the two convolutional layers in them. The numbers after “Max-pooling” and “Padding” stand for kernel sizes. The numbers after “Conv.” are the numbers of filters and the kernel size.

### 2.3. The Attention Block

There are two branches in the attention block and the details are described below. In the attention branch, a 1-by-1 convolutional layer and sigmoid activation is firstly applied to the output of the embedding block \( X' \in \mathbb{R}^{C' \times T' \times 1} \):

\[
X'_S = \text{Sigmoid}(\text{Conv}^{1 \times 1}(X'))
\]

where \( X'_S \) has the same dimensions as \( X' \) and \( \text{Conv} \) stands for a convolutional layer. Then, the attention vectors \( A \in \mathbb{R}^{C' \times T' \times 1} \) are obtained by performing normalization along the \( T' \) dimension to make sure the weights sum up to 1, therefore acting like probabilities:

\[
A(c, t, 1) = \frac{X'_S(c, t, 1)}{\sum_{t'=1}^{T'} X'_S(c, t', 1)}
\]

where \( c \in [1, C'] \) and \( t \in [1, T'] \) are indices of the channel and time dimension. This step guarantees the attention is applied temporally and different across channels. In the other branch, \( X' \) goes through the same convolutional layer but without activation to become \( X'_L \) with the same size:

\[
X'_L = \text{Conv}^{1 \times 1}(X')
\]

Afterwards, the attention weighted feature vectors \( X'_A \in \mathbb{R}^{C' \times T' \times 1} \) are obtained by element-wise multiplication be-
between $A$ and $X_L$:

$$X'_A = X_L \circ A$$

(4)

where $\circ$ stands for Hadamard product. In the end, a single hidden vector $H \in \mathbb{R}^{C' \times 1}$ is obtained by summing up $X'_A$ along the time dimension and squeeze the frequency dimension before it is fed into a final fully connected layer for final classification:

$$H = Squeeze_f(\sum_{t=1}^{T'} X'_A(:, t, 1))$$

(5)

where $t \in [1, T']$ is again the time index and $Squeeze_f()$ stands for the dimension squeeze operation that removes the frequency dimension. Batch normalization and ReLU activation are applied at the end of the attention block. In addition, a dropout with rate 0.3 is applied before entering the final fully connected layer.

### 3. EXPERIMENTAL SETUP

#### 3.1. Datasets

##### 3.1.1. ESC-50 and ESC-10

ESC-50 [13] has 2000 5-second-long audio clips with a sample rate of 44.1kHz, which are organized into 50 balanced classes. ESC-10 serves as a small proof-of-concept subset of 10 classes selected from the main dataset [13]. Both datasets are prearranged into 5 folds and the final classification performance is measured by taking the average of all 5-fold cross-validation accuracies.

To reduce overfitting, data augmentation was performed on each training sample by applying random time shifting, pitch shifting and adding Gaussian noise, resulting in 3 variants for each sample. For random time shifting, the maximum duration to be shifted is 2.5 seconds, which is half the length of an audio sample. The time shifts are only delays so that the information of some samples that only contain transient sound events at the beginning will not be eliminated. For pitch changing, the function `pitch_shift` of *librosa* was used and the pitch factor was set to be randomly chosen between -4 and 4. Finally, Gaussian noise values sampled from a standard normal distribution were added to clean audio samples after multiplying a noise factor of 0.01. After augmentation, the number of samples in total is increased to 8000.

##### 3.1.2. DCASE 2018 task1A and 2019 task1A

The development sets from the DCASE 2018 task1A [19] and the DCASE 2019 task1A [19] are used. Both of them contain 10-second-long audio clips with a 48kHz sampling rate from 10 classes. The DCASE 2018 task1A development set has 6122 clips for training and 2518 clips for validation, and the DCASE 2019 task1A development set has 9185 clips for training and 4185 for validation. No data augmentation was performed on these two datasets.

#### 3.2. Data Preparation

The log-mel spectrograms of all audio samples from the above datasets were extracted with their original sample rates kept. In addition, the deltas and delta-deltas of these log-mel spectrograms were also computed to obtain time-dependent information. The frame length and hop size for short-time-Fourier-transform are 1024 and 512, and the number of mel-bands is 128. All the features were extracted using the *librosa* implementation. Instead of concatenating them together, these three feature maps were appended as three different channels to be the convolutional neural network inputs.

#### 3.3. Single-channel Attention and Non-attention Models

To demonstrate the effectiveness of the proposed multi-channel temporal attention model, we also tested the performance of both the single-channel temporal attention model and the non-attention model using the same embedding block. Fig. 3 shows the architectures of the upper branch in the attention block corresponding to these two models, respectively. In the single-channel case, an average pool is applied on the channel dimension of $X'_S$ before the normalization. The final attention vector $A_S \in \mathbb{R}^{T' \times 1}$ will be element-wisely multiplied with each $T' \times 1$ feature vector in $X'_L \in \mathbb{R}^{C' \times T' \times 1}$. In the non-attention case, $X'_S$ is simply divided by itself element-wisely to form a bunch of identity vectors and the effect of attention will be removed in this way. These two models also have the same number of parameters as the multi-channel model so that these three models are comparable.

#### 3.4. Training the Network

We trained the network using the Adam optimizer with cross-entropy loss. The learning rate was chosen to begin with 0.001 and decayed by a factor of 0.5 if the training losses of two consecutive epochs did not decrease. The mini-batch size
**Table 1.** Comparison of classification accuracy of ESC-50 and ESC-10 datasets with other work. The ⊕ sign means system combination. The * denotes that the results were reproduced by us. The original results reported in [22] were 88.6% and 95.8% for ESC-50 and ESC-10 respectively.

| Method/feature sets                  | ESC-50  | ESC-10  |
|--------------------------------------|---------|---------|
| Piczak CNN [4]                       | 64.50%  | 80.50%  |
| ESC-10                               | 83.50%  | -       |
| FBEs ⊕ ConvRBM-BANK [21]             | 86.50%  | -       |
| Multi-stream temporal attention [15] | 84.00%  | 94.20%  |
| ACRNN [9]                            | 86.10%  | 93.70%  |
| Channel-temporal attention [16]      | 85.80%  | 94.00%  |
| TS-CNN10 [22]*                       | 85.78±0.40% | 94.25±0.28% |
| Non-attention (ours)                 | 81.74±0.56% | 90.95±0.40% |
| Single-channel (ours)                | 85.24±0.12% | 93.15±0.20% |
| MCTA-CNN (ours)                      | 87.05±0.18% | 94.45±0.24% |

is 50 with the number of epochs as 50 for each of the 5-fold cross validation. The number of hidden channels is 512 and the dropout rate is 0.3. The network was implemented with PyTorch and trained on an NVIDIA RTX2080Ti.

### 4. RESULTS AND DISCUSSION

To illustrate the effect of multi-channel temporal attention, experiments were performed using MCTA, a single-channel attention model, and a non-attention model. Each model was trained 5 times and the average classification accuracies and standard deviations were reported. When compared with other work, some results were reproduced by us by adapting the code available from the authors in our own experimental settings and the results were marked by *. Table 1 shows the performance of our proposed model and other state-of-the-art methods including some recent attention models on the ESC datasets (ESC-50 and ESC-10). It was observed that temporal attention did improve the classification results by a noticeable margin and multi-channel temporal attention performed better than single-channel attention only. Our MCTA-CNN model outperformed the CNN baseline [4] by a very large margin, and outperformed the pretrained model on Audioset [20] by Kumar [17]. The FBE-ConvRBM [21] model uses filter-bank learning to extract features and applies system fusion to obtain the final results, and our model outperforms it with just a single model. More importantly, our model performs better than multi-stream temporal attention [15], ACRNN [9], channel-temporal attention network [9], and TS-CNN10 [22], which all represent temporal attention using only one single vector.

Our model was also tested on the two DCASE acoustic scene classification (ASC) datasets described above, and the results are shown in Table 2. It is shown that MCTA can also improve the performance of ASC as well. Our model outperformed several popular attention-based CNN models including the self-attention model [23] and the Atrous-CNN model [24], which were both initially designed for acoustic scene classification. Additionally, the number of parameters of our model is 1.47M, which is much smaller than TS-CNN10 [22] (4.98M) and Atrous-CNN [24] (4.36M).

**Table 2.** Comparison of classification accuracy of DCASE 2018 task1A and DCASE 2019 task1A datasets with other work. The * denotes that the results were reproduced by us. In [22] the original results were 68.7% and 70.6% for DCASE 2018 and 2019 respectively. In [24], the original result for DCASE 2018 was 72.7% and no DCASE 2019 result was given.

| Methods                           | DCASE2018 1A | DCASE2019 1A |
|-----------------------------------|--------------|--------------|
| Self-attention [23]               | 70.81%       | -            |
| Atrous-CNN [24] *                 | 69.07±0.59%  | 69.24±0.99%  |
| TS-CNN10 [22] *                   | 69.68±0.60%  | 69.59±0.68%  |
| Non-attention(ours)               | 70.98±0.66%  | 74.60±0.32%  |
| Single-channel(ours)              | 71.92±0.75%  | 74.88±0.40%  |
| MCTA-CNN (ours)                   | 72.40±0.38%  | 75.71±0.28%  |

**Fig. 4.** 5 random attention vectors for rooster and rain.

### 5. CONCLUSIONS AND FUTURE WORK

In this work, we propose a multi-channel temporal attention (MCTA) model for environmental sound classification. Our model can fully exploit the temporal information contained in all channels and is relatively lighter. The experimental results on ESC and ASC datasets validate the performance of MCTA. In the future, we will further test our model on larger datasets such as Audioset.
6. REFERENCES

[1] Pasquale Foggia, Nicolai Petkov, Alessia Saggese, Nicola Strisciuglio, and Mario Vento, “Audio surveillance of roads: A system for detecting anomalous sounds,” IEEE transactions on intelligent transportation systems, vol. 17, no. 1, pp. 279–288, 2015.

[2] Enrique Alexandre, Lucas Cuadra, Manuel Rosa, and Francisco Lopez-Ferreras, “Feature selection for sound classification in hearing aids through restricted search driven by genetic algorithms,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 15, no. 8, pp. 2249–2256, 2007.

[3] Michel Vacher, Jean-François Serignat, and Stephane Chailiol, “Sound classification in a smart room environment: an approach using gmm and hmm methods,” 2007.

[4] Karol J Piczak, “Environmental sound classification with convolutional neural networks,” in 2015 IEEE 25th International Workshop on Machine Learning for Signal Processing (MLSP). IEEE, 2015, pp. 1–6.

[5] Justin Salamon and Juan Pablo Bello, “Deep convolutional neural networks and data augmentation for environmental sound classification,” IEEE Signal Processing Letters, vol. 24, no. 3, pp. 279–283, 2017.

[6] Zhao Ren, Vedhas Pandit, Kun Qian, Zijing Yang, Zixing Zhang, and Björn Schuller, “Deep sequential image features on acoustic scene classification,” in Proc. DCASE Workshop, Munich, Germany, 2017, pp. 113–117.

[7] Huy Phan, Philipp Koch, Fabrice Katzberg, Marco Maass, Radoslaw Mazur, and Alfred Mortuns, “Audio scene classification with deep recurrent neural networks,” arXiv preprint [arXiv:1703.04770], 2017.

[8] Yong Xu, Quqiang Kong, Wenwu Wang, and Mark D Plumbley, “Large-scale weakly supervised audio classification using gated convolutional neural network,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 121–125.

[9] Zhichao Zhang, Shugong Xu, Shuqing Zhang, Tianhao Qiao, and Shan Cao, “Attention based convolutional recurrent neural network for environmental sound classification,” in Chinese Conference on Pattern Recognition and Computer Vision (PRCV). Springer, 2019, pp. 261–271.

[10] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio, “Neural machine translation by jointly learning to align and translate,” arXiv preprint [arXiv:1409.0473], 2014.

[11] Sanghyun Woo, Jongchan Park, Joon-Young Lee, and In So Kweon, “Cbam: Convolutional block attention module,” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 3–19.

[12] Yequan Wang, Minlie Huang, Li Zhao, et al., “Attention-based lstm for aspect-level sentiment classification,” in Proceedings of the 2016 conference on empirical methods in natural language processing, 2016, pp. 606–615.

[13] Jan K Chorowski, Dzmitry Bahdanau, Dmitriy Serdyuk, Kyunghyun Cho, and Yoshua Bengio, “Attention-based models for speech recognition,” in Advances in neural information processing systems, 2015, pp. 577–585.

[14] Changsong Yu, Karim Said Barsim, Quqiang Kong, and Bin Yang, “Multi-level attention model for weakly supervised audio classification,” arXiv preprint [arXiv:1803.02353], 2018.

[15] Xinyu Li, Venkata Chebiyam, and Katrin Kirchhoff, “Multi-stream network with temporal attention for environmental sound classification,” arXiv preprint [arXiv:1901.08608], 2019.

[16] Zhichao Zhang, Shugong Xu, Shuqing Zhang, Tianhao Qiao, and Shan Cao, “Learning attentive representations for environmental sound classification,” IEEE Access, vol. 7, pp. 130327–130339, 2019.

[17] Anurag Kumar, Maksim Khadkevich, and Christian Fügen, “Knowledge transfer from weakly labeled audio using convolutional neural network for sound events and scenes,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 326–330.

[18] Karol J Piczak, “Esc: Dataset for environmental sound classification,” in Proceedings of the 23rd ACM international conference on Multimedia. ACM, 2015, pp. 1015–1018.

[19] Annamaria Mesaros, Toni Heittola, and Tuomas Virtanen, “A multi-device dataset for urban acoustic scene classification,” arXiv preprint [arXiv:1807.09840], 2018.

[20] Jort F Gemmeke, Daniel PW Ellis, Dylan Freedman, Aren Jansen, Wade Lawrence, R Channing Moore, Manoj Plakal, and Marvin Ritter, “Audio set: An ontology and human-labeled dataset for audio events,” in 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2017, pp. 776–780.

[21] Hardik B Sailor, Dharmesh M Agrawal, and Hemant A Patil, “Unsupervised filterbank learning using convolutional restricted boltzmann machine for environmental sound classification,” in INTERSPEECH, 2017, pp. 3107–3111.

[22] Helin Wang, Yuexian Zou, Dading Chong, and Wenwu Wang, “Environmental sound classification with parallel temporal-spectral attention,” Proceedings of INTERSPEECH 2020, 2020.

[23] Jun Wang and Shengchen Li, “Self-attention mechanism based system for dcase2018 challenge task1 and task4,” in IEEE AASP Challenge on DCASE 2018 technical reports, 2018.

[24] Zhao Ren, Quqiang Kong, Jing Han, Mark D Plumbley, and Björn W Schuller, “Attention-based atrous convolutional neural networks: Visualisation and understanding perspectives of acoustic scenes,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 55–60.