POLYPHONIC SOUND EVENT DETECTION USING CAPSULE NEURAL NETWORK ON MULTI-TYPE-MULTI-SCALE TIME-FREQUENCY REPRESENTATION

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ABSTRACT

The challenges of polyphonic sound event detection (PSED) stem from the detection of multiple overlapping events in a time series. Recent efforts exploit Deep Neural Networks (DNNs) on Time-Frequency Representations (TFRs) of audio clips as model inputs to mitigate such issues. However, existing solutions often rely on a single type of TFR, which causes under-utilization of input features. To this end, we propose a novel PSED framework, which incorporates Multi-Type-Multi-Scale TFRs. Our key insight is that: TFRs, which are of different types or in different scales, can reveal acoustics patterns in a complementary manner, so that the overlapped events can be best extracted by combining different TFRs. Moreover, our framework design applies a novel approach, to adaptively fuse different models and TFRs symbiotically. Hence, the overall performance can be significantly improved. We quantitatively examine the benefits of our framework by using Capsule Neural Networks, a state-of-the-art approach for PSED. The experimental results show that our method achieves a reduction of 7% in error rate compared with the state-of-the-art solutions on the TUT-SED 2016 dataset.

Index Terms— Capsule Neural Network, Polyphonic Sound Event Detection, Time-Frequency Representation

1. INTRODUCTION

Polyphonic Sound Event Detection (PSED) is widely applied in practice (e.g. wildlife monitoring [1][2] and acoustic surveillance [3]). However, the existing approaches suffer from a high error rate. The root cause for this high error rate is the interference and overlaps between sound events in the timeline, and such issues are evidenced by the challenges to develop practical solutions for PSED [4]. Tackling such an obstacle is important for PSED since researchers are working towards effective artificial auditory systems aiming to automatically classify simultaneous sound events and recognize their corresponding onsets and offsets accordingly.

There are growing interests and efforts to use Deep Neural Networks (DNNs) to improve PSED performance, for automatic and accurate detection and localization. Convolutional Neural Networks (CNNs) are first applied to improve PSED tasks in [5][6][7], but suffer from the ineffectiveness of representing sequential features of sound events. Then, DNN models with strong sequential processing modules, are utilized to better abstract the temporal relationships of input sound events, such as Recurrent Neural Networks (RNNs) [8] and Convolutional Recurrent Neural Networks (CRNNs) [9][10][11]. Though these approaches can reflect the features properly, it’s not sufficient to recognize highly-dynamic and complex patterns in PSED. More recently, Capsule Neural Networks (CapsNets), as a new DNN architecture, are introduced to handle dynamic and complex patterns. CapsNet can process much richer features, and enable multi-level feature interactions by dynamic routing between neurons (i.e. capsules). The attractive characteristics of CapsNet breed early attempts for Bird Sound Classification [12] and Weakly-labeled Sound Event Detection [13]. All prior works focus on exploiting different DNN models with the support of a single Time-Frequency Representation (TFR), and none of them can learn the discriminative yet complementary features represented in different TFRs.

Our goal is to maximize the exploitation of the key acoustic patterns in different types and scales of TFRs. The key observation is that, different types and scales of TFRs can reflect different symptoms of overlapped/interfered events, which can be further exploited to mitigate the issues of overlapped/interfered events. To this end, our key idea is to symbiotically combine various types of TFRs and the same type of TFR of different scales for PSED models. We denote this methodology as “Multi-Type-Multi-Scale” TFR. We develop a framework to improve the performance of PSED, via a novel approach to adaptively fusing different models and TFRs symbiotically. Therefore, the impacts of overlapped/interfered sound events can be greatly mitigated, which substantially improves the overall PSED performance.

This work was supported in part by the National Natural Science Foundation of China under Grant 72071116, and in part by the Ningbo Municipal Bureau Science and Technology under Grants 2019B10026.
We quantitatively evaluate the effectiveness of our framework on CapsNet-enabled SED framework, the state-of-the-art approach for SED tasks [14]. Our evaluations on the TUT-SED 2016 dataset, shows a reduction 7% of segment-based Error Rate, compared with the original approach. We also perform an ablation study to understand the source of our improvements. Our results suggest that, our framework can effectively mitigate the overlapped/interfered sound events, which substantially increases the overall PSED accuracy.

2. PROPOSED METHOD

2.1. Overview of Proposed Method

Figure 1 shows an overview of our method. It has three stages: 1) Multi-Type-Multi-Scale Time-Frequency Representation Extraction; 2) PSED Module; and 3) Self-Adaptive Fusion Module. In the first stage, various types of TFRs and multi-scale TFRs are extracted from the sound clips. Then the Multi-Type-Multi-Scale TFRs are utilized by separate PSED modules for detection. Finally a Self-Adaptive Fusion Module is used to fully leverage the predictions from different TFRs. In this work, we choose the CapsNet as the main model architecture as a proof-of-concept.

2.2. Multi-Type-Multi-Scale TFR Extraction

The first stage of our method is motivated by the fact that different classes of TFRs can provide different patterns from the same sound clips, as they profile the characteristics of the audio clips in different ways, which can produce quite different representations, even merely from visual inspections (as shown in Figure 2). Moreover, the same TFRs with different scales also exhibit significantly different characteristics, as the time-frequency trade-off in the TFR may lead to different encoding in terms of resolutions in time and frequency.

![Fig. 1. An overview of our proposed framework. Dimensions of the input vectors are illustrated in Sec 2.2. For PSED prediction results, $T=256$ and $N$ equals to the number of sound event types.](image)

![Fig. 2. (a) is the log mel spectrogram which apply a mel filter bank consisting of 256 triangular filters on a magnitude spectrum. (b) is a spectrogram transformed via the Short-Time Fourier Transform with a window size of 1024.](image)
Filter Bank with \( n \) triangular filters on the extracted spectrogram via STFT, to map the frequencies into even-space mel scales and fit for the properties of the human ear. For the Multi-Scale TFRs for logmel, we set \( n \) to be \{40, 64, 128, 256, 512\}. As for the Multi-Scale TFRs for spectrograms, we set the length of STFT windowed signals \( n_{FFT} \) to be \{1024, 2048\}. The number of selected scales for STFT is smaller as current settings can already construct high dimensional spectrograms, which is equal to \( 1 + n_{FFT}/2 \). Higher scales can incur unnecessary training cost and redundant features. For both spectral representations, we use a window with length of \( T = 256 \) and binaural channels \( C = 1, 2 \) to construct batches as the inputs for training and inference. Therefore, the input vector for spectrograms and logMel coefficients is \( X_{t:T-1} \in \mathbb{S}^{256 \times F \times C} \), where \( F \) is equal to the value of \( n \) and \( 1 + n_{FFT}/2 \) for each spectral representation respectively.

### 2.3. PSED Module: Capsule Neural Network

The second stage of our method uses Capsule Neural Network (CapsNet) \[17\] as the core module for PSED. We use CapsNet proposed in \[14\] for its rich feature representations and (CapsNet) \[17\] as the core module for PSED. We use CapsNet in 100 epochs. The optimizer is AdaDelta optimizer, which marks the activation of the corresponding event if the estimation value exceeds the threshold. The values of \( b^k \) and \( \eta \) are jointly optimized during the fusion process, as the fusion process is completed block-by-block. The learned values for \( b^k, \eta \) and \( w^k \) are stored for later evaluation.

### 3. EXPERIMENTS

#### 3.1. Data Set

To evaluate our proposed method, we use the TUT Sound Events 2016 dataset \[13\], which is the official dataset used in DCASE 2016 challenges (DCASE2016 Task3). The dataset was collected by researchers at Tampere University of Technology. It is categorized into two scenarios, which are “Home” and “Residential Area”. The recordings in “Home” scenario were captured in different indoor scenarios while recordings in the “Residential Area” scenario were from various outdoor scenes. The total length for the recordings in the “Home” and “Residential Area” scenarios are 54 minutes and 59 minutes respectively. The recordings in these two scenarios are further partitioned into Development Set and Evaluation Set (i.e. approximately 70%-30% split).

#### 3.2. Evaluation Metric

We use the segment-based Error Rate (ER) as the main evaluation metric, same as in DCASE Challenge 2016. We acknowledge that there are relatively new evaluation metrics in the recent DCASE challenges, such as Polyphonic Sound Detection Score (PSDS). However, we will still use the segment-based ER for a fair performance comparison with reported results using ER \[14, 16, 19, 18\]. The segment-based ER is calculated by comparing the prediction results and the ground-truth in a one-second segment window, expressed as:

\[
ER = \frac{\sum S(s) + \sum D(s) + \sum I(s)}{\sum N(s)},
\]

where \( s \) represents the segments in an audio clip, \( S(s) \) stands for Substitution which is the number of False Negative (FN) and False Positive (FP) data points in the segment, \( I(s) \) stands for Insertion which is the number of FPs after subtracting the substitutions, \( D(s) \) stands for Deletion which is the number of FNs after subtracting the substitutions and \( N(s) \) stands for the number of events in the ground-truth.

#### 3.3. Experimental Settings

We report the hyperparameters of the best experimental results for the CapsNet in Table 1. In total, we train the CapsNet in 100 epochs. The optimizer is AdaDelta optimizer, with an initial learning rate and decay rate of 1.0 and 0.95, respectively. Early-stop is leveraged to avoid over-fitting, which will halt the training process if the error rate stops to reduce for 20 epochs.
To verify the effectiveness of our method, we select the following methods for comparisons (denoted with their main features): 1) **RNN** [19]: Best solution in the DCASE 2016 Challenge, by using mel energy features; 2) **GNN** [18]: Ranked the 2nd place in the DCASE 2016 Challenge, which uses mel energy; 3) **MLP** [16]: Outperforms [19] by using binaural log mel as features and Multi-Layer Perceptrons as classifiers; and 4) **CapsNet** [14]: State-of-the-art solution on the TUT-SED 2016 Dataset, which obtains the best results using binaural spectrograms.

### 3.4. Comparative Methods

| Model      | Features            | ER   | Model      | Features            | ER   |
|------------|---------------------|------|------------|---------------------|------|
| CapsNet    | logmel_40           | 0.75 | CapsNet    | logmel_64 + logmel_128 | 0.62 |
|            | logmel_64           | 0.65 | Our Method | logmel_40 + logmel_128 | 0.66 |
|            | logmel_128          | 0.78 |            |                      |      |
|            | logmel_256          | 0.64 |            |                      |      |
|            | logmel_64 + STFT_2048 | 0.62 | Our Method | logmel_513 + STFT_2048 | 0.63 |
|            | STFT_1024           | 0.69 |            |                      |      |
|            | STFT_2048           | 0.66 |            |                      |      |

### 3.5. Experimental Results & Ablation Study

Table 3 shows the segment-based ER on the TUT-SED 2016 Development set and Evaluation set. The ER of Development set and Evaluation set is the averaged result among two scenarios. Our method achieves the best SED performance, by jointly leveraging logmel_513 plus STFT_2048 as acoustic features for Development set and logmel_40 plus logmel_128 for Evaluation set, with a reduction of 1% and 7% ER on the Development Set and Evaluation Set respectively, comparing with the state-of-the-art [14]. The overall ER on the TUT-SED 2016 dataset validates the effectiveness of our design.

To further understand the source of the improvements, we conduct an ablation study by breaking down the results into different features and discuss the key observations on the TUT-SED 2016 Evaluation set. We present the results trained on single CapsNet with single TFR and the results trained in our framework by using multiple TFRs, as shown in Table 3. Note that we report results using at maximum 2 TFRs because 1) current fusion results already outperform the best results and 2) extensively training and fusing on numerous TFRs is unpractical and cost-ineffective due to huge computational resource demands. From Table 3, three key observations are concluded. First, **multi-scale TFRs** of the **same type** can incur large variations in terms of ER, as it is shown for logmel_n and STFT_k features in CapsNet, indicating the importance of TFR scales. Second, **the same TFR type with different scales** can provide complementary features to improve SED accuracy. By leveraging logmel_64 and logmel_128 in our framework, we achieve an ER of 0.62, which is less than the ER by using either of these two features solely as model inputs. Such phenomena indicates that the acoustic features represented in different scales are beneficial for neural network inference, which also shows the feasibility of our self-adaptive fusion module to dig out complementary characteristics in outputs generated from different TFRs. Third, **different types of TFRs** can provide complementary features to reduce SED ER. In the table, we show the ER by leveraging logmel_64 + STFT_2048 jointly for SED. Similar to our second observation, the ER of joint-inference is less than the ER of single TFR for inference. This shows that different types of TFRs can also serve as complements for SED.

### 4. CONCLUSIONS

In this paper, we propose a novel framework for polyphonic SED tasks. We emphasize the usage of Multi-Type-Multi-Scale TFRs for full exploration of the acoustic patterns in input audio clips. We validate our framework on CapsNet-enabled SED framework, which achieves a reduction of 7% in ER compared to the original approach.
5. REFERENCES

[1] Zhao Zhao, Sai hua Zhang, Zhi yong Xu, Kristen Bel-lisario, Nian hua Dai, Hichem Omrani, and Bryan C. Pijanowski, “Automated bird acoustic event detection and robust species classification,” *Ecological Informatics*, vol. 39, pp. 99–108, 2017.

[2] Juliette Florentin, Thierry Dutoit, and Olivier Verlinden, “Identification of european woodpecker species in audio recordings from their drumming rolls,” *Ecol. Informatics*, vol. 35, pp. 61–70, 2016.

[3] C. Clavel, T. Ehrette, and G. Richard, “Events detection for an audio-based surveillance system,” in *2005 IEEE International Conference on Multimedia and Expo*, 2005, pp. 1306–1309.

[4] An Dang, Toan H. Vu, and Jia-Ching Wang, “A survey of deep learning for polyphonic sound event detection,” in *2017 International Conference on Orange Technologies (ICOT)*, 2017, pp. 75–78.

[5] Haomin Zhang, Ian McLoughlin, and Yan Song, “Robust sound event recognition using convolutional neural networks,” in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2015, pp. 559–563.

[6] Huy Phan, Lars Hertel, Marco Maaß, and Alfred Mertins, “Robust audio event recognition with 1-max pooling convolutional neural networks,” in *Inter-speech 2016, 17th Annual Conference of the International Speech Communication Association, San Francisco, CA, USA, September 8-12, 2016*, Nelson Morgan, Ed. 2016, pp. 3653–3657, ISCA.

[7] Pablo Zinemanas, Pablo Cancela, and Martín Rocamora, “End-to-end convolutional neural networks for sound event detection in urban environments,” in *2019 24th Conference of Open Innovations Association (FRUCT)*, 2019, pp. 533–539.

[8] Tomoki Hayashi, Shinji Watanabe, Tomoki Toda, Takaaki Hori, Jonathan Le Roux, and Kazuya Takeda, “Duration-controlled lstm for polyphonic sound event detection,” *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 25, no. 11, pp. 2059–2070, 2017.

[9] Emre Cakir, Giambattista Parascandolo, Toni Heittola, Heikki Huttunen, Tuomas Virtanen, Emre Cakir, Giambattista Parascandolo, Toni Heittola, Heikki Huttunen, and Tuomas Virtanen, “Convolutional recurrent neural networks for polyphonic sound event detection,” *IEEE/ACM Trans. Audio, Speech and Lang. Proc.*, vol. 25, no. 6, pp. 1291–1303, June 2017.

[10] Sharath Adavanne, Pasi Pertilä, and Tuomas Virtanen, “Sound event detection using spatial features and convolutional recurrent neural network,” in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2017, pp. 771–775.

[11] Sharath Adavanne, Archontis Politis, and Tuomas Virtanen, “Multichannel sound event detection using 3d convolutional neural networks for learning inter-channel features,” in *2018 International Joint Conference on Neural Networks (IJCNN)*, 2018, pp. 1–7.

[12] Fabio Vesperini, Leonardo Gabrielli, Emanuele Principi, and Stefano Squartini, “A capsule neural networks based approach for bird audio detection,” Tech. Rep., DCASE2018 Challenge, September 2018.

[13] Turab Iqbal, Yong Xu, Qiuqiang Kong, and Wenwu Wang, “Capsule routing for sound event detection,” in *26th European Signal Processing Conference, EU-SIPCO 2018*, Roma, Italy, September 3-7, 2018, 2018, pp. 2255–2259, IEEE.

[14] Fabio Vesperini, Leonardo Gabrielli, Emanuele Principi, and Stefano Squartini, “Polyphonic sound event detection by using capsule neural networks,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, no. 2, pp. 310–322, 2019.

[15] Muhammad Huzaifah, “Comparison of time-frequency representations for environmental sound classification using convolutional neural networks,” *CoRR*, vol. abs/1706.07156, 2017.

[16] Michele Valenti, Dario Tonelli, Fabio Vesperini, Emanuele Principi, and Stefano Squartini, “A neural network approach for sound event detection in real life audio,” in *2017 25th European Signal Processing Conference (EUSIPCO)*, 2017, pp. 2754–2758.

[17] Sara Sabour, Nicholas Frosst, and Geoffrey E Hinton, “Dynamic routing between capsules,” in *Advances in Neural Information Processing Systems*, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds. 2017, vol. 30, Curran Associates, Inc.

[18] Annamaria Mesaros, Toni Heittola, and Tuomas Virtanen, “TUT database for acoustic scene classification and sound event detection,” in *2016 24th European Signal Processing Conference (EUSIPCO)*, 2016, pp. 1128–1132.

[19] Sharath Adavanne, Giambattista Parascandolo, Pasi Pertilä, Toni Heittola, and Tuomas Virtanen, “Sound Event Detection in Multichannel Audio Using Spatial and Harmonic Features,” *CoRR*, vol. abs/1706.02293, 2017.