SUBSPECTRALNET – USING SUB-SPECTROGRAM BASED CONVOLUTIONAL NEURAL NETWORKS FOR ACOUSTIC SCENE CLASSIFICATION

Sai Samarth R Phaye\textsuperscript{1}, Emmanouil Benetos\textsuperscript{2,3}, and Ye Wang\textsuperscript{1}

\textsuperscript{1}School of Computing, National University of Singapore, Singapore
\textsuperscript{2}School of EECS, Queen Mary University of London, UK \hspace{1em} \textsuperscript{3}The Alan Turing Institute, UK

\textbf{ABSTRACT}

Acoustic Scene Classification (ASC) is one of the core research problems in the field of Computational Sound Scene Analysis. In this work, we present SubSpectralNet, a novel model which captures discriminative features by incorporating frequency band-level differences to model soundscapes. Using mel-spectrograms, we propose the idea of using band-wise crops of the input time-frequency representations and train a convolutional neural network (CNN) on the same. We also propose a modification in the training method for more efficient learning of the CNN models. We first give a motivation for using sub-spectrograms by giving intuitive and statistical analyses and finally we develop a sub-spectrogram based CNN architecture for ASC. The system is evaluated on the public ASC development dataset provided for the “Detection and Classification of Acoustic Scenes and Events” (DCASE) 2018 Challenge. Our best model achieves an improvement of +14\% in terms of classification accuracy with respect to the DCASE 2018 baseline system. Code and figures are available at \url{https://github.com/ssrp/SubSpectralNet}

\textbf{Index Terms—} Acoustic Scene Classification, Convolutional Neural Networks, Computational Sound Scene Analysis.

\section{INTRODUCTION}

The problem of recognizing the acoustic soundscapes and identifying the environment in which a sound is recorded is known as Acoustic Scene Classification [1, 2]. The objective is to assign a semantic label (acoustic scene) to the input audio stream that characterizes the type of environment in which it is recorded – for example shopping mall, airport, street. The problem has been very well explored as a single-label classification task [3, 4]. Due to the possible presence of diverse sound events in a sound scene, developing a descriptive representation for ASC is known to be a difficult task [5].

DCASE Challenges, started in 2013, provide benchmark data for computational sound scene analysis research, including tasks for detection and classification of acoustic scenes and events, motivating researchers to further work in this area. Looking at the current trend of challenge submissions in the ASC task, it is clear that researchers are moving towards using deep learning methods for system development [3, 4, 6]. This is because of the fact that the current hand-crafted methods are not sufficient to capture the discerning properties of soundscapes [7]. With time, data-driven approaches are taking over conventional methods which involve more expert knowledge for designing and choosing features. Most published systems typically use a combination of audio descriptors and learning techniques, with a growing inclination towards deep learning [8, 9].

The literature of ASC research is vast and a lot has been done in system design. Earliest works in this field have tried to use numerous methods from speech recognition (for example, using features like Mel-frequency cepstral coefficients [10], normalized spectral features, and low-level features [2, 11] like the zero-crossing rate). General architecture follows a pipeline based on extracting frame-by-frame hand-crafted audio features or learning them using various methods like matrix decomposition of spectral representations (log mel-spectrograms [12], Constant-Q transformed spectrograms [13]), and then performing machine learning based classification. The final decision is a combination of frame wise outputs, for example, by using majority voting or mean probability. Many systems incorporate deep learning approaches, generally by using some kind of time-frequency representation as the input and training deep neural networks (DNNs) or CNNs [14, 15]. Some methods also exploited ideas from the image processing literature, for example, training a classifier using the histogram of gradient representations over spectrograms of audio frames [16, 17].

CNNs are extensively used in ASC. Some systems incorporate the use of convolutional layers with big receptive fields (kernels) to capture global correlations in the spectrograms [18, 19], while some use smaller kernels focusing on local spatial data [20, 14]. We aim to create a better understanding of how CNNs could be used to model acoustic scenes, rather than achieving state of the art results. Our work shows that depending on the scene class, there is a specific frequency band showing most activity, hence providing discriminative features for that class; to the authors’ knowledge this has not been considered in earlier studies. We first develop a motivation for using spectrogram crops, which we term Sub-spectrograms. Finally, we propose a CNN model, SubSpectralNet, to make use of the Sub-spectrograms to capture more enhanced features, hence resulting in superior performance over a model with similar parameters which does not incorporate sub-spectrograms (discussed in Section 4). For all experiments, we used the DCASE 2018 ASC development dataset [21] having 6122 two-channel 10-second samples for training and 2518 samples for testing, divided into ten acoustic scenes.

The rest of the paper is divided as follows – in Section 2, we develop a basic statistical model for ASC which we use as the motivation to design the proposed CNN architecture. Section 3 discusses the methodology used to develop the CNN model and Section 4 describes various experiments performed to prove the efficacy of the system. Finally, we conclude the work in Section 5.

\section{STATISTICAL ANALYSIS OF SPECTROGRAMS}

Magnitude spectrograms are two-dimensional representations over time and frequency, which are very different from real life images. In spectrograms, there is a clear variation in the frequency axis. While
images have local relationships over both spatial dimensions, spectrograms have definitive local relationships in the time dimension, but not in the frequency dimension. In the frequency dimension, for some types of sounds there are local relationships (e.g. sounds that have broadband spectra like noise-like sounds), sometimes they have non-local relationships (e.g. harmonic sounds, where there are relationships between non-adjacent frequency bins), and sometimes there are simply no local relationships at all.

We first create a simple mathematical model to gain more insights on how CNNs could leverage time-frequency features efficiently. We extract log mel-spectrograms using a 2048-point short time Fourier transform (STFT) on 40ms Hamming windowed frames with 20ms overlap and then transform this into 200 Mel-scale band energies. Finally, the log of these energies is taken. Next, we perform bin-wise normalization of the sample space and obtain 6122 energies. Finally, the log of these energies is taken. Next, we perform the following mathematical transform:

$$x_{ij}^{new} = 1 - e^{-k x_{ij}}$$  (1)

where $x_{ij}$ is the prior distance value and $i, j$ are the matrix indices. $k$ is a constant parameter which when increased, enhances the differences of values on the higher range. We used $k$ as 10 so that the matrix resembles a confusion matrix. Next, we normalize again the matrix by dividing with the maximum value and lastly, subtract these values from one. The output of this is shown in Fig. 2. We also compute the Kullback-Leibler divergence [22] and Hellinger distance [23] over these histograms and they result in a very similar matrix, which shows that the statistical model is robust. We can clearly see that some classes are having higher confusions (for example, “metro_station” and “metro”; “shopping_mall” and “airport”), which resembles the confusion matrices obtained from the baseline model results [21] and proposed CNN model (shown in Figure 4).

In the histograms obtained, we observe a definite variation of activation of mel-bins and sub-bands, which is specific to every scene. For example, the “metro” class has more activation in lower frequency bins; the “bus” has less activation in mid frequency bins. For “park” or “street_traffic”, nearly all mel-bins are active and from the DCASE 2018 baseline result [21], we can see that these classes have relatively superior performance. We use these observations to develop SubSpectralNet, which is discussed in the next section.

3. DESIGNING SUBSPECTRALNET

We start off with the DCASE 2018 baseline system for the ASC task and gradually develop the proposed network. The baseline system is based on a CNN, where mel-band energies with 40 mel-bins are extracted for every sample with 40 millisecond frame size and 50% overlap using 2048-point STFT. The samples are further normalized and the size of each sample is $40 \times 500$. These samples are passed for specific classes. This is equivalent to saying that we have 200 small classifiers. Finally, using these 200 outputs for all the test samples, we create one normalized histogram for each class, in which we have frequencies of correct classifications of corresponding mel-bins, shown in Fig. 1. We also calculate the chi-square distance between these histograms to see how similar class-wise distributions are. For this, we normalize the histograms with maximum value to one, and then compute the distance. The lesser the distance, the more confusion exists between those classes. We aim to obtain a matrix which has some resemblance with a confusion matrix. For that, after getting the $10 \times 10$ symmetrical matrix having distances between the classes, we normalize the matrix by dividing with the maximum value. Then, we apply the following mathematical transform:

Fig. 1: Histogram of activation of mel-bins for some sound scene classes. We can infer the importance of specific mel-bins for specific classes from these histograms. This is also intuitively true, for example, in an airport or in a metro, audio may have dominant and discriminative low-frequency noise, and lower bands of the spectrograms show more activation for these classes.

Fig. 2: Resultant Chi-Square Distance Matrix.
to a CNN consisting of two layers with same padding in order – 32 kernels and 64 kernels, each having kernels of $7 \times 7$ size, batch normalization and ReLU activation. After each conv-layer, a max-pooling layer of $5 \times 5$ and $4 \times 100$ pool-size respectively is used to decrease the size of the feature space and a dropout rate of 30% is applied to prevent over-fitting. Finally, a fully connected (FC) layer with 100 neurons is used over the flattened output, which is further connected to the output (softmax) layer.

We train DCASE 2018 baseline models on different channels of the audio dataset – left channel, right channel, average-mono channel and lastly, both channels to the CNN model. The best results are obtained using both channels which is expected as binaural input would give more information on the prominent sound events in soundscapes, for example, a car passing by in “street traffic”.

### 3.1. Incorporating Sub-spectrograms

From the analysis in Section 2, we infer that using bigger convolutional kernels over spectrograms is not a good idea because it tends to combine global context and we lose the local time-frequency information. We perform an experiment (discussed in Section 4) in which we gradually increase the size of the kernels in the first conv-layer of the baseline system. The accuracy decreases with the increase in kernel size. Spectrograms have a definite variation in the frequency dimension. Using smaller convolutional kernels over complete spectrograms works fine because CNNs are very powerful in fitting these receptive fields to understand the variances in the data. But the fact that spectrograms have these variations could be advantageous.

Building upon this idea, we propose SubSpectralNet and its architecture is shown in Figure 3. SubSpectralNet essentially creates horizontal slices of the spectrogram and trains separate CNNs on these sub-spectrograms, finally acquiring band-level relations in the spectrograms to classify the input using diversified information.

We extract the log mel-energy spectrograms for the $N$ samples and perform bin-wise normalization. For creating sub-spectrograms, we design a new layer (we term it as SubSpectral Layer) which splits the spectrogram into various horizontal crops. It takes three inputs – input spectrogram ($C \times F \times T$ dimension, $C$, $F$ and $T$ being number of channels, mel-bins and time-indices respectively), sub-spectrogram size $X$ and mel-bin hop-size (vertical hop) $Y$. This results in $M$ frequency-time sub-spectrograms of $C \times X \times T$ dimension for every sample, where $M = \lfloor (F - X)/Y \rfloor$.

### 3.2. SubSpectralNet – Architecture Details

Two-channel sub-spectrograms are independently connected to 2 conv-layers with same padding and kernel-size of $(7, 7)$ having 32 and 64 kernels respectively. After each conv-layer, there is a batch normalization layer, ReLU activation layer, max-pooling layers of $(X/10, 5)$ and $(4, 100)$ size respectively, and finally a dropout of 30%. After the second pooling, we flatten the layer and add an FC layer with 32 neurons with ReLU activation and 30% dropout, followed by the softmax layer. We call these sub-classifiers of the SubSpectralNet. We do not remove these softmax outputs from the final network because this enforces them to learn to classify the sample based on only a part of spectrogram. We keep most parameters same as the DCASE 2018 baseline model for fair comparison. We believe that sub-spectrograms could be incorporated into more complex architectures [24, 25, 26] that could be used to surpass the state of the art in ASC performance.

To capture the global correlation (de-correlation) between frequency bands, we concatenate the FC (ReLU) layer of the sub-networks and train a DNN with $H$ hidden layers with $R_i$ neurons, where: $H = \max\{\lfloor \log_2(M) \rfloor - 1, 0\}$; $R_i = 2^6 + H - i, 1 \leq i \leq H$. We term this as the global classification sub-network.

All cross-entropy errors from the global and sub-classifiers are back-propagated simultaneously to train a single network. The sub-classifiers learn to classify using specific bands of spectrograms, while the global classifier combines and learns discerning information at a band-level. This modification of training method results in improved performance and faster convergence of the model with minimal addition to the complexity [24].

We create confusion matrices (shown in Fig. 4) from the output of these sub-classifiers and the global classification model discussed in Section 4. We observe that the statistical motivation given in Section 2 fits well with the results. For example, for the “airport” class, statistical distribution says that lower frequencies are more effective in classification. The same is shown in the confusion matrix where the low-band sub-classifier shows better results for this class. For the “bus” class, the mid-band sub-classifier shows relatively better results. For most classes, the global classifier achieves better results than any sub-classifier. It is interesting to note that for some classes like “public square” or “tram”, a sub-classifier performs better than the global classifier, which could mean that using the complete spectrogram adds outliers and it is better to use a specific band of spectrogram in such case.

### 4. EXPERIMENTS

We demonstrate the potential of SubSpectralNet on the DCASE 2018 development public dataset (Task 1A) and compare the results with DCASE 2018 baseline. We use dcase_util toolbox [27] to extract the features from the DCASE 2018 dataset. We implement SubSpectralNet in Keras with TensorFlow backend and experiments are performed on an NVIDIA Titan Xp GPU having 12GB RAM. We train all models 3 times for 200 epochs and report the average-best accuracy. The learning rate is set to 0.01 with Adam as the optimizer. Following are the experiments we perform in this work:

We train DCASE 2018 baseline models on different channels of audio dataset and the test accuracy achieved are 63.24% (left channel), 61.83% (right channel), 64.91% (average-mono channel) and 65.66% (stereo channels). We also train the DCASE 2018 baseline model for various kernel sizes of the first CNN layer – $(7, 7)$, $(15, 15)$, $(25, 25)$ and $(35, 35)$. The corresponding test accuracies are 65.66%, 65.23%, 65.08% and 62.80% respectively. This shows that bigger receptive fields tend to combine information on a bigger
In this paper, we introduce a novel approach of using spectrograms in Convolutional Neural Networks in the context of acoustic scene classification. First, we show from the statistical analysis of Sec. 2 that some specific bands of mel-spectrograms carry discriminative information than other bands, which is specific to every soundscape. From the inferences taken by this, we propose SubSpectralNets in which we first design a new convolutional layer that splits the time-frequency features into sub-spectrograms, then merges the band-level features on a later stage for the global classification. The effectiveness of SubSpectralNet is demonstrated by a relative improvement of +14% accuracy over the DCASE 2018 baseline [21].

SubSpectralNets also have some limitations, including the fact that for some classes, sub-classifiers are performing better than the global classifier. Also in the current model, we have to specify parameters like sub-spectrogram size and mel-bin hop-size. One way to address this could be by using the statistical analysis to choose the most appropriate parameters. In future, we plan to work on further improving the performance of this network, for example, by incorporating well-founded CNN architectures like Squeeze-and-Excitation network [25] and Densely Connected Neural Networks [26].
6. REFERENCES

[1] Tuomas Virtanen, Mark D Plumbley, and Dan Ellis, *Computa-
tional analysis of sound scenes and events*, Springer, 2018.

[2] Antti J Eronen, Vesa T Peltonen, Juha T Tuomi, Anssi P Kla-
puri, Seppo Fagerlund, Timo Sorsa, Gaëtan Lorho, and Jyri
Huopaniemi, “Audio-based context recognition,” *IEEE Trans-
actions on Audio, Speech, and Language Processing*, vol. 14,
no. 1, pp. 321–329, 2006.

[3] Dan Stowell, Dimitrios Giannoulis, Emmanuel Benetos,
Mathieu Lagrange, and Mark D Plumbley, “Detection and clas-
sification of acoustic scenes and events,” *IEEE Transactions on
Multimedia*, vol. 17, no. 10, pp. 1733–1746, 2015.

[4] Annamaria Mesaros, Toni Heittola, Emmanuel Benetos, Pe-
ter Foster, Mathieu Lagrange, Tuomas Virtanen, and Mark D
Plumbley, “Detection and classification of acoustic scenes and
events: Outcome of the dcase 2016 challenge,” *IEEE/ACM
Transactions on Audio, Speech and Language Processing
(TASLP)*, vol. 26, no. 2, pp. 379–393, 2018.

[5] Yifang Yin, Rajiv Ratn Shah, and Roger Zimmermann,
“Learning and fusing multimodal deep features for acoustic
scene categorization,” in *2018 ACM Multimedia Conference
on Multimedia Conference*. ACM, 2018, pp. 1892–1900.

[6] Tuomas Virtanen, Annamaria Mesaros, Toni Heittola, Alek-
sandr Diment, Emmanuel Vincent, Emmanuel Benetos, and
Benjamin Martinez Elizalde, *Proceedings of the Detection and
Classification of Acoustic Scenes and Events 2017 Workshop
(DCASE2017)*, Tampere University of Technology. Labora-
tory of Signal Processing, 2017.

[7] Mathieu Lagrange, Grégoire Lafay, Boris Defreville, and Jean-
Julien Aucouturier, “The bag-of-frames approach: a not so
sufficient model for urban soundscapes,” *The Journal of the
Acoustical Society of America*, vol. 138, no. 5, pp. EL487–
EL492, 2015.

[8] Victor Bisot, Romain Serizel, Slim Essid, and Gaël Richard,
“Feature learning with matrix factorization applied to acoustic
scene classification,” *IEEE/ACM Transactions on Audio,
Speech, and Language Processing*, vol. 25, no. 6, pp. 1216–
1229, 2017.

[9] Huy Phan, Lars Hertel, Marco Maass, Philipp Koch, and Al-
ed Mertins, “Label tree embeddings for acoustic scene clas-
sification,” in *Proceedings of the 2016 ACM on Multimedia
Conference*. ACM, 2016, pp. 486–490.

[10] Jean-Julien Aucouturier, Boris Defreville, and Francois Pachet,
“The bag-of-frames approach to audio pattern recognition: A
sufficient model for urban soundscapes but not for polyphonic
music,” *The Journal of the Acoustical Society of America*, vol.
122, no. 2, pp. 881–891, 2007.

[11] Jurgen T Geiger, Bjorn Schuller, and Gerhard Rigoll, “Large-
scale audio feature extraction and svm for acoustic scene clas-
sification,” in *Applications of Signal Processing to Audio and
Acoustics (WASPAA)*, 2013 *IEEE Workshop on*. IEEE, 2013,
pp. 1–4.

[12] Benjamin Cauchi, Mathieu Lagrange, Nicolas Misdatiis, and
Arshia Cont, “Saliency-based modeling of acoustic scenes us-
ing sparse non-negative matrix factorization,” in *Image Anal-
ysis for Multimedia Interactive Services (WIAMIS)*, 2013 *14th
International Workshop on*. IEEE, 2013, pp. 1–4.

[13] Victor Bisot, Romain Serizel, Slim Essid, and Gaël Richard,
“Acoustic scene classification with matrix factorization for un-
supervised feature learning,” in *Acoustics, Speech and Signal
Processing (ICASSP)*, 2016 *IEEE International Conference on
*. IEEE, 2016, pp. 6445–6449.

[14] Michele Valenti, Aleksandr Diment, Giambattista Parascan-
dolo, Stefano Squartini, and Tuomas Virtanen, “Dcase 2016
acoustic scene classification using convolutional neural net-
works,” *IEEE AASP Challenge on Detection and Classification
of Acoustic Scenes and Events (DCASE2016)*, Budapest,
Hungary, 2016.

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

[16] Victor Bisot, Slim Essid, and Gaël Richard, “Hog and subband
power distribution image features for acoustic scene classifica-
tion,” in *Signal Processing Conference (EUSIPCO)*, 2015 23rd
European. IEEE, 2015, pp. 719–723.

[17] Alain Rakotomamonjy and Gilles Gasso, “Histogram of gradi-
ents of time-frequency representations for audio scene classifica-
tion,” *IEEE/ACM Transactions on Audio, Speech and Lan-
guage Processing (TASLP)*, vol. 23, no. 1, pp. 142–153, 2015.

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

[19] Karol J Piczak, “The details that matter: Frequency resolution
of spectrograms in acoustic scene classification,” *Detection and
Classification of Acoustic Scenes and Events*, 2017.

[20] Yoonchang Han, Jeongsoo Park, and Kyogu Lee, “Con-
volutional neural networks with binaural representations and
background subtraction for acoustic scene classification,” the
*Detection and Classification of Acoustic Scenes and Events
(DCASE)*, pp. 1–5, 2017.

[21] Toni Heittola, Annamaria Mesaros, and Tuomas Virtanen, “A
multi-device dataset for urban acoustic scene classification,”
Tech. Rep., DCASE2018 Challenge, September 2018.

[22] Solomon Kullback and Richard A Leibler, “On information
and sufficiency,” *The annals of mathematical statistics*, vol.
22, no. 1, pp. 79–86, 1951.

[23] Rudolf Beran et al., “Minimum hellinger distance estimates
for parametric models,” *The annals of Statistics*, vol. 5, no. 3,
pp. 445–463, 1977.

[24] Sai Samarth R Phaye, Apoorva Sikka, Abhinav Dhall, and
Deepti Bathula, “Multi-level dense capsule networks,” in *Asian
Conference on Computer Vision*, 2018, accepted,
https://arxiv.org/abs/1805.04001.

[25] Jie Hu, Li Shen, and Gang Sun, “Squeeze-and-excitation net-
works,” in *IEEE Conference on Computer Vision and Pattern
Recognition (CVPR)*, 2018, pp. 7132–7141.

[26] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kil-
lian Q Weinberger, “Densely connected convolutional net-
works,” in *IEEE Conference on Computer Vision and Pattern
Recognition (CVPR)*, 2017, pp. 2261–2269.

[27] Toni Heittola, “DCASE UTIL: utilities for detection and
classification of acoustic scenes,” 2018, https://dcase-
repo.github.io/dcase_util/index.html.