Time-Frequency Feature Decomposition Based on Sound Duration for Acoustic Scene Classification

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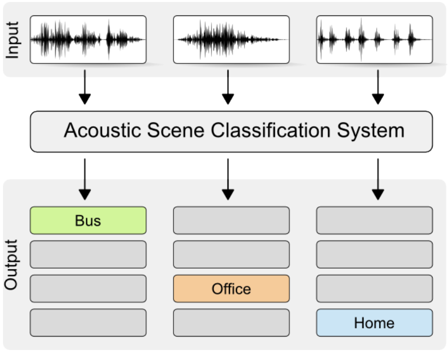
Task Definition

Acoustic scene classification (ASC) is the task of identifying the type of acoustic environment in which a given audio signal is recorded.

Figure: Overview of acoustic scene classification system. *(Image source: http://www.cs.tut.fi/sgn/arg/dcase2016/task-acoustic-scene-classification)*



Characteristics of Acoustic Scene Signal

An acoustic scene signal is a mixture of sounds of diverse properties. It could contain

- long-duration or short-duration sound events in time domain
- wide-band or narrow-band sound events in frequency domain

Sound events are commonly overlapped in time and/or in frequency.

For example, acoustic scene signal recorded in a bus may simultaneously contain

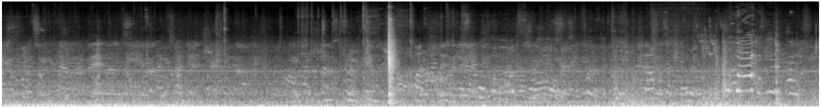
- bus engine sounds
- human speech
- sounds of nearby car horn

Audio Signal Represented as TF Feature

An audio signal can be represented as a time-frequency (TF) feature. For ASC, commonly used TF features are STFT, wavelet-based features, log-mel filter-bank, with

- x-axis representing time
- y-axis representing frequency

Figure: An example of TF feature representing an audio recorded in tram.



Why Feature Decomposition

In the DCASE challenges:

- Convolutional Neural Network (CNN) model has been widely adopted in the ASC task.
- Ensemble of models were found more accurate than a single model.
  - Remain unclear what specific aspects of scene information are addressed by individual component models.

We propose to decompose TF features based on sound duration.

- Facilitating detailed analysis on different types of acoustic scene information.
- Leveraging ensemble models with decomposed TF features.

Median Filtering for Images

In image processing, median filter is used to suppress impulse noise.

- Impulse noise: high positive pixel values concentrated locally in a small region.
- Moving-window median filter can suppress impulse events that are **narrower than half of the filtering window**.

Median Filtering for Time-Frequency Images

In a time-frequency image of an audio,

- Each pixel value indicates signal intensity at the respective time and frequency.
- Aggregations of pixels produce the acoustic patterns that can be perceived by human listeners as sound events.

The proposed feature decomposition method is based on the fact that

- Applying a median filter along the time axis would suppress impulse events of "short" duration (shorter than half of filtering window).
- Subtracting the filtered image from the original image results in an image that contains only "short" impulse events.

Proposed TF Feature Decomposition Method

- $\mathbf{S} = \mathbf{S_{long}} + \mathbf{S_{medium}} + \mathbf{S_{short}}$.
- Modify kernel sizes of median filters to control the sound information in each component image.

Algorithm 1 Proposed feature decomposition method with 2 median filters on time-frequency image.

Require:

The original time-frequency image, S;

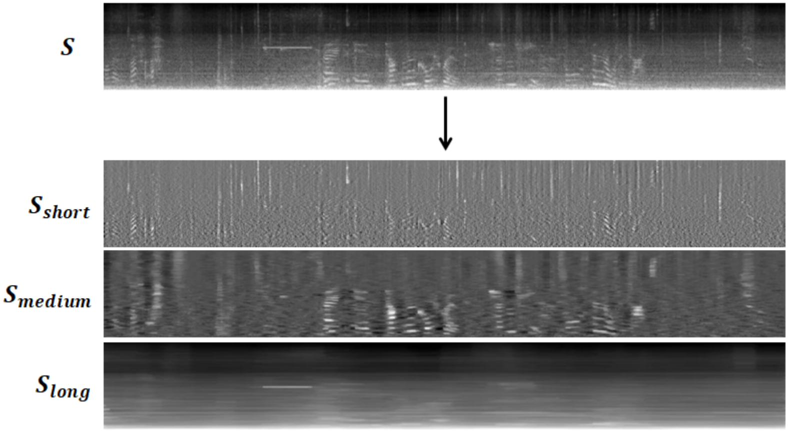
Median filtering function with small kernel size, M_s;

Median filtering function with large kernel size, M_l;

Procedure:

1: $S_r = M_s(S)$;
2: $S_{short} = S - S_r$;
3: $S_{long} = M_l(S_r)$;
4: $S_{medium} = S_r - S_{long}$;
5: **return** $(S_{long}, S_{medium}, S_{short})$;

Example of decomposing a TF image S



ASC System Design

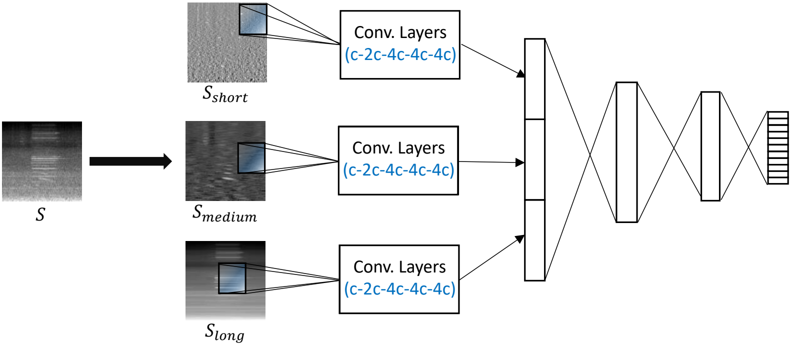


Figure: An illustration of our CNN model with 3 input channels. Independent feature extractor (convolution layers) is applied on each input channel. The "c-2c-4c-4c-4c" means the corresponding number of filters for the 5 convolution layers.

Structure of CNN Model

n is the number of input channels. c is used to control the number of filters in convolution layers.

1	Input $n \times 128 \times 128$
2	3x3 Convolution-BN-ReLU ($c \times n$ filters)
3	2x2 Max Pooling
4	3x3 Convolution-BN-ReLU ($2c \times n$ filters)
5	2x2 Max Pooling
6	3x3 Convolution-BN-ReLU ($4c \times n$ filters)
7	2x2 Max Pooling
8	3x3 Convolution-BN-ReLU ($4c \times n$ filters)
9	3x3 Convolution-BN-ReLU ($4c \times n$ filters)
10	2x2 Max Pooling
11	Flattening
12	Fully Connected (dim-1024)-BN-ReLU
13	Fully Connected (dim-256)-BN-ReLU
14	10-way Sigmoid

Dataset

The TAU Urban Acoustic Scenes 2019 development dataset (Mesaros et al. [2018])

- Used for subtask A of the DCASE 2019 ASC challenge.
- Each audio clip is 10-second long.
- 40-hour binaural audios from 10 different acoustic scene classes.
- Audios recorded with the same device.

We follow the training/test setup officially provided in the DCASE 2019 ASC challenge.

- Training set contains 9185 audio clips
  - covering about 70% of recording locations from 9 cities
- Test set contains 5215 audio clips
  - 4185 audio clips from the 9 cities (seen cities in training set)
  - 1030 audio clips from the 10th city Milan (unseen city).

Experiment Setup

CNN Training:

- 40 training epochs
- Initial LR is 0.0001, halved every 4 epochs
- Adam optimizer is used with $\beta_1 = 0.9$ and $\beta_2 = 0.999$
- Weight decay (coefficient $= 0.0015$) applied for regularization.

Data augmentation:

- The mixup approach (Zhang et al. [2017]).
- Temporal shifting the audio clips in training set.

Model Parameter Study

It can be seen that similar accuracy is achieved for $c \geq 16$.

- This may serve as an evidence for the following experiments that the significant performance gap between different configurations is not due to the change of model size.

Table: CNN model performance for different values of c.

Model Config	Input Feature	Accuracy
$c = 8$, $n = 1$	logmel	70.0%
$c = 16$, $n = 1$	logmel	72.5%
$c = 24$, $n = 1$	logmel	72.2%
$c = 48$, $n = 1$	logmel	72.8%

Decomposed Log-Mel Features

It can be seen from the experiment results that:

- It is helpful to explicitly learn long-lasting background sounds and transient sounds separately.
- All component images contain useful information for ASC.
- S_{long} contains the most pertinent information related to ASC.

Table: Performance of using the standard log-mel feature and the decomposed features.

Model Config	Input Feature	Accuracy
$c = 48$, $n = 1$	logmel	72.8%
$\mathbf{c = 16}$, $\mathbf{n = 3}$	**logmel-LMS**	$\mathbf{75.3\%}$
$c = 16$, $n = 2$	logmel-LM	74.3%
$c = 16$, $n = 2$	logmel-MS	70.0%
$c = 16$, $n = 2$	logmel-LS	73.7%
$c = 16$, $n = 1$	logmel-L	68.3%
$c = 16$, $n = 1$	logmel-M	60.8%
$c = 16$, $n = 1$	logmel-S	63.3%

Decomposed Log-Mel Features for ASC

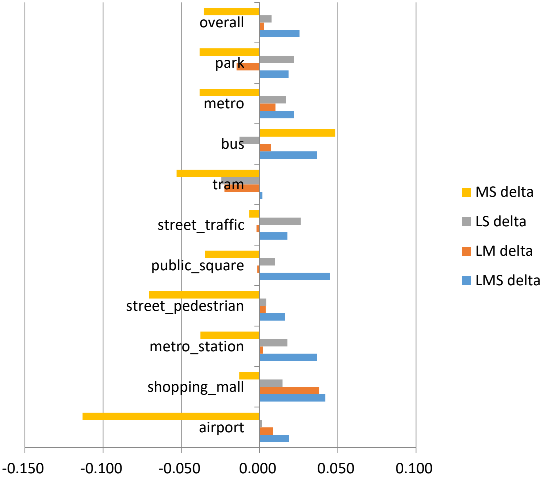


Figure: The F1 score difference between using log-mel image and decomposed log-mel images.

Decomposed Wavelet Filter-bank Features

Wavelet-based TF features were shown very effective in the best-performing system submitted to the DCASE 2019 ASC Challenge Subtask A (Chen et al. [2019]).

Table: Performance of using log-mel, wavelet filter-bank features (scalogram) and their decomposed features.

Model Config	Input Feature	Accuracy
$c = 48$, $n = 1$	logmel	72.8%
$c = 16$, $n = 3$	logmel-LMS	75.3%
$c = 48$, $n = 1$	scalogram	74.6%
$\mathbf{c = 16}$, $\mathbf{n = 3}$	**scalogram-LMS**	$\mathbf{76.7}\%$

Conclusions

A novel time-frequency feature decomposition method has been developed for audio scene classification.

- The CNN model is explicitly guided to learn long-lasting background sounds and transient sounds separately.
- Analysis of component images shows that long-duration sounds are most informative for ASC.
- Our decomposition method can be combined with wavelet based time-frequency features to obtain a further improved accuracy.

Reference I

H. Chen, Z. Liu *et al.*, "Integrating the data augmentation scheme with various classifiers for acoustic scene modeling," DCASE2019 Challenge, Tech. Rep., June 2019.

A. Mesaros, T. Heittola, and T. Virtanen, "A multi-device dataset for urban acoustic scene classification," in *Proceedings of the Detection and Classification of Acoustic Scenes and Events 2018 Workshop (DCASE2018)*, November 2018, pp. 9–13. [Online]. Available: https://arxiv.org/abs/1807.09840

H. Zhang, M. Cisse, Y. N. Dauphin, and D. Lopez-Paz, "mixup: Beyond Empirical Risk Minimization," *arXiv e-prints*, p. arXiv:1710.09412, Oct 2017.