Audio classification using attention-augmented convolutional neural network

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ABSTRACT

Audio classification, as a set of important and challenging tasks, groups speech signals according to speakers' identities, accents, and emotional states. Due to the high dimensionality of the audio data, task-specific handcrafted features extraction is always required and regarded cumbersome for various audio classification tasks. More importantly, the inherent relationship among features has not been fully exploited. In this paper, the original speech signal is first represented as spectrogram and later be split along the frequency domain to form frequency-distributed spectrogram. This paper proposes a task-independent model, called FreqCNN, to automaticly extract distinctive features from each frequency band by using convolutional kernels. Further more, an attention mechanism is introduced to systematically enhance the features from certain frequency bands. The proposed FreqCNN is evaluated on three publicly available speech databases thorough three independent classification tasks. The obtained results demonstrate superior performance over the state-of-the-art.

1. Introduction

Audio classification technologies distinguish audio data by the differences of emotion, accents, speakers'identities, and other factors. Effective audio classification tasks can also contribute to the performance of other tasks, e.g., speech-to-speech translation and automatic speech recognition. For instance, Akagi et al. [1] translated spoken utterances from one language into another by taking into account emotional states in sounds, which enables their model to deal with non-linguistic information and makes a translation system practical. Hansen and Liu [2] improved the generalization and robustness of their speech recognition system by also detecting accent-related variation in speech signals. Intuitively, by considering the variety of dialects, accents, and emotions in speech signals, better performance could be expected in human-machine speech communication tasks.

Because of the high dimensionality of the original audio data, most audio classification are based on the extracted low-dimensional features. Spectrograms are considered to capture comparatively complete energy, frequency, and time information from the original audio signal [3]. However, spectrograms are still considered high-dimensional for traditional classifiers such as support vector machines. To further reduce the dimensions of the input space, the feature extraction of mel-frequency cepstral coefficients (MFCCs) and the linear prediction cepstrum coefficient (LPCC) are widely used in many studies [4,5]. These features are hand-engineered because the corresponding parameters need to be predefined based on expert knowledge. Moreover, these predefined feature sets are designed for specific tasks and often fail to generalize to other ones [6,7]. These difficulties in audio classification research motivate us to find a general solution for automatically learning different features from high-dimensional spectrograms for the corresponding tasks.

Recently, deep neural networks (DNNs) have proved to have an excellent ability to automatically learn salient feature representations from high-dimensional input data [8], as a result of their outstanding performance in many areas [9,10]. The deep architecture in DNNs is a set of non-linear activation functions that enables the network to effectively model complex nonlinear mappings from input to output [11]. Convolutional neural networks (CNNs), which are a type of DNNs, have been popular in pattern recognition [12,13]. A CNN consists of interleaved convolutional layers and pooling layers. The former layers utilize locally connected filters to share weights across the input, which enables translation invariance of the input, and the latter layers are designed to reduce the dimensionality of the data [11]. These convolutional filters also have interpretable time and frequency meanings for audio spectrograms and are able to learn time-frequency feature representations from two dimensions.

Usually, a whole spectrogram is used as the input of a CNN to obtain the global feature representation. To learn more salient features, the

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spectrogram is split into small frames along the time axis, which is called a time-distributed spectrogram [14,15]. Using these small time-distributed segments of the spectrogram as the input into the CNN, different local features at different time steps are learned. However, spectrograms also represent the distribution of energy along the change of frequency. In many approaches [16,17], frequency-domain only features (e.g., MFCCs) also obtain good results in audio classification tasks, which have proved the importance of frequencies information. Beside, several works have researched the effectiveness of sub-band spectral feature [18–20], which enhanced the representation of speech signals and obtained better robustness in many tasks, such as automatic speech recognition (ASR).

Methods based on the time-distributed spectrogram [14,15] focus on the information of the time domain, while this paper investigates how does the changes in certain frequency bands contribute to the final performance of different audio classification. Small segments split along frequencies are called the frequency-distributed spectrogram, and they represent the energy distribution in different frequency intervals. In this way, various features in different frequency intervals can be learned effectively. In some works [21,22], improved DNNs were used in speech related tasks and obtained great performance. Compared with fully-connected DNNs, CNNs have fewer parameters with high non-linearity, which are suitable for smaller dataset. In our work, we finally apply CNN as the main architecture. Both global features extracted from the whole spectrogram and local features extracted from frequency-distributed sub-spectrograms are learned using different convolutional kernels.

In order to better interpret the features and their relationship from various frequency bands, we further propose attention-augmented convolutional neural networks. The idea of attention comes from the human visual system [23], which prefers to focus on the most relevant piece of data rather than using all available information. In DNNs, rather than concatenate all low-level features into a global representation, the attention mechanism enables salient features to automatically receive more focus as needed [24]. This is especially necessary when there are a lot of features in a DNN. Combing attention with DNNs has been proven to be effective in many fields, especially computer vision and natural language processing (NLP) [25,26]. In our work, we demonstrate the efficiency of attention-augmented CNNs in multiple audio classification tasks with state-of-the-art performance.

In this paper, based on frequency-distributed spectrogram, a model called FreqCNN that combines deep CNNs with an attention mechanism is proposed for different audio classification tasks. The proposed FreqCNN is a general model, which automatically learns the relevant feature representation according to auditory categories. The basic idea of FreqCNN is to learn different feature representations from the frequency-distributed segments and a whole spectrogram simultaneously and further integrate different features using the attention mechanism.

The rest of the paper is organized as follows. Section 2 discusses some related work in the audio classification field. Section 3 presents the preliminaries of spectrograms, original CNNs and the attention mechanism. The details of the proposed FreqCNN are described in Section 4. In Section 5, a thorough empirical evaluation of FreqCNN is conducted. The conclusion is drawn in Section 6.

2. Related works

Most audio classification studies focus on a specific task in order to achieve good results. For instance, Poria et al. [6] designed two broad kinds of feature sets, short- and long-time based features, to capture the representation of emotions in audio. In [16], they used MFCCs with a support vector machine to improve the performance on two public databases for audio event classification. Mencattini et al. [27] applied 12 different groups of features to learn emotion-relevant information with prominent results. Recently, increasingly more research has applied DNNs to audio classification tasks. In [4], DNNs combined with transformed MFCCs were used for speaker age classification, which improved the overall recognition accuracy. In speaker recognition, i-vector is a good technique to represent the characteristic of a speaker. Ghahabi and Hernando [28] proposed to combine Deep Belief Networks (DBNs) with i-vector in a speaker verification task, which achieved relative improvements of the recognition performance. In [29], DNN-based gaussian probabilistic linear discriminant analysis system also achieves much improvements in EER values than traditional gaussian methods.

Moreover, several studies using CNNs with spectrograms for audio classification have been conducted recently. In [30], they applied principal component analysis (PCA) whitening to spectrograms to obtain the lower-dimensional representation and achieved better performance by combining with DNNs than traditional well-designed feature sets, i.e., MFCCs, LPCC, and pitch. In contrast to methods using single-input (whole) spectrograms, some studies proposed time-distributed spectrogram combined with CNNs [14,15]. In every time step, one small segment of the whole spectrogram is input to the CNN. Their model can learn the feature representation of audio in a time sequence, demonstrating that distributed spectrograms with CNNs outperforms the whole single-input model.

All these techniques above are restricted to a single audio classification task, and few studies have focused on a uniform framework to deal with different audio classification problems. Lee et al. [31] applied convolutional deep belief networks (CDBN) to classify audio data. The experiments showed that the feature representation learned by this model can achieve high performance on multiple audio recognition tasks. In [32], they employed DNNs to extract the cepstral features of audio, which outperformed competing methods in two audio classification tasks. Scardapane et al. [33] provided multiple functional link expansions on three audio classification problems, achieving the best accuracy in two out of three tasks.

3. Preliminaries

In this section, the conversion of audio into spectrograms and CNNs with attention are presented.

3.1. Spectrograms

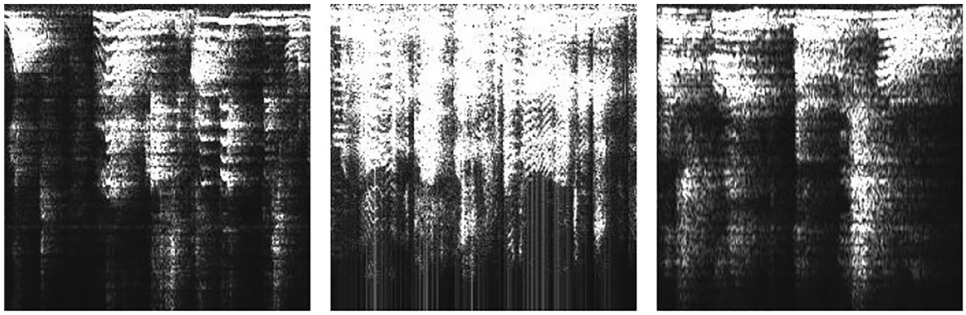
Spectrograms are a visual representation of audio that resemble natural images. However, there are some noticeable differences between spectrograms and natural images. Natural images can be scaled, rotated, and distorted without losing the underlying image structure, but each pixel in a spectrogram has specific meanings. The spectrogram is depicted as a “fixed” structure that displays the change of frequency along the vertical axis and time along the horizontal axis [3]. It is calculated using the short-time Fourier transform (STFT) on windowed audio frames. In this section, we briefly introduce the conversion of audio into spectrograms. Further details can be found in [3].

The spectrogram of audio is generally organized as a two-dimensional matrix as follow:

$$S = \begin{bmatrix} s_0^1 & \dots & s_0^M \\ \vdots & \ddots & \vdots \\ s_{(N-1)}^1 & \dots & s_{(N-1)}^M \end{bmatrix}, \tag{1}$$

where S denotes the raw spectrogram. M denotes that the original audio signal is segmented into M window frames, and the length of each windowed audio frame is N.

Each spectrogram frame is computed as the estimate of the short-term frequency content for the windowed audio. Let the original audio is denoted as a set of windowed frames (x^1, x^2, ... , x^M). Each spectrogram frame is then calculated as follows:



(a) angry (b) sad (c) happy

Fig. 1. Examples of spectrograms for speech with different emotions: angry, sad and happy. Frequencies are shown increasing vertically and the horizontal axis represents time.

$$X_k^m = \sum_{n=0}^{N} x_n^m e^{-i2\pi kn/N}, \quad k = 0, 1, \ldots, N\text{-}1, \text{ and } m = 1, 2, \ldots, M, \tag{2}$$

where x^m denotes the audio segment at the window with index m. Further,

$$s_k^m = (Re\{X_k^m\})^2 + (Im\{X_k^m\})^2, \tag{3}$$

where $Re\{\cdot\}$ denotes the real part of X_k^m and $Im\{\cdot\}$ is the imaginary part. After all spectrogram frames have been computed, they are concatenated together to construct spectrogram S.

The visualization of three different emotional states of audio in the form of spectrograms are shown in Fig. 1. There is a large difference among three images in the distribution of energy as frequencies increase in the vertical direction. They also indicate the ability to distinguish one audio from another using the energy distribution over the frequencies of the spectrogram.

3.2. Convolutional neural networks (CNNs)

CNNs have been broadly applied in pattern recognition using many typical architectures such as VGG nets [12] or ResNet [13]. In a typical CNN architecture, there are three important parts: convolutional layers, pooling layers, and fully-connected layers.

A convolutional layer consists of a set of kernels (also called as filters), each of which has a receptive field. Because of the local connectivity and shared filters, convolutional layers can deal with two-dimensional data with translation invariance [11]. For input s, the convolution operation is described by the following equation:

$$a_{ij} = f\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} w_{mn}\cdot s_{(i+m)(j+n)} + b\right), \tag{4}$$

where a denotes the feature representation (output after convolution). w is the weight values of the convolutional kernel, and b is the bias offset. Further, M and N denote the width and height of the kernel, respectively. (i, j) and (m, n) represents the position indices. Function $f(\cdot)$ is the activation function. Fig. 2(a) shows the convolution operation in Eq. (4).

The pooling layer is generally applied after several convolutional layers. It provides a form of nonlinear down-sampling of the input and aims to reduce the number of parameters in the network. The output of the pooling can be computed as follows:

$$p = \sigma(a'), \tag{5}$$

where p and a' denote the output and the input for the pooling layer, respectively. Function $\sigma(\cdot)$ denotes the down-sampling operation over the receptive filed, i.e., maximum or average function. As shown in Fig. 2(b), the size of input a' is $L \times L$, and the size of output p is $\frac{L}{K} \times \frac{L}{K}$, when a receptive filed of size $k \times k$ is used to reduce it to a single value via function $\sigma(\cdot)$.

After convolutional and pooling operations, the multiple feature maps are aggregated and used as the input to the fully-connected layer. The formulation at fully-connected layer l is as follows:

$$a^l = f(w^l a^{l-1} + b^l), \tag{6}$$

where l denotes the index of the l-th fully-connected layer and a^{l-1} and a^l are the input and the output of layer l respectively.

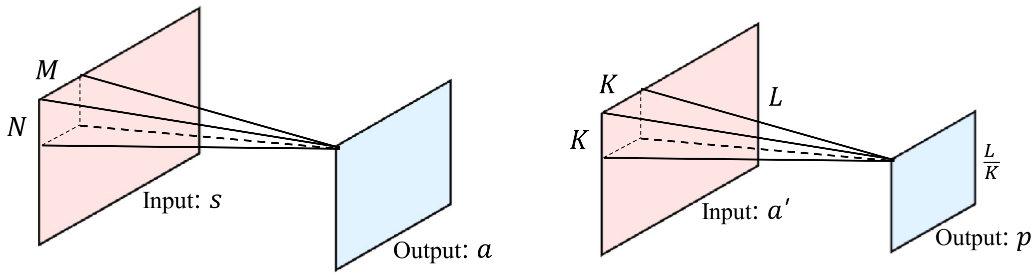
3.3. Attention in CNNs

Attention is widely studied in neuroscience and is gaining popularity in DNNs, especially for CNNs and recurrent neural networks (RNNs). CNNs usually uniformly fuse all feature maps into a global representation for final recognition, while RNNs also usually uniformly fuse the output of the last hidden layer at all time steps. The attention mechanism allows semantically representing relationship among obtained features. Specifically, using an attention is a useful way to get robust performance when there are many features in a network. By using an attention mechanism, different weights are assigned to all features (local parts) that comprise the global representation. If the weight of a certain local part is higher, it means this part is more important.

There are mainly two types of methods introducing the attention mechanism into CNNs: spatial-based [25] and feature-based [26] methods. The difference between the two methods is how to divide the global feature representation into several local parts. For instance, assume that the shape of each feature map is $(N \times N)$ and there are K features maps comprising the global representation, as shown in Fig. 3. In a spatial-based method, the model learns to assign different weights for each vector, which is composed of a pixel at the same location over all feature maps, as shown in Fig. 3(a), and the length of the vector is K. In Fig. 3(b), the feature-based approach assigns different weights for different feature maps. In our model, both attention methods are used for the accent recognition task in Section 5. The experiment shows both attention methods can improve performance.

4. Proposed FreqCNN model

Based on frequency-distributed spectrogram, the proposed FreqCNN model combines CNNs with attention mechanism for feature learning. The overall architecture of the FreqCNN model is illustrated in Fig. 4. Spectrograms are extracted from audio signals as the input for the subsequent CNN blocks. There are two types of convolutional blocks: basic convolutional blocks and attention-based convolutional blocks. These two types differ in whether there is an attention mechanism in the convolutional block. After several convolutional blocks, the output is connected to the fully connected layers. Finally, a fully connected layer with a softmax classifier outputs the final result.



(a) The convolutional layer (b) The pooling layer

Fig. 2. Convolution and pooling operations in a typical CNN architecture.

In the following text, we present details, accompany with examples, of basic convolutional blocks and attention-based convolutional blocks in the FreqCNN model.

4.1. Basic convolutional blocks

A spectrograms can be split into different frames within the time domain [14,15] and is called time-distributed spectrogram, as shown in Fig. 5(a). Each split part includes the whole frequency domain at a certain time interval. In our work, the spectrogram is split into small segments along the frequency axis, as illustrated in Fig. 5(b). Our idea is to pay attention to the energy distribution in different frequency intervals over the entire time window. At the same time, the whole spectrogram is also feed into the model to generate a global feature representation.

Fig. 6 gives a general module of the basic convolutional block. In particular, for each basic block, we perform three steps: first, to obtain the frequency-distributed input, we split the whole frequency-time domain into several local regions along the frequency axis; second, we use multiple convolutional layers to learn different features. Based on the local information input, the model learns the local feature representation as well as the whole frequency-time input; last, we combine the local and global feature representation to form the output of the block.

Let S denote the input of the convolutional block. We split the input S into n local parts (along the vertical axis) and the frequency-distributed input set is denoted as $\{(s^1, s^2, \dots, s^n), S\}$, where s^n is the data at the nth local frequency interval. Convolutions are performed separately on the set of frequency-distributed parts and the whole input. The extracted features from different input can be described as follows:

$$\begin{cases} a^k &= f(w^k s^k + b^k) \quad (1 \le k \le n) \\ A_g &= g(w\,S + b) \end{cases}, \tag{7}$$

where w^k denotes the weight for the kth local frequency information s^k and b^k is the bias parameter. In addition, w denotes the weight for the whole spectrogram S and b is the bias. Functions $f(\cdot)$ and $g(\cdot)$ are activation functions in learning the local and global features, respectively. Note that we only give Eq. (7) to represent the operation of one convolutional layer for simplicity.

After concatenating all local features, we combine them with the global feature representation using element-wise addition as follows:

$$A = A_g + [a^1; a^2; \dots; a^n], \tag{8}$$

where A denotes the final output of the basic convolutional block.

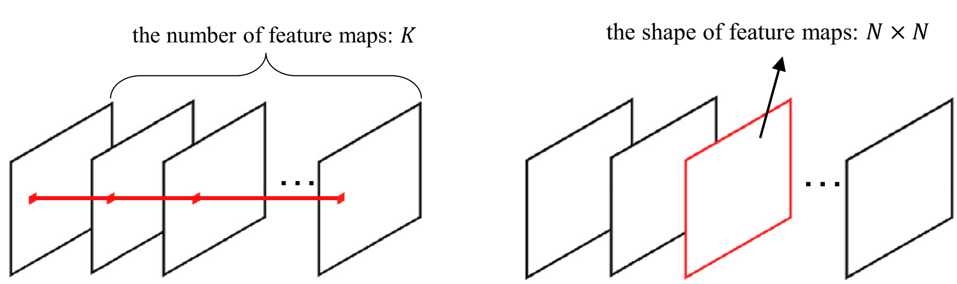
Fig. 7(a) gives an example of the basic convolutional block. The input is split into two local frequency parts, so the frequency-distributed input set is denoted as $\{(s^1, s^2), S\}$. Global data S is followed by two convolutional layers and the output of the convolution is A_g. Outputs for frequency-distributed set s^1 and s^2 after one convolutional layer, i.e., a^1 and a^2, are concatenated together. Finally, global feature A_g plus the concatenation of local features a^1, a^2 are used to compute the final output A.

4.2. Attention-based convolutional blocks

In a basic convolutional block, we simply add the global feature and the concatenation of all local features. In the attention-based convolutional block, utilizing CNNs with an attention mechanism, the model learns to reorganize the global feature representation. Fig. 8 illustrates the structure in the attention-based convolutional block, where the attention method is used to guide the model to focus on more representative parts. Using different local features, the model reorganizes them to form a new global feature representation. By aggregating all attention-based global features and the original global representation, we obtain the final output of the attention-based convolutional block.

Attention methods are generally feature-based or spatial-based. As shown in Fig. 3, a global feature representation A_g may be composed of a set of local parts $\{p_1, \dots, p_m\}$, where m denotes the number of local parts. For different attention methods, the definition of the local parts differs.

Given frequency-distributed input $\{(s^1, s^2, \dots, s^n), S\}$, there are a set of local features $(a^1, a^2, \dots, a^n)$ and global feature A_g. By taking certain



(a) Spatial-based method (b) Feature-based method

Fig. 3. Two kinds of attention methods for CNNs. Each feature map is organized as a rectangle in this figure.

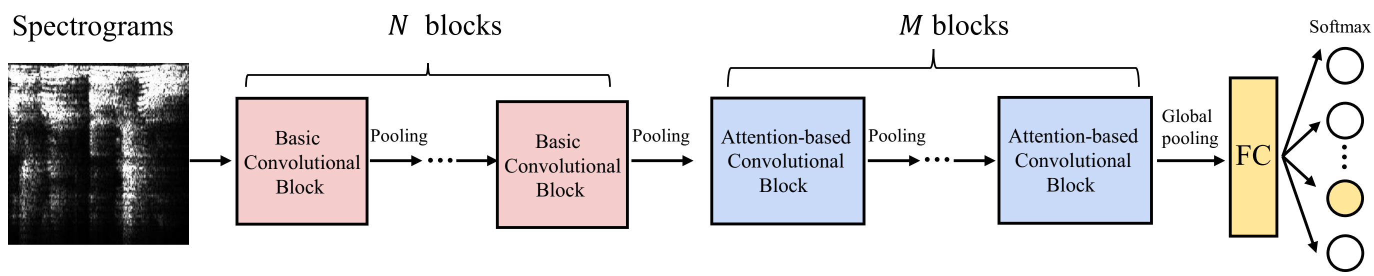


Fig. 4. The Architecture of the proposed FreqCNN model.

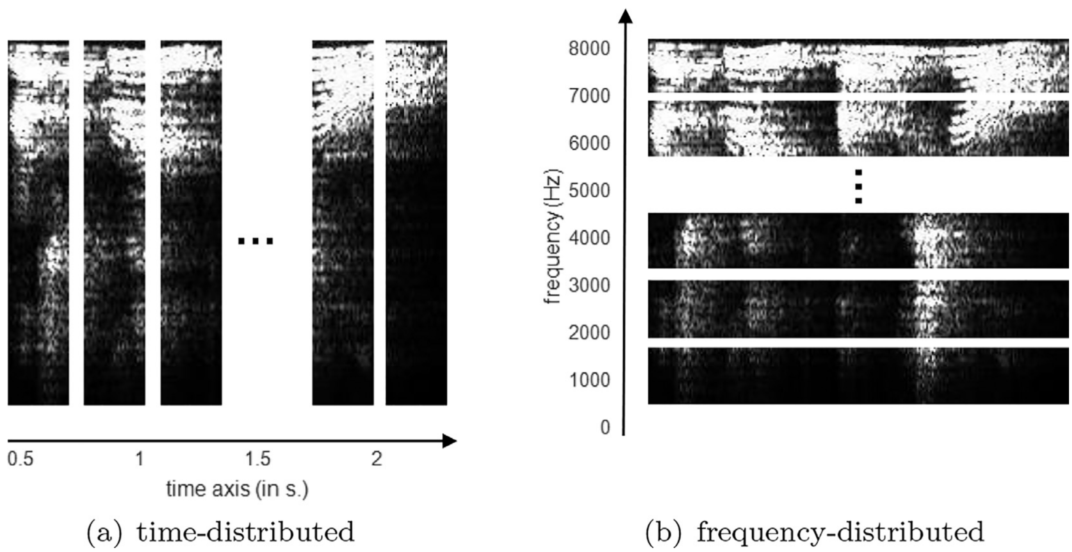


Fig. 5. Visual presentation of spectrograms. Two forms of spectrograms are illustrated: the time-distributed spectrogram and frequency-distributed spectrogram.

local feature $a^k (1 \le k \le n)$ into consideration, the attention method assigns weight $h_i^{(k)}$ to different local parts $p_i (0 \le i \le m)$, to obtain a new global representation A^k. As shown in Eq. (9), the weight $h_i^{(k)}$ for local part p_i is computed by two fully-connected layers:

$$h_i^{(k)} = g(W_2 f(W_1 [p_i; a^k] + b_1) + b_2), \quad i = 1, \ldots, m, \tag{9}$$

where $f(\cdot)$ and $g(\cdot)$ are activation functions. Matrices W_1, W_2 are the weight of the first and second layer, respectively, and b_1 and b_2 denote the bias parameters of different layers. The weighted global feature representation can then be computed as follows:

$$A^k = [p_1 h_1^{(k)}; p_2 h_2^{(k)}; \cdots; p_m h_m^{(k)}], \tag{10}$$

where A^k denotes the attention-based global feature, which is based on corresponding local feature a^k.

Finally, we combine all attention-based global features and the original global representation without attention. The output of attention-based convolutional block is computed as follows:

$$A = \sum_{k=1}^{n} A^k + A_g. \tag{11}$$

where n denotes the number of parts in the frequency-distributed set.

Fig. 7(b) presents an example of attention-based convolutional block. The input is also split into two local parts. The global feature is A_g and local representation are a^1 and a^2. Further more, we apply a^1 to attention global feature A_g and obtain A^1, similarly available for A^2. Finally, adding A_g, A^1 and A^2 are calculated as the output of attention-based block.

5. Experiments

The proposed model is a general model for audio classification tasks, thus, we evaluated the FreqCNN model on three audio classification tasks: (a) accent classification; (b) speaker identification; and (c) speech emotion recognition.

For accent classification, the performance of FreqCNN was compared with the performance of the state-of-the-art method [2] and existing CNN models, i.e., VGG [12] and ResNet [13]. We further explored the performance of the model using a different number of frequency-distributed set and two attention methods. In the speaker identification task, we compared our model with the traditional method (i.e., MFCCs) [17] and typical CNN models. We also tested the FreqCNN model under different activation functions. In the speech emotion recognition experiment, we compared the performance of the proposed model with other related works [5,6,34,35] and presented a confusion matrix of the final recognition.

For all experiments, the extraction algorithm of the spectrograms was implemented using MIRtoolbox.[1] The sampling rate of all records was set to 16 kHz and the size of spectrograms in each experiment was different because of different database scales. The implementation of the FreqCNN is based on the MxNet framework.[2] We used stochastic gradient descent (SGD) with mini-batches. The learning rate started from 0.01, with a weight decay of $1.0e-8$ and a momentum of 0.9. All models were trained from scratch on Nvidia Tesla K40 GPUs.

[1] http://www.mathworks.com/matlabcentral/fileexchange/24583mirtoolbox/.

[2] http://mxnet.io/ MxNet is a scientific computing framework supporting deep learning.

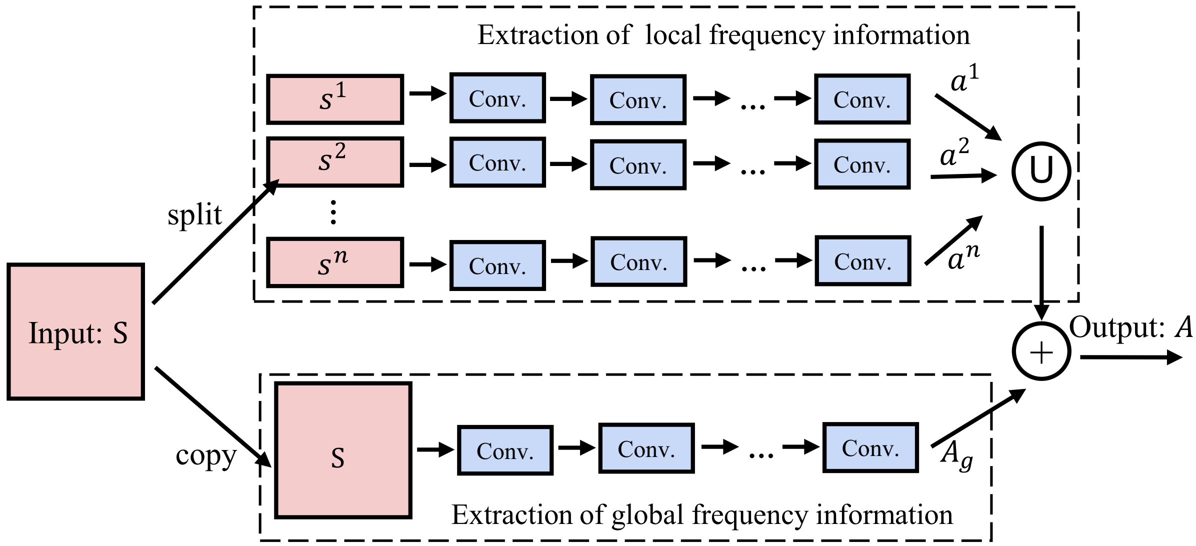


Fig. 6. General module of a basic convolutional block. In this block, "∪" indicates concatenation and "+" indicates element-wise addition.

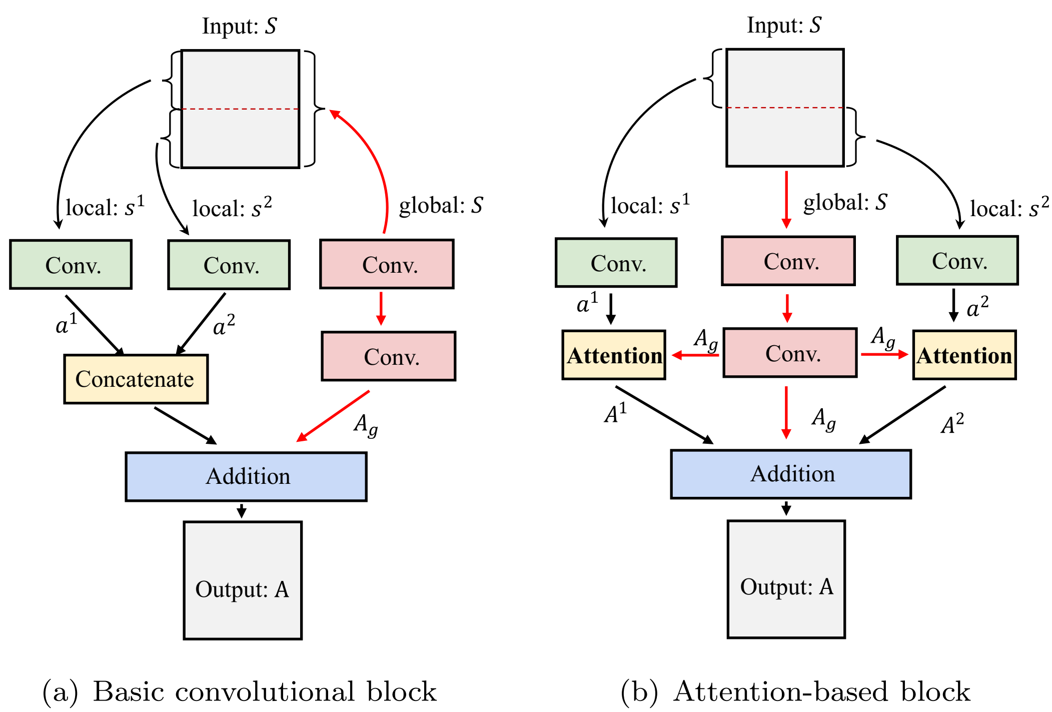


Fig. 7. Examples of basic convolutional block and attention-based convolutional block.

5.1. Accent classification

Accent classification recognizes the difference in accents in one language or dialect. In this experiment, we examine the performance of the FreqCNN model on the UT-Podcast corpus [2].

Database and setting. The UT-Podcast corpus was designed to assist English accent research. It includes English accents from Australia (AU), the United States (US), and the United Kingdom (UK). In Table 1, we give the distribution of audio samples for each accent label. There are 1101 samples for training and 661 samples for testing. We randomly over-sampled some audio for training because of the class imbalance problem. The number of samples used for the experiment is given in Table 1, denoted as Total_2. In this experiment, spectrograms were extracted with a size of 256 × 256 and the batch size was 48.

The best parameters of FreqCNN are listed in Table 2. There are five convolutional blocks, including three basic blocks (**BC**) and two attention-based blocks (**AC**). Each input of the block is divided into two local parts. There are two convolutional layers for global features extraction and one layer for local features. All 3 × 3, 5 × 5, and 7 × 7 convolutions have corresponding zero-padding to retain the size of the receptive field after convolution. We adopted batch normalization layers right before each activation and convolutional layer.

Results and discussion. Hansen and Liu [2] achieved the state-of-art UAR of 74.5% on the UT-Podcast corpus using i-Vector. However, the FreqCNN model exhibits superior performance, achieving a UAR of up to 79.32%. The evaluation of recall score and unweighed average recall (UAR) are illustrated in Table 3. Moreover, several popular DNN architectures were tested in this experiment. We selected some typical CNN architectures with their default hyper-parameters, i.e., AlexNet

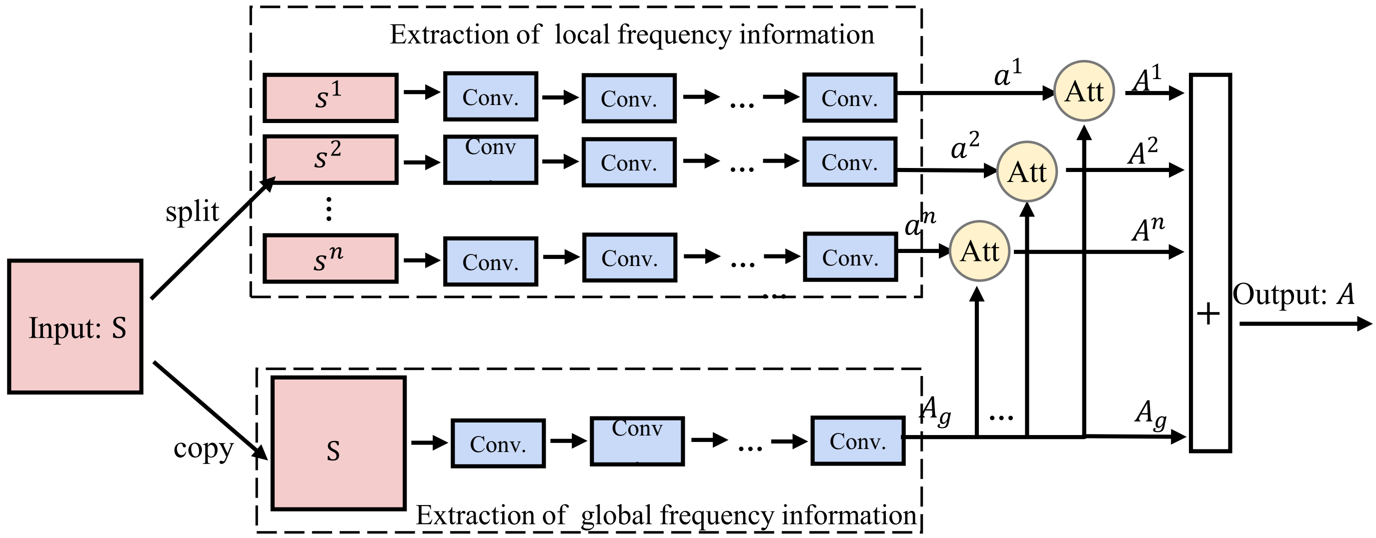


Fig. 8. The structure of the attention-based convolutional block.

Table 1
The number of training and testing records per accent.

#Samples	Accent				Total	
	AU	US	UK	UK_2	Original	Over-sampled
Training	449	406	246	492	1101	1347
Testing	332	240	89	89	661	661

[36], VGG-11 [12] and ResNet-18 [13]. AlexNet is a typical CNN with five convolutional layers and two fully-connected layers. VGG and ResNet have deeper architecture with more convolutional layers. Because of the small dataset, we further designed two small DNN models: a three-layer FNN and a five-layer CNN. As shown in Table 3, FreqCNN achieves the best performance among these models, followed by i-vector method and AlexNet model. Especially, small DNNs (AlexNet and 5-layer CNN) can achieve better results than lager models (VGG-11 and ResNet-18). AlexNet is much better than other methods in the recognition of UK, which is just lower than our proposed method. 5-layer CNN is much better than other methods in the recognition of US, which is just lower than i-vector method. Compared with these methods, our model achieves the best performance in two out of three categories (AU and UK) and its average score is the best. These results demonstrate that the combination of global and local features and the use of attention with CNNs indeed improve the recognition performance.

Table 3
Recall and UAR (%) of different models on the UT-Podcast.

Recall	Methods						
	i-Vector	FreqCNN	FNN	CNN	AlexNet	VGG-11	ResNet-18
AU	78.00	**88.55**	70.78	64.76	58.43	55.72	69.28
UK	61.80	**71.91**	50.56	41.57	64.04	48.31	38.20
US	**83.80**	77.50	62.92	82.08	74.17	59.17	77.50
UAR	74.50	**79.32**	61.42	62.81	64.90	54.40	61.66

Table 4
Comparison of local frequency segments and global-local frequency with different numbers of local partial frequency. “0” partial frequency segment means there is only global spectrogram used.

	Evaluation	Number of partial frequency			
		0	2	4	8
Local frequency only	UAR	–	70.53	75.86	70.27
	ACC	–	76.85	79.27	73.22
Global and local frequency	UAR	72.45	75.41	**77.68**	76.38
	ACC	74.89	76.10	**80.18**	75.49

Furthermore, we evaluated the performance of the model using different numbers of frequency-distributed segments (0, 2, 4, 8) under two kinds of form: local frequency only and the combination of global

Table 2
Best parameters of the FreqCNN model in accent classification on the UT-Podcast.

Name	Local convolution	Global convolution	Pooling
Basic block 1	64, 5 × 5/1, sigmoid	64, 5 × 5/1, tanh	
Conv. and pool		64, 7 × 7/1	max, 2 × 2/2
Basic block 2	64, 5 × 5/1, sigmoid	64, 5 × 5/1, tanh	
Conv and pool		96, 7 × 7/1	max, 2 × 2/2
Basic block 3	96, 5 × 5/1, sigmoid	96, 5 × 5/1, tanh	
Conv. and pool		128, 7 × 7/1	max, 2 × 2/2, dropout 0.2
Attention-based block 4	128, 5 × 5/1, sigmoid	128, 3 × 3/1, tanh	
		fc: 512, tanh; 256, tanh; 1, sigmoid	
Conv. and pool		256, 5 × 5/1	max, 2 × 2/2, dropout 0.2
Attention-based block 5	256, 3 × 3/1, sigmoid	256, 3 × 3/1, tanh	
		fc: 256, tanh; 1, sigmoid	
Conv. and pool		256, 512, 5 × 5/2, tanh	avg (global), dropout 0.5
fc		512, relu, dropout 0.5	
Softmax		3-way softmax	

Table 5
Comparison of two ways of attention methods in CNNs and different numbers of attention-based blocks. “1 A” means that only the last convolutional block uses attention and “2 AC” means that the last two convolutional blocks use attention. “All BC” indicates that there is no attention in the FreqCNN model.

	Attention	Feature-based methods		Spatial-based methods	
		ACC	UAR	ACC	UAR
Frequency- distributed	All BC	ACC: 76.10	UAR: 75.41		
	1 AC	78.37	75.77	77.91	76.33
	2 AC	**82.30**	**79.32**	74.28	74.74
	3 AC	76.55	73.67	77.46	72.59
Time-distributed	All BC	ACC: 74.43 UAR: 73.27			
	1 AC	74.74	75.88	77.46	73.88
	2 AC	73.37	74.46	77.31	74.08
	3 AC	70.65	66.40	75.34	73.81

Table 6
Details of three-fold data set of the CHAINS corpus.

No.	Training	#Samples	Validation	#Samples
#1	f(03), f(04), s(01), s(02)	2484	f(01), f(02)	1530
#2	f(01), f(02), s(01), s(02)	2718	f(03), f(04)	1296
#3	f(01), f(02), f(03), f(04)	2826	s(01), s(02)	1188

and local frequency. Experimental results are listed in Table 4. Compared with only local frequency method or only global information method, the combination of global and local frequency indeed improves the recognition performance. The experimental results show that the best accuracy is up to 80.18%, using the global frequency and 4 partial frequency information together. With global frequency only method, the model can obtain accuracy of 74.89% and recall rate of 72.45%. With local frequency-distributed segments only method, the model can get better accuracy of 79.27% when the number of local parts is 4. As the number of local frequency segments continues to increase, the number of parameters in the model also increases. The performance does not improve.

We also compared the performance of time-distributed form and frequency-distributed form of spectrograms, under different attention-based blocks and attention techniques. There are all two local parts in frequencies or time in each experiment. The results are illustrated in Table 5. These experiments demonstrate that attention technique indeed improves the recognition performance in accuracy and UAR, compared with no attention in the model, for both splitting spectrograms in frequencies or time. Moreover, the overall recognition for frequency-distributed spectrograms is higher than time-distributed spectrograms. In the frequency-distributed form, feature-based attention gives us the best result in the last two convolutional blocks, achieving an accuracy of 82.30%, and spatial-based attention achieves better performance when it is only used in the last convolutional block. In the time-distributed form, spatial-based attention improves accuracy a lot but UAR slightly. Feature-based attention obtains the best result in the last convolutional block, achieving the UAR of 75.88%.

5.2. Speaker identification

Speaker identification determines who is the speaking person. A well-trained text-independent identification model can recognize a speaker from any text, even without training. In this experiment, we tested the FreqCNN model of a text-independent task on the CHAINS corpus [17].

Database and setting. The CHAINS speech corpus is designed to characterize different speakers. The corpus contains 36 speakers, and each speaker provides speech of all text in six different speaking styles, such as solo, synchronous, and retelling. In this experiment, only solo reading was used. A code is provided for six independent text paragraphs: $\{f(01), f(02), f(03), f(04), s01-s09, s10-s33\}$. For brevity, $s01-s09$ is called $s(01)$ and $s10-s33$ is called $s(02)$. For a text-independent speaker identification task, four out of six paragraphs were used for training and the two remaining ones were used for testing. Finally, we adopted three-fold cross-validation for the average accuracy. Details for the training and testing sets are listed in Table 6. Spectrograms were extracted as a size of 224 × 224 and the number of batch sizes was 128.

The best parameters of the FreqCNN model for this task are given in Table 7. Similarly, there were two convolutional layers for global feature extraction and one layer for local features. We also adopted batch normalization layers right before the convolutional layers and zero-padding in the convolution.

Results and discussion. The results of the FreqCNN model, i-vector and typical CNN models with three-fold cross-validation are given in Table 8. Compared with the traditional method [17] using MFCCs with vector quantization and gaussian mixture model, which obtains an accuracy of 91.00%, our model improves accuracy around +7% and obtains a UAR of 98.05% on average. We also tested i-vector and

Table 7
Best parameters of the FreqCNN model in speaker identification on the CHAINS.

Name	Local convolution	Global convolution	Pooling
Basic block 1	32, 5 × 5/1, sigmoid	32, 5 × 5/1, sigmoid	
Conv. and pool		32, 7 × 7/1	max, 2 × 2/2
Basic block 2	32, 5 × 5/1, sigmoid	32, 5 × 5/1, sigmoid	
Conv and pool		32, 7 × 7/1	max, 2 × 2/2
Basic block 3	64, 5 × 5/1, sigmoid	64, 5 × 5/1, sigmoid	
Conv. and pool		64, 7 × 7/1	max, 2 × 2/2, dropout 0.2
Attention-based block 4	96, 5 × 5/1, sigmoid	96, 3 × 3/1, sigmoid fc: 256, tanh; 128, tanh; 1, sigmoid	
Conv. and pool		256, 5 × 5/1	max, 2 × 2/2, dropout 0.2
Attention-based block 5	128, 3 × 3/1, sigmoid	128, 3 × 3/1, sigmoid fc: 128, tanh; 1, sigmoid	
Conv. and pool		256, 5 × 5/2, tanh	avg (global), dropout 0.5
fc		128, relu, dropout 0.5	
Softmax		36-way softmax	

Table 8
ACC and UAR (%) of the proposed model and typical DNNs on the CHAINS. I-Vector* denotes the metrics of (1−EER) and threshold in the bracket.

Methods	data set #1		data set #2		data set #3		Average	
	ACC	UAR	ACC	UAR	ACC	UAR	ACC	UAR
FreqCNN	99.08	99.08	99.85	99.86	95.20	95.21	**98.04**	**98.05**
VGG-11	70.52	70.52	78.16	77.85	76.94	76.95	75.21	75.11
ResNet-18	86.47	86.35	89.58	89.49	49.07	49.11	75.04	74.99
ResNet-34	71.96	72.04	77.55	77.25	48.65	48.70	66.05	66.00
ResNet-50	73.14	73.00	76.77	76.29	50.93	50.96	66.95	66.75
i-Vector*	72.93 (−2.46241)		83.17 (−3.04434)		58.43 (30.2318)			

Table 9
ACC and UAR (%) of different activation functions. $g(\cdot)$ denotes the activation of convolutional layers for the global feature learning and $f(\cdot)$ denotes the activation in the local domains.

Activation function		data set #1		data set #2		data set #3		Average	
$g(\cdot)$	$f(\cdot)$	ACC	UAR	ACC	UAR	ACC	UAR	ACC	UAR
Sigmoid	sigmoid	99.08	99.08	99.85	99.86	95.20	95.21	**98.04**	**98.05**
Sigmoid	tanh	98.17	98.21	99.61	99.65	93.94	93.94	97.24	97.27
Tanh	sigmoid	98.43	98.44	99.15	99.17	95.45	95.47	97.68	97.69
Tanh	tanh	99.02	99.09	99.31	99.34	93.52	93.53	97.28	97.32
Tanh	relu	99.35	99.42	99.23	99.28	90.74	90.79	96.44	96.50
Relu	tanh	95.88	95.99	99.54	99.52	76.85	76.92	90.76	90.81
Relu	relu	96.08	96.17	98.69	98.68	85.94	86.01	93.57	93.62

Table 10
Best parameters of the FreqCNN model in speech emotion recognition on the eNTERFACE.

Name	Local convolution	Global convolution	Pooling
Basic block 1	64, 5 × 5/1, sigmoid	64, 5 × 5/1, tanh	
Conv. and pool		96, 7 × 7/1	max, 2 × 2/2
Basic block 2	96, 5 × 5/1, sigmoid	96, 5 × 5/1, tanh	
Conv and pool		128, 7 × 7/1	max, 2 × 2/2
Basic block 3	128, 5 × 5/1, sigmoid	128, 5 × 5/1, tanh	
Conv. and pool		128, 7 × 7/1	max, 2 × 2/2, dropout 0.2
Attention-based block 4	256, 5 × 5/1, sigmoid	256, 3 × 3/1, tanh fc: 256, tanh; 128, tanh; 1, sigmoid	
Conv. and pool		256, 5 × 5/1	max, 2 × 2/2, dropout 0.2
Attention-based block 5	256, 5 × 5/1, sigmoid	256, 3 × 3/1, tanh fc: 256, tanh; 1, sigmoid	
Conv. and pool		512, 512, 5 × 5/2, tanh	avg (global), dropout 0.5
fc		512, relu, dropout 0.5	
Softmax		6-way softmax	

several CNN models with their default hyper-parameters on the CHAINS. The evaluation of Equal Error Rate (EER) and threshold in i-vector method is given by Kaldi speaker recognition system.[3] EER is calculated using the method proposed in the paper [37], which is different from Error Rate (ERR). The experimental results show that our proposed model obtained the highest accuracy and UAR among all methods. On the whole, i-vector, VGG-11 and ResNet-18 achieve better result than other CNN models (ResNet-34 and ResNet-50). I-vector and VGG-11 have better recognition performance in the data set #3. More importantly, the performance of the FreqCNN model is vastly better than other methods in all three-fold experiments.

In Table 9, we also compared FreqCNN models using different activation functions in the convolutional layers. The lowest accuracy is 90.76% when the activation functions of convolutional layers in global and local feature learning are relu and tanh, respectively. The combination of sigmoid and tanh always yield good performance. From these results, it can be concluded the FreqCNN model can get the best result when the activation function of convolutional layers in both local and global feature extraction is a sigmoid function.

[3] http://kaldi-asr.org/.

5.3. Speech emotion recognition

The aim of speech emotion recognition is to distinguish emotional states from speech signals such as anger, happiness, and sadness. A speaker-independent task means that speakers in the training set are mismatched with those in the testing set. In this experiment, a speaker-independent task was conducted on the eNTERFACE speech corpus [6].

Database and setting. The eNTERFACE database is an audio-visual English emotional corpus that includes 42 speakers. Only speech signals extracted from the video are used in this experiment. Each speaker has 30 records for six types of emotions, namely *happiness, anger, disgust, fear, sadness*, and *surprise*. The distribution of data samples for each emotion label in the dataset is balanced. In this experiment, we used ten-fold cross-validation methods; i.e., we leave four or five speaker records for testing in turns. Spectrograms were extracted as a size of 224 × 224 in this experiment and the batch size was set to 48.

The best parameters of the FreqCNN model for speech emotion recognition task are given in Table 10. Similarly, there are three convolutional blocks and two attention-based convolutional blocks. In each

Table 11
Results of the FreqCNN model and other state-of-the-art proposals in the audio modality on the eNTERFACE.

Input	Methods	ACC (%)
MFCC, BDPCA, LDA features [5]	RBF	75.89
Spectrograms [34]	DNNs	60.53
Long, short time-based features [6]	SVM	78.57
Mel-spectrograms [35]	3D-CNN, DBN	78.08
Spectrograms	FreqCNN	**83.65**

Table 12
Confusion matrix of the best result of the FreqCNN model on the eNTERFACE.

Actual Classification	Predicted Classification					
	Angry	Disgust	Sadness	Surprise	Fear	Happiness
Angry	**180**	8	3	12	5	2
Disgust	8	**167**	5	13	10	7
Sadness	6	4	**165**	14	15	6
Surprise	3	2	3	**186**	6	10
Fear	4	5	6	12	**178**	5
Happiness	2	5	4	11	10	**178**

block, there are two convolutional layers for global feature extraction and one layer for local features. We also adopted *sigmoid* and *tanh* activation functions.

Results and discussion. The accuracy of our model and other prominent methods are listed in Table 11. Compared with previous approaches [5,6,34,35], our proposed model obtains more robust performance and achieves an accuracy 83.62%. To consider the characteristics of spectrograms, we replaced the simple DNNs by a deep convolutional model with an attention mechanism. The latest method [35] also obtain good results using three-dimensional CNNs (3D-CNNs) and deep belief networks. Though other studies used well-designed feature sets or models, to the best of our knowledge, we manage to outperform the state-of-the-art accuracy in the speaker-independent case.

Further, Table 12 shows the confusion matrix of the best results in the speaker independent task. The highest accuracy is obtained for surprise (88.57%), followed by angry (85.71%). The lowest accuracy yielded for sadness (78.57%). Disgust also has a low accuracy (79.52%). This may be because the recognition of less active and unpleasant emotions is more difficult. The average recognition rate over all emotions is 83.65%.

5.4. Discussion

Experiments have shown that for different audio classification tasks, the FreqCNN model brought in different performance improving than traditional methods or DNNs. For different tasks, the architecture of the FreqCNN model is instantiated, by making some changes in the number of convolutional blocks, filters, activation functions, attention and etc. It can be concluded the proposed model has the generalization over different audio classification tasks with prominent performance.

6. Conclusions

This paper proposed a generic framework for different audio classification tasks. Based on the characteristics of spectrograms, the FreqCNN model uses a novel frequency-distributed form of spectrograms and combines them with CNNs and attention. These convolutional blocks consider both local frequency areas and the global frequency-time domain to enable them to learn more distinctive audio-related features. Furthermore, we applied the principle of attention to assist the learning of the frequency-distributed feature set, which improves recognition performance. In the experiment, we used the FreqCNN model to perform multiple audio classification tasks. To the best of our knowledge, we outperform the state-of-art results on these speech databases.

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References

[1] M. Akagi, X. Han, R. Elbarougy, Y. Hamada, Toward affective speech-to-speech translation: Strategy for emotional speech recognition and synthesis in multiple languages, Proceedings of the Signal and Information Processing Association Summit and Conference, (2015), pp. 1–10.
[2] J.H.L. Hansen, G. Liu, Unsupervised accent classification for deep data fusion of accent and language information, Speech Commun. 78 (2016) 19–33.
[3] L. He, M. Lech, N.C. Maddage, N.B. Allen, Time-frequency feature extraction from spectrograms and wavelet packets with application to automatic stress and emotion classification in speech, Proceedings of the International Conference on Information, Communications and Signal Processing, (2009), pp. 1–5.
[4] Z. Qawaqneh, A.A. Mallouh, B.D. Barkana, Deep neural network framework and transformed MFCCs for Speaker's age and gender classification, Knowl. Based Syst. 115 (C) (2017) 5–14.
[5] C.S. Ooi, S.K. Phooi, L.-M. Ang, L.W. Chew, A new approach of audio emotion recognition, Expert Syst. Appl. 41 (13) (2014) 5858–5869.
[6] S. Poria, E. Cambria, A. Hussain, G.-B. Huang, Towards an intelligent framework for multimodal affective data analysis, Neural Netw. 63 (2015) 104–116.
[7] T.F. Li, S.-C. Chang, Speech recognition of mandarin syllables using both linear predict coding cepstra and mel frequency cepstra, Proceedings of the Conference on Computational Linguistics and Speech Processing, (2007), pp. 379–390.
[8] Z. Yi, Foundations of implementing the competitive layer model by Lotka-volterra recurrent neural networks, IEEE Trans. Neural Netw. 21 (3) (2010) 494.
[9] F. Li, L. Tran, K.-H. Thung, S. Ji, D. Shen, J. Li, A robust deep model for improved classification of AD/MCI patients, IEEE J. Biomed. Health Inf. 19 (5) (2015) 1610–1616.
[10] Y. Zhu, S. Lucey, Convolutional sparse coding for trajectory reconstruction, IEEE Trans. Pattern Anal. Mach. Intell. 37 (3) (2015) 529.
[11] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (7553) (2015) 436–444.
[12] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, Comput. Sci. (2014).
[13] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, (2016), pp. 770–778.
[14] M. Espi, M. Fujimoto, K. Kinoshita, T. Nakatani, Exploiting spectro-temporal locality in deep learning based acoustic event detection, Eurasip. J. Audio Speech Music Process. 2015 (1) (2015).
[15] W. Lim, D. Jang, T. Lee, Speech emotion recognition using convolutional and recurrent neural networks, Proceedings of the Signal and Information Processing Association Summit and Conference, (2016), pp. 1–4.
[16] Y. Leng, C. Sun, X. Xu, Q. Yuan, S. Xing, H. Wan, J. Wang, D. Li, Employing unlabeled data to improve the classification performance of SVM, and its application in audio event classification, Knowl. Based Syst. 98 (C) (2016) 117–129.
[17] N.M. AboElenein, K.M. Amin, M. Ibrahim, M.M. Hadhoud, Improved text-independent speaker identification system for real time applications, Proceedings of the Fourth International Japan-Egypt Conference on Electronics, Communications and Computers, (2016), pp. 58–62.
[18] H. Bourlard, S. Dupont, A new ASR approach based on independent processing and recombination of partial frequency bands, Proceedings of the International Conference on Spoken Language Processing, (1996).
[19] H. Bourlard, S. Dupont, Subband-based speech recognition, Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, (1997), pp. 1251–1254.
[20] X.U. Jing-Bo, Y.U. Hong-Tao, C.S. Ran, Speech enhancement using sub-band spectral analysis, J. Appl. Sci. 24 (3) (2006) 232–235.
[21] J. Du, Y. Xu, Hierarchical deep neural network for multivariate regression, Pattern Recognit. 63 (2017) 149–157.
[22] J. Du, Irrelevant variability normalization via hierarchical deep neural networks for online handwritten chinese character recognition, Proceedings of the International Conference on Frontiers in Handwriting Recognition, (2014), pp. 303–308.
[23] R.A. Rensink, The dynamic representation of scenes, Vis. cogn. 7 (1–3) (2000) 17–42.
[24] K. Xu, J. Ba, R. Kiros, K. Cho, A. Courville, R. Salakhudinov, R. Zemel, Y. Bengio, Show, attend and tell: neural image caption generation with visual attention, Proceedings of the International Conference on Machine Learning, (2015), pp. 2048–2057.
[25] V. Mnih, N. Heess, A. Graves, et al., Recurrent models of visual attention, Proceedings of the Advances in Neural Information Processing Systems, (2014), pp. 2204–2212.
[26] M.F. Stollenga, J. Masci, F. Gomez, J. Schmidhuber, Deep networks with internal

selective attention through feedback connections, Proceedings of the Advances in Neural Information Processing Systems, (2014), pp. 3545–3553.
[27] A. Mencattini, E. Martinelli, G. Costantini, M. Todisco, B. Basile, M. Bozzali, C.D. Natale, Speech emotion recognition using amplitude modulation parameters and a combined feature selection procedure, Knowl. Based Syst. 63 (C) (2014) 68–81.
[28] O. Ghahabi, J. Hernando, Deep belief networks for i-vector based speaker recognition, Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, (2014), pp. 1700–1704.
[29] A. Kanagasundaram, R. Vogt, D. Dean, S. Sridharan, M. Mason, I-vector based speaker recognition on short utterances, Proceedings of the INTERSPEECH, (2011).
[30] W.Q. Zheng, J.S. Yu, Y.X. Zou, An experimental study of speech emotion recognition based on deep convolutional neural networks, Proceedings of the International Conference on Affective Computing and Intelligent Interaction, (2015), pp. 827–831.
[31] H. Lee, P. Pham, Y. Largman, A.Y. Ng, Unsupervised feature learning for audio classification using convolutional deep belief networks, Proceedings of the Advances in Neural Information Processing Systems, (2009), pp. 1096–1104.
[32] Z. Fu, G. Lu, K.M. Ting, D. Zhang, Optimizing cepstral features for audio classification. Proceedings of the International Joint Conference on Artificial Intelligence, (2013), pp. 1330–1336.
[33] S. Scardapane, D. Comminiello, M. Scarpiniti, R. Parisi, A. Uncini, Benchmarking functional link expansions for audio classification tasks, Proceedings of the Advances in Neural Networks, (2016), pp. 133–141.
[34] H.M. Fayek, M. Lech, L. Cavedon, Towards real-time speech emotion recognition using deep neural networks, Proceedings of the International Conference on Signal Processing and Communication Systems, (2015), pp. 1–5.
[35] S. Zhang, S. Zhang, T. Huang, W. Gao, Q. Tian, Learning affective features with a hybrid deep model for audio-visual emotion recognition, IEEE Trans. Circuits Syst. Video Technol. PP (99) (2017).
[36] A. Krizhevsky, I. Sutskever, G.E. Hinton, Imagenet classification with deep convolutional neural networks, Proceedings of the International Conference on Neural Information Processing Systems, (2012), pp. 1097–1105.
[37] D.A. Reynolds, R.C. Rose, Robust text-independent speaker identification using gaussian mixture speaker models, IEEE Trans. Speech Audio Process. 3 (1) (1995) 72–83.