A punishment voting algorithm based on super categories construction for acoustic scene classification

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Abstract

In acoustic scene classification researches, audio segment is usually split into multiple samples. Majority voting is then utilized to ensemble the results of the samples. In this paper, we propose a punishment voting algorithm based on the super categories construction method for acoustic scene classification. Specifically, we propose a DenseNet-like model as the base classifier. The base classifier is trained by the CQT spectrograms generated from the raw audio segments. Taking advantage of the results of the base classifier, we propose a super categories construction method using the spectral clustering. Super classifiers corresponding to the constructed super categories are further trained. Finally, the super classifiers are utilized to enhance the majority voting of the base classifier by punishment voting. Experiments show that the punishment voting obviously improves the performances on both the DCASE2017 Development dataset and the LITIS Rouen dataset.

Keywords: acoustic scene classification, DenseNet, punishment voting, CQT, spectral clustering

1 Introduction

Acoustic scene classification (ASC) is attracting more and more attentions in the research community of artificial intelligence. Taking advantage of the audio signals, ASC is able to infer the information of the environment from which the audios are produced. This ability is very helpful for many applications, such as surveillance [1], robotic navigation [2] and recognition of cyclist’s route [3], etc. In recent years, with the upsurge of deep learning research, deep learning based solutions have become more and more popular in the acoustic scene classification. Many popular deep learning architectures have been applied to solve this problem, e.g., CNN [4] [5], RNN [6] [7], LSTM [4], DNN [8] and their combinations [4] [7]. In addition, these solutions have achieved promising results, which surpass the performances of most traditional machine learning methods.

As we all know, the identification process of humans is from coarseness to fineness. For example, when we have to classify a large amount of objects (such as car, plane, train, dog, cat, bird, etc.), we first divide them into several coarse categories intuitively. Specifically, the objects of car, plane and train are classified into the transport category, while dog, cat and
bird are regarded as the animal category. Naturally, we could perform finer classification upon these coarse categories. Moreover, as we can observe from the machine learning works, the accuracies of coarse categories classification tend to be higher compared to the corresponding fine classification tasks. Another motivation is the inter-class similarities among acoustic scene classes. It is easy to find that some acoustic scene classes are more similar in the acoustic properties. It inspires us to cluster these acoustic scene classes into a coarse category. Eventually, we can construct several coarse categories based on the original acoustic scene categories. As these constructed coarse categories are made up by the original scene categories (or classes), they are called as the super categories. We can train super classifiers for these super categories respectively. These super classifiers are responsible for discriminating the coarse categories. As a result, the amounts of their outputs are fewer than the ones of the base classifier. In this paper, the base classifier refers to the classification model which can discriminate all the original categories in a fine-grained manner. As mentioned above, the accuracies of super classifiers are higher. This fact gives us more confidence in these super classifiers. To this end, we propose a punishment voting algorithm to take advantage of these super classifiers to enhance the base classifier for improving the ASC performance.

The framework of our method is as follows. Firstly, we generate the CQT spectrograms [9] from the audio segments. Then a DenseNet-like [10] architecture is proposed as the base classifier, trained by the CQT spectrograms. On the basis of the base classifier, we construct several super categories through the spectral clustering method [11]. For each super category, we further train a corresponding super classifier. Finally, a special voting algorithm which we call the punishment voting is proposed to combine the base classifier and the super classifiers to form a strong classifier. The flowchart of our method is shown in Figure 1.

In this paper, we have proposed a super categories construction method and a punishment voting algorithm. To verify the effectiveness of our proposed method, we use the DCASE2017
Development dataset\(^1\) as well as the LITIS Rouen dataset\(^2\) to evaluate our results. The experiments show that the punishment voting method can obviously improve the performances on both datasets. The remainder of this paper is organized as follows. The transformation of the raw audio is introduced in Section 2. Section 3 describes the details of our proposed methods, including the design of the base classifier, the construction of super categories, the training of super classifiers and the punishment voting algorithm. In Section 4, we demonstrate the experiment results. Finally, we conclude in Section 5.

2 Data Preparation

Recently, CNN is very popular in ASC \([4, 5]\). In these solutions, the audio signals are transformed to special Time-Frequency representations, namely the spectrograms. Inspired by \([12]\), we select the CQT spectrogram \([9]\) as the input of the proposed CNN network. To generate CQT spectrograms from the raw audio segments, we utilize the cqt function in the python library Librosa 0.5.0. For each audio segment, we generate \(N\) CQT spectrograms, where \(N\) is the number of auditory channels. For the DCASE2017 Development dataset, \(N\) equals to 2. However, \(N\) is 1 for the LITIS Rouen dataset. For the convenience of calculation, we resize every spectrogram into the size of 832*143. Moreover, we split the spectrograms into patches with the width of 143 and a shift step of 80. As a result, we can get 10 patches with the size of 143*143 for each CQT spectrogram. In other words, each audio segment can generate \(N\)*10 patches (samples). For both datasets, we use the same way to generate the CQT spectrogram patches.

3 Proposed Method

3.1 Design of the Base Classifier

DenseNet is an excellent deep Learning model proposed by \([10]\) in 2017. It has many advantages, such as encouraging feature reuse, alleviating the vanishing-gradient problem, and substantially reducing the number of parameters, etc. DenseNet is very successful in the image recognition tasks. It even has outperformed ResNet \([13]\) for some datasets. In this paper, we try to build up a DenseNet-like network for acoustic scene classification. We first use this proposed network to build up a base classifier. Besides, we train the super classifiers using the same deep network except some minor modification. As shown in Table 1, the proposed network has three dense blocks, two transition layers and a growth rate of 12. These three dense blocks have 4, 4 and 32 bottleneck layers respectively. Note that compared to the standard DenseNet \([10]\), we have removed the 7*7 global average pooling operation from the network. The input size is 143*143 for this DenseNet-like network. The number of output nodes of this network is equal to the amount of the original acoustic scenes. Specifically, there are 15 output nodes for DCASE2107 Development dataset, while 19 nodes for the LITIS Rouen dataset. As mentioned above, each audio segment can produce several CQT spectrogram patches. In the testing period, these patches are fed into the trained deep network, and the corresponding acoustic scene outputs are predicted. The base classifier fuses these predictions into a voting vector. Each element in

\(^1\)http://www.cs.tut.fi/sgn/arg/dcase2017/challenge/download
\(^2\)https://sites.google.com/site/alamrakotomamony/home/audio-scene
Table 1: the construction of proposed DenseNet model

| Layer Description                                                                 |
|-----------------------------------------------------------------------------------|
| 7×7Conv(pad-2, stride-2)-24-BN-ReLu                                               |
| 3×3 MaxPooling + DropOut(0.2)                                                    |
| 1×1Conv(pad-1, stride-1)-48-BN-ReLu                                              |
| 3×3Conv(pad-1, stride-1)-12-BN-ReLu × 4                                          |
| 1×1(pad-1, stride-1)-12-BN-ReLu                                                  |
| 2×2 Average Pooling + DropOut(0.2)                                               |
| 1×1Conv(pad-1, stride-1)-48-BN-ReLu                                              |
| 3×3Conv(pad-1, stride-1)-12-BN-ReLu × 4                                          |
| 1×1(pad-1, stride-1)-12-BN-ReLu                                                  |
| 2×2 Average Pooling + DropOut(0.2)                                               |
| 1×1Conv(pad-1, stride-1)-48-BN-ReLu                                              |
| 3×3Conv(pad-1, stride-1)-12-BN-ReLu × 32                                         |
| Flatten and SoftMax                                                               |

this voting vector corresponds to a certain acoustic scene class. The value of this element is a non-negative integer which is equal to the number of the votes, contributed by the patches from the same audio segment.

3.2 Super Categories Construction

For some acoustic scenes, they are very similar in acoustic properties and frequently misclassified. It is natural to cluster these similar scenes into a coarse category, which we call the super category. Actually, for some dataset, the super categories information is explicitly provided. For example, these super categories are provided in the DCASE2017 Development dataset. They are the 'indoor', 'outdoor' and 'vehicle'. Specifically, the 'indoor' category includes the Cafe/Restaurant, Grocery store, Home, Library, Metro station and Office scenes; the 'vehicle' category contains the Bus, Car, Train and Tram scenes. The rest of the scenes are regarded as the 'outdoor' category. However, not all the datasets provide super category labels. For example, the LITIS Rouen dataset does not offer any information about these. Obviously, it is necessary to construct super categories from the original acoustic scenes.

For constructing the super categories, it is challenging to find out the acoustic scenes with similar acoustics properties. However, it is easy to figure out the misclassified cases for each acoustic scene, according to a certain classification model. In our proposed method, we use the misclassification information to approximate the similarities among acoustic scenes, as similar scenes are prone to be misclassified as their counterparts. Specifically, using the trained DenseNet-like deep model, we can figure out a confuse matrix M for the testing samples. Let \( M_{ij} \) be the element of the \( i^{th} \) row and the \( j^{th} \) column of \( M \). The \( M_{ij}(i \neq j) \) represents the amount of the patches whose ground-truth label is \( i \) while wrongly predicted as \( j \). On the basis of the confuse matrix, we apply the spectral clustering method [11] to construct the super
Note that the values in the confuse matrix are averaged over multiple testing sets. For example, in the DCASE2017 Development dataset, the confuse matrix is averaged across the test results of the 4 training/testing splits provided by the challenge organizer. The test results are obtained by the base classifier described in Section 3.1 with majority voting [14]. It is worthy to mention that the super category outputs of the DCASE2017 Development dataset in our experiments are exactly the same to the official 'indoor', 'outdoor' and 'vehicle' divisions, where the cluster number is set to 3 and the K parameter in KNN is 2. This proves the effectiveness of our proposed super categories construction method. We also cluster the LITIS Rouen dataset into 3 super categories. The clustering results are as follows: \{Metro-rouen, High-speed train\}, \{Restaurant, Shop, Market, Café, billiard pool hall\} and \{Quiet street, Plane, Bus, Train, Car, Tubestação, Kid game hall, Metro-paris, Student hall, Pedestrian street, Busy street, Train station hall\}.

3.3 Training of Super Classifiers

For each super category, we further train a corresponding super classifier. The super classifier uses the same DenseNet-like architecture as the base classifier. The resultant weights in the base classifier are transferred to initialize the super classifier [15]. The only difference lies in the output layer. Taking the 'vehicle' super category in DCASE2017 as an example, five output nodes are set in the output layer of the super classifier, including four nodes serving as the indicators of Car, Bus, Train and Tram respectively, and the fifth node known as the negative flag. The negative flag is fired when the testing sample is considered as not belonging to the 'vehicle' super category. The patches used to train the base classifier are again utilized to train the newly super classifier. However, labels of some patches should be modified. Specifically, the labels of the patches of Car, Bus, Train and Tram acoustic scenes are left unchanged while the ones of the other patches are all modified into the 'NON-VEHICLE' labels. In this way, each super classifier is responsible for the discrimination of a small range of acoustic scenes. As a result, the accuracies of these super classifiers are improved. Likewise, SoftMax is applied in the output layer of the super classifiers.

3.4 Punishment Voting Algorithm

For the convenience of description, we introduce two data structures before giving the algorithm, the voting vector and the negative flag vector. Assume that we have \(AN\) audio segments in the testing set; \(PN\) patches are produced for each segment; \(SN\) super categories have been constructed from the \(CN\) original acoustic scene classes; One base classifier and \(SN\) super classifiers have been built up as mentioned above. For the \(i^{th}\) audio segment \((i \in [1,AN])\), we generate a voting vector \(VV^i = (vv^i_1, vv^i_2, \ldots, vv^i_{CN})\), which is initialized by all zero elements. For the \(p^{th}\) patch produced by the \(i^{th}\) audio segment, we feed it into the base CNN model, supposed that the \(k^{th}\) node \((k \in [1,CN])\) in the output layer of the base CNN model acquires the maximum value, the value of \(vv^i_k\) is increased by 1. After all the \(PN\) patches are processed, the voting vector \(VV^i\) is completely prepared, where \(vv^i_1 + vv^i_2 + \cdots + vv^i_{CN} = PN\). For the \(i^{th}\) audio segment \((i \in [1,AN])\), we calculate \(SN\) negative flag vectors, denoted as \(NF^j = (nf^j_1, nf^j_2, \ldots, nf^j_{PN}), j \in [1,SN]\), each for a corresponding super classifier. For the \(p^{th}\) patch produced by the \(i^{th}\) audio segment, we feed it to the \(j^{th}\) super classifier, if the negative
flag node (see Section 3.3) acquires the maximum value, the \( n_{f_i} \) is set as 1; otherwise it is set as 0. After the \( P_N \) patches are all processed by the \( S_N \) super classifiers and the related elements in \( N_F_i^j (j \in [1, S_N]) \) are set up, the preparation of negative flag vectors for the \( i^{th} \) audio segment is done.

**Algorithm 1** Punishment Voting

**Input:** \( C_N; S_N; P_N; VV^i = (vv^i_1, vv^i_2, \ldots, vv^i_{CN}); N_F_i^j = (n_{f_j, 1}, n_{f_j, 2}, \ldots, n_{f_j, PN}), j \in [1, S_N]; AS_j, j \in [1, S_N] \) : the original acoustic scene set corresponding to the \( j^{th} \) super category.

**Output:** \( R_i \): the resultant acoustic scene of the \( i^{th} \) audio segment;

1: for \( j = 1 : S_N \) do
2:  count=0
3:  for \( k = 1 : P_N \) do
4:    if \( n_{f_j, k} == 1 \) then
5:      count++
6:    end if
7:  end for
8:  if \( count > P_N \times 5/8 \) then
9:    for \( p = 1 : C_N \) do
10:   if \( p \in AS_j \) then
11:      \( vv^i_p = vv^i_p \times 0.25 \)
12:  end if
13: end for
14: end if
15: end for
16: \( R_i = \arg\max\{vv^i_t | t \in [1, CN]\} \)
17: return \( R_i \);

These \( S_N \) negative flag vectors are applied to punishment vote towards the voting vector. Specifically, for the \( n^{th} \) super classifier, we observe the negative flag vector \( N_F_n^i \). If a majority of elements in \( N_F_n^i \) is equal to 1 (the threshold is set to \( P_N \times 5/8 \) in our implementation), it means that the \( i^{th} \) audio segment does not belong to the \( n^{th} \) super category according to the \( n^{th} \) super classifier. As we are more confident in the super classifiers, the judgement is used to rectify the voting vector. All elements corresponding to the \( n^{th} \) super category in the voting vector are multiplied with a punishment factor \( \gamma \) (\( \gamma \) is set to 0.25 in the experiment). Once all the super classifiers have finished punishment vote, we can figure out the final result from the voting vector. The pseudocode is shown in Algorithm 1.

4 Experiment and Results

4.1 Experimental Settings

All the experiments are executed on an Intel(R) Core(TM) i7 system with 64GB RAM and NVIDIA GTX 1080 Ti GPU. We implement the DenseNet-like models using TensorFlow with a learning rate of 0.0001, a batch size of 32 and a dropout rate of 0.2. Adam is applied as
the optimizer with a maximum epochs of 1000. We evaluate the proposed punishment voting algorithm on the DCASE2017 Development dataset and the LITIS Rouen dataset. There are 15 acoustic scenes in the DCASE2017 Development dataset. For each scene, there are 312 10-second audio segments. We follow the 4-fold cross validation on this dataset. The LITIS Rouen dataset contains 3026 30-second audio segments which can be categorized into 19 acoustic scene classes. We randomly select three splits out of the 20 standard splits on this dataset and evaluate the average accuracy over these three splits.

4.2 Results of the Base Classifiers with Majority Voting

We have trained two DenseNet-like base classifiers for the two datasets respectively. The one for the DCASE2017 Development dataset has 15 output nodes each of which is corresponding to an acoustic scene class, while the other for the LITIS Rouen dataset has 19 output nodes. The average accuracy achieved by the DCASE2017 base classifier with majority voting is 79.4% (the baseline accuracy is 74.8% according to the DCASE2017 challenge). The average accuracy by the LITIS Rouen base classifier with majority voting is 92.13%.

4.3 Results of the Super Classifiers

As mentioned above, we construct three super categories for both datasets. The constructed super categories in DCASE2017 Development dataset are exactly the same as the 'indoor', 'outdoor' and 'vehicle' separations originally provided by official organizer. We have trained super classifiers for the super categories. By performing majority voting, as shown in Figure 2, the average accuracies for the three super classifiers are 88.05%, 88.51% and 93.34% respectively for the DCASE2017 Development dataset. Compared to the accuracy of the base classifier, the accuracies of super classifiers are significantly improved as we expect. As shown in Figure 3, the average accuracies of the three super classifier with majority voting are 96.19%, 93.36% and 93.57% respectively for the LITIS Rouen dataset.
4.4 Results of the Punishment Voting Algorithm

Figure 4 makes a comparison between the results of punishment voting and those of the base classifier with majority voting on the DCASE2017 Development dataset. An accuracy of 81.92% is obtained by our proposed method, which outperforms the base classifier by 2.52%. Similarly,
Figure 4: Comparison of majority voting and punishment voting on DCASE2017 Development dataset

Figure 5: Comparison of majority voting and punishment voting on LITIS Rouen dataset

Figure 5 shows the superiority of our proposed punishment voting on the LITIS Rouen dataset. Through our method, the accuracy is raised to 94.83% which has an increase of 2.7% over the
base classifier with majority voting.

5 Conclusion

In the acoustic scene classification research domain, majority voting is frequently used. In this paper, we proposed a punishment voting algorithm for acoustic scene classifications. There are two main contributions in this work. They are the punishment voting algorithm and the super categories construction method. Firstly, we transform the audio segments into CQT spectrograms. Using these CQT spectrograms, we train a DenseNet-like model as the base classifier. Based on the results of the base classifier, we construct the super categories by the spectral clustering. For each super category, we train a corresponding super classifier. Finally, we develop a punishment voting algorithm to combine the results of the base classifier and those of the super classifiers to acquire the final results. Compared to the base classifier, the punishment voting method has a 2.52% improvement on the DCASE2017 Development dataset and a 2.7% boost on the LITIS Rouen dataset. We believe that the punishment voting method is useful for other recognition tasks as well, such as image recognition, behavior recognition, etc. We will extend our method to these tasks in our future studies.

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