1-D CNN BASED ACOUSTIC SCENE CLASSIFICATION VIA REDUCING LAYER-WISE DIMENSIONALITY

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ABSTRACT

This paper presents an alternate representation framework to commonly used time-frequency representation for acoustic scene classification (ASC). A raw audio signal is represented using a pre-trained convolutional neural network (CNN) using its various intermediate layers. The study assumes that the representations obtained from the intermediate layers lie in low-dimensions intrinsically. To obtain low-dimensional embeddings, principal component analysis is performed, and the study analyzes that only a few principal components are significant. However, the appropriate number of significant components are not known. To address this, an automatic dictionary learning framework is utilized that approximates the underlying subspace. Further, the low-dimensional embeddings are aggregated in a late-fusion manner in the ensemble framework to incorporate hierarchical information learned at various intermediate layers. The experimental evaluation is performed on publicly available DCASE 2017 and 2018 ASC datasets on a pre-trained 1-D CNN, SoundNet. Empirically, it is observed that deeper layers show more compression ratio than others. At 70% compression ratio across different datasets, the performance is similar to that obtained without performing any dimensionality reduction. The proposed framework outperforms the time-frequency representation based methods.

Index Terms— Acoustic scene classification, CNN, PCA, ensemble.

1. INTRODUCTION

Acoustic scene classification (ASC) utilizes sounds produced in the physical environment to classify the underlying scene [1]. Initially, the hand-engineered features such as Mel-frequency cepstral coefficients (MFCCs) and log-mel energies inspired from speech and music recognition fields have been utilized for ASC. As hand-engineered features are not adaptive and do not generalize well, recent techniques employ learning-based approaches such as deep learning [2–5] and dictionary learning [6–8]. Typically, the learning-based frameworks use time-frequency representations of an audio signal to learn discriminative representations. The time-frequency representations involve short-time Fourier transform, which may not be sufficient to represent diverse sound activities such as slowly varying sounds (sea waves, music) and impulsive sounds (gunshot, clock tick) both at the same time. This is due to the fixed time-frequency resolution of the Fourier atoms. This study analyzes how well the representations obtained using a learned basis perform compared to commonly used time-frequency representations.

Only a few studies [5, 9, 10] apply convolution neural networks (CNNs) to learn representations from the raw audio directly. The study [10] utilizes representations obtained from various intermediate layers of a pre-trained neural network SoundNet in the ensemble framework. As large-scale networks are trained on large-scale datasets, it may be possible that the network is over-parameterized for the underlying problem due to redundancy [11].

This study also focuses on reducing dimensionality of intermediate layer representations in the ensemble framework [10]. For this, the work assumes that the responses produced by the filters in a given intermediate layer have an intrinsic low-dimension structure. This is based on the hypothesis that there is redundancy in the network [13, 14] and a subset of filters or parameters may be sufficient to represent audio signals for the underlying problem as a large-scale dataset is used to train SoundNet. Empirically, it can be seen in Figure 1 which shows that the representations in the intermediate layers result into rapid decay in their singular values. This suggests that the embeddings have a low-dimensional structure. In the context of the ensemble framework, reducing layer-wise dimensionality decreases the computational complexity during learning and inference of the layer-wise classifiers. However, the appropriate dimensionality of the embedding space is unknown.

To identify the dimensionality of the intermediate layers, a dictionary learning framework is employed, which selects the appropriate dimensionality of the embedding space by minimizing the reconstruction error and the correlation among dictionary atoms during the learning process itself.

The major contributions of this paper are summarized as follows:

• An alternate feature representation framework for ASC that
uses intermediate layers of SoundNet to commonly used

time-frequency representations.

• To select the appropriate dimensionality of the embeddings in
  SoundNet, a dictionary learning framework is used.

• Our experiments reveal that the deeper layers show more
  compression ratio than other layers.

The rest of this paper is organized as follows. First, a brief
overview of the ensemble framework using SoundNet is presented
in Section 2. Second, the proposed framework to identify layer-wise
performance evaluation. Finally, the conclusion is presented in Sec-

2. A BRIEF OVERVIEW ABOUT ENSEMBLE
FRAMEWORK ON SOUNDNET

SoundNet [5] is a pre-trained one dimensional (1-D) CNN, which
is trained on a raw audio signal using a teacher-student based transfer
learning framework. The architecture of SoundNet is shown in Figure
2. Different intermediate layers of SoundNet represent different
sound-related concepts. For example, the middle layer (fifth con-
volution layer) represents concepts such as music-tone like, babycry
like, tapping like, etc. The seventh convolution layer represents high-
level concepts such as music like, voice like, etc. The convolution
layer consists of “p-conv” and “conv” layers. Here, conv represents
convolutional layer with ReLU activation, and p-conv layer repre-
sents the convolution layer without ReLU activation.

In [10], an ensemble framework is proposed to incorporate vari-
ous features learned at different intermediate layers of SoundNet.
The feature maps from a given intermediate layer are transformed
into aggregated representations (fixed-length feature vector) by ap-
plying a global sum pooling operation. An illustration to obtain
intermediate layer is shown in Figure 3. Next, a classifier is learned for each intermediate layer in-
dependently. Finally, the probability scores from each classifier are
aggregated to compute the ultimate classification scores.

This paper utilizes the ensemble framework [10] and aims to
reduce the dimensionality of intermediate layer features without de-
grading the performance.

3. PROPOSED METHODOLOGY

Consider a 1-D CNN having $L$-layers with indexes $\{1,2,\ldots,L\}$. Let there be $n_l$ number of feature maps, each of length $s_l$ in the $l^{th}$ layer. Let $X_l$ of size $(n_l \times s_l)$ denotes the feature map matrix, produced by stacking all the feature maps in the $l^{th}$ layer. Let there are $C$ acoustic scene classes, and $M_l$ denotes the number of acoustic examples in a $c^{th}$ class. Let $M$ represents a total number of acoustic examples in all classes.

Let $H_l \in \mathbb{R}^{n_l \times 1}$ denotes the aggregated intermediate representation obtained in the $l^{th}$ layer by performing a global sum pooling operation across feature maps on $X_l$.

Let $X_c \in \mathbb{R}^{n_c \times M_c}$ denotes a $c^{th}$ class-specific data matrix obtained by stacking aggregated intermediate representations of the $c^{th}$ class examples in the $l^{th}$ layer. Let a data matrix $Y_l = [Y_{1l}, Y_{2l}, \ldots, Y_{Cl}, Y_{Cr}] \in \mathbb{R}^{n_l \times M_c}$, is obtained by stacking the class-specific data matrices of all classes.

3.1. Obtaining low-dimensional embeddings

Given $Y_l \in \mathbb{R}^{n_l \times M}$, our aim is to compute embeddings $Z_l = T_l Y_l, Y_l \in \mathbb{R}^{n_l \times M}$ using a transformation $T_l \in \mathbb{R}^{d_l \times n_l}$ with $d_l << n_l$ for $l^{th}$ layer.

To obtained $T_l : \mathbb{R}^{n_l} \rightarrow \mathbb{R}^{d_l}$, principal component analysis (PCA) is performed on $Y_l$. Here, $d_l$ is a hyper-parameter and commonly it is chosen as the number of significant singular values that represents a given variance of the underlying data. However, it may result into overestimation of dimensionality as the discrimi-
native information is not accounted for computing low-dimensional representations. This study proposes to utilize a dictionary learning framework to identify $d_l$.

3.2. Obtaining layer-wise optimal dimensions ($d_l$) using ACDL

An automatic compact dictionary learning (ACDL) [13] method is employed to obtain the dimensionality of the embedding space in the $l^{th}$ layer. The ACDL-method gives a compact dictionary by optimizing the objective function as given in Equation 1. The optimization process jointly minimizes reconstruction error, classification loss and eliminates redundant atoms in the dictionary. The number of optional dictionary atoms ($A^*$) thus obtained is chosen as the dimensionality of the embedding space.

$$\begin{align*}
A^*, W^* &= \arg \min_{A^*, W} \|Y - A^*F(A, W)Z\|^2_F + \gamma \|G - W^*F(A, W)Z\|^2_F \\
&\quad + \lambda \|Z\|_1 \quad \text{s.t. } \|Z\|_1 \leq 1
\end{align*}$$

(1)
Feature map matrix

PCA transformation

matrix

Fig. 4. An overall proposed framework is shown. (a) The procedure to obtain embeddings for an acoustic signal from \(l^{th}\) layer of SoundNet. (b) The ensemble framework is shown which utilizes embeddings from various intermediate layers. Here \(z_l\) denotes the one of the columns of \(Z_l\).

In Equation 1, the first term represents reconstruction error, the second term denotes the classification loss, and \(Z\) denotes the non-negative convex coefficients. \(G\) represents class-information of each column in \(Y\) in the form of a one-hot encoding vector, and \(A\) denotes a dictionary and \(W\) is a weight matrix. \(A^*\) and \(W^*\) represents optimal dictionary and the weight matrix respectively obtained after optimization process. \(\lambda\) and \(\gamma\) are the regularizes. \(\tau \in [0, 1]\) denotes a threshold to eliminate similar atoms. An alternate-minimization procedure is applied to obtain the optimal dictionary. The redundant elements are eliminated by using an indicator function \(\mathcal{F}(A, W)\) as given in Equation 2. The indicator function removes highly correlated dictionary atoms as measured in Euclidean distance, which shows less discrimination as measured in entropy. The \(A_c\) and \(W_c\) are equivalent to \(A\) and \(W\) respectively, but the redundant atoms that do not belong to the \(c^{th}\) class are set to zero.

4. PERFORMANCE EVALUATION

In this section, we present the dataset used, experimental details and performance analysis using the proposed framework.

4.1. Datasets used and Experimental setup

The proposed framework is evaluated on fine-tuned SoundNet using various acoustic scene classification datasets, which include; (a) TUT DCASE Acoustic scenes 2017, development [16] (DCASE-17) comprises of 15 acoustic scene classes and (b) TUT Urban Acoustic Scenes 2018 development (DCASE-18) [17] consists of 10 acoustic scenes. The fine-tuning process is performed end-to-end using C1 to C7 intermediate layers of SoundNet followed by a fully connected layer and a classification layer for both datasets separately. After fine-tuning, \(L \in \{p-conv3, conv3, \ldots, conv7\}\) layers, a total of 10 layers, are utilized in the ensemble framework. The classification at each intermediate layer is performed using a non-linear SVM with a polynomial kernel. The hyper-parameters of the SVM are selected by cross-validation. The performance is measured in terms of accuracy. The performance is computed over multiple folds as given in each dataset. The baseline accuracy obtained for DCASE-17 and DCASE-18 datasets is 76.12%, and 62.98%.

In ACDL framework, the reconstruction error equals 0.01 is chosen as the stopping criterion. The deeper layers meet the stopping criterion at \(\tau \geq 0.7\). On the other hand, \(\tau\) varies between 0.3 and 0.5 for shallow layers to achieve the desired stopping criterion.

The effectiveness of selecting layer-wise dimensionality using the proposed method is compared with that of PCA-based explained variance ratio based dimensionality selection. The ratio is varied 4

4A baseline is an ensemble framework without any dimensionality reduction.

5PCA-based explained variance ratio is the ratio of a number principal components that represents the given variance of the underlying data points to the total number of components.
from 85% to 100%. A relatively low explained variance ratio yields more compression ratio.

4.2. Results and analysis

![Fig. 5](image) Layer-wise compression ratio obtained in SoundNet for DCASE-17 and DCASE-18 datasets using the proposed method.

The compression ratio obtained using the proposed method across various intermediate layers of SoundNet is shown in Figure 5. The deeper layers (p-conv7, conv7) show a high compression ratio (≥ 95%) compared to other layers. This suggests that the aggregated representations from the deeper layer are more sparse than the shallow layers.

Figure 6 shows the embeddings obtained before and after reducing layer-wise dimensionality using the proposed method from C3 and C7 convolutional layer. It can be observed that the discrimination between different scene classes is preserved in the low-dimensional embedding space.

The accuracy obtained at different compression ratios for DCASE-17 and DCASE-18 dataset is shown in Figure 7. Also, the accuracy and the compression ratio obtained using the proposed method is shown. The proposed method gives 70% compression ratio and 76.08% accuracy (accuracy drop is 0.10% w.r.t to that of baseline). The accuracy obtained using the proposed method is better than that obtained at different PCA-based explained variance ratio. This shows that the proposed method selects an appropriate compression ratio at a relatively marginal accuracy drop for DCASE-17 and improves performance for DCASE-18 compared to that obtained without any compression.

Performance comparison: The performance comparison of the proposed framework with similar existing methods that use raw-audio or time-frequency representation (log-mel spectrogram or MFCCs) as input is shown in Figure 8. For DCASE-17, the comparison methods uses features such as spectro-temporal features [18], log-mel energies [12, 19]. For DCASE-18, the comparison method includes log-mel energies [20], MFCCs [9] and raw-waveform [9] as input to the classifier. The proposed method performs better than that of time-frequency representations and equivalent to that of existing raw-audio based framework.

5. CONCLUSION

This paper proposes a raw-audio based acoustic scene classification framework by incorporating different intermediate layers of SoundNet and reducing the dimensionality of each layer by identifying optimal dimensions using automatic compact dictionary learning framework. The proposed framework performs better than that of...
existing time-frequency representation frameworks with an advantage of using raw-audio directly as input. Building an end-to-end network that uses learned pooling to represent intermediate layer features and reducing dimensionality using non-linear dimensionality reduction methods are some of the future directions.

6. REFERENCES

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