On the performance of different excitation-residual blocks for Acoustic Scene Classification

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Abstract—Acoustic Scene Classification (ASC) is a problem related to the field of machine listening whose objective is to classify/tag an audio clip in a predefined label describing a scene location such as park, airport among others. Interest in this topic has grown so much over the years that an annual international challenge (Detection and Classification of Acoustic Scenes and Events, DCASE) is held to propose novel solutions. Solutions to these problems often incorporate different methods such as data augmentation or with an ensemble of various models. Although the main line of research in the state-of-the-art usually implements these methods, considerable improvements and state-of-the-art results can also be achieved only by modifying the architecture of convolutional neural networks (CNNs). In this work we propose two novel squeeze-excitation blocks to improve the accuracy of an ASC framework by modifying the architecture of the residual block in a CNN together with an analysis of several state-of-the-art blocks. The main idea of squeeze-excitation blocks is to learn spatial and channel-wise feature maps independently instead of jointly as standard CNNs do. This is done by some global grouping operators, linear operators and a final calibration between the input of the block and the relationships obtained by that block. The behavior of the block that implements these operators and, therefore, the entire neural network can be modified depending on the input to the block, the residual configurations and the non-linear activations, that is, at what point of the block they are performed. The analysis has been carried out using TAU Urban Acoustic Scenes 2019 dataset presented in DCASE 2019 edition. All configurations discussed in this document exceed baseline proposed by DCASE organization by 13% percentage points. In turn, the novel configurations proposed in this paper exceed the residual configuration proposed in previous works.

Index Terms—Acoustic Scene Classification, Machine Listening, DCASE, Pattern Recognition, Squeeze-Excitation, Residual learning, Classification

I. INTRODUCTION

The analysis of everyday ambient sound can be very useful when developing intelligent systems in applications such as domestic assistants, surveillance systems or autonomous driving. Acoustic scene classification (ASC) is one of the most typical problems related to machine listening [1]–[4]. Machine listening is understood as the field of Artificial Intelligence (AI) that attempts to create intelligent algorithms capable of extracting meaningful information from audio data. Therefore, ASC can be defined as the area of machine listening that attempts to tag an audio clip in one of the predefined tags

related to the description of a scene (for example, airport, park, subway, etc.). The illustration of an ASC framework can be found in Fig. 1.

Fig. 1: Acoustic Scene Classification framework. Given an audio input, the system must classify it into a given predefined class.

The first approaches to the ASC problem were centered on the analysis of the input characteristics to the classifier, this is, feature engineering. Most of the research tried to create a significant representations of the audio to later feed a GMM or a SVM. Multitudes of representations were proposed such as MFCC [5], [6], Wavelets [6], CQT or HOG [7] among others. With the years and the emergence of convolutional networks in the field of image, the most common option among machine listening investigations was the implementation of a CNN generally fed with a 2D audio representation, usually a log-Mel spectrogram [1], [8]. These networks have shown very satisfactory results when they are trained with large databases, this is why, data augmentation techniques are a common option. The most frequent are mixup [9] or temporal cropping [10].

In addition, many studies use ensembles to obtain better results. The ensemble technique is the one that combines the output of different classifiers, in our case CNNs, to obtain a single more robust prediction, therefore it is more difficult to analyze the contribution to the classification performance of a single new CNN architecture that is part of the ensemble. In our study, the contribution made by CNN when it is implemented with different residual blocks based on squeeze-excitation methods is analyzed without any extra modifications during training or inference phase.
CNNs are built with stacked convolutional layers. These layers learn its filter coefficients by capturing local spatial relationship (neighbourhood information) along the input channels and generate features maps (filtered inputs) by jointly encoding the spatial and channel information. In all application domains (image classification/segmentation, audio classification/tagging, etc.), the idea of encoding the spatial and the channel information independently is less studied, although it has shown promising results \cite{11}, \cite{12}.

In order to give insight about the behaviour of the CNNs when analyzing spatial and channel information independently several Squeeze-Excitation (SE) blocks have been presented in the DL for image classification literature \cite{11}, \cite{12}. In \cite{12} a block that ‘squeezes’ spatially and ‘excites’ channel-wise with linear relationships was presented. The idea behind this block, labelled as cSE in this work, is to model the interdependencies between the channels of feature maps by exciting in a channel-wise manner. This block show its effectiveness in image classification tasks surpassing state-of-the-art networks only by inserting it in a specific point of the network. Following this idea, two more blocks were presented in \cite{11}. The first one was named sSE because it ‘squeezes’ along the channels and ‘excites’ spatially, whereas last block scSE is the combination of both strategies. The scSE block recalibrates the feature maps along spatial and channel information independently (cSE and sSE) and then combines the information of both paths by adding there outputs. This last block showed the most promising results in image domain tasks. According to \cite{11}, this block forces the feature maps to be more informative, both spatially and channel-wise.

The following of the paper is organized as follows: in Sect. IV the different novel squeeze-excitation blocks proposed in this work are explained. Section V explains the dataset used for validating the premises previously explained plus the audio pre-processing in order to feed the CNN. Section VI shows the experimental results and Section VII concludes our work.

II. SQUEEZE-EXCITATION BLOCKS

SE blocks can be seen as modules for channel recalibration of feature maps. In a cSE module (depicted in Fig. 2(a)) for spatial squeeze and channel excitation a unique feature map of each channel is rst obtained using a Global Average Pooling. In the case of an sSE block \cite{11}, as shown in Fig. 2(b), a unique convolutional layer with one iter and (1,1) kernel size is implemented thus obtaining channel squeeze and spatial excitation effect. That is, squeezing channel-wise converting all channels into a one channel feature map with the specific convolution explained before. The activation function corresponds to a Sigmoid function.

The scSE block \cite{11} is implemented by declaring a cSE and sSE blocks in parallel and then adding both outputs (see Fig. 2(c)). It has been reported that csSE block shows better performance than cSE and sSE used independently \cite{11}.

![Diagram of different SE blocks: (a) cSE proposed in \cite{12}, (b) sSE and (c) csSE, both proposed in \cite{11}. Block in (c) is the outcome of combining blocks (a) and (b).](image)

III. RESIDUAL BLOCKS

According to \cite{12}, SE blocks exhibit better performance when deployed on networks with residual configuration than on VGG style networks. Therefore, two novel residual blocks implementing scSE modules are presented in this paper. The performance of these two newly proposed blocks is compared against other state-of-the-art residual configurations that incorporate SE modules.

In this work, in order to to avoid possible duplications or expansion processes, the identity branch is replaced by a convolutional layer with a kernel size of (1, 1) with the same number of filters as the residual branch.

The alignment of residual and csSE blocks is the same as in \cite{12} for Standard SE and SE-POST blocks: the csSE module is stacked after the residual block (see Fig. 3). Taking this as starting point, two novel configurations depicted in Fig. 3(c) and (d) are presented in this work. The difference between both newly presented blocks is the final activation function (set to ELU \cite{13}, \cite{14} in configuration (d)), whereas the difference with previous works from other authors resides in the residual-block shortcut connections.

All configurations analyzed in this work can be seen in Figure 3 Conv-residual, shown in Fig. 3(f), is inspired by
TABLE I: Proposed network for validating the scSE configurations of Fig. 3. Values preceded by # correspond to the number of filters. Kernel sizes are set as indicated in Fig. 3.

| Configuration | Description |
|---------------|-------------|
| Residual-scSE block (#32, ratio=2) | MaxPooling(2,10) Dropout(0.3) Residual-scSE block (#64, ratio=2) MaxPooling(2,5) Dropout(0.3) Residual-scSE block (#128, ratio=2) MaxPooling(2,5) Dropout(0.3) Flatten [Dense(100), batch normalization, ELU(1.0)] Dropout(0.4) [Dense(10), batch normalization, softmax] |

In order to analyze the influence of the activation function in the results, se-POST from [12] is used as a baseline in order to validate the network performance without any squeeze-excitation and how much it can be improved when incorporating these blocks. In the present work some slight modifications for a more clear implementation were introduced: the shortcut connection was implemented with a convolutional layer and the activation after the addition was set to an ELU function. Conv-Standard, shown in Fig. 3(e), is inspired by [12] where the SE block is stacked after the residual layers and the shortcut is added to the output of the scSE block. Conv-POST and Conv-POST-ELU, shown in Fig. 3(a) and (b) respectively, are inspired by se-POST from [12]: in this case, the objective is to analyze the influence of the activation function in the results. Unlike in the case of Conv-Standard, the shortcut ends before the csSE block. Finally, in Conv-StandardPOST and Conv-StandardPOST-ELU, the two novel configurations proposed in this work shown in Fig. 3(c) and (d) respectively, the addition is done before and after the scSE block. It has been decided to incorporate an ELU activation before the scSE block as in Conv-POST-ELU. As it can be seen in VI, this two residual configurations show the best performance amongst all the ones analyzed in this paper for acoustic scene analysis.

IV. METHODOLOGY

The CNN implemented in order to validate the behaviour of the different squeeze-excitation configurations has been inspired on [16] where a VGG-style [17] network with 3 convolutional blocks followed by different max-pooling and dropout [18] operators is implemented. In the present work, the original convolutional blocks have been replaced with the different residual squeeze-excitation blocks proposed in this study. The max-pooling, dropouts and linear layers remain the same parameters as in [16]. The network architecture can be found in Table II.

As the database used in the current work is much smaller than the one in [12], some of the hyperparameters that define the components of the csSE block had to be modified. The number of elements in the Dense layer with ReLU activation in Fig. 2(a) has been set to 16 in the first Residual-scSE block, the same as in [12] in its csSE block, but the number of filters at the input, C, has been set to C = 32. Therefore, the ratio between these parameters is two in all network as it can be seen in Table I.

V. EXPERIMENTAL DETAILS

A. Dataset

To check the behavior of these implementations in an ASC problem, the TAU Urban Acoustic Scenes 2019, Development dataset presented in Task 1A of the 2019 edition of DCASE has been used [8]. The database consists of 40 hours of stereo audio-recording in different urban environments and landscapes such as parks, metro stations, airports, etc. making a total of 10 different scenes. These have been recorded in different cities such as Barcelona, Paris or Helsinki among others. All audio clips are 10-second length. They are divided in two subsets of 9185 and 4185 clips for training and validation configuration respectively.

B. Audio processing

The input to the network used in the experimentation of this paper is a 2D log Mel-spectrogram representation with 3 audio channels. The three channels are composed of the harmonic and percussive component of the signal converted to mono and the difference between left (L) and right (R) channels. That is, the first channel corresponds to the log Mel-Spectrogram of the harmonic source, the second channel corresponds to the same representation but over the percussive source and the last one to the log Mel-Spectrogram of the difference between channels calculated by subtracting left and right channels (L−R). This representation, known as HPD, was presented in [16]. The log-Mel spectrogram is calculated using 64 Mel filters with a window size of 40 ms and 50% overlap. Therefore, an audio clip becomes a 64 × T × 3 array with T being the number of temporary bins. In this specific dataset, the input audio representation corresponds to an array of dimension 64 × 500 × 3.

VI. RESULTS

In order to analyze the contributions of this study to the state-of-the-art, the results obtained with the different configurations presented in this work (see Fig. 3) are compared against the results obtained by different authors in Task 1A of DCASE 2019 using the same dataset. Submissions that made use of data augmentation techniques have not been taken into account. In the case of submissions that presented an ensemble of several models, the comparison is made with only one of the models of the ensemble: the one with the highest accuracy. For example, in [19] a global development accuracy of 78.3% is reported, but that value was obtained by averaging 5 models. The best individual model obtained 72.4%, so this
Fig. 3: Different residual squeeze-excitation blocks analyzed in this work. All have in common the replacement of identity mapping by a convolution (1, 1). (a), (b) and (d) are inspired by the work done in [12]. (f) is inspired by the first residual block proposed in [15]. (c) and (d) are the two novel configurations proposed in this work.

| System                  | Development accuracy (%) |
|-------------------------|--------------------------|
| Baseline [8]            | 62.5                     |
| Wang_NWPU_task1a [19]   | 72.4                     |
| Fnta91_KNToosi_task1a   | 70.49                    |
| MaLiu_BIT_task1a [21]   | 76.1 (evaluation)        |
| DSPLAB_TJU_task1a       | 64.3                     |
| Kong_SURREY_task1a      | 69.2                     |
| Liang_HUST_task1a [24]  | 70.70                    |
| Salvati_DMIF_task1a [25]| 69.7                     |
| Conv-Residual           | 74.51 ± 0.65             |
| Conv-Standard           | 75.16 ± 0.33             |
| Conv-POST               | 75.84 ± 0.65             |
| Conv-POST-ELU           | 75.81±0.47               |
| Conv-StandardPOST       | 76.72±0.59               |
| Conv-StandardPOST-ELU   | 76.00±0.55               |

is the value presented in Table II. This said, please be aware that the accuracy of the final submission may differ from that presented in Table II.

- **Wang_NWPU_task1a [19]**: the audio is represented in two channels by harmonic and percussive sources. A CNN is used as a classifier.
- **Fnta91_KNToosi_task1a [20]**: Wavelet scattering spectral features are extracted from the mono audio signal. A random subspace acts as a classifier.
- **MaLiu_BIT_task1a [21]**: Deep Scattering Spectra features (DSS) are extracted from each stereo channel. Classification is performed with a Convolutional Recurrent Neural Network (CRNN). For this network, Table II does not report the development accuracy, instead, the evaluation accuracy is the reported value. This is because of some mismatch reported by the authors in the validation procedure with the configuration of the dataset.
- **DSPLAB_TJU_task1a [22]**: this submission approaches the problem in a more classical way extracting audio statistical features such as ZRC, RMSE, spectrogram centroid, etc. A GMM is used as a classifier.
- **Kong_SURREY_task1a [23]**: this submission can be defined as the state-of-the-art framework in ASC problem. The representation of the audio correspond to the log-Mel Spectrogram. The classifier is a VGG [17] based CNN. This network is a fully convolutional network with no linear layers implemented. The feature maps are reshaped into a one dimensional vector using a global average pooling before the decision layer.
- **Liang_HUST_task1a [24]**: log Mel-Spectrogram is first extracted after converting the audio signal to mono. Interestingly, log-Mel spectrogram is divided into two seconds spectrograms, that means that spectrogram shapes change from $[F \times T \times 1]$ to $[F \times (T/5) \times 1]$. A CNN with frequency attention mechanism is implemented as classifier. For more detail of the attention implementation, see [24].
- **Salvati_DMIF_task1a [25]**: unlike the other submissions, this one works directly on the audio vector. To this end, a 1D convolutional network is implemented. Although some recent efforts have been made in this direction [26], the state-of-the-art literature shows that 2D
audio representations, such as spectrograms, still obtain the better classification results [27].

- **DCASE baseline [8]**: the audio is first converted to mono and a log-Mel spectrogram is extracted. In this case, only 40 Mel bins are calculated instead of 64, the typical state-of-the-art choice. A CNN is used as a classifier with 2 convolutional layers. The reshaped function is done by a flatten layer. A dense layer is stacked before the decision layer.

Unlike the results of DCASE challenge that only report the mean accuracy value, in the present work 10 runs have been performed so that not only the mean value but also the variance could be reported.

As it can be seen in Table II all configurations detailed in Fig. 3 obtain better accuracy than the DCASE baseline. The contribution of scSE block is easily justified as Conv-Residual gets the lowest performance among the studied configurations. POST configurations show a little improvement compared to the Standard configuration. This behaviour differs from what was reported in the original paper, [12], in which these blocks were analyzed in the image domain. There is no remarkable difference between Conv-POST and Conv-POST-ELU.

Table II shows how the networks that incorporate the two novel blocks presented in this work, the ones depicted in Figs. 3(c) and (d), exhibit the largest values of accuracy. The shortcut addition at two different points of the residual block, this is, before and after the scSE block allows the network to obtain a more precise classification in ASC problems.

VII. Conclusion

Usual state-of-the-art solutions, many of them based on the well-known VGG network [8], [16], [17], [23] use classical convolutional layers where spatial and channel information are jointly encoded. In this work another direction is followed. As in [11] the present approach makes use of scSE blocks where spatial and channel information are excited separately.

Many audio classification (including ASC) frameworks incorporate other contributions different from the network architecture such as data augmentation [28]–[31] or the ensemble of various models [32]–[34]. This paper focuses on the design of the network architecture, showing that this approach can still make important contributions to the state-of-the-art. Here, it is shown that by incorporating a squeeze-excitation process in a residual convolutional network the performance of a classical residual network can be clearly improved. Besides, it is shown how the configuration of the residual block that incorporates the SE block is in turn crucial, proposing two novel configurations that considerably improve the performance of classical configurations and frameworks that do not use data augmentation or ensemble techniques.

This work shows that the configuration of a residual block that implements a csSE module together with the architecture of the residual block itself is a research topic that can still be exploited.

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