Transfer Learning and SpecAugment applied to SSVEP Based BCI Classification

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Abstract

In this work, we used a deep convolutional neural network (DCNN) to classify electroencephalography (EEG) signals in a steady-state visually evoked potentials (SSVEP) based brain-computer interface (BCI). The raw EEG signals were converted to spectrograms and served as input to train a DCNN using the transfer learning technique. We applied a second technique, data augmentation, mostly SpecAugment, generally employed to speech recognition. The results, when excluding the evaluated user’s data from the fine-tuning process, reached 99.3% mean test accuracy and 0.992 mean F1 score on 35 subjects from an open dataset.

Keywords: Transfer Learning, SSVEP, BCI, Neural Networks, SpecAugment

1. Introduction

In this study, we propose the use of deep convolutional neural networks (DCNNs) as classifiers in brain-computer interfaces (BCIs) based on steady-state visually evoked potentials (SSVEP). Deep neural networks (DNNs) perform very well when trained on a large amount of data [1], but large SSVEP datasets are not commonly available for open use. Our way to overcome this problem was to employ data augmentation and transfer learning techniques to train the DNNs, as both are known to improve the performances of DNNs on smaller datasets [2].

We started with an open SSVEP dataset [3], which we consider to be large in comparison with other open databases. The electroencephalography (EEG) signals where transformed into images, specifically spectrograms, using the short-time Fourier transform (STFT). By doing so, we take advantage of the ability of convolutional DNN in classifying images, which is well documented [1].

The neural network used in this study [4] is a DCNN based on the original VGG [5]. While the original VGG was trained on the ImageNet dataset [1], the

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VGGish DCCN we used was trained for classifying spectrograms from AudioSet [6], a very large dataset composed of natural and artificial sounds. We decided to investigate this DCNN as our pretrained network for transfer learning, due to the potential task similarity between classifying spectrograms from sounds and classifying spectrograms from SSVEP signals. The structure of this network is found in Table 1. The modified version, fine-tuned for SSVEP classification, is available in Table 2.

We trained the network to classify EEG signals from subjects focusing on a 12 Hz or a 15 Hz flickering visual stimulus. We did not include the data from the test subject in the training or validation datasets in order to establish a scenario in which the BCI final user does not influence the classifier adjust. During the training period, to avoid overfitting the DNN, we used data augmentation, mostly the technique called SpecAugment [7]. It is considered a simple method with very good results in improving the performances of DNNs in the task of speech recognition using spectrograms [7].

This paper is divided according to the following way: in section 2, we present the SSVEP paradigm and the dataset; in section 3, we discuss data augmentation and the techniques we applied (SpecAugment [7] and window slicing [8]); in section 4, we introduce the transfer learning and the VGG network [4]; in section 5 we describe how we processed the dataset, created our network and trained it; in section 6, we present the results, analyzing the use of different augmentation techniques and comparing the DNN performance to that of an SNN (a shallow neural network, commonly used in SSVEP classification). Finally, in section 7, we present our conclusions.

2. BCI and SSVEP

2.1. Fundamentals of SSVEP-based BCIs

A steady-state visually evoked potentials (SSVEP)-based brain-computer interface (BCI) utilizes a visual stimulation device, like a computer monitor, showing patterns flickering in certain frequencies. When the user focuses his/her attention on one pattern, he/she sends a command to the system: different frequencies allow different commands [9].

The visual oscillations engender brain activity oscillations (SSVEP) in the same frequency, and their harmonics can be detected with EEG, particularly on the visual cortex. The process is non-invasive, making it a good alternative to create BCIs [10].

In order to identify the oscillations in the EEG signals, we need a classifier. In our work, this role will be played by a deep neural network. Moreover, we want to be able to use the BCI in users that did not take part in its design, hence we do not include the test subject's data in the training set of the DNN. This makes the problem more challenging, increasing the need for regularization and other techniques to avoid overfitting.
2.2. The dataset

The authors of the dataset used in this work [3] built it to evaluate a virtual keyboard consisting of a computer display showing 40 visual flickers, with different frequencies and phases, corresponding to different letters. The decision to use this dataset was due to its size and availability. It consists of data from 35 subjects, of which 8 subjects are experienced in using BCIs, and 27 subjects do not have any prior experience in using BCIs. The data was recorded with a 64-channel whole head electroencephalography (EEG) in 40 different stimulation frequencies, ranging from 8 to 15.8 Hz, with an interval of 0.2 Hz, while adjacent frequencies had a 0.5 $\pi$ phase difference. Each subject observed the stimuli in six blocks of 40 trials, one for each frequency. Each trial lasted 5 seconds. More details about the dataset, as well as image examples, can be found in [3].

From this dataset, we analyzed frequencies 12 and 15 Hz, and only the Oz electrode (based in the international 10-20 system), as it is placed on the region of the visual cortex. In a previous study based on DNNs [11], our group had a better classification performance using this electrode in comparison with other combinations of electrodes.

3. Data augmentation

3.1. Fundamentals of data augmentation

When the neural network inputs become larger, like 224x224 images, the DNN input space becomes high dimensional. This leads to the problem known as “Curse of dimensionality”, and, in order to create a good statistical model of the input and label distributions, our neural network will need more data [12].

Another problem is that, when neural networks become deeper and with more trainable parameters, their ability to model a given data distribution increases. If we do not have enough data, the DNN will learn slight variations and noise in the training dataset, which are exclusive to that database and do not reflect the task the network is trying to solve. This is known as overfitting, and will make the network perform badly in the test dataset [2].

One way to avoid this problems is to use more training data, giving the network a better statistical representation of the analyzed task. But, sometimes, like in SSVEP classification, large datasets are not available, in which cases we may use data augmentation.

Data augmentation consists in generating more training data from the available training dataset [2]. There are many techniques to accomplish this goal, generally depending on the neural network task. For example, in pattern recognition it is common to rotate or translate the original image, generating new ones.

3.2. Window slicing

The first augmentation technique we used in our study was window slicing (WS) [8]. Our original EEG data consisted of a time series with a duration of 5 seconds, from which we took slices of a fixed size. The first slice starts at
the beginning of the time series, and, for each subsequent slice, we add a fixed displacement considering the start position from the previous slice. The process stops when a slice does not entirely fit in the time series anymore. With this procedure, for each original time series, we create many smaller slices, used as inputs to our neural network, with the same desired output as the original time series taken as the source for the slices.

3.3. SpecAugment

One of the areas DCNNs have prominence is image classification. To be able to benefit from this, the EEG signals from the dataset were converted into spectrograms. In addition to that, the process of generating spectrograms creates another opportunity: spectrograms are largely applied to audio classification [4]; thus, techniques used for augmenting audio and speech datasets might also be useful for our study.

To test this new possibility, we used a technique called SpecAugment [7], originally created for data augmentation in speech recognition. It is a modern augmentation method successfully used with DNNs, achieving state-of-art performance in the datasets LibriSpeech 960h and Switchboard 300h [7]. The original augmentation strategy consists of three parts [7]: time warping, frequency masking, and time masking. Time warping consists in using the TensorFlow sparse_image_warp function to warp a random point in the horizontal line passing through the center of the spectrogram to the right or left, by a random distance. Frequency masking consists of masking random frequency channels in the spectrogram (rows). One mask can take just one channel or multiple adjacent ones, in a random manner. At last, time masking consists of masking random time steps (columns) in the image, and, like in frequency masks, each mask can have a random length (taking one or many adjacent columns). In order to mask rows or columns, we can substitute their values for the spectrogram average value. More information about SpecAugment can be found in [7]. In this study we made some changes to the technique, as explained in Section 5.1.

4. Transfer learning

4.1. Fundamentals of transfer learning

The dynamics of knowledge transfer refers to the use of adjusted parameters from a model in a given environment, problem, or database to explore a possible improvement in the generalization of another model in another environment, problem or database [13].

A common approach is to apply the knowledge transfer technique in situations of data scarcity, since the training of deep models tends to overfit in an insufficiently sized dataset [14]. Taking advantage of model parameters adjusted on sufficiently large datasets can overcome this problem.

Another feasible approach to knowledge transfer can benefit problems in different domains. Fine-tuning the parameters from a model with good generalization in its domain, using the data from a problem on a different domain,
may improve the possibility of solving the problem. The adjusted model can benefit from the original representations of a model to quickly generalize from little data in the new domain [2].

The two most common uses of knowledge transfer are [14]:

a) Feature extraction models. The output of a model without its fully connected layers represent the features from the samples; thus, this new model behaves as a feature extractor. Using this feature extractor on an existing dataset generates a new dataset of features. The newly generated dataset serves as input to smaller models when compared to the full model, responsible for the classification or regression, depending on the problem. Training these small models are less time consuming when compared to the training time for a full model.

b) Fine-tuning the model. The strategy is to use a new dataset to fine-tune the parameters of a pretrained complete model, through a few more training iterations. The two options for this approach are whether the model will be fully adjusted or only the layers closer to the end of the model will be adjusted. This decision is related to the similarity between the new dataset and the original dataset, initially used to train the model. The first layers of a deep model tend to extract simple and general features (like locating borders on images), but the last layers tend to learn more complex and task related representations. Thus, the more different the two datasets and tasks, the more layers, starting from the last, will need to be fine-tuned in the new dataset.

To decide how knowledge transfer best fits into a new dataset, at least two factors must be analyzed: the size of the new dataset and its similarity to the original dataset. There are four possibilities, taking into consideration that the layers at the beginning of the model are responsible for detecting generic features and the layers at the end of the model are responsible for detecting specific features in the original dataset [15]:

1. The new dataset does not have enough samples to adjust the model, and the samples are similar to the original dataset. As the amount of data may not be enough to fully adjust the model, and considering the ability of the model layers to recognize features from the new dataset based on its similarity to the original, adjusting the fully-connected layers may be more reasonable and lead to a better performance.

2. The new dataset has enough samples to adjust the model, and the samples are similar to the original dataset. With enough samples and similar to the original dataset, it is possible to adjust the complete model without worrying about overfitting.

3. The new dataset does not have enough samples to adjust the model and, its samples do not relate to the original dataset. This case turns out to be the most complex as there is not enough data to adjust the fully connected layers of the model, and the data is unrelated to the original dataset. An option is to remove the fully connected layers and some layers from the end of the model, responsible for recognizing specific features from the dataset, connecting a new model, e.g., linear or fully connected layers, at
the end in an attempt to improve the possibility to adjust it.

4. The new dataset has enough samples to adjust the model, and the samples do not relate to the original dataset. With enough data, it may be suitable to train the whole model from the beginning [2]. Still, it can be beneficial to initialize the model with pretrained parameters as the amount of data in the new dataset would be enough to adjust the model.

When the choice to address a new problem is knowledge transfer, it is crucial to remember that the solution will be tied to the original architecture, reducing the flexibility of the model. The chosen pretrained model may have input size restrictions, for example. Additionally, an important detail is related to the learning rate. It is common to use lower learning rates when the model parameters are undergoing adjustments since the base to use a pretrained model is its relatively good parameters. Another strategy is to train the DNN layer by layer, that means, start adjusting only the last layers, then unfreezing other layers and training again, until you train the whole model (a frozen layer means that its parameters are not being adjusted in training). This allow us to adjust more the last layers, that are more task specific.

The use of knowledge transfer can lead to benefits such as reduced training time and better accuracy. In any case, its use requires a careful analysis of the datasets and a thorough adjustment to make it work as expected.

4.2. The VGG network trained in AudioSet

Searching for a network suitable for transfer learning in the task of SSVEP classification we looked for something deep, trained in a large dataset and in a task somewhat related to SSVEP classification. We could not find any network that met this criteria and was originally trained with SSVEP. But, because we were trying to classify spectrograms, we thought that our task could be related to classifying sounds in a noisy environment.

AudioSet [6] is a dataset that contains over one million 10-seconds human-labeled sound clips from YouTube, with hundreds of classes, covering human made sounds, musical instruments and environmental sounds. Google released CNNs trained in the task of classifying this dataset, having spectrograms as inputs [4]. The network called VGG [4] presented a very good result and a variant of it can be downloaded pretrained (also called VGGish). So, that was our choice for transfer learning in this study.

The pretrained network architecture is very similar to the original VGG configuration A [5], a network trained on the dataset ImageNet [1] for image classification. The downloaded network structure can be seen in Table 1. All layers (convolutional and dense) have a rectified linear unit (ReLU) activation function. All convolutional layers are 2D have 2x2 sized kernels, with 1x1 stride and padding. All max pooling layers are also 2D, with 2x2 kernel, stride 2 and dilatation 1. This architecture was modified to create the network we used in this study. We will talk about this changes in this paper’s section 5.2.
### Table 1: VGGish network architecture

| Convolution, 64 channels | Maxpool |
|-------------------------|---------|
| Convolution, 128 channels | Maxpool |
| Convolution, 256 channels | Maxpool |
| Convolution, 256 channels | Maxpool |
| Convolution, 512 channels | maxpool |
| Fully connected, 4096 neurons | Fully connected, 4096 neurons |
| Fully connected, 128 neurons |         |

5. Methodology

5.1. Signal preprocessing and data augmentation

We started with the EEG time series. We had 6 trials of 5 seconds per subject per stimulus frequency. The signal sampling rate was 250 Hz (down sampled from a 1000Hz EEG system). So, each trial provided us with 1250 samples. These data, obtained from [3], were already filtered by a notch filter at 50 Hz in the data recording, to remove common powerline noise. We also applied a common average reference (CAR) filter. With 35 subjects, the frequencies of 12 and 15 Hz and the data from electrode Oz, we had a total of 420 time series.

We started signal preprocessing by applying WS. After some preliminary tests (changing the WS slice size and our STFT window size), we opted for a slice size of 4 seconds with a displacement of one second, thus generating two 4-second time series for each original one, yielding 840 signals.

Then, we applied a short-time Fourier transform (STFT) to our new series, generating a spectrogram for each signal. This STFT used a rectangular window with length of 500 (2 seconds) and hop length of 250 (1 second). Such values were chosen to give us a good frequency resolution. The STFT output modulus were converted to decibels and normalized between 0 and 1, creating images. To visualize them, we can multiply their values by 255 and have a gray scale image. We also tried Hann and Blackman windows in the STFT, but their results were worse than the rectangular one, probably due to its better frequency resolution.

The images were filtered, removing columns representing frequencies we had no interest in. In SSVEP classification we are searching for signals in the stimuli frequencies (12 and 15 Hz) ans it’s harmonics. Thus, in the final spectrograms, we had only frequencies between 11 and 13 Hz, 14 and 16 Hz, 23 and 25 Hz and between 29 and 31 Hz. The resulting images had size 20x5, with a frequency resolution of 0.4 Hz and a time resolution of 0.8 s. An example can be seen in Figure 1.
The next step was applying SpecAugment. We made some changes in the original technique. Firstly, we did not use time warp. In the article presenting this method [7], the authors already noted that time warp provided little benefit and was the most computationally expensive operation in SpecAugment. With some early tests we confirmed this, the benefit was marginal and required a significant CPU time. Secondly, our spectrograms were much smaller than the ones used for speech recognition in [7]. So, in order to avoid losing too much information, we chose to use only one time mask of 1 column and one frequency mask of 1 line. In this way, in our 5x20 spectrograms, we had only 6 time masking options (one for each row or no mask) and 21 frequency masking options, leaving us with 126 possibilities per image. To avoid repetitions and save training time, we did not use the randomized and online approach suggested in [7], but, instead, we generated and saved all the masking options for each spectrogram before training. This yielded us a new dataset of 105,840 images. In order to test SpecAugment’s benefits we also trained networks without it and networks with time masks only (that gave us a dataset of 5,100 images).

In this study, we wanted to simulate the use of a BCI in a person who did not participate in the classifier training. Thus, when we choose a test subject, its data is not used in the training or validating datasets. To create these datasets, we removed the test subject data and randomly selected 66.6% of the remaining spectrograms as the training dataset and 33.3% as the validating one (but maintaining the balance between classes). The test dataset is created with all spectrograms from the test subject. We note here that SpecAugment was only applied to the training dataset and never to testing or validating.

To feed the 20x5 spectrograms to the network, they were resized (using nearest neighbor interpolation) to 96x64, the pretrained VGG input size.

5.2. Training and transfer learning

To create our network, we started from the pretrained VGG, described in section 4.2. But, after some preliminary testing, we decided to maintain the
Table 2: Our DCNN

| Convolution, 64 channels | Maxpool |
|-------------------------|---------|
| Convolution, 128 channels | Maxpool |
| Convolution, 256 channels | Maxpool |
| Convolution, 256 channels | Maxpool |
| Convolution, 512 channels | maxpool |
| Dropout, 50% |
| Fully connected, 512 neurons | Dropout, 50% |
| Fully connected, 2 neurons |

convolutional layers, but to replace the fully connected ones (the last 3 layers) by two new fully connected layers, with random weights, and add dropouts, as shown in Table 2. The first fully-connected layer has ReLU activation functions and the last layer is linear (the model will be trained in PyTorch with cross-entropy loss, which adds a softmax activation to the output). We also made tests without removing layers and just adding new ones to the end of the VGG, or changing the last VGG layer, but their results were worse.

Preliminary tests also shown that the best results were achieved without freezing any layers weight when training. We also tried first freezing the convolutional block, training only the fully connected one, and then training the rest of the network (at once or unfreezing and training layer by layer).

Because we are not using the test subject’s data in training or validating, much regularization was needed to avoid overfitting, in form of max pooling, dropout, weight decay and early stopping. We trained one network for each of the 35 subjects as the test one.

The networks were trained in a NVidia GTX1080 GPU, with stochastic gradient descent (SGD), momentum of 0.9, learning rate of 0.001 or 0.0001, weight decay of 0.01, early stop between 50 and 200 epochs (depending on validation curve) and maximum of 500 epochs (never achieved), cross-entropy loss and mini-batches of 128. Training times are very dependent on the SpecAugment utilization. Using time and frequency masks (generating our biggest dataset), each epoch lasted about 20 seconds, with only time masks, 1.2 seconds, and without SpecAugment, 0.7 seconds. The number of epochs in training were generally bigger when using less augmentation, but at maximum by a factor of two. With time and frequency masks, training one network took about 30 minutes.

We created linear support vector machines (SVMs) to classify our dataset, so we could compare our transfer learning results to a commonly used classification
method in SSVEP. We also compared the benefits of SpecAugment both in a shallow and a deep model. This networks were trained with SGD, momentum of 0.9, learning rate of 0.001, hinge loss with a regularization parameter (c) of 0.01, early stop of 50, maximum number of epochs of 3000 (also never achieved) and mini-batches of 128. With or without SpecAugment, training one SVM took about 3 to 4 minutes (epochs were faster without augmentation but, because of early stopping, the network took more epochs to stop training).

6. Results

We tested our DCNN with SpecAugment’s time and frequency masks, with time masks only, and without this augmentation. We also tested the linear SVM with SpecAugment (time and frequency masks), and without the augmentation. These configurations are represented in the columns of Table 3. The test accuracies we got using them are shown in the table, where each row represents a different subject taken as the test subject. The last row shows the mean accuracy in the 35 test subjects for each of the 5 configurations.

Table 3: Test accuracies for DCNNs and SVMs, with different data augmentation methods

| Test subject | DCNN with SpecAugment | DCNN without SpecAugment | DCNN with time masks | SVM without SpecAugment | SVM with SpecAugment |
|--------------|------------------------|--------------------------|----------------------|------------------------|---------------------|
| 1            | 100                    | 100                      | 100                  | 100                    | 100                 |
| 2            | 100                    | 100                      | 100                  | 100                    | 100                 |
| 3            | 100                    | 100                      | 100                  | 100                    | 100                 |
| 4            | 100                    | 100                      | 100                  | 100                    | 100                 |
| 5            | 100                    | 100                      | 100                  | 100                    | 100                 |
| 6            | 100                    | 100                      | 100                  | 100                    | 100                 |
| 7            | 100                    | 100                      | 100                  | 100                    | 100                 |
| 8            | 100                    | 100                      | 100                  | 100                    | 100                 |
| 9            | 100                    | 100                      | 100                  | 100                    | 100                 |
| 10           | 100                    | 100                      | 100                  | 100                    | 100                 |
| 11           | 100                    | 100                      | 91.7                 | 100                    | 83.3                |
| 12           | 100                    | 100                      | 100                  | 100                    | 100                 |
| 13           | 83.3                   | 75                       | 75                   | 83.3                   | 66.7                |
| 14           | 100                    | 100                      | 100                  | 91.7                   | 100                 |
| 15           | 100                    | 100                      | 100                  | 100                    | 100                 |
| 16           | 100                    | 100                      | 100                  | 91.7                   | 100                 |
| 17           | 100                    | 58.3                     | 100                  | 91.7                   | 100                 |
| 18           | 100                    | 100                      | 100                  | 100                    | 100                 |
| 19           | 100                    | 100                      | 100                  | 100                    | 100                 |
| 20           | 100                    | 100                      | 100                  | 100                    | 100                 |
| 21           | 100                    | 100                      | 100                  | 100                    | 100                 |
| 22           | 100                    | 100                      | 100                  | 100                    | 100                 |
From table 1 we can see that our best mean accuracy (99.3%) in the 35 test subjects was achieved with our DCNN with SpecAugment’s time and frequency masking. We can also observe that this augmentation much improves the deep network results, but has almost no effect on the shallow and linear SVM (actually, its mean accuracy is reduced by a very small value, 0.3%). It is also visible that, without SpecAugment, our deep network would have results worse than the linear SVM. The usage of time masks only already made a big difference in performance, but the using time and frequency ones gave us the best result.

Our best DNN (with SpecAugment time and frequency masks) had a F1 score of 1 in every subject with the exceptions of subjects 13 and 29, where it got 0.8 and 0.909, respectively. The mean F1 score this neural network got in all subjects was 0.992.

Other results are worth noting: training our network with frozen weights, and then unfreezing layers and retraining, did not improve our accuracies. Also, we tried transfer learning with the original VGG network (configuration A) [5], pretrained on ImageNet [1], but we got bad results. Maybe they could improve with more training time, but we did not test it, because our results with the VGG pretrained on AudioSet [6] were already much better.

7. Conclusion

With this study we could observe that deep convolutional neural networks can improve the accuracy of a SSVEP based BCI, even without training in the test subject. The greatest challenge for the usage of this networks is that we generally do not have very large SSVEP datasets, which would be really helpful for DCNNs.

We overcame this problem by using transfer learning and data augmentation (mainly our modified SpecAugment). The good result (99.3% mean accuracy
and 0.992 mean F1 score) we got with the VGG pretrained on AudioSet [4] shows that sound classification is a good option for the first task in transfer learning. This conclusion is also backed by the poor result we got with the VGG pretrained on ImageNet [5]. But freezing layers in training did not improve our accuracy, which shows that a deep network pretrained in a more similar task (like in a large EEG classification dataset) could maybe generate even better results.

SpecAugment made a big difference in our performances with the DCNN. Even using transfer learning, without this augmentation, the DNN’s results would be worse than the SVM’s. Also, as expected, the data augmentation had much more effect on the deep model than on the shallow one.

This study shows that deep neural networks can improve the performance of SSVEP based BCIs, when trained with the proper methods to avoid overfitting and the challenges of having a not so big dataset. Also, we think that efforts in creating larger and open SSVEP classification datasets will improve DCNNs’ results even more.

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