Optimizing a convolutional network model in a hand-squeeze task classification

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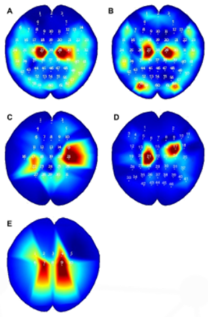
Abstract

- Motor imagery based BCI can help individuals with movement disorders such as locked-in syndrome, tetraplegia, cerebral palsy by developing a correlation between brain and external devices, for example, speller, wheelchair, and prosthetics.

- Inspired by recent BCI research, in this paper, a convolutional neural network is applied to EEG signals collected through hand squeeze tasks both in terms of classifying and evaluating the accuracy.



Introduction

- The systems based on Brain Computer-interface (BCI) creates a correlation between human brain and external devices. In recent research, a non-invasive scheme such as an electroencephalogram (EEG) considered for BCI tasks, utilizing The Motor Imagery(MI) tasks and event-related synchronization/desynchronization and the effect of unilateral limb motions on mu and beta rhythms in the sensorimotor area of the contralateral hemisphere and the ipsilateral hemisphere, respectively,

- The Convolutional neural network (CNN) is a new approach in feature extracting and classifying tasks like image and video recognition, Natural language processing (NLP), recommender systems, signal classifying, etc. CNN is biological-inspired variants of multilayer perceptron design to use the minimal amount of preprocessing.

- The CNN architecture used for classifying MI tasks that regarded as a series of images. The method considered the spatial correlations among neighboring EEG channels by accounting for the arrangement of electrodes on the scalp .

- The researchers have compared CNN and Long Short-Term Memory (LSTM) methods to extract features and classify MI BCI tasks which are proposed CNN method is more efficient than the LSTM method.

Methods

- Classification model
  - Since one of our tasks is comparing accuracies among 2-labeled and 3-labeled datasets, we apply a specific classifier, based on our number of classifications, to our datasets.
  - We applied a high-level CNN architecture that illustrated in figure1. For extracting features from our datasets, two sequential convolutional layers, with k and 2k of Relu-activated neurons implemented and for classifying a fully connected layer of m Relu-activated neurons followed by m SoftMax-activated neurons for 3-labeled datasets or Sigmoid-activated single neuron for 2-labeled datasets used in the output layer.
  - In contrast with image processing and computer vision tasks where use a small kernel window, we used a window of width w and height equal to the number of EEG channels to capture dependencies between all channels instead of the local dependencies between channels that happen to be close in the input data.
  - Both the order in which channels are presented to the classifier and optimal channel order do not affect this method. To examine our theory, we executed several shuffles on our input channels. The result approves that channel order does not affect the performance.
  - We implemented and trained the model in the Keras framework. The training method used was backpropagation with stochastic gradient descent using various batch sizes, learning rates and epochs. Therefore, in each of the training epochs, 100 random samples from the input were selected for training.

Results

- A. Optimizing the architecture

Patient	Best Case	Worst Case
B	f=8, d=50, w=5, b=70, e=110, l=0.01	f=128, d=50, w=1, b=100, e=100, l=0.3
C	f=8, d=50, w=1, b=90, e=100, l=0.03	f=64, d=50, w=11, b=80, e=90, l=0.3
D	f=8, d=150, w=1, b=100, e=80, l=0.01	f=128, d=50, w=11, b=70, e=70, l=0.1
E	f=8, d=50, w=11, b=90, e=90, l=0.01	f=128, d=50, w=7, b=100, e=100, l=0.3

- B. Reducing channels

Patient # of Channels	B	C	D	E
2	71%	81%	78%	78%
3	77%	84%	84%	83%
4	79%	86%	85%	84%
5	84%	85%	86%	85%
10	84%	83%	87%	86%
All channels	80%	88%	89%	86%

Patient # of Channels	B	C	D	E
2	57%	59%	51%	67%
3	57%	60%	57%	74%
4	---	61%	60%	76%
5	---	63%	62%	76%
10	58%	61%	63%	81%
All channels	56%	66%	72%	81%

- C. Comparison between 2 and 3 classes classification

Accuracy Patient	2 Classes		3 Classes	
	Average	Variation Range	Average	Variation Range
B	61%	19%	52%	4%
C	78%	10%	57%	9%
D	68%	21%	63%	9%
E	73%	13%	67%	14%

Conclusion

The classification accuracy affected by changing hyperparameters indicates that the simpler our architecture is the more efficient our classification is.

• Our research proposes that the classification accuracy of a simple architecture and using few influential channels can be as efficient as a complicated neural network and using the whole channels of EEG.

References

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