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Deep Convolutional-recurrent neural network for SMR classification

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Introduction

A Brain-Computer Interface (BCI) is a system that permits the communication between the brain and the machine. It uses neural activity to translate a mental state to instruction using machine learning algorithms and neuroscience. Such technology allows many applications in several fields like neurological diseases detection, prosthesis control, security, gaming, and educational fields.

Motivation

Sensorimotor rhythm signals is a rhythm that is occurred in the motor cortex in a frequency band mu [8Hz, 13Hz] and beta [13Hz, 30Hz].it is triggered by motor action like the movement of a hand or legs. The most significant fact about those rhythms is that they are occurred by just imagining the movement. This is what is called Motor Imagery (MI). Such a signal is characterized with a low signal-to-noise ratio which make its detection a complicated challenge [3].

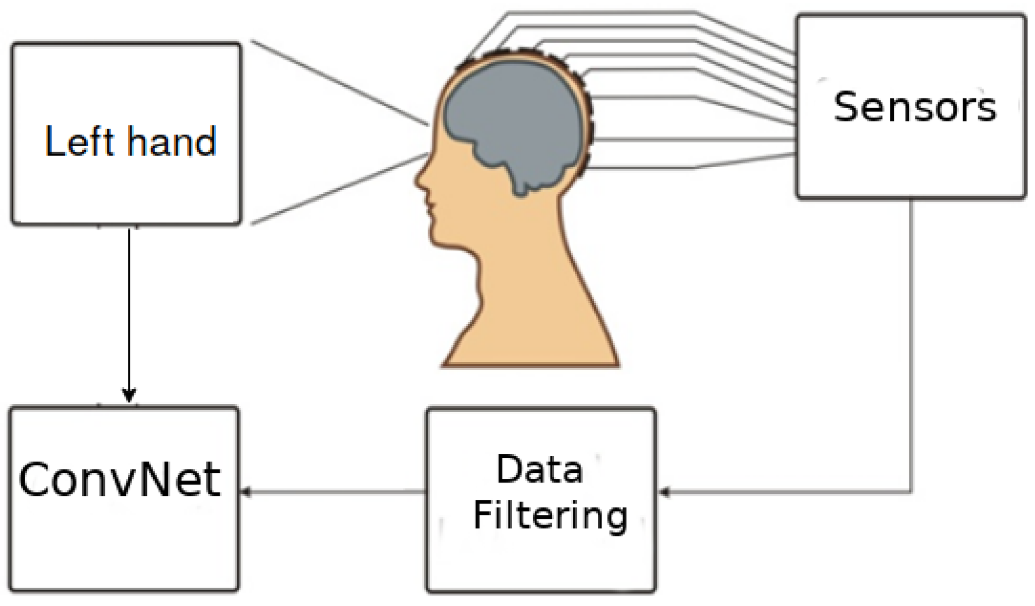

Figure 1:The paradigm of the P300 speller

Our aim is to design a deep recurrent-convolutional neural network (Convnet) for sensorimotor rhythm detection where the features will be extracted automatically. We choose the raw signals as input without any transform and a minimum of pre-processing.

Method

The proposed ConvNet will be composed of three stages:

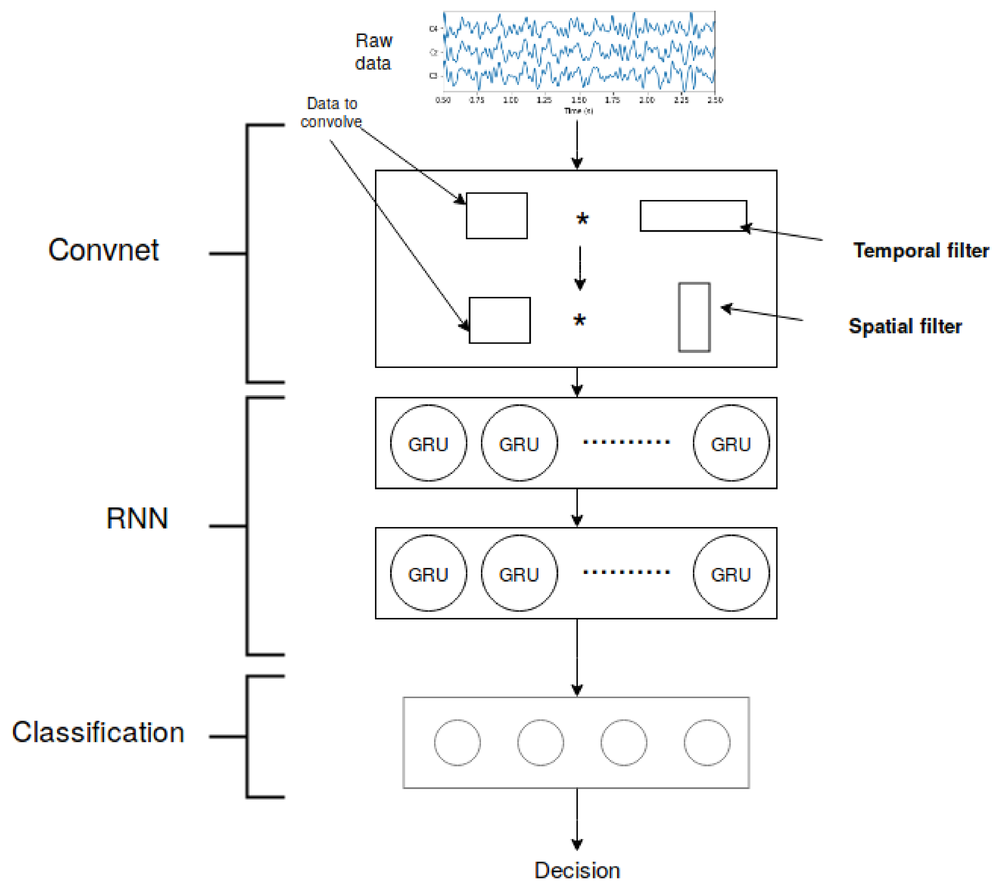

Figure 2:Architecture of the neural network

The Figure 2 illustrates the architecture. The first convolution is dedicated to temporal filtering, and a depthwise convolution is used to filter spatially . Then, we use two layers of bidirectional Gated Recurrent Units (GRU) cells. The last layer is a regression that classify the features. Also, the Batch Normalization, Exponantial linear unit, max norm constraint, and dropout are used after each convolution to regularize the network.

Hyperparameter

We use Adam optimizer due to its efficiency and fast learning compared to other optimizers. Also, we fix a learning rate of 0.0001 to get smoother learning and avoid then avoid the overfitting. Moreover, a batch size of 64 is chosen which is a standard in the field. We pick the best model with the lowest validation loss.

Data

The electroencephalography (EEG) data that is used is coming from the BCI Comp IV set IIa [4]. It is a cue-based BCI paradigm where 9 subjects were asked to perform motor imagery of four movements: Left hand, Right hand, feet, and tongue. We follow the experimental protocol as described by Lawhern et al. [2].

Results

By comparing the proposed method and EEGNet with ANOVA, we found a P_{values} of **0.6** which mean that the two model are quit similar.
We display the temporal filter to show the learned frequency.

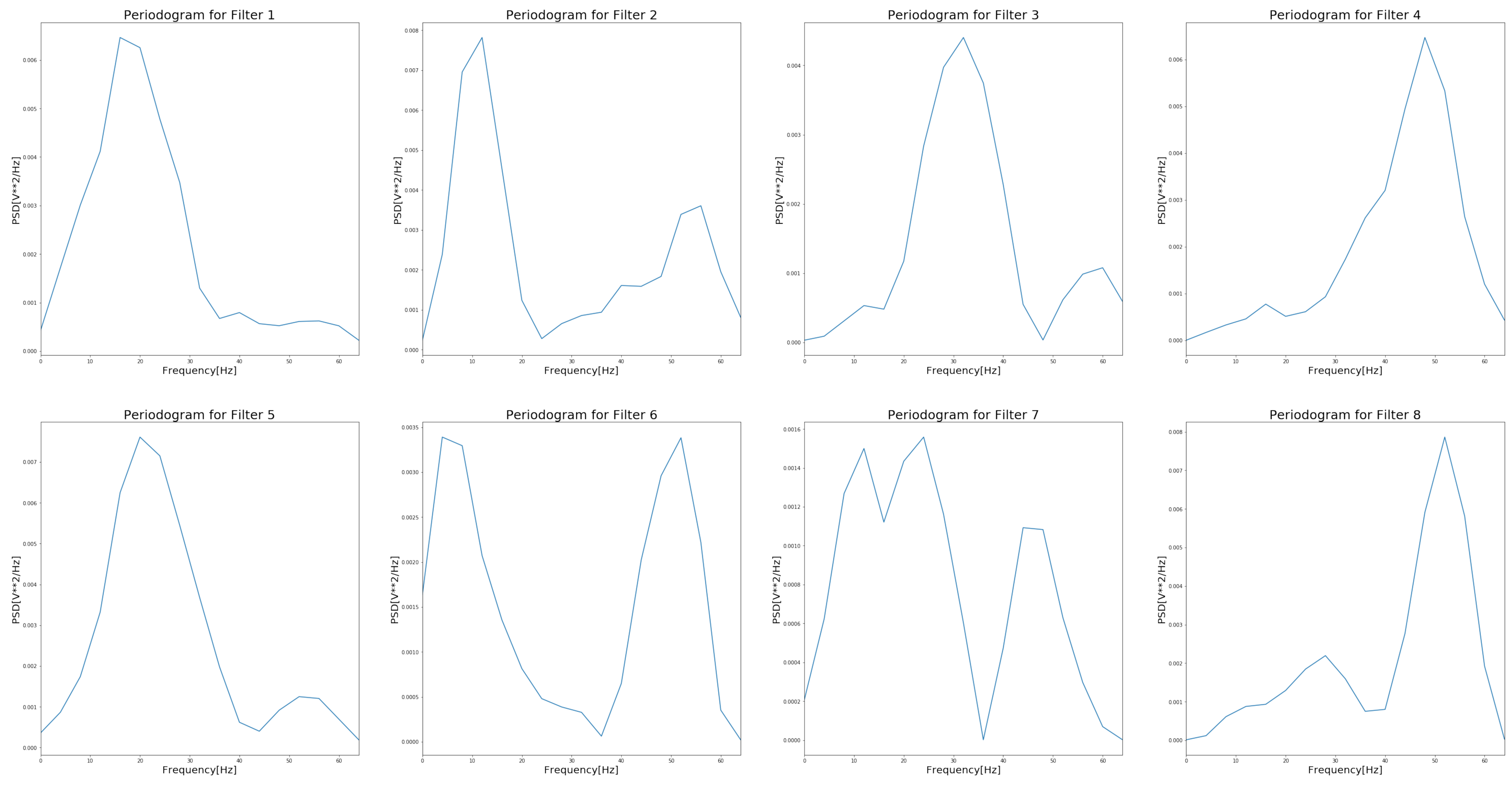

Figure 3:Visualization of the most relevant frequency

We also display also the spatial filter to locate the most impotant area of the brain.

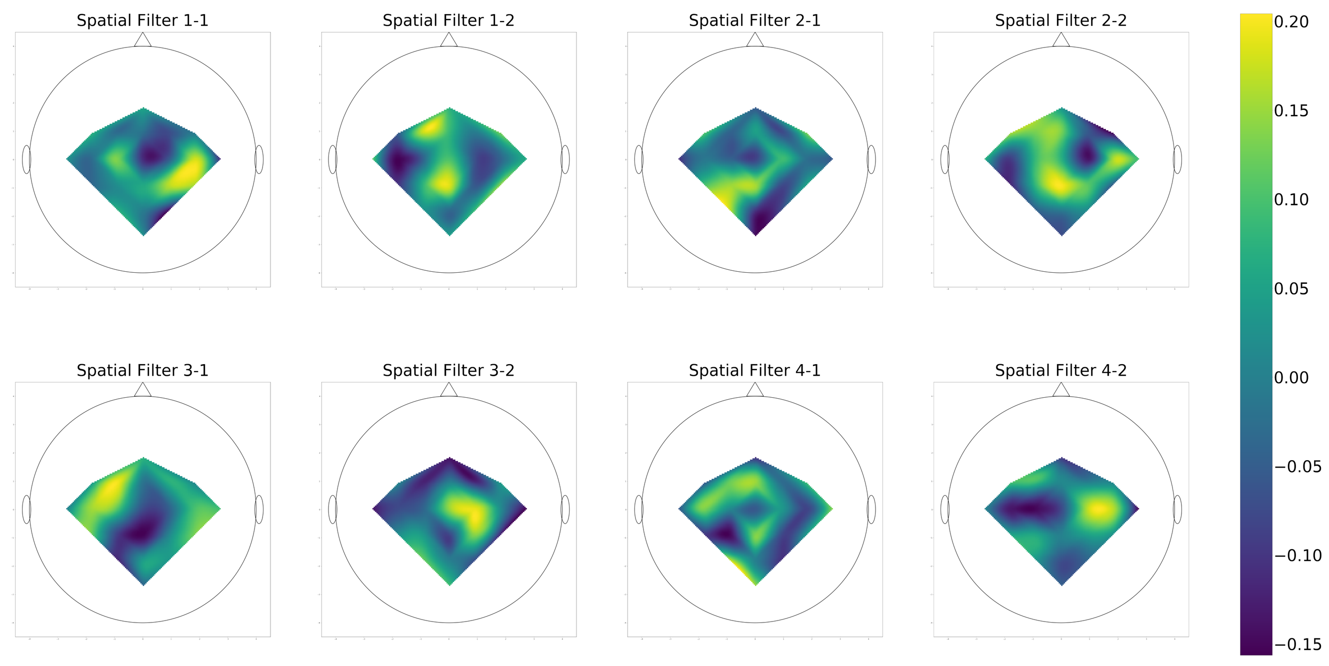

Figure 4:Samples of the visualization of the most relevant area

Conclusion

In this work, we designed a hybrid network composed of a ConvNet and an RNN. CNN was used to extract the temporal and spatial features and compressed the data, and RNN was used to process the data as a sequence. With the previous observations, we conclude that the proposed architecture is strongly compatible with brain waves detection problems and equivalent to the existent state of the art techniques. Also, we visualize the learned filters and we observe that the network learns to extract the mu and beta frequency bands.

References

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