Senior Thesis Progress Report

Topic: EEG motor imagery signal classification

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Introduction

A brain-computer interface (BCI) system enables users to communicate via neural signals such as EEG. The applications of BCI involve classification of EEG signals to convert them into control signals. Among many, Motor imagery (MI) is a popular signal. Motor imagery refers the simulation of a physical action e.g. imagining lifting arm without actually lifting it. The topic of this thesis is to develop a classification process for motor imagery signals. Several machine learning techniques such as logistic regression, SVM as well as methods presented in the literature are tested using a dataset with 3894 samples. Spatial covariance matrix appears to be an effective feature even across different people. To investigate the underlying pattern in the spatial covariance matrix, a convolutional neural network was built to classify spatial covariance matrices.

Data & Preprocessing

The dataset used for this project is from PhysioNet [3], one of the largest datasets online. The EEG data is collected with 64 channels and a sampling rate of 160 Hz. The data set contains motor imagery of both hand movements and foot movements from 109 volunteers.

It is known that motor imagery will decrease the energy in mu band (7 – 12 hertz) and increase the energy in alpha band (13 – 30 hertz). Therefore, a band pass filter of 7-30 hertz has been applied to the raw signal to get rid of the noise. In order to divide continuous signals into time-locked epochs for machine learning, the EEG signals come with time stamps when visual stimuli was presented to the volunteer. To avoid mixing motor imagery signals with evoked response of the visual stimuli, only signal 1 second after the visual stimuli was used. Each epoch lasts for 1 second.

The preprocessing of data is done with the help of MNE, a python library for visualizing and analyzing neurological signals. [4]

Input Format

The data that will be feed into machine learning classifiers is a 3D tensor of shape (samples, channels, time points). In the code, 3115 samples are used for training. There are 64 electrode channels. Since the sampling rate is 160Hz, the input data format is (3115, 64, 161).

Linear Classifiers on Raw Temporal Data

Linear classifiers including logistic regression and SVM perform poorly on raw time series of EEG.

Trained on 3115 samples and tested on 779 samples, a logistic regression with C=1 achieve only 49.1% accuracy.

To investigate useful information in the frequency domain, discrete Fourier transform was applied to each channel of the EEG data. The transformed data was then feed into the logistic regression classifier. However, the test accuracy came out to be only 49.5%.

Classification on Riemannian Geometry and Covariance Matrix

It is shown that the spatial covariance matrix could be related to motor imagery tasks[1]. In [1], the author proposes two classifiers based on the spatial covariance matrix. The spatial covariance matrix can be simply calculated by:

$$\mathbf{P}_i = \frac{1}{T_s - 1}\mathbf{X}_i\mathbf{X}_i^T.$$

Where X_i is a matrix of shape (num_channels X num_timepoints)

Since covariance matrices are always positive definitive, the author proposes that Riemannian geometry should work better than Euclidean geometry.

The first classifier, MDM (Minimum distance to mean) is similar to k nearest neighbor algorithm. It has three steps:

1. Converting the input EEG data into covariance matrices
2. Projecting the covariance matrix onto a Riemannian space. Find the centroid of each class.
3. To classify a new covariance matrix, simply identify the class with nearest centroid.

When MDM is used to classify EEG from the same person, the accuracy reached 72%. However, when applied to the whole dataset with 109 different subjects, the accuracy was only 53%.

Another classifier based on Riemannian geometry, tangent space classifier [1], is the application of LDA on Riemannian geometry. When applied to 150 samples across 3 different subjects, the accuracy reached 72%. When applied to the whole dataset with 3894 samples, the accuracy was 63.6%, still impressive considering 109 subjects have different EEG patterns even in doing the same MI task. It shows that the covariance matrix could contain useful underlying patterns.

It makes sense since covariance matrix is related to the energy in a signal. Covariance matrix also represents the correlation between channels. It is mentioned in [1] that different electrode corresponds to different motor imagery tasks (C3 corresponds to right hand, C4 corresponds to left hand, Cz corresponds to foot). It is also proposed in [2] that FC5, FC3, C5, C3, CP5, CP3 are affected by right hand, FC2, FC4, FC6, C4 are affected by left hand. It makes sense to assume motor imagery tasks will change the correlation between channels. When no mental task is performed, the channels appear in perfect synchronization with each other.

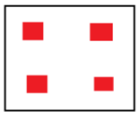
Covariance Matrix as An Image used for CNN

Since CNN is known to be good for object detection in image, we can consider a covariance matrix as an image and train CNN to detect the underlying pattern in the covariance matrix.

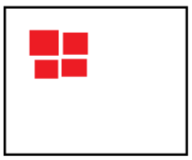
Rearranging channel orders

Before taking covariance matrix of a input matrix (64 channel X 161 timepoints), it makes sense to arrange closeby eletrodes togather. When we put relevant electrode togather, it should make it easier for CNN to detect the pattern.

If the relevant eletrode are spread out as shown in the pictuer below, the CNN kernel might not able to capture the pattern, especailly in case when kernel size is small (3 X 3)

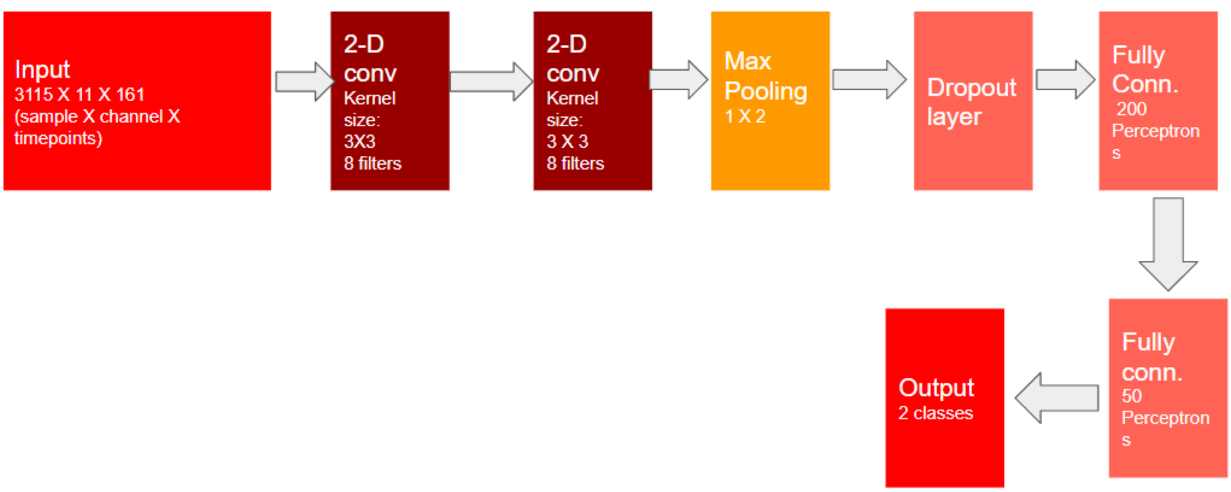


If we put the relevant electrodes togather, it is more likely for the kernel to recognize this pattern.



From[2], the author proposes that FC2, FC4, FC6, C4 are affecting left hand MI, FC5, FC3, C5, C3, CP5, CP3 are related to right hand MI, and from [1] CZ is related to foot MI. We can discard the rest electrodes since they will likely introduce noise. The new arrangement of electrode is: FC2, FC4, FC6, C4, FC5, FC3, C5, C3, CP5, CP3, CZ.

Architecture of Convolutional Neural Network



The first two layers are convolution layers. The kernel size is set to be 3 by 3. There are 8 filters in this layer. Relu is used as the activation function.

A max pooling layer is used for dimension reduction.

A dropout layer is used to prevent overfitting.

Two fully connected layers with 200 and 50 perceptron are used

Softmax function is used for the classification on the last step.

Result

The loss function does not show a significant decrease. The classification result is 59.23%.

Discussion and next steps in research

Even though CNN for covariance matrix does not show a significant improve on the accuracy, covariance matrices are indeed effective in classifying motor imagery EEG data. There are two difficulties: signal to noise ratio and transfer learning. Since EEG is notoriously noisy due to stronger biosignals such as EOG and EMG, rejecting artifacts in the training set should be a focus in the next phase of the research. Another difficulty is that the experience learned from one person cannot be easily transferred to another person. However, the tangent space classifier and CNN on covariance matrix displays a 60% accuracy even when applied to data across 109 patients, proving that the covariance matrix does contain a useful underlaying pattern. Another focus in the next phase of research should be on transfer learning in the classification of EEG.

Work cited:

[1] Barachant, A., Bonnet, S., Congedo, M., Jutten, C., Apr. 2012b. Multiclass Brain Computer interface classification by riemannian geometry. IEEE Transactions on Biomedical Engineering 59 (4), 920–928.

[2] Marchesotti S., Bassolino M., Serino A., Bleuler H., Blanke O. (2016). Quantifying the role of motor imagery in brain-machine interfaces. Sci. Rep. 6:24076. 10.1038/srep24076

[3] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. *Circulation* **101**(23):e215-e220

[4] A.Gramfort, M. Luessi, E. Larson, D. Engemann, D. Strohmeier, C. Brodbeck, R. Goj, M. Jas, T. Brooks, L. Parkkonen, M. Hämäläinen, MEG and EEG data analysis with MNE-Python, Frontiers in Neuroscience, Volume 7, 2013, ISSN 1662-453X