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Improving accuracy of brain-computer interface with multiple tries

Master's Thesis (30 ECTS)

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Abstract:

Brain-computer interface (BCI) is a computer system for extracting brain electronic neural signals and using them to control computer applications. Beside measuring, BCI converts raw signals to digital data and maps the data to the exact computer commands. Unfortunately, the probability of the right command prediction is usually below 100% and therefore it could be improved.

This is a problem for BCI systems, since they will not be widely trusted and used until the prediction accuracy is relatively low. There are many existing solutions which provide increase of the prediction accuracy mainly based on trying out different classification techniques and algorithms. Existing methods focus mostly on a training part of the system. Our approach is to try to improve the accuracy upto 99.9% experimenting with test part algorithms and to determine how many tries it is required during the test mode to reach the desired provided accuracy.

The solution described in a thesis is based on Condorcet's jury theorem. It means that if we have single events which probability is more than 50%, then by combining them together the total probability for these events will rise. This work shows the actual results (prediction accuracies) and provides their comparison using the ensemble techniques based on the Condorcet's jury theorem. It also describes the dependency of the number of test mode measurements and accuracies.

The BCI technology is relatively young direction. In order to fully integrate it to our ordinary life the contribution from the scientist and engineers is required for composing and choosing the most reliable system with the components. The following work represents a contribution to the brain-computer interface field.

Keywords: Brain-computer interface, Random Forests

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1 Introduction

Motivation

Many health issues can disrupt the neuromuscular channels which brain uses to communicate with different parts of organism. Channels are used to control muscles and pass the feelings. With these controls, a human can successfully participate in an ordinary life, controlling the surrounded environment. Amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, and numerous other diseases cause problems in neural channels or the muscle control performance. There are three ways how to restore muscle disabilities. The first is to increase capability of the existing neural channels. Which means to use existing well-functioning muscles to fulfill suffering ones (e.g use of hand movements to produce artificial speech). The second one is to use control signal measurement systems (electromyography) in order to record signals sent to muscles, translate them and repeat the action in a prosthesis. The last option is to attach to a brain non-muscular communication module as a control channel which is BCI.[1]

Unfortunately, BCI systems have relatively low prediction accuracy, which makes nowadays their implementations too "raw". There a lot of ways how BCI data is handled in order to get better results, but none of them are perfectly accurate.

Scope

This work consists of creating a BCI application which will communicate with Emotiv EPOC headset and try to predict user distinct thoughts about the targets provided by the application. The application will work in two modes. The first learning mode for obtaining test data samples to "teach" an algorithm and give better output results in future. This is necessary step to perform for every new user (subject). The second testing mode is for checking the accuracy of prediction by the algorithm. When the predictions based on a single measurements will give a relatively high accuracy, a multi-measurement session will be run. A multi-measurement mode considers taking into account several classification results made in a row and choose the most suitable with ensemble voting algorithms. Expected to get higher results with increase of the number of classification samples participating in voting. The results from single and multi-try sessions will be recorded and compared to the expected. The application will be available to work in offline (classification will be done after the dataset is recorded) and online modes (classification will be done instantly after sensors data is recorded).

Research problem

Multi-measurement could bring better prediction result than single. The objective is to determine how multi-measurement mode's accuracies differ from single-measurement's and how the number of classification samples will improve the statistics. The results will be compared to theoretically calculated ones.

Contribution

Implement an application to get measurements first of all from a single try. Select and teach the system to process the results. Calculate the theoretical prediction accuracy for multi-try sessions based on single try session results. Run of multi-try sessions with validating results and compare them to the theoretical values.

Structure

Current thesis structure is as follows:

- Background / State of the Art - significant technologies which are used in current work are described along with comparison to similar projects
- Contribution - list of work done, grouped by the domains of the system followed with meaningful details
- Validation - test sessions with output results described
- Discussion - difference to theoretical model and limitations of the system are provided
- Conclusion - sum up of the goal, expected and actual results with brief explanations and future adaptation propositions

2 Background / State of the Art

2.1 Brain-computer interface

Brain-computer interface (BCI) is an interface that does not require muscle control from user to communicate with a device. It requires user to think about the distinct target. The interface records electroencephalographic (EEG) signals from the scalp surface which represents our brain activity. These signals have low amplitude (usually measured in microvolts) whereas frequencies above 30 Hz have especially low values which tends to zero.[2]

The signals could be translated into a control commands for the certain devices, what is especially useful for the people suffering from lock-in (e.g. Brainstem stroke, or severe polyneuropathy) or lack of muscle control. BCI systems could give such people a possibility to answer simple question quickly, control the environment, perform word processing or even operate a neuroprosthetics or orthosis. There are two types of BCI available: one way and two way. In case of one way type, a computer is accepting signals from the measuring device. Two way system deals with exchange of information between both sides.[3]

BCI system structure could be divided into the four modules[3]:

1. Source Module This module digitizes and saves signals coming from brain without handling them. This component knows how to obtain data from the sensors and store it to the specifically formatted file. This data samples are usually mapped to the sensor names (every sensor located on the scalp has it's own name determined by location) and event classifier.
2. Signal Processing Module This module is responsible for conversion of raw data signals into something more meaningful for controlled machine or the commands. Conversion is divided on two stages: feature extraction and feature translation. The extraction considers receive a data from source module and prepare it for translation module which means obtain of the signal properties like frequency domain values for the given sensors. The feature translation is an algorithm which determines which control signal was sent with a given signal data.
3. User Application Module: Next to signal processing module an application module takes the control signal to perform operations in an application. Usually an application has it's own graphical interface which allows user to select and think about some sort of targets like letters, images, icons or directions. A user could also give his feedback about the prediction validity through the application. The feedback could be given orally or tactilely.

4. **Operator Module** It is a module which defines system constants and parameters like learning mode length, targets or any kind of signal processing variables. In addition, this module could plot the information on graphics without knowing of the input data nature. This allows a user to see real-time feedback about happening events.

BCI use is a skill which requires practicing. An algorithm which translates the signal features to the control signal should “learn” to output with the more accuracy. A learning is performed based on the feedback user gives to it. That means, a user should participate in the algorithm teaching for many sessions. In addition, a user should try to think in the same way he do it usually during the sessions. Otherwise, it might get a negative impact when subject feels some sort of distractions. These exercises require concentration and it takes time to get used to it.

2.2 Emotiv EPOC

To obtain a raw signal data from the scalp we use Emotiv EPOC BCI headset. It is a multi-channel wireless (communicates using Bluetooth) headset with 14 channels (sensors) for the following international locations: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. The device converts an analog signal to a digital with a 14 bits resolution and 128 Hz sampling rate. The bandwidth is 0.2 - 45 Hz. This suite can monitor the user’s emotional state in real time.[4]

It comes with the out of the box softwares Control Panel and TestBench which visualize the features based on the signal. The Control Panel software outputs recognized emotional states, facial expressions and mental commands. With TestBench it is possible to see a raw or EEG signal regarding distinct channels. In addition it provides a signal quality for the sensors and the connection status between the headset and Bluetooth receiver.

2.3 Short Time Fourier Transform

In a features extraction level a raw complex signal wave should be decomposed to the subwaves. Subwaves helps to construct a frequency domain representation of the complex signal where frequencies and respective amplitudes are mapped together. Although in terms of spectral analysis Fourier Transform is dominating, in case of nonstationary signals where EEG signal belongs better to use short time Fourier transform (STFT).[5]

In STFT, a signal is split on datasets (frames) with N samples, where N represents a window length. This frames overlap with 50% between each other. Before

the Fourier transform a Hanning window is applied to reduce aliasing of the signal. Finally, after Fourier transform within STFT the result is outputted.

2.4 Random Forests algorithm

As described above, the goal of translation phase is to understand what control signal has been described with signal features received from the extraction phase. That means we should classify our data samples, where the classes would be a set of targets a user should deal with. There are many classification machine learning algorithms available.

A machine learning algorithm itself is a data-driven algorithm, that predicts in which data group a new input value belongs. These decisions are made based on the existing data samples which are grouped by some property. There exist two types of algorithms: supervised and unsupervised. A supervised algorithm deals with labeled (classified) data samples, so that groups of data have own class label, whereas an unclassified algorithm does not know anything about the data as well as the classes. Unsupervised algorithm is a good way to analyse the data without knowing it well and what to get from it. However, in our case we know that we should recognize the targets and thus, we will choose supervised type.

For the classification we will use Random Forest algorithm which is the most suitable for the work with EEG data, according to the [6]. It shows better classification accuracy and performance than the other modern algorithms. It's accuracy dominates over the other algorithms in case of parameter optimization, which we plan to do as well.

A Random Forest Tree is an adaptation of Decision Tree algorithm developed by Leo Breiman and Adele Cutler, where instead of using single tree, a bunch of trees are used. Every one of these trees is generated by using randomly selected subsets of the existing data samples. Finally, each of every tree is handled separately to find out it's predicted class and with a majority vote from every tree a final result is defined. Random Forest model does not overfit. Using the right kind of randomness brings accuracy in solving classification and regression problems, however regression problems have lower accuracy.[7]

2.5 Collaborative Brain-Computer Interface

Yijun Wang *et.al* describes in [8] a technique which has similar approach to this work. The main idea of their work to use collaborative EEG input data for predictions. They made a decision-making experiment using multiple users (subjects) thinking about the same targets simultaneously. Subjects must make Go (target) or NoGo (non-target) decisions in scope of their application.

The application shows them images where are animal images (target) and others (non-target). With a period of 20ms one of the shown images is flashing and the subjects must make a decision about does it belong to a target group or not. The decision is done by pressing or releasing a button, thus a motor inhibition process was invoked (movement-related signal).

Every subject had to train the algorithm and test it in a single user mode. Subjects managed to reach mean classification accuracy of 75.8% with using mean response time (reaction time) 377 ms. Already this pointed on reliable prediction with single-trial usage. A collaborative classification was tried considering 5,10,15 subjects simultaneously which resulted 91.4%, 97.6% and 99.1% accuracy respectively. This clearly shows improvement over the single-trial classification.

In case of multi-user approach a weighted voting system was used, where a subject with a better prediction statistics got more weight and influenced the output result more in the future classifications. This is the technique what our solution will use along with multi-try classification. Our goal is to use multiple tries of a single user instead of single tries of several users as the related work tends to do. Our way is to use optimized Random Forests classification algorithm which according to [6] could bring the more precise result, than support vector machine (SVM) algorithm which is used in animal classifications. Finally, a single user approach has wider fields of use and less complex in implementation as a multi-user technique.

3 Contribution

3.1 Application overview

For fulfilling goals in the related topic a custom application was written using Python 2.7 programming language. The application contains the following components:

- Raw data reader - connects to a BCI headset over Bluetooth and reads raw data
- Preprocessing - does Short-time Fourier transform of a bulk raw data and determines signal amplitudes for desired frequencies (features)
- Data storer - stores preprocessed data to a file system (e.g CSV file)
- Classifier - a machine learning algorithm which teaches classifier and uses it to predict preprocessed a target based on features
- Voting handler - in case of multi-try sessions it is used to select the right answer
- Main application - provides a command-line user interface to select application modes and run necessary components

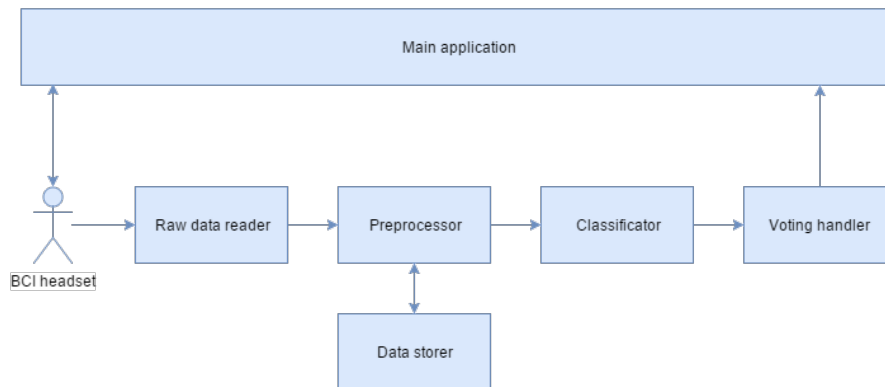


Figure 1: Application component model

3.1.1 Raw data reader

This component is required to poll the Emotiv EPOC headset and store sent data to a temporary buffer. The communication between computer and headset is established over a Bluetooth Smart network through a USB dongle provided from the manufacturer. Emokit[9] open-source library with minor changes is used to read the data coming to USB dongle from a headset, decrypt and encode it. Polling is done in an infinite loop. Taking into account sampling frequency of the device - 128 Hz, every 8 ms a new signal is received from the headset and stored in a queue.

3.1.2 Preprocessing

During preprocessing a set of raw samples is converted to a frequency domain representation. To do this the Short Time Fourier Transform is used with a sliding window. Sliding window technique allows to capture more precisely non-constant signals. Sliding window length equals to 1 s with 0.5 s overlapping. These factors increase the number of samples to:

$$2 * N - 1$$

where N is the original number of samples.

According to Emotiv EPOC specifications[4] 45 Hz is the maximum bandwidth value for the signal. In our implementation we use 1 - 45 Hz for the frequency range.

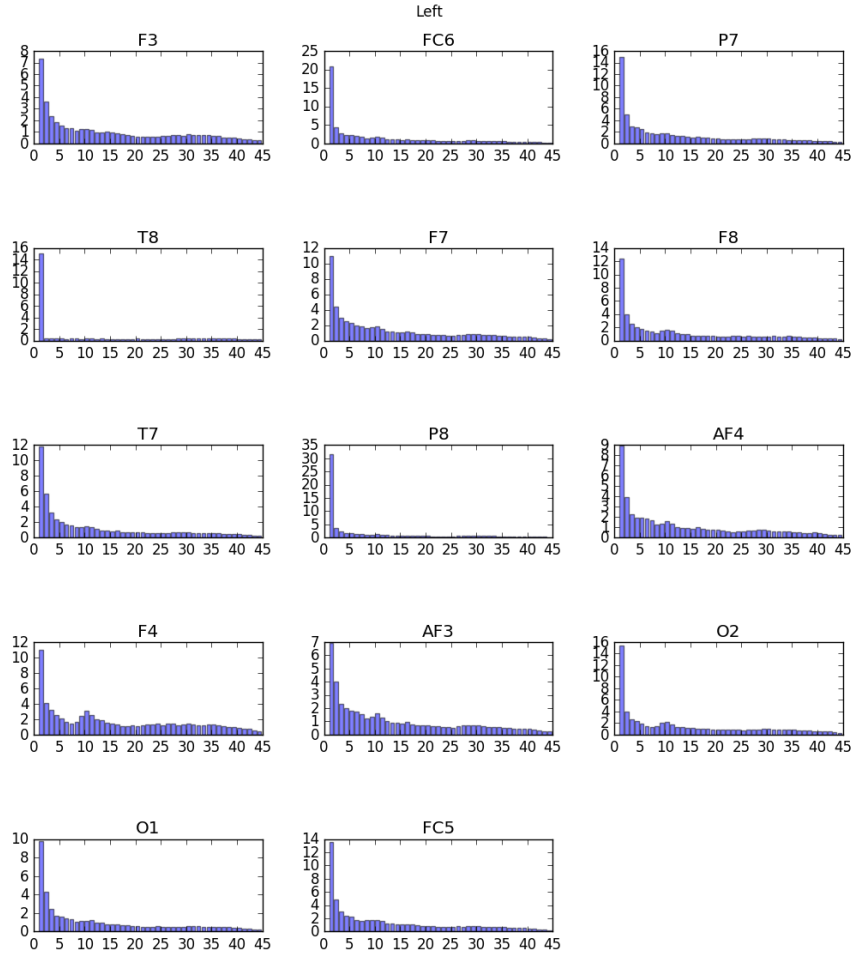


Figure 2: A sample frequency domain plot while concentrating on "Left" target.

4 Validation

5 Discussion

6 Conclusion

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