Requirements for Brain – Computer Interface

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Abstract

Brain – Computer Interface (BCI) aims to create a direct communication between the brain and an external device. The main data source for BCI systems is cortically evoked electro potentials recorded via an electroencephalogram (EEG). Originally this technology was intended for paralyzed people, however recently low cost, portable EEG recording devices became available, making non-clinical applications possible.

In this paper non-functional requirements for commercial BCI system are discussed. Main requirements for data acquisition are ease of use and reliable transmission to signal processing devices. For signal processing speed, accuracy and adaptivity are important.

An experiment in case study section shows an example how implemented requirements affect performance of BCI.

1. Introduction

Brain – Computer Interface (BCI) is a technology, which aims to convert electrical brain activity into control commands for a computer or other devices. The major goal of BCI research is to develop systems that allow disabled people to communicate with their environment [1]. However, as this technology becoming cheaper other applications including multimedia communication, robot control and game development are emerging.

Like most control systems, a BCI has three basic elements: an input, an output and a translation algorithm that converts the former to the latter [2]. Additional unit may be used to manage communication between system elements. BCI systems require correct classification of signals from the brain for useful operation. After acquiring the data, feature extraction and dimensionality reduction is performed, before machine learning algorithms can be applied to classify the signals into classes, where each class corresponds to a specific mental state of the user (Fig. 1).

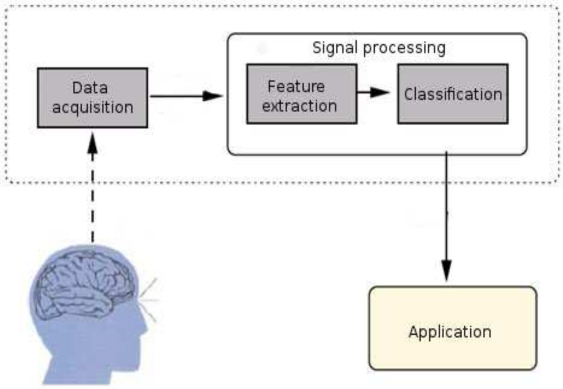

Fig.1. BCI elements.

The main data source for BCI systems is cortically evoked electro potentials recorded via an electroencephalogram (EEG). Since EEG is relatively cheap and non-invasive method of recording brain activity many scientists across the world are trying to analyze this data and differentiate the classes of metal states. However, this is difficult task, because EEG signals are non-linear and usually interfered by eye and muscle movements [3].

EEG recording devices usually consist of electrodes, analog amplifier and analog-digital converter (ADC). Number of electrodes varies from 1 to 128 or even more. Each electrode represents different position on a scalp and referred as EEG channel. In medicine electrolyte gel is used to improve contact between electrode and skin. Nevertheless dry capacitive electrodes can also be used [4].

Recently low cost, portable EEG recording devices became available, making non-clinical applications possible [5]. However, there are some non-functional requirements that need to be addressed in order to create commercially successful BCI system. These requirements are discussed in following sections.

The rest of the paper is organized as follows. Section 2 discusses requirements for data acquisition, while section 3 presents requirements for signal processing algorithms. Section 4 shows how implemented requirements affect performance of BCI system. Finally, conclusions are presented in section 5.

2. Data acquisition

The EEG signal has become the main data source of BCI study due to its low cost and non-invasive nature. Despite the fact that data acquisition is a medical process, it should be as easy as possible for the user. Traditional gel electrodes are difficult to use in real world environment. It takes a lot of time to prepare for work and may cause discomfort. Beside that gel may dry out over the time, so it is not suitable for long-term use.

To overcome these limitations dry capacitive electrodes can be used. In this case the signal is measured by capacitive coupling between body and electrode. With capacitive electrodes the preparation procedure for measuring the EEG is reduced dramatically, especially for a high number of channels. In 2007 Popescu et al. made comparison between dry and gel electrodes [4]. Performance of 6 dry electrodes and 64 gel electrodes was tested in the context of a well-established BCI cursor control paradigm. Experimental results shows, that dry electrodes were less accurate, however amount of raw EEG data was significantly lower.

Despite advantages of dry electrodes, modern BCI system should use as less channels as possible. This would reduce hardware complexity and increase user-friendliness.

During EEG recording large amount of raw data is obtained, so reliable transmission to signal processing device is required. Portable recording devices often use wireless communication channel with limited bandwidth. Due to the large data size of the EEG resulting from large number of electrodes, long recordings and usually high sample rate, data compression is required for efficient data transmission. Efficient compression of the EEG signal is a difficult task due to randomness inherent in the signal, and hence high compression rates cannot be achieved with lossless compression methods [6]. However, for non-clinical applications lossy compression techniques can produce acceptable results.

3. Signal processing algorithms

Since Brain – Computer Interface are aims to control real world objects, time constrains are important. As any other system BCI has delay between input and output. This delay consists of hardware and software delays. Besides that, BCI has physiological delay, which occurs while change of mental state is register by a recording device. Hardware and physiological delays are hard to overcome, but software delay can be reduced by using efficient signal processing algorithms.

As mentioned before, EEG data is non-linear and inherent complex, its analysis requires lots of computations [7]. As a result computation time is considerably higher than hardware delay, therefore fast and efficient algorithms must be used.

Usually the algorithms are divided into feature extraction and classification. Feature extraction generates the feature vectors with data useful for classification, while noises are eliminated. Classification attempts to assign each input value to one of given set of classes. An important factor affecting the efficiency of BCI is the number of EEG features. Reducing the number of features is an important way to improve the speed [8]. A number of feature extraction methods exist for BCI applications, such as Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) [8].

BCI system must be adaptive and function correctly with different users. A variety of machine learning and artificial intelligence methods are used for EEG data classification such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and Artificial Neural Network (ANN) [7]. These methods use training to adapt to specific user. One of the requirements for commercially successful BCI system is short training time. Training is a numerical optimization of a non-linear error function. There is no single best method for this problem. Usually training time can be reduced by reducing number of inputs and neurons. Also early stopping may be applied. This technique is a simple but efficient way to deal with prolong training time and the problem of overfitting [8].

Another important factor concerning signal processing is classification time. After training stage machine learning algorithm should classify input before new one comes.

4. Case study

4.1. Materials and method

To evaluate how discussed requirements affect performance of BCI we have designed an experiment [8]. For experiment dataset Ia (Tubingen, ‹self-regulation of SCPs›, subject 1) [9] from the BCI competition datasets (http://bbci.de/competition/) was used. The dataset were recorded using a healthy subject during feedback sessions. Training dataset consists of 268 trials, testing of 293 trials. Each trial consists of 896 samples from each of 6 channels. Since commercial BCI should use as less channels as possible, we used data from channel 1 only.

In this experiment, all computations were carried out using MATLAB. Classification error measured as a ratio of false results and total number of trials (1):

$$err = \frac{n - n_{true}}{n} \cdot 100\% \tag{1}$$

where n is total number of trials, n_{true} is the number of trials with correct classification result. Training speed was evaluated by an average time needed for one artificial neural network training. A PC running Debian Linux with an AMD Phenom II X4 (3.6 GHz) processor and 8GB RAM was used.

For feature extraction the method of DCT (2) was applied to convert the time domain data to frequency domain [10].

$$Y(u) = \sqrt{\frac{2}{N}}\alpha(u)\sum_{x=0}^{N-1} f(x)\cos\left(\frac{\pi(2x+1)\cdot u}{2N}\right) \qquad (2)$$

where

$$\alpha(u) = \begin{cases} \frac{1}{\sqrt{2}} & if\ u = 0 \\ 1 & if\ u \neq 0 \end{cases}$$

The input is a set of N data values and the output is a set of N DCT transform coefficients Y(u).

Using this method low frequency components are concentrated in first coefficients and high frequency – in last ones. Since in EEG signal low frequencies are dominant [7], only the first coefficients can be used for classification using machine learning algorithm. Therefore, first 50 coefficients of every trial were taken for further investigation.

Afterwards, different topologies of feed forward artificial neural network with one hidden layer were created. Number of hidden neurons (denoted as N) was 2, 5, 10, 20, 30, 40, 50 and 70. In all cases output layer has only one neuron with a tan-sigmoid transfer function (Fig. 2). With each chosen configuration 15 artificial neural networks were trained and average training time and error measured.

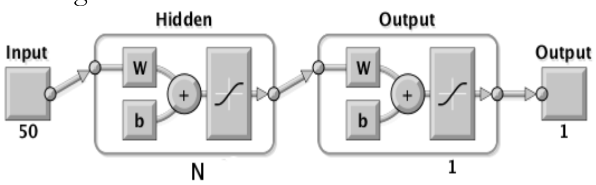

Fig.2. Neural-network configuration.

Networks with the same configuration were presented with raw EEG data, without feature extraction. In both cases the same computer and training function was used [8].

4. 2. Results

Experiment results are summarized in Tab. 1.

Tab. 1.

Comparison table.

	DCT		Raw EEG	
Hidden neurons	Training time, s	Average error,%	Training time, s	Average error, %
2	0.87	19.3	1.32	21.0
5	0.84	14.0	1.32	15.9
10	0.85	13.0	1.57	15.3
20	0.90	12.7	1.69	12.6
30	0.94	14.3	1.89	12.6
40	1.00	15.8	1.98	12.7
50	1.04	15.4	2.35	11.9
70	1.18	15.6	2.50	13.9

Results show that using feature extraction, we can decrease training time by over 50%. This is very important for real time applications. Also input vectors of raw EEG are bigger and more hidden neurons are needed to classify raw data. This requires more memory to a train neural network and store weights. Besides that, classification time is longer with more hidden neurons.

On the other hand, raw EEG classification shows slightly lower error. Classification error of reduced dataset is about 1% higher, but it is acceptable for real world non-critical applications like game development.

We can see that by improving training speed classification accuracy is lost. This conflict between requirements is frequent when designing real world applications.

5. Conclusions

In this paper, we discussed requirements for commercial Brain – Computer Interface. In BCI system there are two kind of non-functional requirements. Main requirements for data acquisition are ease of use and reliable transmission to signal processing devices. Portable EEG recorders can be easily used, however wireless data transmission is challenging. For signal processing speed and accuracy are important. Besides brain signals of every person are different, so BCI system must be adaptive.

As expected, requirements are in conflict with each other. By improving one of the requirements, other may be hurt. This is illustrated by an experiment. Experimental results show that training and classification time decreases drastically when a reduced dataset is used. This is very important for real time applications. However, classification accuracy of reduced dataset is slightly lower. This trade-off must be set according to specific application of BCI system.

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