Design of an EEG-based Brain-Computer Interface (BCI) from standard components running in real-time under Windows

Entwurf eines EEG-basierten Brain-Computer Interfaces (BCI) mit Standardkomponenten das unter Windows in Echtzeit arbeitet

Christoph Guger [1], Alois Schlögl [1], Dirk Walterspacher [1], Gert Pfurtscheller [1,2]

[1]Institute of Biomedical Engineering, Department of Medical Informatics

[2]Ludwig-Boltzman Institute for Medical Informatics and Neuroinformatics

University of Technology Graz

Brockmanngasse 41, 8010 Graz, Austria

Tel.: (+43) 316 8735311

Fax: (+43) 316 812964

e-mail: guger@dpmi.tu-graz.ac.at

pfu@dpmi.tu-graz.ac.at

Abstract

Key words: adaptive parameter estimation, brain-computer interface (BCI), event-related desynchronization (ERD), on-line EEG classification, rehabilitation

An EEG-based brain-computer interface (BCI) is a direct connection between the human brain and the computer. Such a communication system is needed by patients with severe motor impairments (e.g. late stage of Amyotropic Lateral Sclerosis) and has to operate in real-time.
This paper describes the selection of the appropriate components to construct such a BCI and focuses also on the selection of a suitable programming language and operating system. The multichannel system runs under Windows 95, equipped with a real-time Kernel expansion to obtain reasonable real-time operations on a standard PC. Matlab controls the data acquisition and the presentation of the experimental paradigm, while Simulink is used to calculate the recursive least square (RLS) algorithm that describes the current state of the EEG in real-time.
First results of the new low-cost BCI show that the accuracy of differentiating imagination of left and right hand movement is around 95 %.

Schlüsselwörter: Adaptive Parameterschätzung, Brain-Computer Interface (BCI), Event-Related Desynchronization (ERD), On-line EEG Klassifikation, Rehabilitation

Unter einem EEG-basierten Brain-Computer Interface (BCI) versteht man eine direkte Verbindung zwischen dem menschlichen Gehirn und einem Computer, die von Patienten mit schweren motorischen Störungen für eine verbesserte Kommunikation mit der Umwelt verwendet werden kann. Voraussetzung ist eine Interaktion in Echtzeit.
Dieser Artikel beschreibt die Auswahl geeigneter Hardware-Komponenten, sowie eines passenden Betriebssystems und passender Software um ein BCI aufzubauen. Das realisierte Mehrkanalsystem läuft auf einem normalen PC unter Windows 95, das mit einem zusätzlichen Echtzeit-Kernel ausgestattet wurde, um die geforderte Antwortzeit zu erfüllen. Die Datenaufnahme und der Ablauf des Experiments werden von Matlab gesteuert, während Simulink zur Berechnung des rekursiven Parameterschätzungs-Algorithmus verwendet wird, der den aktuellen Zustand der bioelektrischen Hirntätigkeit beschreibt.
Erste Ergebnisse des neuen BCI-Systems zeigen, daß vorgestellte rechte und linke Handbewegungen mit einer Genauigkeit von rund 95 % klassifiziert werden können.

1. Introduction

EEG-based communication systems realize a direct connection between the human brain and the computer [4, 15, 16]. They represent an important area of EEG analysis and can help patients who suffer from severe motor impairments (e.g. Amyotropic Lateral Sclerosis). A patient without control of voluntary movements could use such a system to install an alternative communication channel through thoughts, whereby such an interaction must be realized in real-time. A possible application of such an EEG-based brain-computer interface (BCI) is not only to move a cursor by mental control, which allows the patient to select letters or words [16], but also the control of e.g. a Functional Electrical Stimulation device for patients with spinal cord lesions [12].

These applications can be controlled by at least one binary output signal of the BCI which is obtained, for example, by classification of EEG-patterns during imagination of left and right hand movements. Imagination of unilateral hand movement causes an event-related desynchronization (ERD) of sensorimotor rhythms close to contralateral primary motor areas [9, 10, 11]. Sensorimotor rhythms include Rolandic mu rhythms and central beta rhythms as well, whereby the desynchronization of both related to movement is slightly different with a beta ERD focus more anterior. EEG classification results can be improved therefore, when not only 2 EEG channels close to electrode position C3 and C4 are used, but an array of electrodes overlaying sensorimotor areas [8, 13].

Currently used EEG-based BCIs need a DSP-board in addition to a PC [4, 6, 16] to ensure enough computing power. This results in high complexity, is difficult to program (sometimes even in assembler language) and is relatively expensive. Such systems run under operating systems which can only be controlled by people with technical background.

The goal of this paper is to show the development of an efficient, inexpensive and easy to handle BCI-system that is capable of analyzing multichannel EEG-data in experimental and clinical settings and can also be used by patients with severe motor disabilities who live at home.

Building a multichannel data acquisition system from basic components is expensive, but recent advances in electronics have made it possible to build such a system with standardized components available from many different suppliers capable of fulfilling the following requirements:

- recording, analyzing and classifying EEG-data in real-time,
- using the results of the classifications to control a device on-line,
- designing different experimental paradigms and giving multimodal stimulations,
- displaying the EEG channels on-line on a monitor,
- storing all data for later off-line analysis.

This paper describes the selection of the appropriate high-level components that fulfil these requirements and also focuses on the selection of a suitable operating system and programming language.

2. Designing an EEG-based BCI-system

STEP 1 - Identification of I/O signal types

The system that was set up in our lab is capable of managing a maximum of 96 EEG channels, which might be useful for future research when electrodes will be implanted [5]. The channels are multiplexed to reduce the number of analog to digital converters (ADC) needed. The number of multiplexed channels per ADC is limited by the sampling rate necessary for each EEG channel (128-512 Hz).

Digital Input/Output (I/O) channels are needed to control external hardware such as a remote control or to simply give a trigger signal to an external device.

Further, it might be necessary to give commands via a digital to analog converter (DAC) to the external world for controlling a device in real-time.

Figure 1

STEP 2 - Selection of an appropriate data acquisition I/O device

For our system we use RTI800a boards from Analog Device, with 32 single ended analog input channels each as shown in Figure 1. It employs a high speed parallel bus interface and is a single slot board typically mounted inside a PC. Every card works with one ADC and a 32 channel multiplexer to enhance the channel count. The ADC has a resolution of 12 Bits and has a flexible acquisition rate which can be varied via software. Our experiments commonly use a sampling rate at 128 Hz. A Programmable Gain Amplifier (PGA) allows low-level signals to be measured accurately. Several different levels of input signals can be brought in simultaneously with a different gain being used for each.

EEG signals are amplified, filtered, converted from analog to digital and stored under control of a computer. These functions are accomplished with commonly available products. The components communicate via a bus system. For a BCI-system the selected bus standard must provide a data troughput that is able to keep up with the chosen sampling rate of the input channels. A system, for example with 96 channels, 128 Hz and 12 Bit resolution, needs a continuous data troughput of approximately 20 kByte/s. A widely accepted bus that is suitable for this is ISA. ISA has the advantage that the costs are low and the physical dimensions are small. The signal types that are described under step 1 are available on many ISA boards. The RTI800a board is equipped with 8 digital inputs and 8 digital outputs which is sufficient to relay trigger signals or to control, for example, a remote control. VXI or GPIB busses are too expensive and larger than ISA. The prices of the new PXI bus products are comparable to those of ISA, but PXI is an entirely new standard and therefore, only a few boards are available.

The great advantage of ISA compared to other bus standards is that the synchronization of the boards is handled from a normal PC motherboard and therefore requires no extra controller cards.

Of course, the PCI bus would also be suitable for the BCI-system, and at present, every PC is equipped with PCI slots, but these are more expensive than ISA boards.

The mainboard of our choice was finally a TOMCAT (TYAN Computer Corporation, Milpitas, USA) equipped with a 233 MHz Pentium II MMX processor and three ISA slots for three long ISA DAQ-boards.

The system is expandable to 96 channels if we use three RTI800a DAQ-boards and a suitable amplifier, thus. All data acquisition boards are housed in a normal PC mainframe.

Simultaneous sample&hold is not necessary for EEG processing. At a conversion time of 12 μs and 32 channels per ADC, a maximum synchronization error of 384 μs is introduced which is negligible for 128 Hz sampling rate.

Graphic controller and network adapter were plugged into PCI slots to keep the ISA slots free.

STEP 3 - Selection of an operating system and software programming method

In order to control all the hardware, it is important to have a powerful software package that includes all the necessary drivers for the DAQ-boards. Further, it is important to support new standards of operating systems. At present, Windows is the de facto desktop standard and a tremendous amount of software is available. But it is not real-time. Therefore, the PC, with Windows 95 installed, was equipped with a real-time Kernel expansion. Windows enables users with less experience on computers to comfortably handle this new BCI-system. For the same reason, it is important to choose a programming language that enables an easy set up or adaptation of the programs for data acquisition, the experimental paradigm and signal analysis methods.

For this purpose Matlab (MathWorks, Inc., Natick, USA), in combination with the signalflow oriented Simulink Toolbox (MathWorks, Inc., Natick, USA), was chosen. Simulink is used for the calculation of different parameters which describe the current state of the EEG in real-time, while Matlab handles the data acquisition, timing and presentation of the experimental paradigm. EEG signals and results of algorithms can also be displayed on-line on a monitor. During operation, EEG data is transferred into the RAM of the PC and can be stored to harddisk at the end of simulation for off-line analysis. Our PC was equipped with 128 Mbyte RAM.

Obviously, similar functions can also be realized with other programming languages such as Basic, C or Turbo Pascal but with greater programming effort.

3. Experimental paradigm and EEG recording

The first tests with the new system were performed with a male, right handed student (g3) of age 25. The student was paid per session and was free of medication and central nervous system abnormality. He already participated in a number of experiments [7, 11] with our "old BCI-system" [4].

Two bipolar EEG-channels were recorded over left and right sensorimotor hand areas, near electrode positions C3 and C4 of the international 10-20 system. The EEG was amplified by an 8-channel *Raich* amplifier system, sampled at 128 Hz and bandpass filtered between 0.5 and 30 Hz. Artifacts, such as eye movements, were not discarded.

The subject sat in a comfortable armchair 100 cm in front of a computer screen and the experiment started with the display of a fixation cross that was viewed in the center of a monitor as shown in Figure 2. After two seconds an acoustic stimulus was given in form of a "beep“. From second 3 until 4.25 an arrow (cue stimulus), pointing to the left or right, was shown on the screen. The subject was instructed to imagine a left or right hand movement, depending on the direction of the arrow. Between second 4.25

and 8 the EEG was classified on-line and the feedback stimulus in form of a horizontal bar, appeared in the center of the screen. If the person imagined a left movement, then the bar pointed to the left and vice versa (correct classification assumed).

One trial lasted 8 seconds and the time between two trials was randomized in a range of 0.5 to 2.5 seconds to avoid adaptation. Each session was divided into 4 experimental runs of 40 trials, with randomized cues (20 left and 20 right) and lasted about 1 hour.

Figure 2

4. Parameter estimation and classification

For the parameter estimation an adaptive autoregressive (AAR) model was used:

$$x_k - a_{1,k}x_{k-1} - \ldots - a_{p,k}x_{k-p} = \varepsilon_k$$

An EEG sample x_k is predicted from a number of samples in the past with a resulting error ε_k for every iteration k. The model is of order p and $a_{1,k} \ldots a_{p,k}$ are the time varying AR-coefficients, which are estimated with the recursive least square (RLS) algorithm. For a detailed description see [3, 11, 14]. The AAR-model was implemented with Simulink and C-Mex S-Functions [2]. An order of p=6 and an update coefficient of 0.006 was used [14]. The algorithm was initialized at second 2 of every trial to avoid instabilities [2].

In session 1 the experiment that is described in Chapter 3, but without feedback, was performed to obtain a weight vector which was used to give the feedback in the next sessions. The output of the RLS-algorithms consisted of six time varying AR-coefficients for each channel. The AR-coefficients at a fixed time point were applied off-line to Fisher's linear discriminant analysis (LDA) [1] to set up a weight vector for the following experiments with feedback as illustrated in Figure 3 [11]. In sessions 2 and 3 the outputs of the RLS-algorithms were calculated and classified with the weight vector in real-time to show on-line the feedback in form of a bar on the screen. The bar pointed to the left if the output of the linear classification was positive and to the right if negative. The absolute value of the classification result is a measure of how reliable the side was determined and controlled the size of the bar.

Figure 3

After 8 weeks a new weight vector was set up with the data of session 4, again without feedback (Figure 3, right side). This weight vector 2 was used in session 5 to give the feedback.

To obtain a more general view of the ability of classification, a 10 times 10 fold cross validation was performed off-line for each session of 160 trials [1].

All computation was done with Matlab 4.2c (MathWorks, Inc., Natick, USA) on an IBM compatible Pentium II MMX with 233 MHz. The precision was 8 byte floating point.

5. Classification results

Classification results obtained with subject g3 are graphically presented in Figure 4. Altogether five sessions were made. Session 1 and 4 were performed without feedback where the subject was instructed to imagine a right or left movement just after the cue presentation. In these sessions the classification error increased slowly up to second 6 after motor imagery. The classification error was lowest at second 4.8 in session 1 and at second 5 in session 4 and therefore these time points were used to set up the weight vectors [11].

Sessions 2, 3 and 5 were performed with feedback as described before. The feedback was displayed on-line on the monitor from second 4.25 until second 8 and was calculated in real-time with the weight vector obtained in session 1 and 4 respectively. The classification error ranged from 5 to 19 % for all classification time points. Particularly second 6 showed extra low error rates of 5 to 8 %. It is of interest to note that the similar results obtained in session 2, 3 and 5 (all with feedback) are clearly different from session 1 and 4 (without feedback). Also important is that it was again possible to reach low error rates 8 weeks later.

Figure 4

6. Discussion

It was shown that by using of a single PC, without an expensive DSP-board, EEG on-line analysis can be done in real-time. The growth of the PC market, which has both shrunk prices and increased the computing power of PCs, has therefore enabled a quicker and easier system development with tremendous cost savings in manpower and equipment.

The data acquisition, analysis (e.g. RLS-algorithm), presentation of the experimental paradigm and control of feedback and monitoring of the EEG derivations on a monitor, can all be handled by the same system. It is easy to program, and the costs of an additional DSP-board are eliminated.

The PC offers powerful software packages to the user and allows the use of new operating systems. The multichannel system runs under Windows 95 and is equipped with a real-time Kernel expansion to obtain reasonable real-time operations on a standard PC. Therefore, for the first time it was possible to use other Windows based utilities for the data acquisition, analysis and control.

Our choice was Matlab which handles the data acquisition and the presentation of the experimental paradigms while the signalflow oriented Simulink is used to describe on-line, the current state of the EEG. These technical features enable non-engineers to configure and operate the BCI with minimal programming required. Programmers can take advantage of the huge language possibilities of Matlab and Simulink. After real-time operation, the data can be stored on harddisk and thus used for off-line analysis. The entire system can also be realized with a laptop computer and is therefore, portable and can comfortably be used by patients. Analyzed data can easily be interfaced to other programs to be used in presentations because everything runs on the same PC and operating system.

The advantages of the new BCI system can be summarized as followed:

- Runs under Win95 and therefore, easy to use for everybody,
- Can be installed on every normal PC or portable computer (with docking station),
- Data acquisition and analysis are done in real-time,
- Software allows up to 256 channels; more than one DAQ-board can be installed,
- Easy implementation of algorithms as Simulink blocks,
- Very easy use of existing algorithms in the Simulink environment,
- Simple realization of different experimental paradigms with Matlab or Simulink,
- Off-line analysis can be done in Matlab with low programming effort,
- Variable sampling rates of ADC,
- Low costs allow an installation at patients' home.

Acknowledgments

This work was supported by the Fonds zur Förderung der wissenschaftlichen Forschung, project P11208MED, by the Allgemeine Unfallversicherungsanstalt (AUVA) and by the Land Steiermark. We like to thank Thomas Strein, Britta Ortmayr and Christa Neuper for critically reading the article and the valuable advice.

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Legend of Figures

Figure 1: BCI hardware and software architecture.
Our new BCI system consists of a normal PC, with Windows 95, Matlab and Simulink installed, and equipped with a real-time Kernel. The system is expandable to 96 EEG derivations if three RTI800a DAQ-boards and a suitable amplifier are used. Digital I/O channels are used to control an external device.

Figure 2: Timing of one trial of the experiment with feedback (FB) in form of a horizontal bar. The cue stimulus (arrow) indicates the side of imagination.

Figure 3: Session 1 was performed without feedback (FB) and the data was used to set up a weight vector 1. In session 2 and 3 the weight vector 1 was used to give feedback in form of a bar. Eight weeks later in session 4 a new weight vector 2 was made. It was used in session 5 to give the feedback.

Figure 4: Classification results (10 times, 10 fold cross validation of a Linear Discriminant) over classification time points for subject g3 obtained with the new BCI system. The diagram on the top shows the classification errors of the first 3 sessions. The diagram on the bottom shows the classification errors of two session which were performed 8 weeks later.

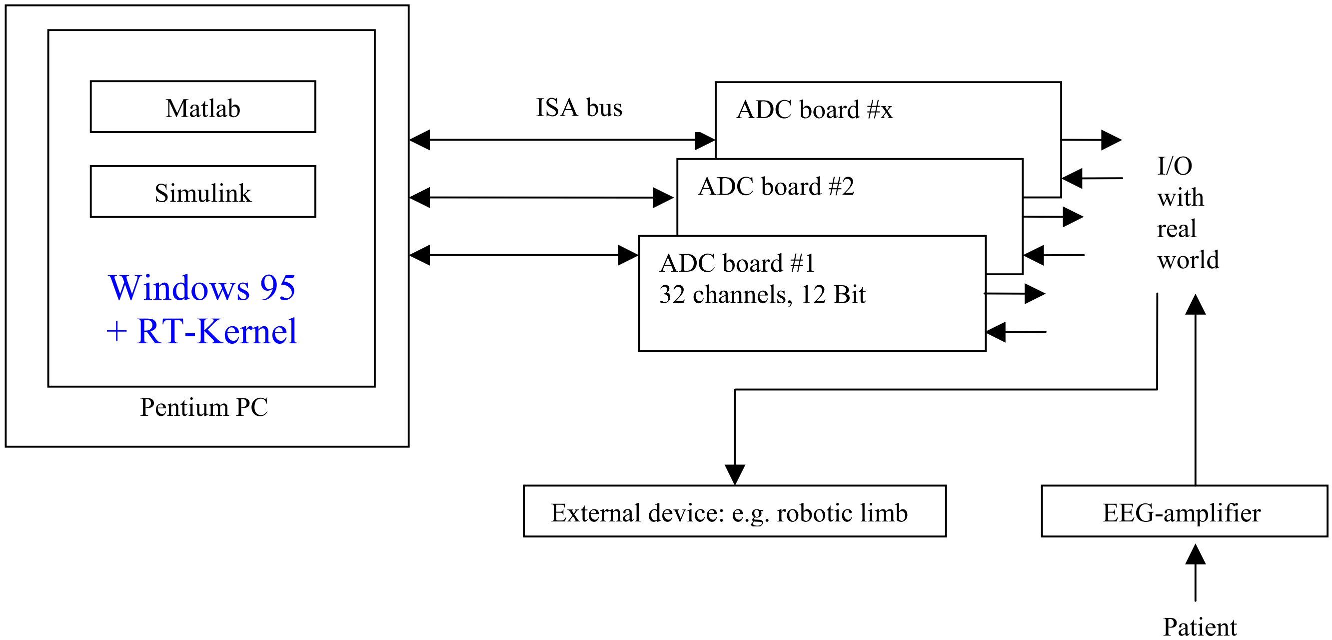


Figure 1

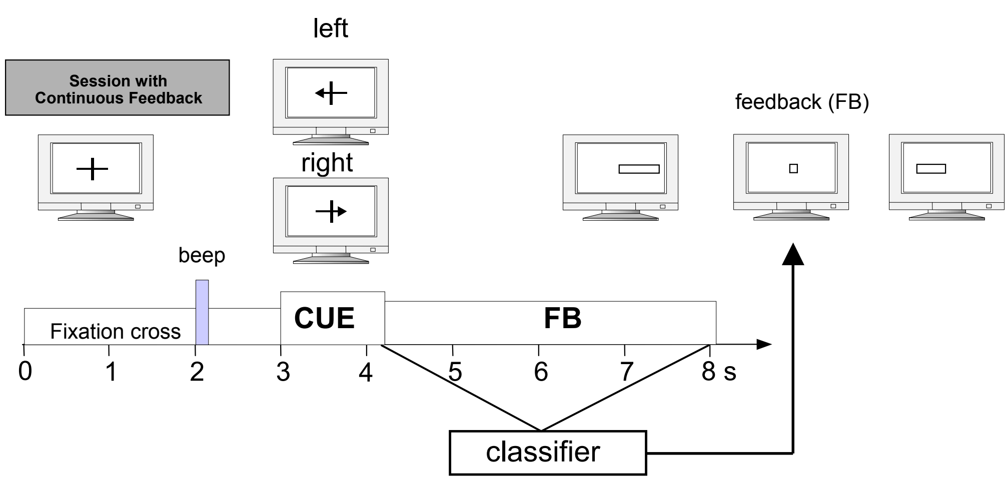


Figure 2

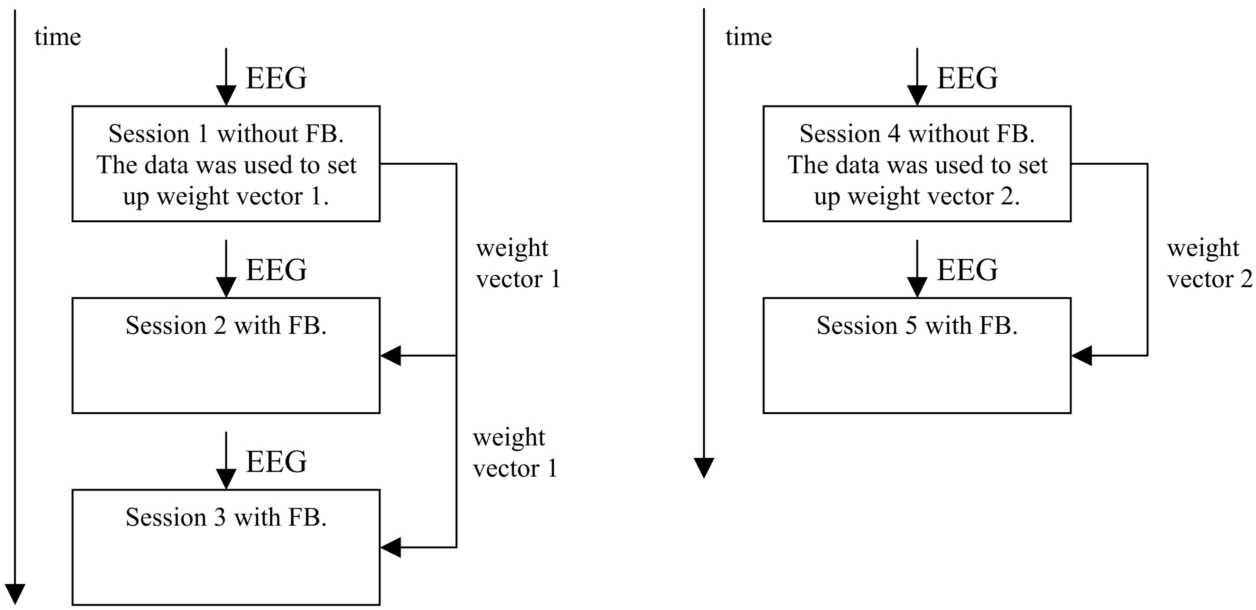
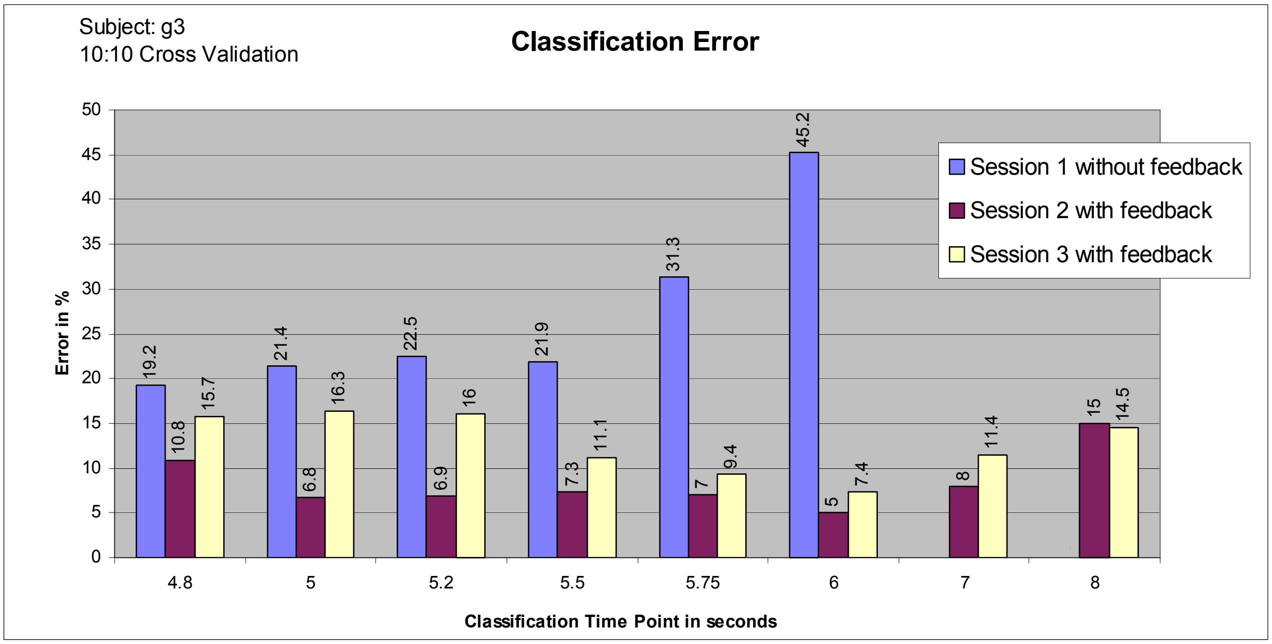

time
EEG
Session 1 without FB.
The data was used to set
up weight vector 1.
weight
vector 1
EEG
Session 2 with FB.
weight
vector 1
EEG
Session 3 with FB.
time
EEG
Session 4 without FB.
The data was used to set
up weight vector 2.
weight
vector 2
EEG
Session 5 with FB.

Figure 3


Subject: g3
10:10 Cross Validation
Classification Error
Session 1 without feedback
Session 2 with feedback
Session 3 with feedback
Error in %
Classification Time Point in seconds
4.8
5
5.2
5.5
5.75
6
7
8
19.2
10.8
15.7
21.4
6.8
16.3
22.5
6.9
16
21.9
7.3
11.1
31.3
7
9.4
45.2
5
7.4
8
11.4
15
14.5

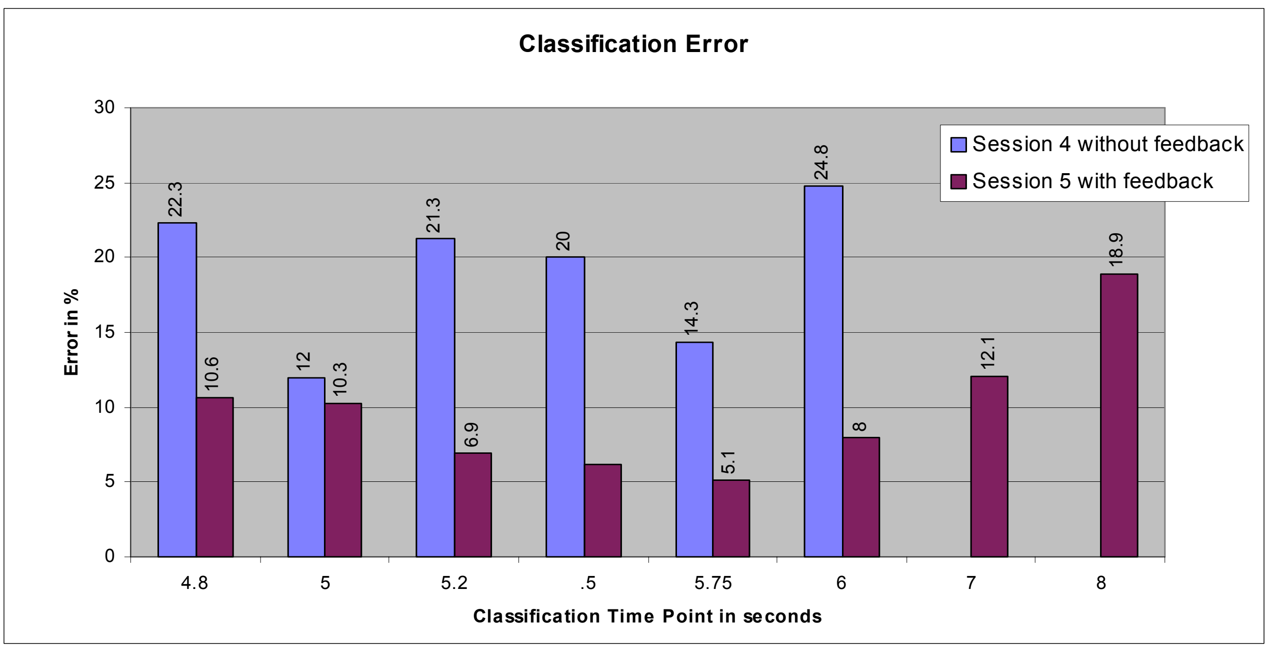

Classification Error
Session 4 without feedback
Session 5 with feedback
Error in %
Classification Time Point in seconds
4.8
5
5.2
.5
5.75
6
7
8
22.3
10.6
12
10.3
21.3
6.9
20
14.3
5.1
24.8
8
12.1
18.9

Figure 4