An Inexpensive Brain-Computer Interface Based on Spatial and Temporal Analysis of EEG

Charles W. Anderson
Department of Computer Science
Colorado State University
Fort Collins, CO 80523
anderson@cs.colostate.edu

James N. Knight
Department of Computer Science
Colorado State University
Fort Collins, CO 80523
nate@cs.colostate.edu

Michael J. Kirby
Department of Mathematics
Colorado State University
Fort Collins, CO 80523
kirby@math.colostate.edu

Abstract

Exciting results have recently been reported in the technical literature and popular press showing that patterns in the electrical activity of the brain exist that relate to intended movement or that discriminate between different cognitive tasks. If these patterns can be reliably detected, a new mode of human-computer interaction becomes possible by identifying a subject's choice directly from the brain, an approach that has become known as a brain-computer interface (BCI). On the surface of the scalp, the brain's electrical activity (EEG) is very weak and noisy; considerable research is required to determine the best electrode sites, signal representations, and classification techniques for relating EEG to underlying cognitive activity. Since access to clinical EEG systems is often limited or not available, progress in this field would be facilitated by the design of an affordable, flexible system for experimenting with EEG analysis techniques and BCI applications. This article describes the design of such a system composed of off-the-shelf hardware and custom open-source software.

1 Introduction

A number of physiological signals have been measured to obtain indications of decisions or intentions of the user of a computer. All but one are based on muscular responses to those decisions. Diseases, such as amyotrophic lateral sclerosis (ALS), that greatly reduce voluntary muscle control can make HCI systems that detect muscle movement impractical or useless. When voluntary muscle response is not detectable, the only available signals for HCI control are those generated directly by the brain. The field of research in detecting decisions and intentions directly from brain signals is called Brain-Computer Interface (BCI) or Brain-Machine Interface (BMI).

It has been known since 1929 (Berger, 1929) that electrical activity in the brain can be detected in small scalp electrodes that rest on the surface of a person's scalp. These electroencephalogram (EEG) signals are in the microvolt range and result from the summation of cortical activity. Electrical activity in the cortex is spread in space and time by bone, skin, and other tissue near the electrode site and thus is a very gross measure of the underlying brain activity. Recorded EEG is greatly affected by electrical noise in the recording environment, in the recording equipment and by other physiological events, such as heart beat, breathing, and eye blinks. In spite of these difficulties, recent studies have shown that cognitive activity like imagined hand movements and selections of letters from a table of the alphabet can be identified by detecting patterns in the EEG from multiple electrodes (Wolpaw, et al., 2002).

Here we describe the hardware and software that comprise an inexpensive system for conducting experiments in BCI. Rather than developing around an expensive clinical EEG recording system, we base our design on the 16-channel MindSet EEG amplifier and a notebook computer with a SCSI interface. Custom software was written for Linux as the interface between the EEG amplifier and Matlab.

The remaining sections of this paper describe our approaches to filtering out EEG artifacts, transformations of the signals, and their classification. Then we describe our system and some initial results in the last section of this paper.

2 Filtering Out Artifacts

Signal separation techniques, such as independent component analysis (ICA) (Hyvarinen, 1999), have been used extensively in the analysis of EEG data (Jung, et al., 1998). ICA methods are based on approximating high-order statistics and can require considerable amounts of data. Knight (2004) shows that another approach, maximum signal fraction (MSF) which is based on generalized singular value decomposition, can separate artifacts from signals better than an ICA approach when given small amounts of data. Sarela, et al. (2003), discuss related problems with the ICA approach due to overfitting. Parra and Sajda (2003) describe several related ways of formulating the blind source separation problem as a generalized singular value decomposition problem. For the results reported here, MSF is used and is summarized in this section.

Let X be an n x p matrix of EEG data recorded from p channels for a total of n sequential samples. Assume that X is composed of signal S and additive noise N:

$$X = S + N. \tag{1}$$

We wish to find the set of vectors v_i that satisfy

$$\max_{Nv_i \neq 0} \frac{\|Sv_i\|_2}{\|Nv_i\|_2} \tag{2}$$

which is equivalent to

$$\max_{Nv_i \neq 0} \frac{\|Xv_i\|_2}{\|Nv_i\|_2}. \tag{3}$$

if $S'N = N'S = 0$ (Hundley, et al., 2001). As in principal component analysis, the set of solutions are defined recursively by constraining all solutions v_i to be orthogonal with respect to the weighted inner product, $v_i'X'Xv_j = 0$ for all $i \neq j$. The solutions v_i are the generalized eigenvectors defined by

$$X'Xv_i = \mu N'Nv_i \tag{4}$$

which can be solved by computing the generalized singular value decomposition of X and N if they are known. Usually the noise covariance matrix $N'N$ is not known and must be estimated. One approach is to estimate N by the temporal difference of X. Let X_s represent a shift forward in time by one sample. $N \approx (X - X_s)$ and $N'N \approx (X - X_s)'(X - X_s)$ if we assume that $N'N_s = N_s'N = 0$, $S'N = N'S = 0$, and $(S - S_s)'(S - S_s) \approx 0$. If we set $V = (v_1, v_2, \ldots)$ where each v_i is a column vector, then XV is a matrix of separated components, ordered from strong signal to strong noise components. The components that contain mostly artifact are removed by setting them to zero and calculating the inverse transform.

Even when the assumptions are only approximately met, this procedure has been shown to work well (Knight, 2004; Hundley, et al., 2002). An example application for artifact removal is demonstrated in a later section.

3 EEG signal transformation and classification

The biological processes in the brain that underlie particular cognitive activity are not understood to the level of detail required for the construction of a model for predicting EEG activity. Without such a generative model, we must resort to classifiers based on statistical relationships found in EEG recorded during the performance of several different mental activities.

The first step in classifying EEG is to transform the EEG data into a representation that is more easily classified. Typical signal representations used in BCI include frequency components and autoregressive models (Anderson, 1995). The results described here use the MSF method to transform the EEG data. If the signal transformation produces a representation in which EEG data from different mental tasks are easily separated, simple classifiers such as linear discriminant analysis (LDA) can be applied. If the data is not easily separated, nonlinear classifiers may be required, such as artificial neural networks or kernel-based classifiers. (See Hastie, et al., (2002) for thorough discussions of various classifiers.)

Kirby and Anderson (2003) provide results of classifying MSF-transformed data that is first delay-embedded by augmenting each EEG sample with samples from previous time steps, forming a vector of lagged values. The transformed components of the delay-embedded data was classified using LDA (and several other transformations and classifiers). They showed that EEG recorded from subjects performing either a mental multiplication task or an imagined letter writing task could be correctly classified with about 90% accuracy. Accuracy decreases to about 70% when classification is performed over five mental tasks (Garrett, et al., 2003).

This is one approach for performing spatial and temporal analysis of EEG data. Temporal patterns in the data are represented by the delay-embedding. Temporal variations that often occur are identified by the MSF procedure. Similarly, by including EEG data from multiple electrodes in one sample, the MSF components indicate relationships between electrodes, or over the spatial extent of the scalp.

4 An experimental BCI system

In the work cited above, analysis and classification were performed long after the EEG data was recorded. In this section, the design of a real-time BCI system is described in which EEG data is recorded, filtered, transformed and classified as the user interacts with the system. The goals of the design are to use readily available hardware that is relatively inexpensive, and open-source software that is easily modified to develop a variety of BCI experiments.

4.1 Hardware

The most important piece of hardware in a BCI system is the EEG amplifier. For our system, we chose the 16-channel Mindset MS-1000 EEG amplifier (see http://www.mindset-eeg.com). This amplifier sells for $2,195, much less than turn-key systems designed for clinical use. The Mindset is built for laboratory use and the technical support provided for the Mindset is very helpful for anyone wanting to develop custom software for use with the Mindset.

The Mindset communicates with a computer via its SCSI interface. For our system, we interface the Mindset with a notebook PC using a PCMCIA SlimSCSI 1460 card from Adaptec, which costs about $100. The open software architecture is maintained by targeting all development and use to the Linux operating system.

A standard electrode cap from Electro-cap (see http://www.electro-cap.com) is used in our system. One cap with supplies can be purchased for approximately $450. To use the cap a simple procedure is followed. The cap is gently placed on a subject's head and a chin strap is secured. For each electrode to be recorded from, an electrically conductive gel is applied to the electrode via a small hole in the electrode. The gel makes electrical contact with the subject's scalp through the hair. The quality of the connection is checked with an impedance meter and additional gel is inserted until the impedance at each electrode is less than 10 kOhms.

4.2 Software

The purchase of a Mindset amplifier includes a suite of software tools for Microsoft Windows for displaying and analyzing EEG. To maintain the open architecture desired for laboratory settings, we chose to develop custom code to communicate between the notebook PC running Linux and the Mindset. The completed interface code provides the capabilities needed to develop experimental BCI systems. For chose to implement the BCI system in Matlab to take advantage of EEG signal analysis code that is already available. The interface code and the experimental BCI systems are now described.

4.2.1 SCSI Interface with Mindset Device

The open-source generic SCSI library in Linux was used to develop our SCSI interface. This was a simple matter of understanding the SCSI commands built into the Mindset hardware. A few subtle issues with the interaction of the generic SCSI library and the Mindset communication protocol were easily resolved with the help of technical support from the makers of the Mindset. Our SCSI-Mindset interface is written in C and consists of the following five functions:

- `int setSampleRate (int fid, SampleRate rate);`
- `int setBlockSize (int fid, BlockSize blocksize);`
- `int ready(int fid);`
- `int readData(int fid, char *dest, int len, int nblocks, int blocksize);`
- `int readStatus(int fid, int *numDataBytes, int *sampleRate, int *blockSize);`

This library of functions is used to specify the size of each transferred block of EEG data and the sampling rate and to check the status of the Mindset and to read EEG data. With these functions, a BCI application may be written in any language that can call these compiled C functions.

4.2.2 Matlab-to-SCSI Interface

Since we wished to use Matlab as our main application software environment, we needed an interface between Matlab and our SCSI-Mindset interface library. This was developed as a set of Matlab mex functions, which are C functions with passed and returned parameters that must follow the Matlab interface conventions. The result is the following five mex functions that are called from Matlab to perform the summarized procedures:

- `mindinit`: Initialize the Mindset amplifier and the communication link as a file descriptor;
- `mindstart(Fs)`: Instruct the Mindset to begin recording EEG data at a sampling rate of Fs samples per second;
- `mindget`: Retrieve all EEG data currently stored in the Mindset buffer;
- `mindstop`: Instruct the Mindset to stop recording.
- `mindclose`: Close the communication link with the Mindset.

4.2.3 Matlab BCI Application

A versatile software architecture was desired in Matlab for constructing a number of different BCI applications. Some of the common capabilities required for all BCI applications include the specification of which electrodes to record from and how to map each signal to a row in the EEG data matrix, the display of the data from multiple EEG channels as it is being recorded, the calculation and display of separated sources and the ability to select the components to be filtered out of the data.

These capabilities plus others would need to be easily selected by the user. A set of tabbed panels was chosen as an intuitive way of seeing all the capabilities included in an application and an obvious way to select each one. An example display of one of our BCI applications is shown in Figure 1. The first three tabbed panels in this application are for specifying channels, for monitoring EEG, and for constructing an artifact filter. The fourth panel is for transforming the EEG into several audible tones to provide immediate feedback to the user. Figure 1 shows that the application is set up to record from six EEG channels, C3, C4, P3, P4, O1 and O2, and one electrooculogram (EOG) channel for an electrode placed near an eye to directly measure eye movement. These channels are specified in a simple text file that can be edited and loaded from this panel.

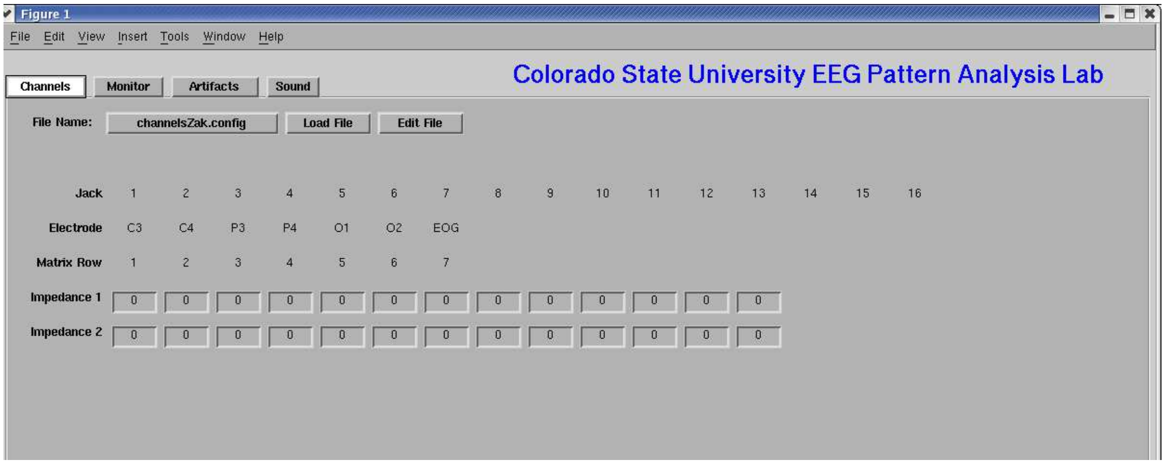

Figure 1: BCI application with capabilities as tabbed panels. The first panel, called "Channels" has been selected. This panel allows the user to specify channels used, name them, indicate which row of the EEG data matrix each channel of data is stored in, and to enter measured impedance values for each electrode.

Once the channels are specified, we can observe the data being recorded from the Mindset by selecting the "Monitor" panel. Figure 2 shows this panel about 5 seconds after the "Start" button has been clicked in this panel. Two eye blinks are very obvious in this display, one at about 0.5 second and another at about 3 seconds. The eye blink is very apparent in the EOG channel, but it is also has a strong effect in several of the EEG channels.

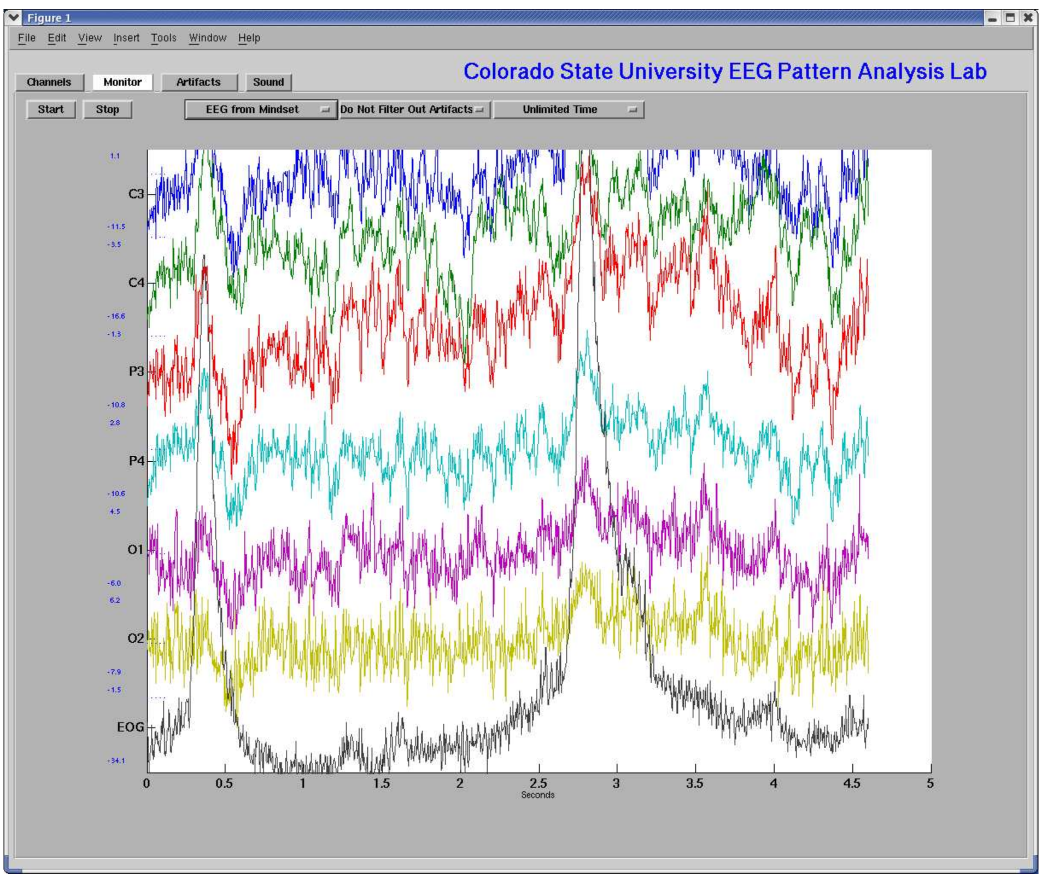

Figure 2: The state of the "Monitor" panel about five seconds after starting the recording. Eye blinks occur at 0.5 and 3 seconds.

We can now construct an artifact filter to remove the eye blinks from this data using the MSF procedure summarized above. This is performed by selecting the "Artifacts" panel as shown in Figure 3. This figure shows all seven components that have been separated out of this seven-channel data set. The eye blink source has clearly been isolated in the seventh component. The components are ordered from most noise at the top to most signal at the bottom. Recall that a noisy signal was defined as one with relatively large changes in amplitude from one sample to the next. The eye blink component on average changes the least, except near the blinks, so it ends up at the "signal end" of this spectrum. While this is "strong signal" according to the MSF formulation, it is clearly an artifact that we would like to remove. The first component, the most noisy component, is a high frequency noise that we choose to also remove.

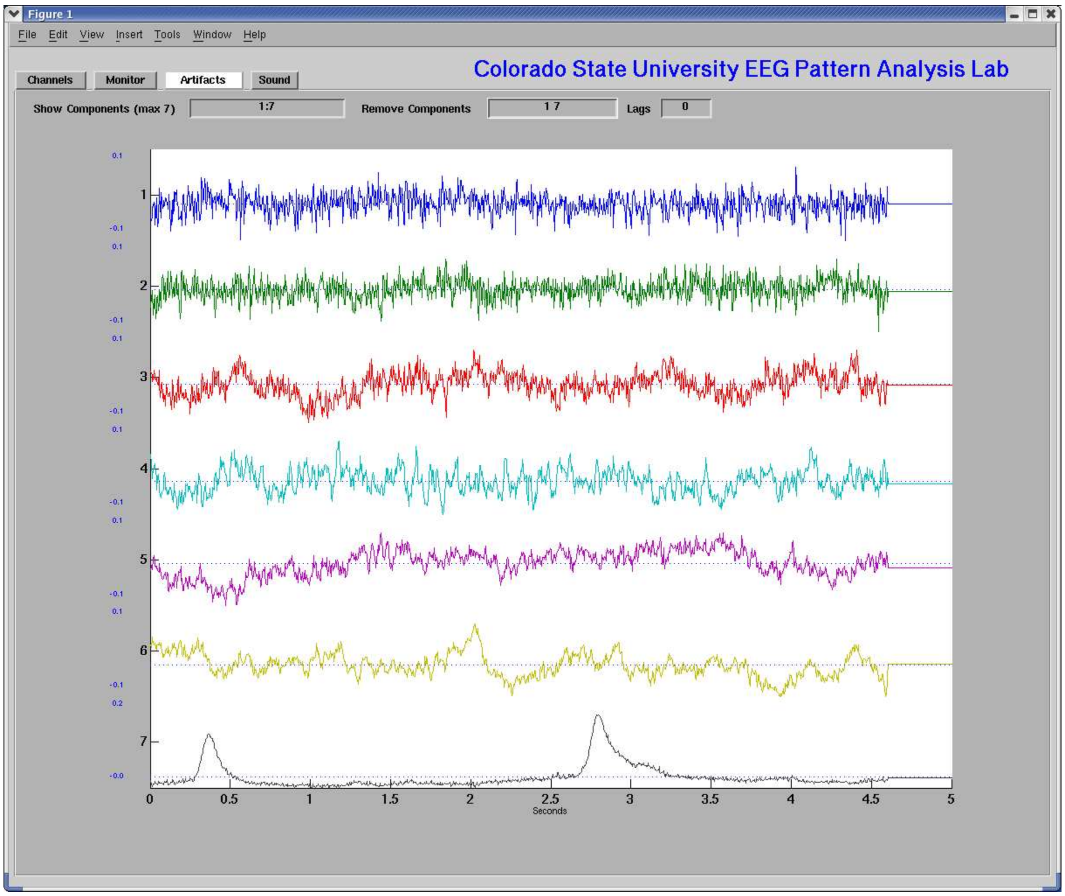

Figure 3: Components separated from the data in Figure 2 by the MSF procedure. Components are ordered from top to bottom as most noisy to least noisy. The first and last components are selected for removal.

Now when the "Monitor" panel is selected again, and the artifact filter is applied to the same data, the result is as shown in Figure 4. The effects of the eye blinks at 0.5 and 3 seconds have been mostly removed. Details in the EEG channels that had been swamped by the eye blinks are now visible.

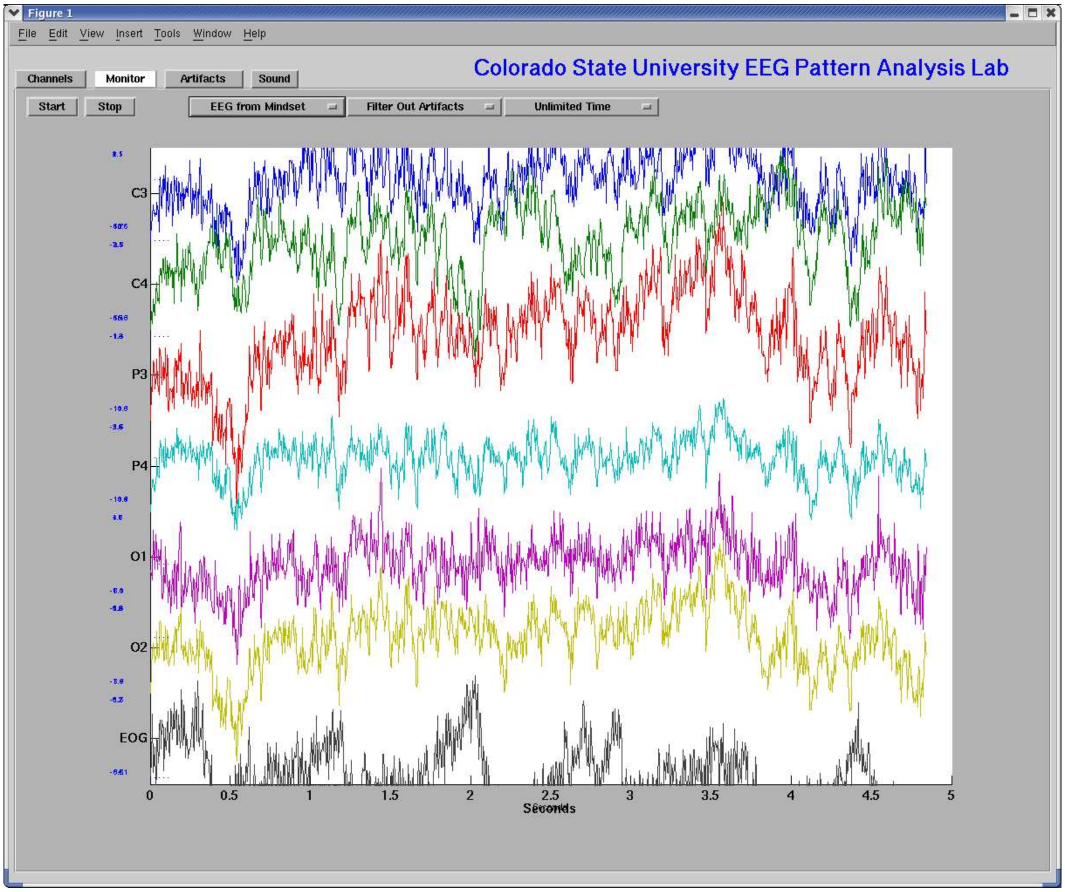

Figure 4: EEG data from Figure 2 after the artifact filter has been applied. The effects of the two eye blinks have mostly be removed, revealing other structure in the EEG signals.

New panels are currently being developed for several initial BCI experiments. At this time we have experimented with a real-time sonification experiment in which data from a single EEG channel is Fourier transformed into a spectrum of power levels and the frequencies with the most power are scaled into an audible range of frequencies and played on the notebook computer. This provides instant feedback to the user and a chance to consciously modify the way in which they are performing a mental task in order to produce a repeatable sound. Figure 5 shows the display of the sonification panel.

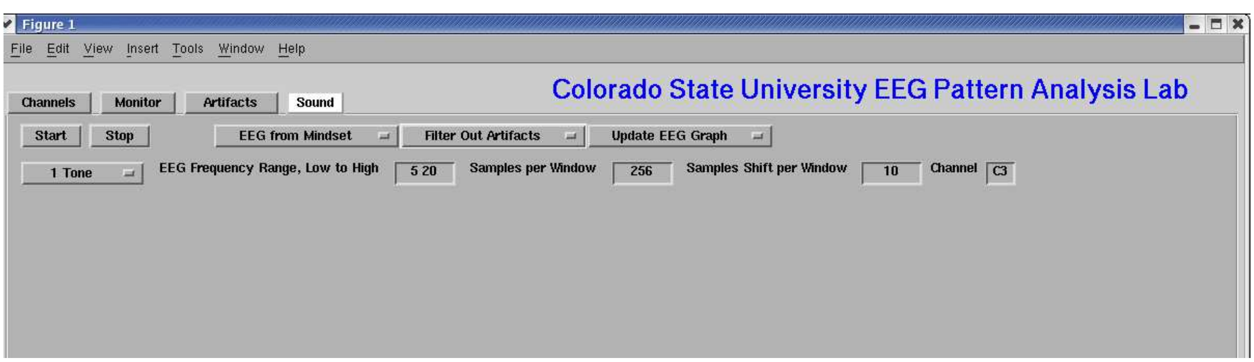

Figure 5: EEG sonification panel for providing real-time feedback of which EEG frequencies have the most power.

5 Conclusion

A system composed of inexpensive off-the-shelf hardware and custom software has been developed for experimenting with EEG analysis algorithms and user-interface protocols for brain-computer interface (BCI) studies. Modular design of Matlab code simplified the addition of new panels for visualizing, filtering, transforming and classifying EEG. To-date, panels have been implemented for filtering out artifacts using maximum signal fraction (MSF) and for real-time audio feedback of frequency components. Currently additional panels are being developed for controlling a variety of classification techniques and for using the classifiers to control cursor movement on the screen and for selecting items from a menu. The status of this project is available at http://www.cs.colostate.edu/eeg.

One objective of this work is to provide the design and the software to others who wish to work in the BCI field. It is hoped that our open-source software developed for Linux will facilitate the adaptation of our approach to other applications.

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