Brain Computer Interfaces

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Abstract. Brain-computer interfaces (BCI) are a combination of computer hardware and software that allow users to control artificial devices using only their brain's naturally-occurring electrical signals. BCI have a wide range of potential applications, from simple entertainment to granting autonomy and the ability to communicate to the severely disabled. BCI are still in early stages of development and researchers have many challenges to overcome before a consumer-friendly BCI device becomes a reality. This work gives an overview of the field of BCI and discusses filtering applications.

1 Introduction

Brain-computer interfaces (BCI) provide a method of interaction and communication that circumvent the "brain's normal output pathways" [A1], by detecting and interpreting electrical signals produced by brain activity, and translating them directly to input signals for artificial devices. Brain-computer interfaces can use either "neural activity recorded from the surface [of the skull], such as [electroencephalogram] EEG, or neural activity recorded from inside the skull or brain" [D1]. These techniques are known as non-invasive and invasive, respectively.

Most BCI research is devoted to medical purposes. BCI have great potential to help patients who are severely paralyzed, either through injury or disease, but still have intact cognitive functions. Sufferers of advanced Amyotrophic Lateral Sclerosis (ALS) and Cerebral Palsy can become, what is known as, "locked in" to their own bodies – developing the inability to move or speak, though possessing a sound mind. Dr. Stephen Hawking of Cambridge University is, perhaps, the world's most well known person living with ALS. Dr. Hawking relies heavily on computer technology in his day to day life, but his famous talking wheelchair does not utilize a Brain-computer interface. Many areas of BCI research have the common goal of allowing people, such as Dr. Hawking, to live a life without dependencies on other human caregivers. Applications such as user mobility, environment control, and communications are popular in the field of BCI.

Brain-computer interfaces have far-reaching potential outside of the medical fields as well. Theoretically, BCI could monitor a person's state of mind at work, or while driving, and give feedback designed to reduce stress or prevent accidents. BCI could, in fact, conceivably be applied to every application for which we use computers today - from business to education to entertainment - giving users control of their high tech devices at the speed of thought.

2 Background

Researchers have been making great improvements in brain-computer interfaces, but BCI systems are still incredibly complex, unwieldy systems that rarely achieve the levels of performance that would be required of a consumer electronics device. There are many stages through which brain signals must pass before they can be useful as input for artificial devices, and each of those stages present researchers and developers with unique challenges.

Non-invasive techniques usually involve taking recordings from the scalp. Electroencephalography (EEG) is a popular technique where features are either "regulated by the BCI user... or elicited by visual, tactile, or auditory stimulation" [D1]. EEG is relatively inexpensive to use, but the recorded signals can be quite low in resolution, are limited to two dimensions, and are often cluttered with noise from the environment. Other non-invasive techniques exist. Functional magnetic resonance imaging (fMRI) measures the blood oxygen level dependent response (BOLD) in active areas of the brain. "Compared to EEG, fMRI allows spatial resolution in the range of millimeters and a more precise allocation of neuronal activity. Additionally, activation in subcortical areas can be detected" [D1]. "Near infrared spectroscopy [NIRS] offers a comparable [three dimensional] spatial resolution" [D1] to that of fMRI. But unlike fMRI, NIRS is portable and less expensive.

Invasive methods require surgery and pose serious risk to the patient [D1].

Once recorded, brain signals must usually pass through a filtering process, before they can be fed as input to interpretation software. This is especially true of noisy EEG data. Many things can reduce the quality of a recorded EEG signal. Even something as seemingly innocuous as a subject blinking can create erroneous data and must be filtered out. In a real-time BCI system, a user's brain activity has to be quickly interpreted and looped back to give the user feedback as quickly as possible. In such cases, the signal processing and interpretation software must be extremely fast and efficient.

3 Experiment

Our experiment was to read the raw data, and filter it like the BCI equipment does. The programs were written using MATLAB. The key advantage is that we have much more control over the filtering operation, and can always go back to the original data if needed.

We implemented a low-pass filter, with a 45 Hz cut-off and Hanning window. The frequencies of interest from the BCI devices are the low ones on the frequency scale, including Alpha waves (8-13 Hz), Beta waves (13-30 Hz), and Theta waves (4-8 Hz) (Thanks to Mr. Toby Amoss for providing this information). The low-pass filter allows us to retain these frequencies of interest, while dramatically reducing all frequencies above the 45 Hz cut-off. This cut-off value is somewhat arbitrary in that it must be greater than 30 Hz and less than 60 Hz (discussed below). The Hanning window is a standard windowing function, used to reduce the effects in the frequency domain of suddenly reading samples and later abruptly stopping. The window function smoothes the transitions by scaling the initial and final samples. There are many windowing functions to choose from, but this choice is not a critical one for this application.

MATLAB has filtering operations in the signal processing toolbox, allowing the user to obtain filter coefficients after specifying the cut-off and window to use. Our code instead uses our own function to generate filter coefficients, a modified version of the code found in chapter 10 of Digital Signal Processing using MATLAB and Wavelets [W1].

We perform the fast Fourier Transform on the raw data and the both sets of filtered data (the first done by the BCI equipment, and the second set generated by our program). Figure 1 (left) shows a snapshot of both sets of filtered data, plotted together, along with the unfiltered data. This is one second's worth of data from channel 3, a signal chosen to be representative of the other channels. We see that the filtered sets of data correspond well to each other. In fact, when we compare our filtered data to the original (raw) data (Fig. 1, left), we see that the frequencies of interest are more faithfully reproduced. This figure has the DC component (0 Hz) removed, to make the other frequency content stand out. The top plot shows our filtered data, the middle plot shows it filtered by the BCI equipment, and the bottom plot shows the frequencies in the raw data. Figure 1 (right) shows a plot of the differences in the frequency content, indicating that the differences between our filtered data and the raw data is and the data that the BCI-equipment filtered is better. In fact, the accumulated difference in magnitude for our data (from 1 to 30 Hz) is only 14.57, compared with 45.93 for the BCI-equipment's filtered data.

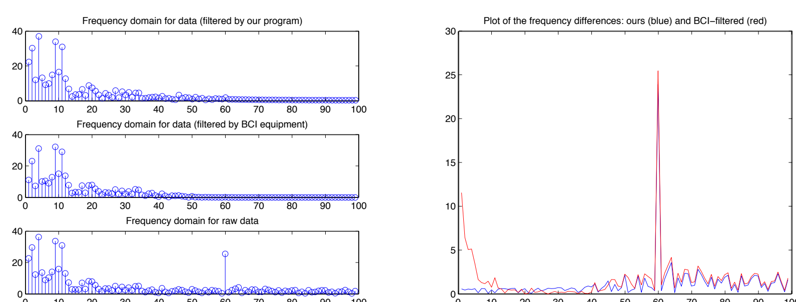

Fig. 1. Frequency domain comparisons of our filtering versus the BCI equipment and unfiltered data (left), and the frequency differences (right).

Since our filtering more faithfully matches the original (raw) data for the frequencies of interest, we argue here that our method is better.

4 Conclusions

Once a set of EEG signals has undergone a noise filtering process, it remains to be interpreted. Event related potentials (EP), such as the P300, are popular subjects of investigation in EEG interpretation research. However, EP are usually binary "electro-physiological phenomena" [M1]. giving only an on/off or yes/no distinction.

The ultimate goal of brain-computer interfaces is to give users an easy, reliable way to translate their thoughts directly into interactions with the world. This implies some sort of portable, consumer-friendly device that is to be used by people with very little specialized training. But many challenges remain, such as low transfer rate, errors, non-portability of the equipment, and interference from other sources such as emotions and interactions with people [M2].

According to a poster presented by R. Toby Amoss on the project, the approximate setup costs of his lab was $12,000 [A2]. Setting up a BCI lab may cost in the range of $50,000-$150,000 [C1] according to one vendor's pricelist.

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