

A Survey of Brain Computer Interfaces and Their Applications

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Abstract—This paper concerns the theory behind developing a brain computer interface (BCI) and the applications of such a system. Signal acquisition methods such as Functional Magnetic Resonance Imaging (fMRI), Near-Infrared Spectroscopy (NIRS), Magnetoencephalography (MEG), Electrocorticography (ECoG), and Electroencephalography (EEG) are discussed. There is also a review of the different types of Event Related Potentials (ERP) and signal extraction methods for generating filters from the captured data to generate a model for a BCI. Finally, this paper covers a review of notable BCIs that are being utilized in a wide range of applications and gives a working example using BCILAB to generate results from a sample data set using the techniques discussed in the paper.

Index Terms—Brain Computer Interface, Electroencephalography, Control Systems, Signal Processing

I. INTRODUCTION

Brain computer interfaces (BCI) are a relatively new technology that takes advantage of the innate computing power of the brain. Developing BCIs have, up until recently, been thought of as science fiction. Ever since the first discovery of electroencephalography (EEG) by Berger, scientists have been trying to decode signals from the brain[1].

A BCI traditionally consists of four main parts; a sensing device, an amplifier, a filter, and a control system. The sensing device consists of a cap with electrodes placed to the International 10-20 standard[2], [3]. The amplifier can be one of numerous biological amplifiers on the market[4]. The filter and control system applied to the brain signals is the focus of BCI research.

Due to the inherent size of the field, all techniques can not be covered in a paper of this size. This paper is concerned with presenting the basic background information and the more common technologies of BCIs. Section 2 provides a background of overall BCI concepts, including signal acquisition methods while comparing the benefits and drawbacks of each method. Section 3 covers the different types of event related potentials (ERP) and covers which method would be used for a certain type of task. Section 4 provides a quick reference as to how a signal may be manipulated in post processing of obtaining the signal to identify certain aspects of a signal. Section 5 is a comprehensive overview of the applications of BCI in research and in practice. Section 6 gives a quick

example of how a BCI may be developed using the BCILAB plug-in for MATLAB.

II. BACKGROUND

The first proposed application of a BCI was for use in therapeutics and for mental disorder classifications[5], [6]. Modern BCI research focuses on patients with amyotrophic lateral sclerosis (ALS), also known as "locked-in" syndrome[7], [8], [9], [10], [11], [12], [13]. BCI research has also expanded to include systems that healthy individuals can utilize to expand normal human capabilities[14], [15].

A. Dependent and Independent BCI

BCIs are categorized into two different types; dependent and independent. A dependent BCI relies on element pathway in the brain to generate activity. An example of this BCI type would be the spelling program shown in Figure 1[16].



Fig. 1. Example of a P300 Type Spelling BCI using a 6X6 Matrix of Letters and Numbers, and a Backspace[17]

This system is monitoring the brain waves for event related potentials (ERP), recognizable patterns in brain waves that occur during stimuli, such as being presented with a specific image or an imagined movement. A matrix containing the desired outputs, such as an array of letters in a spelling

program, flashes at a specific rate. Utilizing the data from the flashing and the timing of the ERP, the desired letter is extrapolated. The specific ERP that is being monitored in the case of the spelling program is called a visual evoked potential (VEP). The contribution from the visual cortex is the dominant signal in VEPs, so naturally this signal is used to determine which letter the subject is observing. The dependent BCIs are accurate and commonly used, however this model is inadequate for a person with severe neuromuscular disabilities since the signal is derived from an extraocular muscles in this case.

An independent BCI does not depend on any of the normal pathways in the brain for the output. One example is the utilization of the flashing matrix of letters idea discussed previously, but looking for a different identifying signal. This study is looking for a signal produced by the person, called a P300 evoked potential, that corresponds to a specific flashing letter[18], [19]. For this example the output EEG signal generation is based on intent and not eye orientation. This is the preferred area of theoretical research as the brain makes new pathways to control an output. This is a great advantage to patients with disabilities who lack normal output pathways, such as a patient with ALS.

B. Signal Acquisition

Signal acquisition is a substantial challenge in the field of BCIs. Traditional approaches focus on EEG signals[1], however, other methods exist that can capture neurological activity. Each method has their strengths and weaknesses for capturing different portions of signals from the brain. End use, intended by the designer, is the factor that filters out which method to move forward with.

1) *Functional Magnetic Resonance Imaging (fMRI)*: One of the more practiced methods for detecting neurological activity for research purposes is called Functional Magnetic Resonance Imaging (fMRI). This process involves observing a subject's change in blood flow (hemodynamic response) while they are laying in a Magnetic Resonance Imaging (MRI) machine. The response that active neurological processes produce is known as the Blood Oxygen Level Dependency (BOLD)[20]. This response arises from the basic principal that regions of the brain that are more neurologically active will require a higher hemodynamic response than areas of the brain that are not engaged. One of the main drawbacks of using fMRI is the relatively slow reaction time of the system. This delay is attributed to the response time of the BOLD response of the brain which typically can delay anywhere from 3 to 6 seconds[21]. However, there is research that suggests that this delay can be overcome with techniques that look for finer BOLD responses in specific areas and using that information for a real-time BCI or as an initial guide for fine tuning EEG procedures[22].

The drawbacks of an fMRI do not exclude it as usable and viable technique for BCI control. The BOLD signal response has successfully been used as an indicator for intended movement[21]. A study placed participants in an MRI machine

that showed high variance between BOLD responses for different intended movement. This analysis was performed off-line, but clearly shows the feasibility of using fMRI for an on-line BCI. This study occurred with four volunteers and consisted of two calibration sessions and a feedback session. During the feedback section the volunteers were shown the activity levels through a video projection of the regions of interest (ROIs). A custom developed software that ran separately on another computer made this process possible. During the experiment it was very important, as it is with all BCIs, to remove artifacts, such as background noise from eye and muscle movement a.k.a. electromyography (EMG), would override the desired signals. Real-time motion correction was used to remove the contributions from muscular movement.

Another example of fMRI use for brain control method is the detection of imagined and executed unimanual and bimanual movements[23]. In this experiment eight healthy right-handed volunteers were chosen to participate. Their handedness was verified using the Edinburgh Handedness Inventory[24]. The experiment consisted of three parts: two unimanual movement and one bimanual movement. Subjects were asked to individually move their fingers, excluding thumbs, in predefined repeating sequences. Once the sequence was completed, the trial was performed again with imagined movements as opposed to actual movements. While there was predicted variability in each individual subject, there was also a clear trend. Actual movements were consistently at a higher potential level than imagined movements, and thereby providing a more accurate signal, but the imagined movements still provided a cluster of neurons acceptable for reliable signal detection.

2) *Near-Infrared Spectroscopy (NIRS)*: NIRS is a method that uses light close to the infrared spectrum to monitor a response that is similar to the BOLD response called regional cerebral blood flow (rCBF)[25]. NIRS is used to look over a general area of the brain for activity, though LEDs have been used for more precise detection. Pairs of illuminators and detectors form channels for the signals. Near-infrared rays emit from each illuminator and pass through the skull and brain tissue to be received by the detectors. An example of NIRS being used for an on-line BCI spelling program can be found[25]. This study involved five individuals who underwent a baseline trial, a partition, and a motor task. The motor task involved finger tapping which would be dictated by on screen prompts. One of the weaknesses of NIRS measuring is the dependency of passing through the skull; this means that things like hair can greatly hamper the signals and give faulty readings.

3) *Magnetoencephalography (MEG)*: MEG provides more sensors, and thus more spatial information, than traditional a EEG. In order to take MEG recordings, a subject, in a magnetically shielded room, is placed in a chair with an array of superconducting quantum interference devices (SQUIDS) around their head as the magnometer. The obvious drawback to this approach is the dependency of a magnetically shielded room and a large machine to sense the brainwaves. Research

has proven that even with these constraints that MEG is still a viable and reliable enough of a method to be explored further[26].

4) *Electrocorticography (ECoG)*: Differing from the previous methods ECoG is an invasive method. ECoG requires surgery to implant electrode pads directly onto the surface of the brain to receive signals from the cerebral cortex. The advantages of this are immediately clear: high spatial resolution, broad bandwidth, high amplitude, and less vulnerability to EMG[27]. ECoG is also widely used as an identifier for the localization of epilepsy focal points. An array of 64 electrodes is implanted onto a portion of the brain called the epileptic focus to identify the part of the brain that should be removed by resection surgery. During one study, patients with epilepsy were implanted with these electrodes. In the period of the one to two weeks that the electrodes are recording data to localize the seizure area, researches used the electrodes to generate a BCI. While the electrodes were removed in this instance due to the epileptic nature of the patients, the success of this study proves that these arrays are a valid method for use in BCI development and not just epileptic identification.

5) *EEG*: EEG is a technique involving the placement of electric field sensing electrodes around the scalp of an individual. The placement of these electrodes is standardized with a technique called 10/20 positioning[3]. A subject is instructed to clean their hair vigorously the night before the readings are taken. Measurements are taken according to the international 10/20 manual and the electrodes are placed against the scalp of the subject with a conductive medium, such as conductive gel, placed on the pads to facilitate the acquisition of signals.

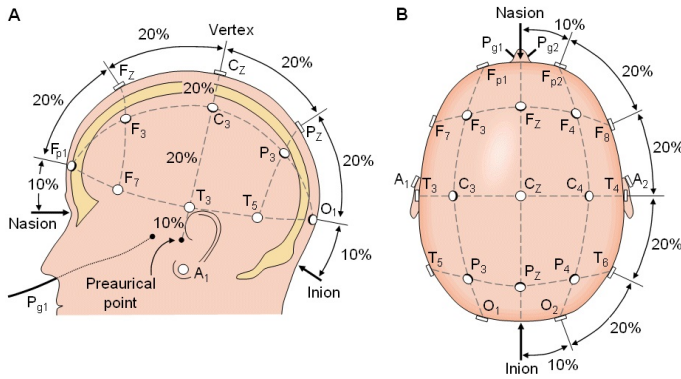


Fig. 2. The 10/20 International Positions and Associated Labels[28]

This method is, by far, the most popular for capturing signals from the brain. A few of the factors that make EEG such an attractive method are as follows: standardization of electrode placement, information on acquisition techniques well documented and plentiful, established as a reliable method with known filtering techniques, and the relatively low cost compared to other methods.

Since this is the most popular method, there is ongoing research to simplify the use of EEG for commercial applications, rather than the often complex and time consuming task

of applying the 10/20 system[29]. Systems such as these are predicted to be the on the user end of a BCI as opposed to the research end. These types of headsets are attractive to the user for their ease of set up and very low calibration times; with this example being in the range of ten seconds. Another big advantage to this system is that it can potentially work with many different types of headsets that are already available in the market.

One big caveat about EEG signals through, is that a sensed signal does not necessarily mean that that electrode is the source of the signal[30]. This counter intuitive phenomena is due to the fact that the brain is folded. In order to find the source of the signals, methods such as independent component analysis (ICA) are being widely used now as a localization technique. EEG signals are thus classified as being dipolar, meaning that in representations it is shown that there is a signal and an associated direction for the propagation of that signal[31].

III. EVENT RELATED POTENTIAL (ERP)

An evoked potential (EP) is a signal that occurs in the nervous system after the presentation of a stimulus. This signals is usually much smaller than the surrounding signals and as such requires special filtering techniques to recognize and extract. In the signal processing terms this signal is referred to as an event related potential (ERP). In the simplest terms the recognition of the evoked response is the goal of a BCI. This identification is made harder by the presence of artifacts in the signal. These artifacts in an EEG signal can originate from eye movements, blinks, or facial muscle movement. These potentials typically occur in the alpha spectra that originates from the occipital lobe region of brain waves which lies between 8-13 Hz. A curious effect of ERP is the tendency to be slightly different across multiple trials; for this reason many trials of the responses to the same stimuli are measured. With the onset of machine learning there has been a semi reliable method of signal trial detection or ERP[32], but the majority of the field is focused on averaging multiple trials.

ERP data is typically analyzed in the frequency domain. The data is transformed from the time domain to the frequency domain via the Fourier transform. When the signals are transformed into the frequency domain this represents the spectral power of the signal. This power shows in what frequency the signal is presenting itself; typically in the alpha range. By looking in this range and with more statistical analysis it is possible to distinguish between different signals; the core of BCI development[33]. A typical ERP response is shown in Figure 3.

As for stimuli that evoke the potential there are two main types that researches have focused on in recent years; imagined movement and visual evoked potentials (VEPs)[35]. While these phenomena are generally kept separate, there has been precedence set for them to be used in conjunction to increase accuracy[36].

The components of Event Related Potentials

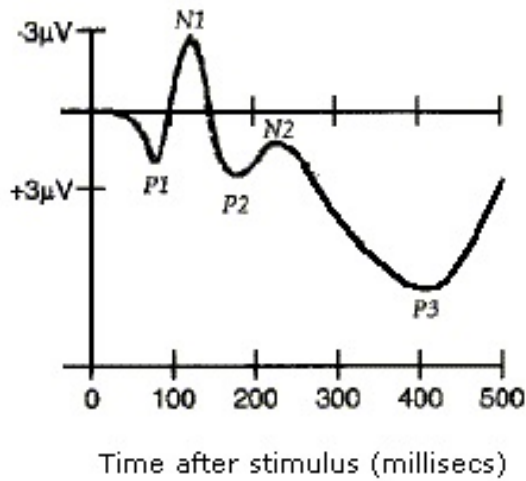


Fig. 3. A standard ERP waveform showing the amplitude and time delays associated with the phenomena[34].

A. Imagined Movement

Imagined movement is the desired method for researchers who are trying to appeal to a more robust market; that is to say these BCI can be used by both people without disorders and those with disorders, given that the neurological signals have remained intact[14]. As the name implies, an imagined movement BCI is one that discerns intent from the user as to what the action should be. The better the BCI is at identifying different ERPs, the more actions that a user can make. Without invasive means such as ECoG or the use of specially implanted sensors this can be quite a challenge.

B. Visual Evoked Potentials

The general procedure for VEP systems involves presenting a subject with visual stimuli and recording the EEG waves with timestamps. These recordings are preprocessed off-line to generate the BCI that is to be used on-line[37]. This technique works due to the fact that the off-line data can be compared to a labeled event signal from the testing material, that is, the presence of the stimuli is tracked in the EEG through time. Knowing when a signal is present in the EEG signal stream allows researchers to categorize a specific signal to a specific process. This method is predominately used in spelling programs using a part of the signal called the P300 response. The P300 response is used in VEP systems as a characteristic because it is an easily observable and reliable response. The P300 derives its name from a drastic peak in EEG signal, generally in the range of 150 microvolts, that occurs 300 milliseconds after a stimulus is recognized by an individual. The real power of this come from the fact that the person

need not be fully aware of the stimulus. Spelling programs use this property to the greatest effect so far. By displaying an array of letters and numbers, traditionally in a 6x6 pattern, and having the rows and columns flash at a constant rate a BCI can be developed that determines which letter the subject is looking at[19]. By simply changing the background colors to a checkerboard pattern rather than a single color, one group has been able to greatly increase the size of the matrix[7]. The reason this works is because the addition of dissimilar colors in the background removes false positives due to eye drift around the desired letter.

IV. SIGNAL EXTRACTION

Even though it is easy to say that engineers extract a signal, the question of exactly how they do this in the best way is still being explored. One of the leading ways to do this is called individual component analysis (ICA)[38], [39], [40]. This method is used in statistics to determine the individual components that make up a signal that comprises of many different signals. It tries to discern which parts of the signal that an electrode picks up belongs to a particular source. This is necessary because, as was mentioned earlier, the signals are dipolar in nature, thus a sensor picks up more activity than just the area of the brain it is placed over. This method tries to, and succeeds to a degree, isolate signals sources from areas such as the motor cortex to reduce noise and reject false signals from other areas of the brain. Expanding upon this idea, other researchers have looked into wavelet analysis[41] and even using wavelets to enhance ICA[42].

V. APPLICATION OVERVIEW

The most exciting and alluring thing about BCIs is that as long as a human is involved there is no end to the amount of fields the technology can expand in to. Any industry that involves humans has to possibility to be enhanced through the use of a BCI.

For patients with disabilities the use of a BCI can make the difference in moving towards independence. A problem that is being overcome is the long-term use of such BCIs by disabled patients in their own homes[8]. Concerns in this study are the ease of use and long-term application by the individual. The P300 system used by the individual only needs the caretaker to place the electrode cap and start the program, from there the subject is independently in control of the system. The functions of this system move beyond the traditional text-to-voice spelling system to include television and email control. It accomplishes this through the use of macros alongside the placement of letters in the grid system.

Another application of a BCI intended to help those with disabilities is the use of deep brain stimulation (DBS) to help relieve movement disorders such as essential tremor and Parkinson's disease[43]. Studies such as this are complex in the sense that there is little research on the characteristics of the local field potentials of tremors. A feedback loop is created using an implanted electrode that serves as both the neurological sensor and stimulator. The loop automatically

adjusts to the magnitude of the oscillatory tremor signal to compensate for the movement. An alternative approach of using an open loop system was performed, but with a substantial decrease in performance. This research is still in the early stages and is continually seeing updates on the classification of the stimulation parameters.

Moving beyond spelling there is research into reconstructing three dimensional spatial movement, in other words, prosthetic control. Breakthroughs in this area of BCI is new though as the problem is a very complex one. Trials of this sort were first extensively carried out on monkeys[9]. For the experiment the arms of the monkeys were restrained in stationary horizontal tubes and food was suspended in front of them in a clamp. The monkeys had to "reach out" with a robotic arm to grab the food to feed themselves. Monkeys have been a popular human analog for over a decade in these types of classifications and tasks[10]. This research showed many similarities to the previously mentioned one, such as restraining the arms of the monkeys. While the monkeys were not moving a physical prosthetic arm, they were manipulating a cursor in three dimensional space. The point that the monkeys had to move to changed from trial to trial to ensure that control was establishing, rather than the monkeys only figuring out how to move the cursor to a single position. For each day of testing the baseline readings of the monkeys were taken via a routine calibration task; this was to account in the day to day variability of the same signals. In each trial the monkeys had ten to fifteen seconds to move the cursor to the desired location. Initially the monkeys resisted the restraints and had a low completing rate. After two weeks of training though the monkeys improved dramatically, with some days seeing a 7% increase in performance. Yet another example of this type of research can be found elsewhere[11]. This research also uses implanted electrodes to record the ECoG response to control neural prosthetics. Microwires are used to reach down in between the folds of the brain to reach single unit action potentials of individual neurons. This is unique in the aspect that it gives a much higher spacial resolution than even the local field potential signal. The studies presented builds a framework that shows the overall feasibility of using this method and others mentioned here as a tool of movement restoration.

A more recent example of this type of control with human participants is a woman feeding herself a bar of chocolate[12]. This experiment involved a woman with tetraplegia, paralysis that involves the total loss of all four limbs. Implanting two specially made intracortical microelectrode arrays, each equipped with 96-electrode shanks, was the key to making this sort of fine control possible. The total 192 electrodes from which to take readings made for a very high resolution signal with enough test points to distinguish between many different signals. The other contributing factor towards the overall success of this experiment were the many trials of testing that were performed to account for daily changes that occur in signals that were discussed earlier.

One common element in the neural prosthetic applications

mentioned so far is that they require invasive means of sensing. This is primarily a problem relating to the resolution of the signal. As discussed, other methods such as ECoG have much greater signal resolution due to the inherent closeness to the source signals. EEG measurements are distorted by the scalp, thus reducing the spacial resolution. This makes reconstructing hand movements using only EEG challenging[44]. However, relatively new source localization algorithms have allowed researchers to more accurately pinpoint signal sources. This is a great help, as it increases the resolution without the need to fit more electrodes onto a sensing cap. There is a trend emerging using this data to build a framework for the use of EEG with more complex designs[45]. With this method previous research that has had to include upwards of sixty-four electrodes could also be theoretically reduced. For consumer applications in BCIs, this is a major step forward.

On the cutting edge of the field is using BCIs to control non-human-like systems, such as a quadrotor[15]. Minnesota is the first group of researchers to successfully control a quadrotor in three dimensional space. The person who is controlling the quadrotor is wearing a EEG cap with electrodes and with imagined movements, such as closing hands and moving feet, is able to fully control the flight path to navigate an obstacle course. In order to obtain this level of control, there were five separate calibration and verification steps. Before the final test with the real quadrotor a virtual quadrotor was flown using the EEG signals to validate safety and the overall effectiveness of the system. The final system was flown in an obstacle course which consisted of floating rings made of balloons placed around a basketball court.

VI. EXAMPLE USING BCILAB

Now that all of the background data has been presented an offline example using some of this technology will be shown. This example comes from the Swartz Center for Computational Neuroscience's BCILAB toolbox which contains the sample data, and Dr. Christian A. Kothe's accompanying lectures[46].

First let us talk about the data. Some available sample data in the toolbox was captured from a set of identical twins; we will only be examining one data set for this example though. The data was captured using an EEG cap during what they call a "flanker task". This task they are referring to involves a person being presented with images and pressing a button based on some criteria. We will be examining the responses from the EEG to determine whether the person made an error in pressing the button. This time stamping is important due to the ERP analysis that was carried out. This example uses a technique called "windowed means" to use windowed averages of the signal to compute features of the signals and then uses those features in a machine learning stage.

Figure 4. shows the setup to the approach that was used. The chosen epoch ranges from -0.2 seconds to 0.8 seconds around each time window of a button press to include any features from the signal that are present. The frequency filter is set up to 15 hertz to capture the relevant brain frequencies associated

Fig. 4. Window showing the correct parameters for sampling the data at 500 millisecond intervals

with this task. Without any extensive prior knowledge of the data set we must be careful to choose which epoch features to take as samples; if too few are chosen then the BCI will not be accurate, too many and the features calculated will be too strict and will take too long to run. This example uses 500 millisecond windows ranging from 200-500 milliseconds. A window is added at the end that contains the data from 500-600 milliseconds to capture any of the data associated with positivity[47]. For the machine learning function that was used, the default of LDA (linear discriminant analysis) was chosen. It should be noted that these are not all of the features available for use. There are many more advanced options in BCILAB that can be explored, but these are the minimum ones needed for this working example.

At this stage we want to train a new model in BCILAB with the approach that was just defined and the dataset the was previously loaded. The first thing to look at is the desired target markers. In the data set, which can be seen by clicking the button next to the field, target markers are labeled on the data. For any data this is should always be carefully documented throughout the experiment procedures ; since this is sample data from another source it is worthwhile to go ahead and take a look at the data and markers. There are two groups of markers in the set, containing errors and no errors for both left and right hand movements. Due to this nature it is necessary to use nested markers, documentation of which is provided with inside the BCILAB plug-in. Looking at the syntax of the marker sets it is determined that the appropriate markers to use to separate the data are $\{\{'S101', 'S102'\}, \{'S201', 'S202'\}\}$. For this example we will leave the parameter search to automatic, which will choose MCR (mis-classification rate). We will also leave the number of cross-validations for the computations at 5. The window that controls this is shown in Figure 5.

After clicking OK to run the model the computations will start. It should be noted that this will take some time for cross-validation which can equate to a long processing time. Choosing different methods can also exponentially increase the amount of time it can take to train the model. Figure 6 shows the output and how well this particular model worked for this task. We can see that this model had an error rate

Fig. 5. Parameters for labeling the targeted markers and parameter search. This example finds error rates on left and right hand button presses.

of only 5%, which means that this model is only wrong 5% of the time for this task. This is already a very good model without changing anything at this point.

Data Summary					
True positive rate : 0.79 +/- 0.15 (N=5)					
False positive rate : 0.21 +/- 0.15 (N=5)					
True negative rate : 0.97 +/- 0.02 (N=5)					
False negative rate : 0.03 +/- 0.02 (N=5)					
Error rate : 0.05 +/- 0.02 (N=5)					

Data Details					
	True positive r...	False positive r...	True negative r...	False negative ...	Error rate
1	0.6000	0.4000	0.9565	0.0435	0.0886
2	1	0	0.9600	0.0400	0.0375
3	0.8750	0.1250	0.9577	0.0423	0.0506
4	0.7273	0.2727	1	0	0.0375
5	0.7500	0.2500	0.9722	0.0278	0.0500

Fig. 6. Effectiveness of the BCI is shown. This trial was concerned with the error rate, which turned out to be 5% with the current model.

Now that we have the model, it is a good idea to visualize it. This visualization is what is typically presented in papers to show the effectiveness of the model and the research. This visualization is a powerful tool in communicating a lot of data to the reader in a short time. To give you an example, most of this section could be cut by including just this visualization. However, that would defeat the purpose of presenting the knowledge for this paper. Figure 7 shows the linear weights of the classifiers we designated to the features that were chosen. These are the spacial filters that the computer uses in considering the signal for classification. By looking at Figure 7 we see that Window1 and Window3 have big contributions to the analysis; this is most likely to to the positivity and negativity of the ERP response. Moving forward and refining the method, it may be a good idea to discount the other windows as noise to increase accuracy.

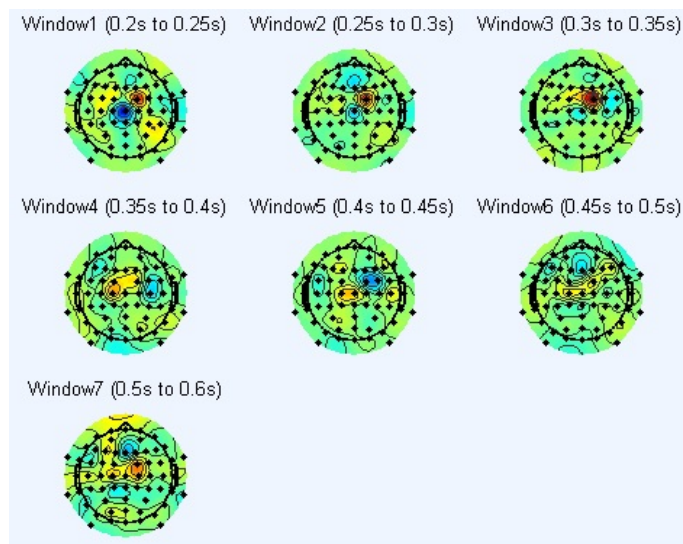


Fig. 7. Visualization of the linear weights from each sample epoch that was chosen. Window1 and Window3 are shown as having the greatest effect on the signal.

Now that there is a model it is possible to apply this more data sets or to save it for later to refine the method. This is more than sufficient for a results section for a paper. BCILAB is much more robust than what has been presented here and should be explored further.

VII. CONCLUSION

This survey only mentions the most notable examples and techniques in the field. There are still other nuances to BCIs that are too many to go into in this paper, such as the different machine learning techniques used in generating models. There are also other methods of disabled persons controlling computers, such as EMG[48] assisted signal acquisition, but those are outside the scope of this paper. It is believed that the information presented here highlights the most general uses and contains information that applies to the greatest number of the population that would potentially use or develop a BCI. The reader is encouraged to explore this budding field as it

rapidly develops and to present new ideas to the problems mentioned herein. There are data sets that are publicly available from many sources, most offering easy compatibility with MATLAB for manipulation. For free software EEGLAB[49] and BCILAB[14] are both plug-ins for MATLAB and offer extensive tutorials online for those interested[46].

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