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OPTIMIZATION OF FEATURE SELECTION IN A BRAIN-COMPUTER INTERFACE SWITCH BASED ON EVENT-RELATED DESYNCHRONIZATION AND SYNCHRONIZATION DETECTED BY EEG

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OPTIMIZATION OF FEATURE SELECTION IN A BRAIN-COMPUTER INTERFACE SWITCH BASED ON EVENT-RELATED DESYNCHRONIZATION AND SYNCHRONIZATION DETECTED BY EEG

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University

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List of Abbreviations

BCI	Brain Computer Interface
ALS	Amyotrophic Lateral Sclerosis
EEG	Electroencephalogram / Electroencephalography
ERD	Event-Related Desynchronization
ERS	Event-Related Synchronization

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Abstract

OPTIMIZATION OF FEATURE SELECTION IN A BRAIN-COMPUTER INTERFACE SWITCH BASED ON EVENT-RELATED DESYNCHRONIZATION AND SYNCHRONIZATION DETECTED BY EEG

By Mason Montgomery, M.S.

A Thesis submitted in partial fulfillment of the requirements for the degree of Master in Sciences at Virginia Commonwealth University.

Virginia Commonwealth University, 2012

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There are hundreds of thousands of people who could benefit from a Brain-Computer Interface. However, not all are willing to undergo surgery, so an EEG is the prime candidate for use as a BCI. The features of Event-Related Desynchronization and Synchronization could be used for a switch and have been in the past. A new method of feature selection was proposed to optimize classification of active motor movement vs a non-active idle state. The previous method had pre-selected which frequency and electrode to use as electrode C3 at the 20Hz bin. The new method used SPSS statistical

software to determine the most significant frequency and electrode combination. This improved method found increased accuracy in classifying cases as either active or idle states. Future directions could be using multiple features for classification and BCI control, or exploiting the difference between ERD and ERS, though for either of these a more advanced algorithm would be required.

CHAPTER 1

INTRODUCTION

1.1 The Brain Computer Interface

1.1.1 Need for BCIs

It is estimated that 30,000 people in America alone have Amyotrophic Lateral Sclerosis. ALS is a common cause of "locked-in syndrome." Locked-in syndrome refers to the state of a person's body becoming immobile but their mind remaining active. The only way such people have been able to communicate in the past is through eye movement and blinks, but BCIs could allow them to use more of their brain that has been cut-off from the rest of their body.

Another group that could benefit from BCIs is amputees. There are hundreds of thousands of amputees in the US who could potentially benefit from a BCI prosthetic. A majority of amputees experience phantom limb pain, but also other sensations because parts of their motor cortex are still devoted to the missing area. That input is looking for an output, and a BCI prosthetic could serve as that output.

There are two main categories of BCIs: invasive and non-invasive.

1.1.2 Invasive BCIs

Now there are two main divisions of BCIs, invasive and non-invasive. Of the invasive division, there are two subsections: fully invasive and semi-invasive. The fully invasive section is further divided into single site recording and multiple site recording. Semi-invasive recording is called Electrocorticography, where electrodes are placed under the skull, but on top of the cortex, not implanted within the cortex. In single site recording, one electrode is implanted into the cortex and receives signals from a small group of neurons (Evarts et al, 1960). This kind of interface is simple and easy to implement. However, it suffers from the variability associated with a small sample population, because neuron firing patterns vary greatly between neurons and even the same neuron can fire differently at different times. Multiple site recording avoids variance of single neurons and temporal variance by getting a larger population to average. Because of this, it has the potential to produce more and cleaner signals for a computer to read. The difficulty with this technique is the requirement of more advanced algorithms to make sense of all of the data picked up by the electrodes.

Much research has been done on non-human primates and somewhat more limited research has been done on humans. In 2003, an experiment was carried out on three rhesus monkeys that had microwire arrays implanted into their cortexes. The subjects had 100 to 700 microwires each in up to five cortical areas. Up to 250 individual neurons were recorded each session (Nicolelis, et al 2003). This experiment demonstrated the ability to obtain neuronal signals in real-time from multi-electrode recordings at multiple sites.

1.1.3 Non-Invasive BCIs

The greatest benefit of non-invasive BCIs is the lack of surgery and the risks associated with brain surgery. The greatest detriment is the imprecision of having to pick up relatively faint signals through skin, bone, and everything else that cushions the brain from the outside world. Often a choice has to be made between temporal and spatial resolution. The fMRI offers unaparalleled spatial resolution down to 1mm, but the temporal resolution is as high as 1-2s. This makes it better suited to studying the localization of cortical activity than for control of any device. Electroencephalograms, however, have unmatched temporal resolution of ~1ms, but lack spatial resolution greater than a centimeter or two at the surface (Pfutscheller et al, 2006). Fortunately for EEGs, most brain activity of interest occurs at or near the outermost layer of the cortex. This leads to a maximum information transfer rate of 25 bits per second (Wolpaw et al, 2002). That rate could be sufficient to operate a computer cursor or keystrokes, but not a prosthetic limb as complex as a real limb. Another drawback is that it can take several sessions to learn how to use an EEG-based BCI effectively. Some require the subject to find out what works on their own, while others use algorithms that look for and recognize common firing patterns.

One such pattern is the P300, a potential increase observed 300ms after a stimulus presentation. It has been used to create a letter matrix to allow those who cannot move to spell out words at about 2 letters per minute (Nijboer et al, 2003).

In the proposed experiment, the common firing patterns that were utilized were the Event-Related Desynchronization and Synchronization.

1.2 Event-Related Desynchronization and Synchronization (ERD/ERS)

The natural state of neurons that are not in use is to fire action potentials in synchrony. Up to two seconds before a motor action is initiated, the neurons in use desynchronize and this is called an Event-Related Desynchronization. The ERD lasts until one second after the action ceases (Toro et al, 1994). Following the action, the neurons resynchronize, a phenomenon called Event-Related Synchronization. ERS can be observed a few tenths of a second after an ERD ceases. Because of the nature of synchrony and desynchrony, ERD is associated with a relative power drop and ERS with a relative power increase in certain frequency bands, especially the Beta Band ~15-30Hz (Bai et al. 2005; Pfurtscheller et al 2009; Deeke et al, 1969). Previous studies have proposed using the beta band in the motor area as a control for a BCI (McFarland, 2003). These patterns appear both during real and imagined movement (Pfurtscheller and Lopes da Silva, 1999). Because it can appear out of imagined movement it has possible applications to locked-in patients and may even be a natural-feeling solution to amputees. It is also a very stable feature that exists in most individuals and remains across trials (Pfurtscheller and Nueper, 2006).

1.3 Objective

There already exists a technique to use ERD/ERS signals, however there was no method for finding the best signal. The signal was chosen by educated guess as the 16-20Hz frequency bin of electrode C3 (Qian et al. 2010, Bai et al. 2008). The proposed method seeks to improve on this by developing a method of feature selection customized to each individual. A large volume of data is collected with each experiment: 25 frequency bins over 15 electrodes, ERD and ERS, which make 750 features in all, so it is likely that at least one has greater significance than the feature used by the current paradigm. This paper will propose the use of the statistical software SPSS to select the most significant features for a BCI switch. To be successful, the new paradigm will need to be able to better discriminate between active and idle states than the current paradigm, especially in motor imagery because of its use for those who can no longer execute physical movement. There would still need to be at least two tests for calibration, but the analysis should be able to be completed within the same time frame of 3 to 4 hours.

CHAPTER 2

METHODS

2.1 Subjects:

Four healthy volunteers aged twenty to twenty-three (two males, two females) participated in this study. Each subject was tested for handedness by filling out a survey asking which hand was dominant in a variety of tasks, and all were found to be right-handed. Their scores on the Edinburgh scale ranged from 0.6 to 0.9, where 1 is completely right-handed, zero is ambidextrous, and -1 is completely left-handed (Oldfield, 1971). None of them had any prior experience with Brain-Computer Interface. The protocol was approved by the Institutional Review Board. All of the subjects gave informed consent.

2.2 Set up:

Subjects were equipped with an elastic 64-channel Electroencephalography cap (Electro-Cap International, Inc.). Of the available channels, 16 were used, 15 for data recording and one for ground: FZ, C3A, CZA, C4A, C5, C3, C1, CZ, C2, C4, C6, C3P, CZP, C4P, and PZ. FPZ was used for the ground. The resistance of each was monitored and reduced to under five Kilo ohms.

In addition to the data-recording electrodes, there was a reference electrode attached to the subject's ear. Finally, an electrode was applied to the subject's right forearm for the purpose of monitoring muscle activity via Electromyography.

Once the subject was equipped with the cap, the experimenter sat them down in a comfortable chair three to four feet in front of a monitor. The electrodes were then plugged into a Guger Technologies USB Biosignal Amplifier. The amplifier was already plugged into a computer equipped with MATLAB and the BCI2VR Toolbox (Bai et al, 2007). The set up typically took one hour.

2.3 Paradigm design, task, implementation:

The paradigm for this experiment was similar to an earlier experiment (Qian et al. 2010). Each subject was allowed to watch the program run while the researcher explained the paradigm. There were two frequencies of tones, higher-pitch (5000Hz) and lower-pitch (2000Hz), each played for 0.05 seconds. When the higher pitch tone played the subject was to move their right hand for 1.5 seconds. After the duration, the lower pitch tone played indicating a 2.5 second rest period. This task was repeated 8 times in a set. The same method was used to collect data from the idle state. The same pattern of tones played, but the subject was instructed to avoid innervating any muscles if possible. In total there were six sets per session: three idle and three active for a total of 48 tasks per session. In each experiment there would be at least two sessions of physical movement and two sessions of imaginary movement.

If the researcher observed physical movement on the EMG at incorrect times, they informed the subject and asked them to cease movement. The two particularly troublesome movements were movements of the right arm, observed via activity on the EMG channel, and movement that affected the head, observed by large shifts in most channels as the connection of the tin electrode to the scalp was stressed.

2.4 Data acquisition:

Signals were amplified and digitized at a rate of 256 hertz. The signals from each electrode were divided into 25 bins of 4Hz each. The first bin was 1-4Hz; the second was 5-8Hz, etc. After each high pitch tone, the Event-Related Desynchronization was recorded. The ERD was defined as the average power for each frequency from 0.5s to 1.75s after the high pitch tone. The Event-Related Synchronization was recorded in the same manner and defined as 2.25s to 3.25s after the initial high pitch tone.

Similarly to the previous study, the Welch method was used with FFT length of 128 for Bin width sampling, segment length 64, 16 for frequency analysis on every slide increase, window length of 256 for frequency analysis, 0.5 overlapping rate, and a ‘hamming’ window (Qian et al, 2010).

2.5 Classification:

The data from the sessions were analyzed off-line using SPSS/PASW 18. The Wilks' lambda method for discriminant analysis was used. Each frequency bin being analyzed from each electrode under analysis was set as a separate category. Using state (idle or active) as the grouping variable, the categories were then classified and given an 'F' value. The 'F' value is the same as those calculated in a one-way analysis of variance, which is also the square of the *t* value calculated from an independent samples *t* test (George and Mallory, 2011). The frequency bins with the highest F values were then analyzed separately to determine how accurately they could predict idle vs active state group membership.

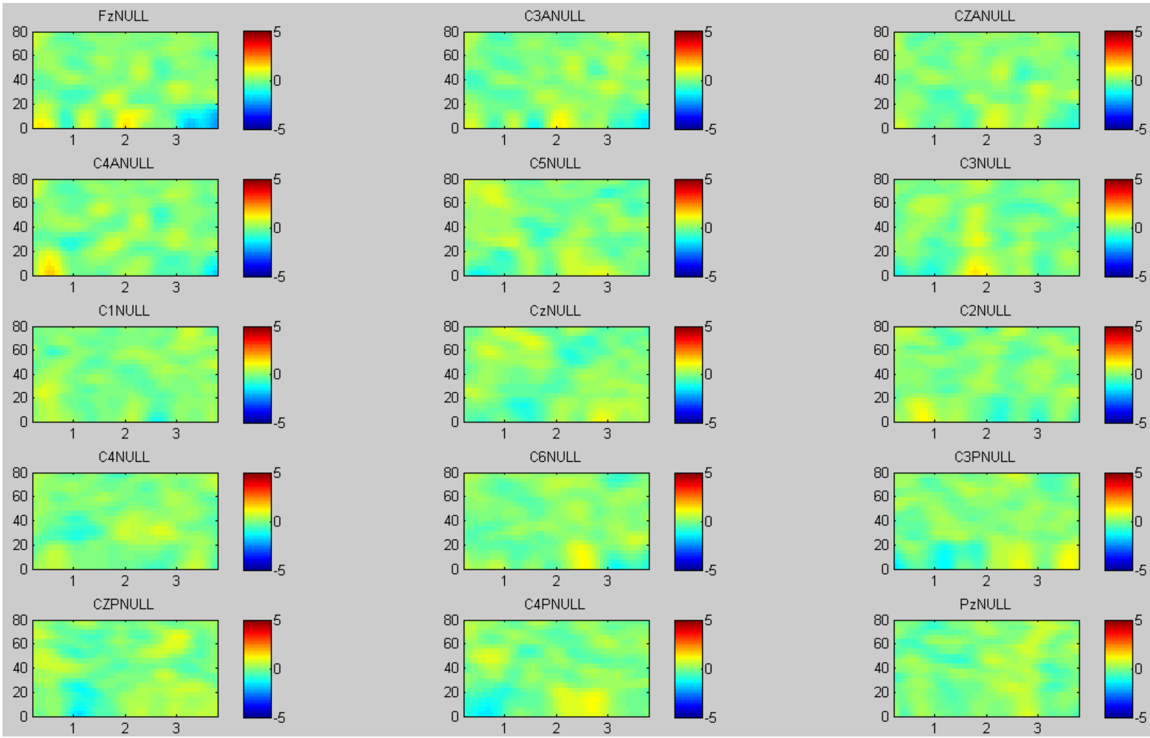

Figure 0: Idle state of Subject 1. Each subject's active states were compared to their correlated idle state in the differentiation process.

CHAPTER 3

RESULTS

3.1 Topographical Analysis

It has been understood since the time of Galan that each hemisphere of the brain controls the contralateral side of the body. As expected, in Figure 1, activity from moving the right hand can be observed in the left motor cortex area. It manifests as a power decrease during the motion, then, shortly after the motion, the neurons resynchronize and the power greatly increases.

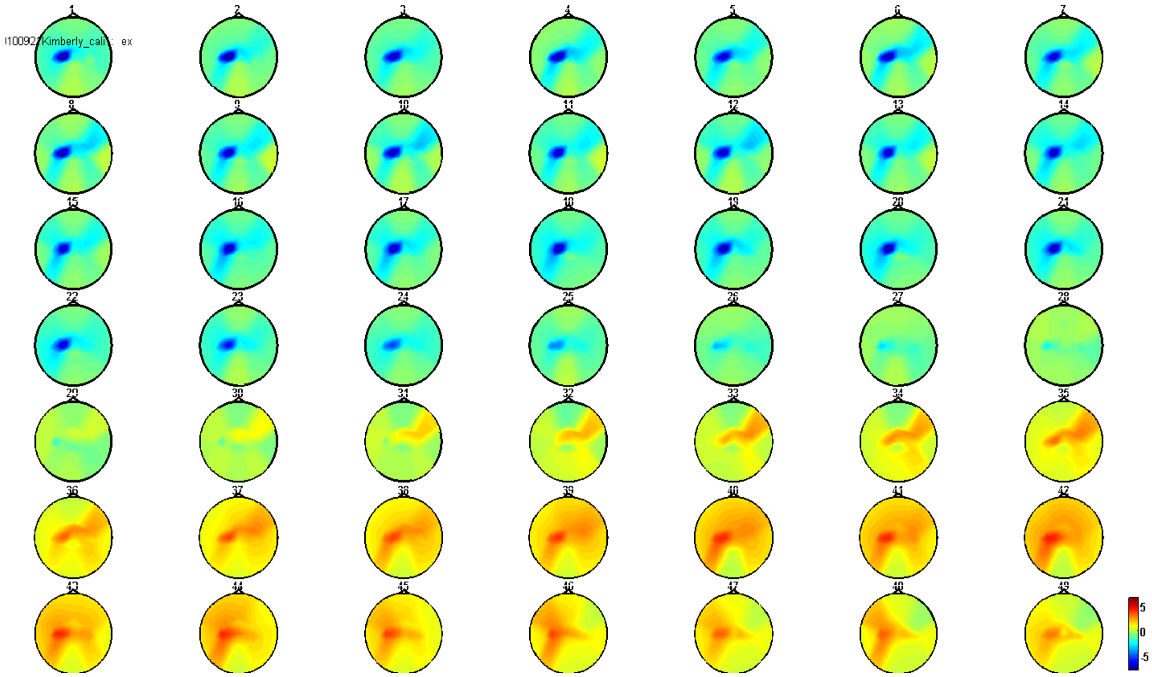

Figure 1: Topography plot from subject 2 physical movement
Each display is a top-down view of the head, with the nose pointed up. The display is read like text, from top left to bottom right. The time window displayed is the beginning of ERD to the end of ERS, so each head is about 0.06s after the previous one. The color represents the relative power, where blue indicates a relative power decrease and red indicates a relative power increase.

3.2 Time-Frequency Analysis

Subjects performed a movement task before the imagery task to familiarize them with the paradigm, have a reference point for their motor imagery, and for analysis comparison. As expected the subjects performed significantly better at the motor movement task than at motor imagery. Figure 2 shows the best example of any performance on physical movement. There is a clear distinction between the (red) synchronization and (blue) desynchronization phases. The clear activity is in the beta-band (frequencies between 13-30Hz). In theory the best channel should have been C3 because it is situated roughly where the hand of the motor homunculus should be, however, this did not always prove to be the case. In some channels a distinction can even be made between the beta and alpha bands. This is as close to the ideal signal as was observed.

The imaginary task provided generally worse results than the physical task. The difference could be observed subjectively between the time-frequency plots for each task and also empirically through decreased percent correct classification. On average the difference was 5.6 percentage points.

A wide variation between subjects can be observed subjectively and objectively. Subject 2 had very clear ERD/ERS patterns across a broad band of frequencies in several channels and correct classification near 95%. Subject 1 displayed the ERD/ERS pattern in a few channels, though most strongly in C3P and in more narrow frequency bands. Their correct classification was 78%. Subject 3 had a discernable but weak ERD/ERS pattern in a few channels. It was also unusually-timed and led to a correct classification of 60%. The signals of Subject 4 could be loosely interpreted as a weak ERD/ERS pattern in a few channels, but classification was little better than chance at 55%.

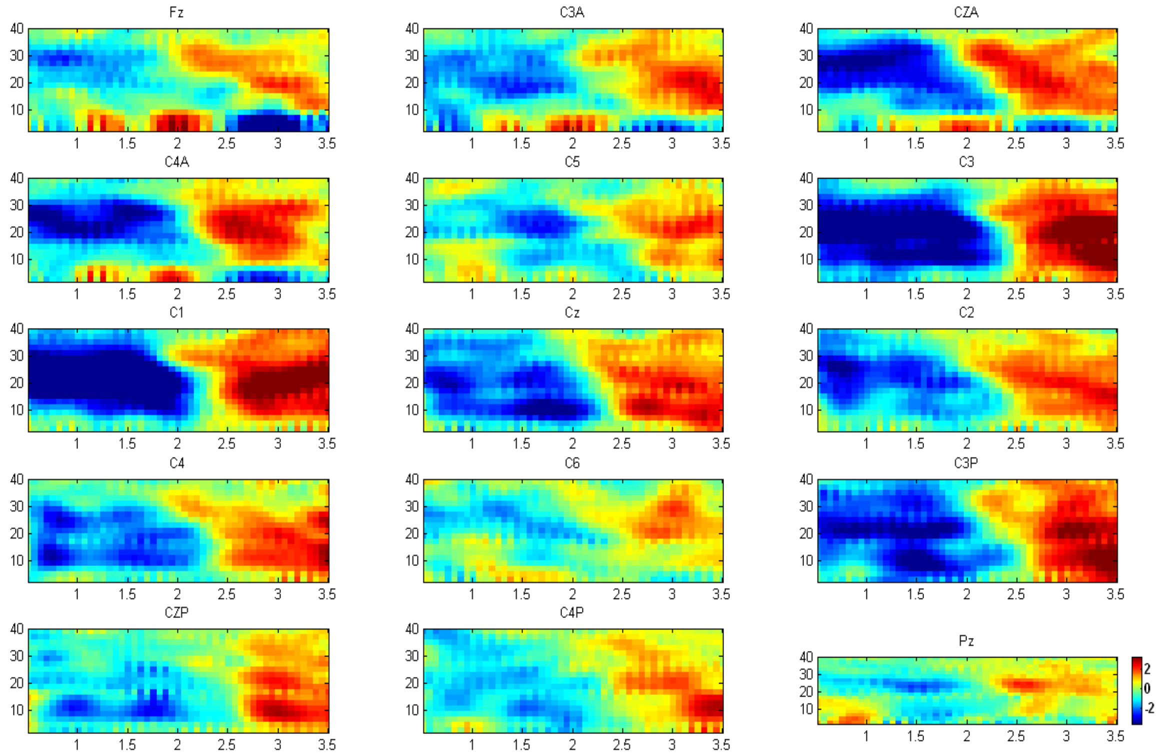

Figure 2: Time-Frequency plot from subject 2 physical movement For comparison. The x-axis is time in seconds. The y-axis is frequency in Hertz. The color represents the relative power, where blue indicates a relative power decrease and red indicates a relative power increase. ERD can be observed on the left, ERS on the right.

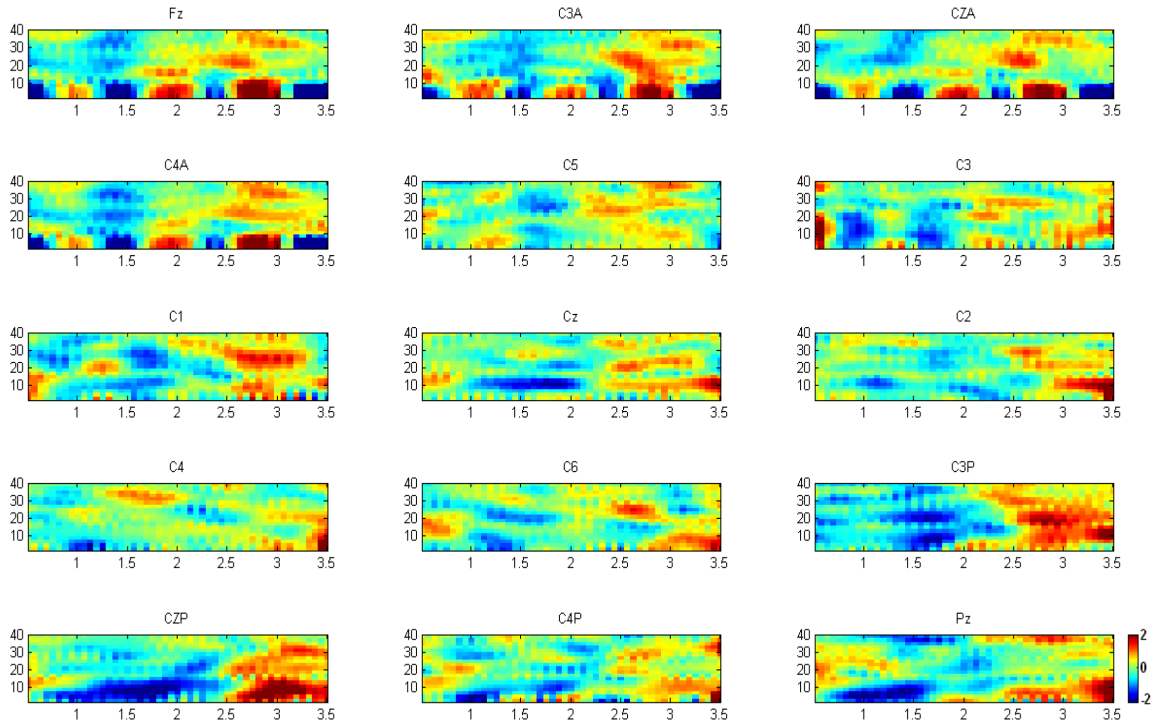

Figure 3: Time-Frequency plot from subject 1 imaginary movement
The x-axis is time in seconds. The y-axis is frequency in Hertz. The color represents the relative power, where blue indicates a relative power decrease and red indicates a relative power increase. ERD can be observed on the left, ERS on the right, especially in C3P.

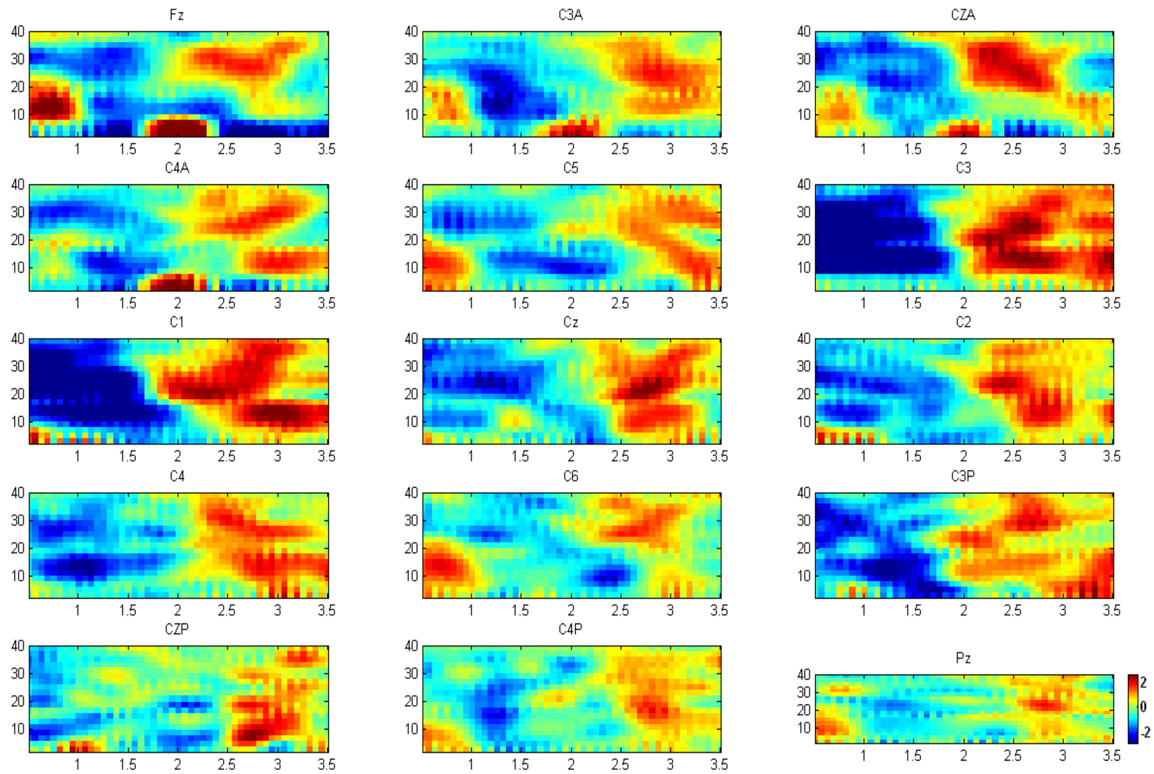

Figure 4: Time-Frequency plot from subject 2 imaginary movement
The x-axis is time in seconds. The y-axis is frequency in Hertz. The color represents the relative power, where blue indicates a relative power decrease and red indicates a relative power increase. ERD can be observed on the left, ERS on the right.

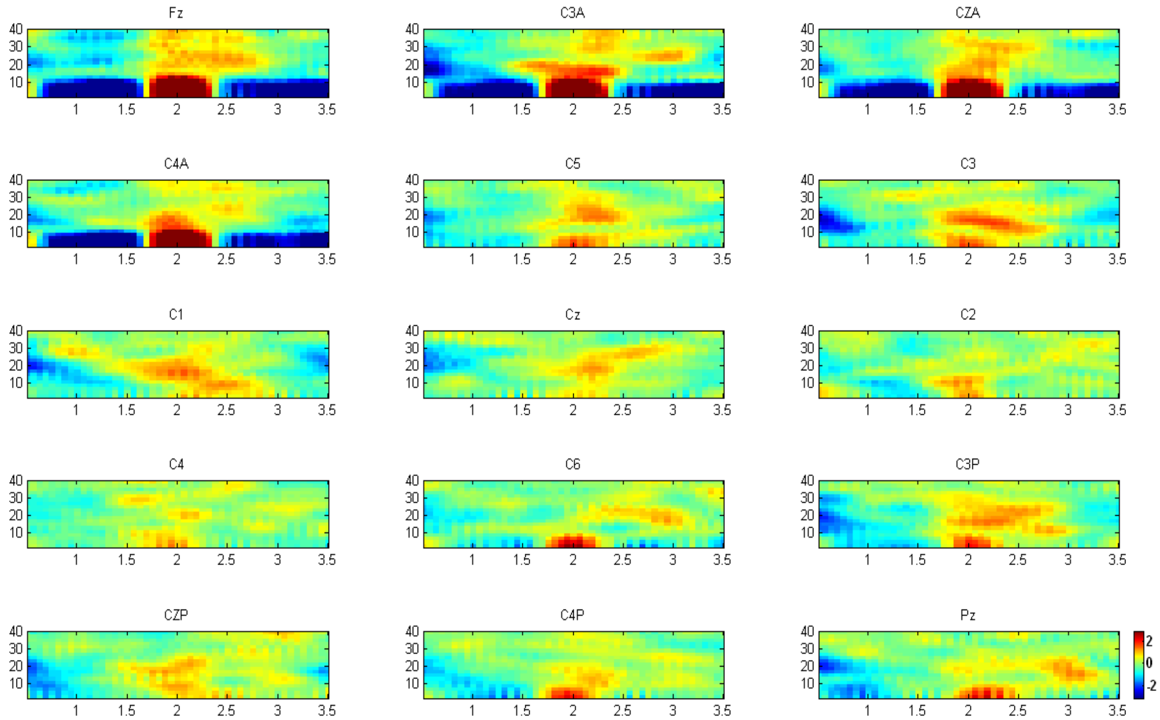

Figure 5: Time-Frequency plot from subject 3 imaginary movement
The x-axis is time in seconds. The y-axis is frequency in Hertz. The color represents the relative power, where blue indicates a relative power decrease and red indicates a relative power increase.

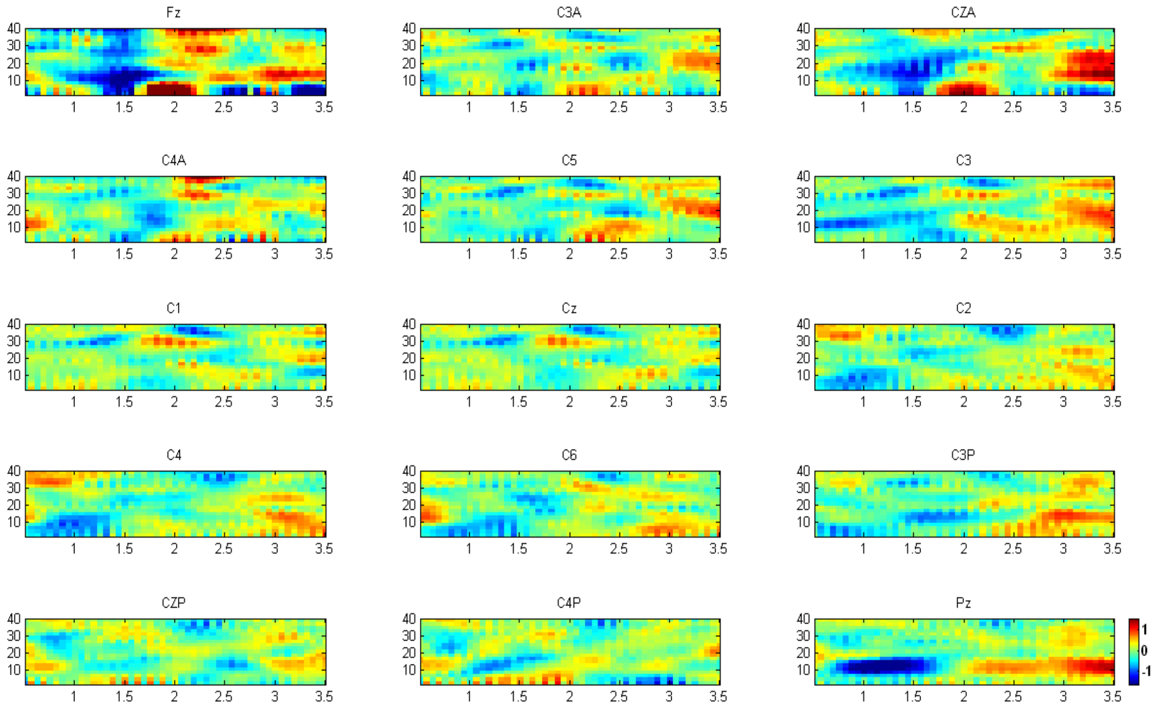

Figure 6: Time-Frequency plot from subject 4 imaginary movement
The x-axis is time in seconds. The y-axis is frequency in Hertz. The color represents the relative power, where blue indicates a relative power decrease and red indicates a relative power increase.

3.3 Classification

3.3.1 Previous Method

The previous method used the ERD signal in channel C3 at 20Hz. The results of using that method are shown in Table 1. Displayed therein are the F value and accuracy of classification using the SPSS discriminant analysis function for both imaginary and physical movement. The F value is the same as those calculated in a one-way analysis of variance, which is also the square of the *t* value calculated from an independent samples *t* test. Accuracy indicates what percent of idle and active states were correctly classified as such.

Table 1: Accuracy of Classification for ERD/ERS Switch using ERD in C3 with 17-20Hz Bin

Subject Physical/Imaginary Movement	F	Accuracy
Subject 1 Physical Movement	137.600	89.6
Subject 1 Motor Imagery	38.187	78.1
Subject 2 Physical Movement	256.700	94.8
Subject 2 Motor Imagery	271.372	94.8
Subject 3 Physical Movement	9.624	54.5
Subject 3 Motor Imagery	12.009	59.5
Subject 4 Physical Movement	67.822	70.0
Subject 4 Motor Imagery	.291	54.0

3.3.2 New Method

Included in the SPSS discriminant analysis were F values for each variable entered. Those were every frequency bin recorded (0Hz to 100Hz) from 5 channels of interest (C1, C2, C3, C4, and C3P) including ERD and ERS values. The most significant value was always an ERD. Full results are shown in Table 2. It gives the most significant channel and frequency combination. For each variable that was found most significant, a single variable discriminant analysis was performed and the accuracy was recorded.

Table 2: Accuracy of Classification for ERD/ERS Switch Using the Most Significant Channel and Frequency Bin

Subject Physical/Imaginary Movement	**Channel and Frequency**	**F**	**accuracy**
Subject 1 Physical Movement	**C3P 16**	**257.9425**	**93.8**
Subject 1 Motor Imagery	**C3P 20**	**119.6347**	**87.5**
Subject 2 Physical Movement	**C3 32**	**262.219**	**93.8**
Subject 2 Motor Imagery	**C3 16**	**280.319**	**94.8**
Subject 3 Physical Movement	**C1 28**	**162.5426**	**82.5**
Subject 3 Motor Imagery	**C3P 8**	**29.75547**	**65.5**
Subject 4 Physical Movement	**C3 16**	**77.81327**	**72.5**
Subject 4 Motor Imagery	**C1 20**	**6.839754**	**59.0**

3.3.3 Comparison

Compared to the previous method of using channel C3 at 20Hz to the new method of finding the most significant channel and frequency, the new method yielded significantly improved results. The greatest improvement came in the physical movement of Subject 3, an astonishing 28% increase from 54% to 82% accuracy. Though the physical movement was included mostly for a frame of reference, this shows how much of a difference the few centimeters and 8Hz between C3 20Hz and C1 28Hz can make. The greatest improvement in motor imagery came from Subject 1 as a 9% improvement from 78% to 87% accuracy. Put another way, the number of errors was reduced by 41%.

The only subject to not see improvement was Subject 2, but her accuracy was already the highest of all the subjects, and as can be seen in figure 2 and figure 4 her signals were by far the clearest. The decrease seen in her physical movement accuracy is likely due to a single extra miscategorization.

Though it was never the most significant channel and frequency combination, the original assumption of C3 at 20Hz being the most significant was not misguided. All of the most significant frequencies found, 8Hz to 32Hz, fell in the beta band except for Subject 3’s motor imagery, which could be classified as being in the alpha band. Likewise, the most significant electrodes were C3, C3P, and C1. The electrode C3 is positioned over the expected position of the hand of the motor homunculus. C1 should be closer to the torso and legs of the motor homunculus, but each person’s brain is configured slightly differently, so finding significance there should not be too surprising. The observed significance from C3P can be explained one of two ways: 1. the fit of the cap and the shape of the subject's head put C3P over motor cortex and shifted C3 to premotor cortex, or 2. C3P was over sensory cortex as it should have been and the area was stimulated by increased attention to that area.

Table 3: Percentage Point Improvement of Best Variable over C3 20Hz ERD in Offline Analysis

	Subject 1	*Subject 2*	*Subject 3*	*Subject 4*
Physical Movement	4	-1	28	2.5
Motor Imagery	9	0	6	5

CHAPTER 4

DISCUSSION

4.1 Success of Improved Feature Selection

The goal of the ERD/ERS switch was to create a reliable on/off command using only signals detected by an EEG. A perfect switch would be as functional as a real-world switch which, barring mechanical failure, will have 100% accuracy in classification of off (idle) and on (active). The realized accuracy of either method is still not up to that standard, and may not be for some time. However, up to 50% error reduction from the first method to the enhanced method is a good start. This improvement has even been achieved without making further computational demands on the device itself, so much more improvement is likely to be found in enhanced computational methods.

One might notice how much better subjects 1 and 2 were at the task than subjects 3 and 4. It might be worth looking into whether females have some natural advantages over males in this task as subjects 1 and 2 were both female and subjects 3 and 4 were both male. The best performance of either male was still worse than the worst performance of either female. The sample is far too small to prove anything, but the dramatic difference in performance warrants some further investigation.

Another factor whose impact is as yet unknown is the nature of a signal from an amputee. The cortical activity associated with 'moving' the missing limb may turn out to be more similar to the activity associated with real movement than like the motor imagery of healthy subjects. One way to reproduce the effect of being unable to innervate limbs in healthy subjects would be the use of localized paralytic agents, however, complications associated with this option may make it unfeasible.

4.2 Further Improvements

4.2.1 Multiple Signals

One proposal for improving the paradigm is to use multiple signals at once. When all of the signals are analyzed offline 100% accuracy can be achieved for every subject. However, this would be very computationally demanding on any device. Another, more likely, possibility is that using hundreds of features to differentiate between 96 data points resulted in over-fitting of the data. Using two or more of the most significant electrodes could provide a high enough accuracy that averaging only two trials would give an acceptable accuracy. Tables 4 through 7 show the F values of each subject's frequencies in ERD and ERS at five different electrodes. In most cases there are clusters of significance around certain frequencies in each electrode. One interesting aspect is that the frequencies at the center of these clusters vary across electrodes. In a single subject the most significant frequencies in a given electrode can vary by as much as 20Hz.

Table 4: F values for Subject 1 at every frequency and electrode

	ERD	ERD	ERD	ERD	ERD	ERS	ERS	ERS	ERS	ERS
Hz	C3	C1	C2	C4	C3P	C3	C1	C2	C4	C3P
4	28.129	24.240	26.455	13.962	91.008	7.939	15.538	11.965	26.655	43.747
8	32.843	30.383	27.716	15.116	98.834	10.231	20.027	14.289	28.287	47.673
12	38.028	39.730	28.782	16.084	106.736	13.194	25.407	16.518	29.020	51.748
16	40.590	50.847	29.550	16.784	113.071	14.876	30.613	17.791	29.017	53.952
20	38.187	67.360	29.703	17.558	119.635	13.774	38.169	17.162	26.974	50.555
24	20.166	68.800	24.060	12.805	107.330	7.919	35.890	10.460	15.116	28.496
28	4.047	46.497	16.030	1.760	81.822	1.958	17.926	9.970	7.578	10.296
32	1.891	25.688	11.883	.013	60.618	.008	13.541	9.003	8.579	10.671
36	.684	10.500	5.531	.188	32.356	.208	6.589	3.523	2.182	13.036
40	.040	4.186	.358	1.486	11.747	.033	2.693	.447	.239	10.274
44	.015	2.345	1.026	1.655	6.982	.009	1.132	.003	.093	5.562
48	.001	1.185	2.117	1.254	4.396	.000	.276	.494	.351	1.285
52	.306	.583	.775	.297	3.356	.398	.002	2.617	3.775	.481
56	.676	.717	.387	.009	1.744	2.466	.230	3.878	6.402	.001
60	.105	1.126	.913	.007	1.668	4.632	.792	2.074	3.994	.195
64	.002	1.003	2.776	.010	1.285	3.717	.671	.774	2.305	.230
68	.091	1.023	2.123	.214	.477	.273	.618	.232	2.023	.809
72	.584	1.005	1.985	.240	.144	.000	2.381	.469	.345	1.332
76	.016	.235	1.656	.200	.000	1.450	2.942	.006	.454	.657
80	.312	.078	.817	.028	.027	5.091	2.599	.556	.824	.657
84	.486	.472	.988	.507	.239	3.676	2.034	.181	.017	.530
88	.437	.548	4.533	.572	.097	1.879	1.905	.206	.175	.726
92	2.403	.213	6.578	.072	.137	1.929	2.325	.379	.186	1.367
96	2.898	.091	3.369	.094	.571	1.188	1.359	.011	.254	2.263
100	.490	.006	.887	.647	.522	.033	.380	.112	.368	.864

Table 5: F values for Subject 2 at every frequency and electrode

	ERD	ERD	ERD	ERD	ERD	ERS	ERS	ERS	ERS	ERS
	C3	C1	C2	C4	C3P	C3	C1	C2	C4	C3P
4	207.81	108.10	29.113	57.870	40.471	17.896	10.191	7.483	2.708	6.853
8	239.65	123.66	36.387	59.829	44.252	16.949	11.499	8.115	2.610	8.345
12	267.32	136.42	43.601	59.708	48.517	15.334	12.523	8.455	2.361	9.920
16	280.31	144.77	48.638	58.583	54.063	13.338	11.414	8.531	2.030	11.153
20	271.37	157.03	53.203	57.900	66.320	9.544	5.490	8.124	1.449	12.219
24	229.34	167.46	54.797	58.325	86.571	2.378	.075	4.880	.390	9.840
28	211.26	126.54	48.380	60.808	82.982	.119	9.087	.045	.166	3.768
32	226.97	88.857	43.655	54.823	78.143	1.828	21.257	.921	1.361	1.100
36	165.37	70.244	37.328	39.153	78.784	2.119	19.910	1.060	.920	.139
40	117.91	76.600	34.359	28.288	67.897	.222	6.527	.231	.587	.009
44	96.213	57.942	20.903	19.904	48.422	.046	3.038	.017	2.169	.005
48	41.929	35.114	6.405	8.759	25.645	.077	2.088	.002	.617	.090
52	13.246	17.976	2.086	2.270	12.538	.018	1.397	.437	.001	.000
56	6.820	4.646	1.247	.113	3.036	.000	1.417	1.688	.056	.409
60	3.974	1.283	.441	.000	1.088	.101	.724	.697	.060	2.297
64	.060	1.400	.038	.285	.135	.038	1.489	.277	.039	3.247
68	1.291	2.332	.181	.001	.574	.871	1.534	.622	1.479	.977
72	.251	.291	.010	.022	.945	1.281	.375	.366	2.234	.009
76	.007	.074	.545	.095	.323	1.137	.097	.001	.887	.008
80	.249	.221	.172	.000	.556	1.588	.086	1.299	.008	.001
84	.055	.233	1.158	.386	.072	2.106	.072	1.084	1.114	.094
88	.066	.151	3.329	.221	.302	3.816	.384	.380	1.616	.048
92	.165	.175	2.731	.028	.015	4.952	.051	3.542	.482	1.670
96	.000	.320	.570	.243	.293	1.717	.851	4.281	.168	.888
100	.098	.338	.077	2.768	.225	.362	.005	2.500	.051	.310

Table 6: F values for Subject 3 at every frequency and electrode

	ERD C3	ERD C1	ERD C2	ERD C4	ERD C3P	ERS C3	ERS C1	ERS C2	ERS C4	ERS C3P
4	18.633	12.444	12.151	9.136	28.909	5.691	.033	2.858	7.343	5.769
8	23.444	16.893	16.742	11.839	29.755	4.723	.114	3.941	7.842	4.564
12	25.642	23.004	21.733	14.372	27.967	3.203	.506	5.302	7.463	3.080
16	20.658	24.581	23.627	14.616	24.958	1.636	1.526	5.973	5.885	1.613
20	12.009	17.014	19.372	11.304	22.894	.501	2.375	4.634	2.712	.696
24	10.776	8.447	10.093	5.970	17.574	.084	1.998	2.178	.502	1.056
28	15.845	1.931	5.330	2.626	11.531	.056	.766	1.279	.002	2.788
32	15.753	.049	6.353	.663	3.578	.222	.052	1.128	.593	5.232
36	10.365	.183	7.284	.976	.938	.059	.000	1.025	1.011	7.277
40	7.509	.360	2.445	.891	3.686	.002	.033	.572	1.162	8.514
44	3.505	.411	.062	.078	8.348	.835	.215	.033	.427	5.110
48	3.246	.022	.796	1.463	10.293	5.310	.935	.113	.003	2.239
52	4.194	.631	.696	2.049	12.678	8.391	2.674	.021	.015	2.148
56	3.398	.735	.301	.461	13.986	6.553	3.413	.051	.001	5.097
60	2.230	.768	.020	.106	15.309	5.139	2.023	.128	.105	8.811
64	2.676	.466	.011	.894	15.271	5.217	.043	.318	.277	10.359
68	2.856	.002	.000	.892	12.015	3.296	.037	.458	.020	7.580
72	1.060	.320	.520	.000	11.251	2.711	.006	.503	.622	6.848
76	.287	.678	3.371	1.228	12.040	1.454	.021	.580	1.943	6.430
80	.368	.166	7.070	1.640	12.728	.511	.037	.028	.587	4.988
84	.890	.037	6.138	.440	12.699	1.132	.264	.765	.529	3.970
88	1.656	.046	3.804	.393	12.650	4.148	.000	.329	3.212	3.958
92	3.411	.354	2.061	.628	13.984	7.249	.356	1.081	3.461	5.434
96	6.698	2.184	.704	.842	13.453	4.407	1.000	3.993	.797	9.412
100	8.878	1.514	.605	1.271	10.753	1.927	.352	3.993	.064	13.030

Table 7: F values for Subject 4 at every frequency and electrode

	ERD C3	ERD C1	ERD C2	ERD C4	ERD C3P	ERS C3	ERS C1	ERS C2	ERS C4	ERS C3P
4	3.767	.001	2.892	2.816	.098	1.729	.138	.639	.257	.526
8	3.229	.175	3.175	2.972	.034	2.108	.000	.606	.641	1.001
12	2.305	1.031	3.129	2.844	.017	2.476	.251	.456	1.184	1.580
16	1.405	2.716	2.887	2.465	.015	2.786	.777	.292	1.534	2.186
20	.291	6.840	3.120	2.060	.000	2.829	.734	.144	1.523	3.174
24	.605	6.787	3.118	1.909	.077	.850	.016	.014	.640	2.664
28	.718	2.755	2.485	1.845	.112	.094	.042	.240	.532	1.728
32	.117	.381	2.792	2.124	.432	.612	.441	2.208	1.989	2.293
36	1.809	.000	2.261	1.544	1.107	3.133	1.984	4.921	4.165	4.883
40	.131	.094	.065	.019	.001	1.811	.419	5.424	3.999	8.202
44	.186	.251	.257	.807	.535	.147	.087	3.695	3.451	4.514
48	.203	.169	.026	.227	.323	.003	.429	2.607	3.197	1.754
52	.117	.082	.194	.027	.086	.175	1.087	2.430	3.173	1.376
56	.230	.306	1.738	1.273	.285	1.147	3.032	2.506	3.165	1.568
60	.365	1.147	4.495	4.247	3.366	3.125	6.512	2.233	2.621	1.364
64	.008	.640	5.246	5.921	3.823	4.202	8.661	.758	.858	.389
68	.037	.385	2.425	3.755	.697	1.222	1.924	.150	.263	.153
72	.796	1.281	.418	1.104	.017	.002	.007	.544	1.032	.210
76	2.628	3.216	.045	.004	.137	.100	.058	.504	.961	.008
80	2.321	2.698	.148	.482	.166	.488	.413	.083	.167	.004
84	.968	.475	.332	.008	.072	.788	1.188	.106	.145	.022
88	.228	.034	.171	.038	.299	.001	.312	.718	.689	.003
92	.017	.259	.249	.126	.326	.265	.050	.861	.785	.022
96	.188	.247	.780	.385	.458	.251	.234	1.358	1.413	.015
100	.124	.015	.853	.587	.490	.000	1.335	1.966	2.499	.002

4.2.2 ERD/ERS Difference

Another aspect that can be exploited is the difference between ERD and ERS. While each is only so much different from the Idle state, the difference between ERD and ERS is equivalent to their combined difference from the Idle state. If an algorithm was to measure the difference between two timings, the measurement should be close to zero in the idle state, but the number for the active state would be greater than either the ERD or ERS alone. This is hinted at in the SPSS discriminant analysis. In the analysis, it not only gives significance values to each feature, it also runs a stepwise analysis of which feature would add the most significance to the selection process. When it does this, the feature with the highest F value is always the first feature used, however, the feature with the second highest F value is not always the second used. In several of the analyses the second or third feature added is an ERS feature. This implies that, while the ERD is almost always the most dominant feature for classification, it is better used in conjunction with an ERS feature than with another ERD feature, even if that signal would be more significant by itself than the ERS feature by itself.

CHAPTER 5

CONCLUSION

An improved method of feature selection was used on an EEG ERD/ERS paradigm for use in a BCI switch. The previous method preselected the feature while the new method proposed to use statistical software to find the most significant feature. The statistically-selected features led to greater accuracy in classification of idle vs active states for most subjects. Future studies can look into the effect of gender on feasibility of EEG-based ERD/ERS BCI switches, the use of more advanced software to use multiple features in switch operation, and the utilization of the difference between low-power ERD and high-power ERS.

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