A Comparison of Signal Processing and Classification Methods for Brain-Computer Interface

by

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Abbreviations

ALS - Amyotrophic Lateral Sclerosis

AR - Autoregressive

BCI - Brain-Computer Interface

CAR - Common Average Reference

CWT - Continuous Wavelet Transform

DWT - Discrete Wavelet Transform

EEG - Electroencephalogram

ERD - Event-Related Desynchronization

ERS - Event-Related Synchronization

SCI - Spinal Cord Injury

SVM - Support Vector Machine

WD - Wavelet Decomposition

A Comparison of Signal Processing and Classification Methods for Brain-Computer Interface

Abstract

by

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Non-invasive Brain-Computer Interface (BCI) methods have been investigated for use in physical therapy of stroke patients with motor deficits. This study investigates several methods of feature extraction and classification for suitability for use in such therapy. Electroencephalographic (EEG) data were collected during a motor task from four healthy control subjects and three subjects with motor deficiencies resulting from stroke. The EEG data were filtered using autoregressive (AR), mu-matched, and wavelet decomposition (WD) methods. The filtered data were classified using Support Vector Machines (SVM) and a linear classifier. Wavelet filtering showed a statistically significant ($p < 0.05$) improvement in classification accuracy over AR filtering for one subject when using the linear classifier. SVMs showed a statistically significant improvement over the linear classifier for all filtering methods for three subjects. No difference in classification accuracy was seen between linear and nonlinear SVMs.

Chapter 1

Introduction

A Brain-computer interface (BCI) is a system for direct communication between a human and a computer. The computer accepts a subject's brain signals as input, processes them to find features present in the signal (such as the presence or absence of brain waves of a certain frequency), and assigns some classification to the signal based on its interpretation of the features. A typical application of a BCI system is moving a cursor on a computer screen [8]. Improvement in data collection equipment and computer processing speed has led to an increase in BCI research in recent years. Much of this research has been aimed at improving the lives of patients who have severely reduced motor control, such as those with Amyotrophic Lateral Sclerosis (ALS) or spinal cord injuries (SCI) [18]. Studies have been done investigating the suitability of BCI for aiding the physical therapy of stroke patients [10]. This study was done with the aim of improving BCI methods for use with motor rehabilitation of patients with motor disabilities due to stroke.

The brain feature of interest in this study is the cortical mu rhythm, which is a signal feature that is observable in the EEG of most adults, especially over motor areas of the brain [21]. The mu rhythm is an arch-shaped oscillation that is strongest in the 8 - 13 Hz range (the alpha component of mu), but is also present around 20

Hz (the beta component) and 40 Hz (the gamma component). Mu rhythm is attenuated by motor activity, a phenomenon known as event-related desynchronization (ERD), which makes it a good feature to use to detect motor activity in a subject. Additionally, most people can be trained to have a great deal of control over their mu rhythms [17, 28]. Several methods are used in this study to detect mu waves in EEG: autoregressive (AR) methods, wavelet decomposition (WD) and mu-matched filtering.

After extracting features from EEG, a BCI system must decide what they mean, i.e. it must assign a classification to each data sample based on the features calculated for that sample. The performance of two classification techniques is investigated: a linear combination of the EEG features with a constant weight vector that is determined by an expert, and support vector machines (SVM) with several different kernel functions.

1.1 Outline

This thesis is organized as follows: relevant background topics are discussed in chapter 2, and existing research is discussed in chapter 3. Chapter 4 describes the methods used in this study, and the results of this study are reported in chapter 5. Findings and suggestions for further research are discussed in chapter 6.

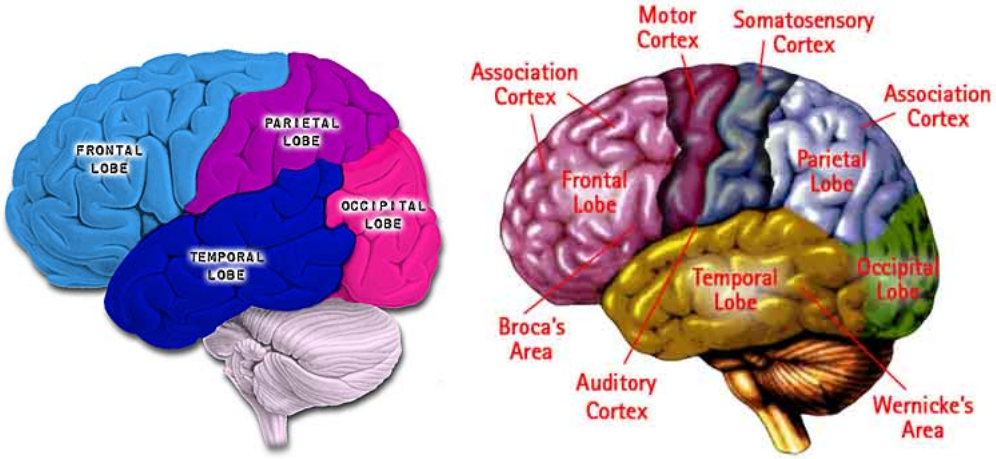
Chapter 2

Background

This section discusses information regarding EEG, BCI, and the methods of signal processing used in this study.

2.1 Brain Anatomy

The human brain is an extremely complex structure, composed of approximately 100 billion neurons, each linked to thousands of other neurons. Neurons are the primary functional component of the nervous system; these are electrically active cells which communicate with other neurons by sending small electrical signals. At a higher level, the brain is composed of several distinct structures, or lobes, each responsible for a different broad function (Figure 2.1(a)). The frontal lobe is responsible for conscious thought; the parietal lobe is important for sensory processing and mental manipulation of objects; the occipital lobe is responsible for sight; and the temporal lobe is responsible for the senses of smell and sound, and for processing of speech and memory [15]. The brain can be further divided into cortices. The most important cortex for the purposes of this study is the motor cortex, which is a strip at the rear of the frontal cortex, and is responsible for planning and execution of voluntary motor functions (Figure 2.1(b)) [15].



(a) Major lobes of the brain [26]. (b) Motor cortex location [3].

Figure 2.1: Brain anatomy.

Electroencephalography (EEG) is the technique of measuring brain activity by means of electrodes placed on the scalp, invented by Hans Berger in 1920 [21]. The recorded signals are caused by changing extracellular fields surrounding neurons in brain tissue. Synapses altering the electric signals to a neuron produce a fluctuating field potential around the neuron, which, if present around a large enough number of neurons, can be detected by electrodes on the scalp. It is theorized that brain waves arise as a result of idle neurons synchronizing their activities with each other [21]. These signals are on the order of microvolts and must be amplified by a high-fidelity amplifier. Electrodes are typically arranged according to the International 10-20 Standard (Figure 2.2 [9]), in which electrodes are lettered according to their scalp location (F: Frontal lobe, T: Temporal lobe, C: Central lobe, P: Parietal lobe, O: Occipital lobe) and numbered so that odd-numbered electrodes are on the left hemisphere, Z (zero) electrodes are on the middle of the head, and even-numbered electrodes are on the right hemisphere [21].

Several distinct types of waves have been identified in EEG. These are classified by their typical frequencies and named in order of their discovery. Five of the most commonly studied waves are alpha waves, which occur at approximately 8 - 13 Hz,

typically in the occipital cortex, and are associated with idleness of the visual cortex, beta waves, which occur from 14 - 30 Hz and are associated with waking consciousness or concentration, gamma waves, which occur from 30 - 70 Hz and are associated with perception and consciousness, delta waves, which occur from 0.1 - 4 Hz and are associated with sleep, and theta waves, which occur from 4 - 8 Hz and have been associated with memory and sensation [21].

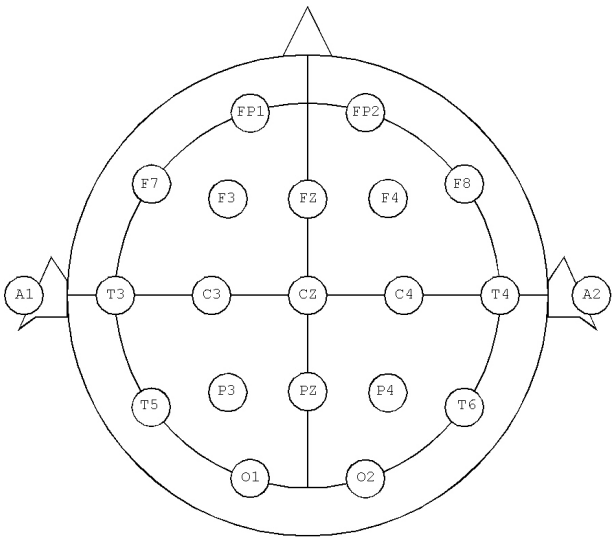


Figure 2.2: The International 10-20 Electrode Standard.

2.2 Mu (Rolandic) Waves

Mu waves, also called Rolandic waves, are a class of brain waves associated with motor activity in the brain. It is present in EEG except when the subject is engaged in movement, tactile sensation, or motor planning, a phenomenon known as event-related desynchronization (ERD). Mu is characterized by its "wicket-like" shape (Fig. 2.3) and has frequency components at around 10 Hz (the alphoid component), 20 Hz (the beta component) and 40 Hz (the gamma component). The alpha component originates in the somatosensory cortex, while the beta component originates in motor cortex. Both alphoid and beta components are attenuated by motor activity, while

gamma components may be enhanced (event-related synchronization, ERS) [21].

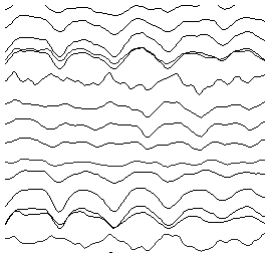


Figure 2.3: A portion of an EEG scan with visible mu waves.

2.3 Brain-Computer Interface

A brain-computer interface (BCI) is a system for direct communication between a human or animal and a computer. The computer uses a subject's brain signals as input, processes them by finding and classifying features present in the signal, and performs some action based on its classification, such as moving a cursor [8]. BCI can be divided into three distinct major operations: signal acquisition, feature extraction, and translation or classification (Figure 2.4).

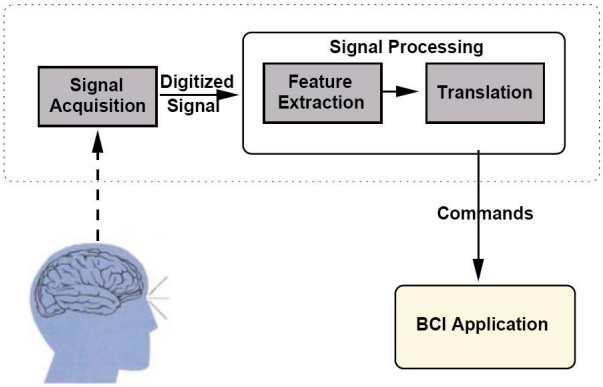


Figure 2.4: The structure of a brain-computer interface.

Chapter 3

Literature Review

This section discusses the existing literature in three topics relevant to this thesis: 1) EEG characteristics in stroke patients, 2) extraction of movement-related information from EEG, and 3) classification of EEG signals.

3.1 EEG Characteristics in Stroke Subjects

EEG signals relating to motor activity are well-characterized in normal adults [21, 27]. The characteristics of EEG of subjects suffering from damage to the motor cortex due to stroke are less well known. Daly *et al.* studied the ERD of 10 stroke and 8 control subjects engaged in a shoulder-elbow reaching task and found that stroke patients exhibited a significant delay in the onset of pre-cortical motor planning activity compared to the control subjects [6]. Fu later showed that the peak ERD of stroke subjects engaged in a reaching task was significantly lower than that of control subjects [10]. These studies suggest that movement-related information is more difficult to detect in EEG of stroke subjects compared to controls.

A later study by Ang *et al.* studied the performance of 35 BCI-naive stroke subjects and 8 BCI-artful control subjects engaged in a motor imagery task [1]. The study found that stroke subjects performed as well as control subjects, and further

found that stroke subjects' performance was not correlated to their level of disability as measured by the Fugl-Meyer Assesment. The authors caution that the performance of the stroke subjects may have been due to tapping by the healthy arm rather than motor imagery with the disabled arm.

3.2 EEG Feature Extraction and Classification

A wide variety of approaches exist for the extraction and classification of features from EEG. In general, all consist of spatial filtering, frequency filtering, optional feature selection, and classification of the computed features.

For example, Ang *et al.* use a 4-level filtering scheme consisting of frequency filtering by Chebyshev bandpass filtering, spatial filtering using the common spatial filters (CSP) algorithm, feature selection of the best CSP features, and classification by the Mutual Information Best Individual Feature and Naive Bayes Parzen Window algorithms [1]. Pfurtscheller *et al.* extract features using predefined bandpass filters, autoregressive filters, and common spatial filters, and classify features using a neural network as well as a linear discriminant analysis [22].

This study is based on the BCI2000 BCI framework [25]. The framework includes an autoregressive filter for feature extraction and a linear classifier which is mimicked for use in this study.

Wavelet methods are used to extract feature information in addition to AR and bandpass methods. Bostanov uses a continuous wavelet transform (CWT) method [2], and Quiroga [23] describes a 5-level discrete wavelet transform scheme to extract α, β, and γ components of EEG for detection of movement-related information. The wavelet transform method used in this study is based on Quiroga's.

Krusienski *et al.* describe a matched filter empirically derived from the canonical mu rhythm [16]. They analyze EEG with it and compare it to the results from an

AR filter, finding that it performs favorably.

There is a relative lack in the literature of studies comparing the classification rates of EEG for various feature extraction and classification methods. This thesis is an attempt to fill that gap by choosing several methods of classification and feature extraction and comparing their performance.

Chapter 4

Methods

4.1 Subjects

EEG data were collected from seven subjects while they were engaged in a motor task. Three subjects had right-side motor deficiencies resulting from hemorrhagic or ischemic stroke, designated s1331plas, s1332plas, and s1333plas.. The remaining four subjects were healthy control subjects, designated c1339plas, c1344plas, c1346plas, and c1350plas.

4.2 Data Collection

EEG data were collected using a 58-channel ECI ElectroCap EEG cap and Compumedics Neuroscan software and amplifiers. The electrode locations on the cap conformed to the International 10-20 standard and all electrodes were referenced to ground electrodes placed on the subject's earlobes. All electrode-scalp impedances were reduced to 5 kΩ or less by use of an electrically conductive saline gel and the impedance-measurement facilities provided by Neuroscan Acquire software. EEG data were sampled and digitized by Neuroscan Acquire, with a gain of 500 and a sampling rate of 250 Hz, and bandpass filtered from 0.1 - 40 Hz.

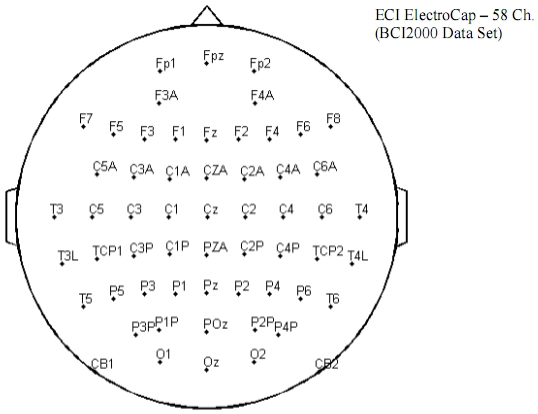


Figure 4.1: Electrode locations on the ECI ElectroCap.

4.3 Task

Subjects were seated in a relaxed manner in front of a computer screen while wearing an EEG cap. The subjects performed the BCI200 D2Box screening task, which consisted of eight 180-second trials in which one of two targets was presented on an otherwise blank screen for three seconds at a time, followed by a three second pause in which no target was presented. When the upper target was presented, the subjects contracted their right hand or imagined doing so. When the lower target was presented, the subject relaxed. Targets were presented in a pseudorandom order such that an equal number of upper and lower targets were presented and no more than two targets of the same type appeared in a row.

On odd-numbered trials, the subjects were instructed to make a fist with the right hand when the upper target was presented. On even-numbered trials, subjects were instructed to imagine performing that action. In all trials, subjects were told to relax when the lower target was presented.

A total of 240 target presentations were recorded for each subject, consisting of

1440 seconds of data. 120 target presentations were for real trials, and 120 were for imagined trials. Of each of these, 60 were activation or (real or imagined) movement trials, and 60 were relaxation trials.

The data collected in the sessions were saved as binary files containing the voltage and target value for each sample.

4.4 Data Analysis

4.4.1 Overview

The EEG data collected from the subjects were analyzed offline by a variety of methods and the results compared. Several types of feature extraction were performed to extract information about the EEG signal's properties, and several types of classification were performed to determine the meaning of the extracted features. Feature extraction was done in BCI2000 and the resulting features saved. Classification of features was done in MATLAB for ease of analysis.

A custom BCI2000 module was written that read the previously saved screening sessions as input. It read the EEG saved during the BCI screening sessions sample-by-sample, and the target which was displayed while the sample was collected. This data was temporally processed by various signal processing modules, some of which were custom, and the resulting features written to a file.

Classification was done on the saved files in MATLAB. Two types of classifiers were used - an implementation of the BCI2000 linear classifier and SVMs. SVMs were trained that looked at various subsets of features. The accuracy of the predictions produced by each method were then compared statistically.

4.4.2 Spatial Filtering

A preliminary step of signal processing is spatial filtering, which is done to reduce the effect of noise common to all electrodes [19]. The method of spatial filtering that was chosen is Common Average Referencing (CAR). In CAR, the average value of all channels is subtracted from each channel. CAR can be expressed mathematically as

$$V_i^{CAR} = V_i^{raw} - \frac{1}{N}\sum_{j=0}^{N} V_j^{raw} \tag{4.1}$$

where V_i^{raw} is the potential between the ith electrode and the reference electrode, and N is the number of channels, in this case 58, and V_i^{CAR} is the spatially-filtered signal.

4.4.3 Temporal Filtering / Feature Extraction

Following spatial filtering, the signal was processed by one of three methods: Autoregressive filtering, mu-matched filtering, and wavelet filtering.

Autoregressive Filtering

Autoregressive spectral estimation is a parametric approach that uses the input signal to estimate the coefficients $a_p(k)$ of an all-pole model [16]. A signal's spectral density can then be estimated with the equation

$$\hat{P}(e^{jw}) = \frac{1}{\left|1 - \sum_{k=1}^{p} a_p(k) e^{-jkw}\right|^2} \tag{4.2}$$

where p is the AR model order. The result is that $\hat{P}$ is a series of values that give the strength of the input signal in various frequencies. An important consideration is the selection of the proper AR model order. An order that is too low will result in an overly smoothed spectrum, because the model is not complex enough to adequately

model the input signal, but a model that is too high will produce false spikes. A 12th order AR model was used, as it has been shown to be the optimal order to extract information from the EEG alpha band for BCI [16].

Autoregressive filtering is known to be suited for processing EEG because EEG is a highly nonstationary signal [24], and so it must be processed in short samples where stationarity can be assumed. The spectral resolution of an AR model is not affected by the length of the input signal and so AR models are able to provide good resolution on the short signal segments.

10 spectral estimates were obtained, each representing the power of a 3 Hz slice of the spectrum from 0 - 30 Hz. This method therefore produces 580 features: 10 per channel.

Mu-matched Filtering

Mu-matched filtering compares the signal from each channel with an empirically-derived match filter that approximates the canonical mu rhythm. It is a sharp rectified sinusoid defined by the equation

$$s_n(n) = h \left| sin\left(\frac{n\pi f_F}{f_S} + \frac{m\pi}{K}\right)\right|,\ m = 0, 1, ..., K$$

$$h_l s(x) = \frac{1}{1 + e^{-Ax+B}} \tag{4.3}$$

where n is the sample number, f_S is the sampling frequency, f_F is the frequency of the template, and A, B, and K are experimentally determined parameters [17]. This produces a single feature per channel, representing the strength of the mu rhythm in that channel.

Wavelet Filtering

Wavelet filtering was the last method used to extract movement-related information from EEG. Wavelet decomposition of a signal X is done by first choosing a wavelet function ψ, which has four filters associated with it: a high-pass decomposition filter G, a low-pass decomposition filter H, a high-pass reconstruction filter G', and a low-pass reconstruction filter H'. Then the convolution between X and the filters G and H is computed, giving two sets of coefficients. Both these sets of coefficients are decimated by a factor of two to remove redundant information. This produces the signals D, which carries the high-frequency information of X, and A, which carries the low-frequency information. The process may be repeated recursively on D or A to extract desired frequencies. X can be reconstructed exactly by upsampling D and A (i.e., inserting a zero after every sample), and convolving with the reconstruction filters G' and H' and then summing [7].

The EEG data was sampled at 250 Hz, and so by Nyquist's rule carries frequencies from 0 - 125 Hz. Alpha, beta, and gamma components of EEG can then be extracted using a 4-level decomposition and reconstruction scheme, as shown in Fig. 4.2. Four wavelets of two different families were tested in this study: Biorthogonal 4/4 wavelets and Daubechies 2nd, 8th, and 25th order wavelets. These mother wavelets are shown in Figure 4.3.

4.4.4 Classification

In order to produce a usable BCI signal, the extracted features must be classified in some manner. Two methods are compared in this thesis: a MATLAB implementation of the BCI2000 linear classifier, referred to here as the "clinical classifier", and Support Vector Machines (SVM) implemented in MATLAB using the LIBSVM library [4].

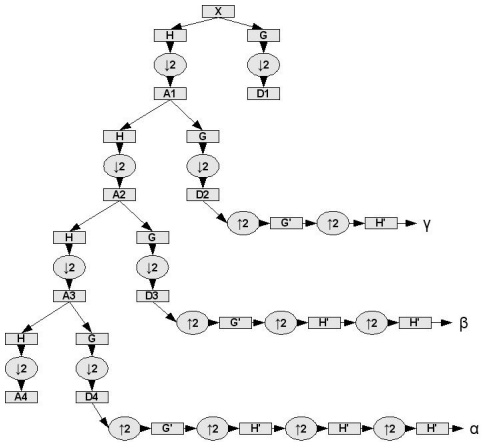
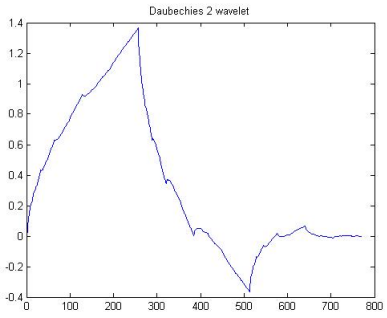
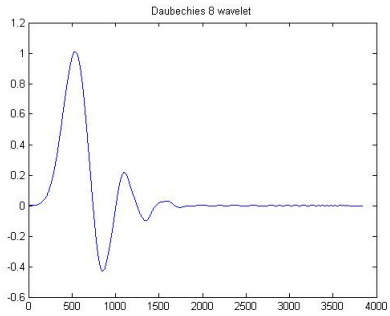


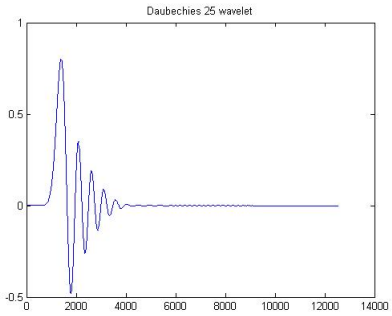
Figure 4.2: The wavelet decomposition scheme used to extract the alpha (8 - 16 Hz), beta (16 - 31 Hz) and gamma (31 - 62 Hz) components of EEG.



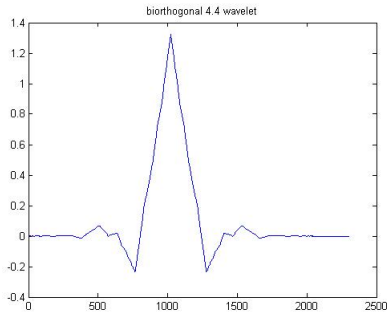
(a) 2nd order Daubechies



(b) 8th order Daubechies



(c) 25th order Daubechies



(d) Biorthogonal 4/4

Figure 4.3: The mother wavelets used for wavelet feature extraction.

Clinical Classifier

The clinical classifier is a linear classifier in which the weight vector is set manually by an expert after examination of the subject's EEG. It is described by the equation

$$d = (W^T X) \times g + b \tag{4.4}$$

where X is the vector of EEG features for one sample, W is the weight vector, g is a gain term, b is a bias term, and d is the value that the cursor is to be moved in the BCI trial. b and g are set by BCI2000's statistics module such that d is zero-mean and unit variance. For this study, g is ignored and b is set in order to maximize the number of correctly classified samples.

d is considered to be the *decision value*. The *classification value* is considered to be the sign of the decision value, i.e.

$$\mathbf{c} = sgn(d) \tag{4.5}$$

If a sample's classification value matches the value of the target shown during data collection, The sample is considered to be correctly classified.

Support Vector Machines

SVMs use a learning algorithm that maximally separates the samples of distinct classes by solving the equation

$$\mathbf{x} = sgn(\mathbf{w}^T \phi(\mathbf{x}) + b) \tag{4.6}$$

where ϕ is a function that maps $\mathbf{x}$ into some possibly high-dimensional space. This is known as the *kernel trick*, and can be exploited to use the SVM as a nonlinear classifier [5].

Linear	$\phi(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j$
Polynomial	$\phi(\mathbf{x}_i, \mathbf{x}_j) = (\gamma \mathbf{x}_i^T \mathbf{x}_j + r)^d, \gamma > 0$
Gaussian Radial Basis Function (RBF)	$\phi(\mathbf{x}_i, \mathbf{x}_j) = e^{-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2}, \gamma > 0$
Sigmoid	$\phi(\mathbf{x}_i, \mathbf{x}_j) = tanh(\gamma \mathbf{x}_i^T + r)$

Table 4.1: SVM kernel functions.

An SVM implementation was made using LIBSVM, a free SVM library[4] which is available in C and Java versions. LIBSVM was chosen due to having a simple C API which made possible to integrate into BCI2000, support for several different kernels, and available MATLAB tools for training and validation of SVM models. LIBSVM's SVM implementation produces both a decision value and a classification value. These were used in the same manner as those of the clinical classifier.

Kernels SVMs using four kernels were tested. SVMs using linear kernels act as linear classifiers, while SVMs using the other kernels act as nonlinear classifiers. The equations for the kernel functions ϕ are shown in Table 4.1, where d, r, and γ are kernel parameters [13].

Chapter 5

Results

5.1 Introduction

This chapter presents the performance of the feature extraction and classification methods described in Chapter 4. A method's correctness is measured by counting the samples for which the classifier correctly predicted the target which was shown to the subject during data collection. Results are presented in terms of mean classification accuracy percentage, and for statistical purposes each target presentation is considered a trial. Results are shown on a subject-by-subject basis due to the small number of subjects and the high variability in their results. Statistical comparisons are done using Student's t-test, with p-values below 0.05 being considered statistically significant. Results are presented on a per-subject basis due to the high variability between subjects.

Section 5.2 shows the results of autoregressive feature extraction and clinical classification, which is considered to be the baseline method. Accuracies are low for all subjects, and are barely better than 50% for most.

Section 5.3 shows the results of using different feature extraction methods in combination with the clinical classifier. A significant improvement is seen for one subject

when using db8 wavelet feature extraction, but no other improvements are seen.

Section 5.4 shows the classification accuracies that would be achieved if the clinical classifier's weights were fixed rather than being set manually by clinicians. No difference is seen between the clinical classifiers and the classifiers with hard-coded weights, suggesting that manual tuning of classifier weights may be ineffective.

Section 5.5 shows the results of using SVMs to classify the signals from all feature extraction methods. A significant improvement over clinical classification was found for three subjects.

Section 5.6 compares the results of linear and nonlinear SVMs. No difference was found, suggesting that any benefit of nonlinear classifiers is too small to make a difference in classification.

Section 5.7 compares the results of SVM classifiers which are given data from restricted subsets of channels. Certain subjects showed a significantly better performance when data from many channels was used rather than data from fewer channels, suggesting that activity was occurring in several brain regions simultaneously.

Section 5.8 uses a "success rate" metric that attempts to measure how well each classification method would perform in a BCI session. Several classification methods are tested using the success rate metric and its correlation to classification accuracy is calculated. The success rate is highly correlated to classification accuracy, suggesting that classification accuracy is a valid measure for classification of EEG in a BCI context.

5.2 Baseline Accuracy

This section shows the results achieved for AR feature extraction and the clinical classifier, i.e., the linear classifier with weights chosen manually by an expert. This is considered the baseline method because it is the method used for BCI therapy

sessions.

The overall classification rates are low for all subjects, as seen in Table 5.1(a). The highest is 64.14% and the lowest is 49.61%, or slightly below chance, which shows that the classifier has not found a usable control singal. All subjects show a high standard deviation, showing a high variability between per-trial classification accuracies.

A large difference is seen between the classification rates of the activation and relaxation trials, as seen in Tables 5.1(b) and 5.1(c). For example, subject c1339plas has a mean accuracy of only 6.17% for the activation trials, but 94.49% for the relaxation trials. This means that the classifier is guessing the same output for nearly all inputs, i.e., it has not learned any meaningful relationship from the data.

Only one subject, c1344plas, shows a classification rate substantially higher than 50%; this subject has a total mean rate of 64.14%. The rate 85.68% for activation trials and rate of only 42.59% for relaxation trials. In other words, the classifier guessed incorrectly most of the time for one trial type even for the best subject.

(a) baseline accuracies for all trials

	mean	**median**	**std. dev**
Control Subject c1339plas	50.33%	51.23%	44.72%
Control Subject c1344plas	64.14%	68.52%	23.93%
Control Subject c1346plas	50.43%	51.23%	45.03%
Control Subject c1350plas	56.26%	61.11%	30.70%
Stroke Subject s1331plas	50.82%	57.41%	44.59%
Stroke Subject s1332plas	49.61%	49.38%	44.59%
Stroke Subject s1333plas	54.98%	56.17%	30.17%

(b) baseline accuracies for active trials

	mean	**median**	**std. dev**
Control Subject c1339plas	6.17%	5.56%	4.52%
Control Subject c1344plas	85.68%	87.65%	6.07%
Control Subject c1346plas	5.88%	5.56%	3.29%
Control Subject c1350plas	84.40%	86.42%	7.40%
Stroke Subject s1331plas	6.83%	4.94%	5.71%
Stroke Subject s1332plas	93.66%	93.83%	3.69%
Stroke Subject s1333plas	84.36%	83.95%	4.44%

(c) baseline accuracies for passive trials

	mean	**median**	**std. dev**
Control Subject c1339plas	94.49%	95.06%	3.78%
Control Subject c1344plas	42.59%	44.44%	12.96%
Control Subject c1346plas	94.98%	95.06%	3.07%
Control Subject c1350plas	28.11%	27.16%	14.94%
Stroke Subject s1331plas	94.81%	96.30%	2.80%
Stroke Subject s1332plas	5.56%	4.94%	3.97%
Stroke Subject s1333plas	25.60%	26.54%	6.77%

Table 5.1: Baseline accuracies.

5.3 Accuracies for Multiple Feature Extraction Methods and Clinical Classification

This section examines the effect of changing feature extraction methods while keeping the clinical classifier. AR feature extraction is considered the baseline method, and all other feature extraction methods are compared to it. In addition, all feature extraction methods are compared to whichever method has the highest overall classification accuracy for all trials.

For all feature extraction methods, the classifiers used the same channels as in the baseline AR feature extraction. For wavelets, classifier weights were set such that the alpha (8-16 Hz) frequency band feature had twice the weight of the beta (16-32 Hz) and gamma (32-64 Hz) features. This was done because the mu rhythm is known to occur most strongly from 8-12 Hz.

Only one subject, c1344plas, shows a significant difference at the $p = 0.05$ level between feature extraction methods. This subject had the highest classification rates for this method, so it is reasonable to assume that his signal was the strongest, suggesting that wavelet and mu-matched matched feature extraction may be more effective than AR feature extraction for relatively clear signals. The fact that no improvement was seen for the other subjects suggests that there was no signal present in their data, or that wavelets and mu-matched filtering are no more effective than autoregressive filtering for extracting information from noisy signals when clinical classification is used.

Control Subject c1339plas Table 5.2(a) shows the total results for this subject. No significant difference was seen between different feature extraction types.

Control Subject c1344plas Table 5.2(b) shows the results for all trials for this subject. Wavelet feature extraction with db8 wavelets is statistically superior to

baseline AR feature extraction. Db2 and db25 feature extraction methods show high p-values when compared with db8 processing, suggesting that there is little difference in effectiveness between wavelets in the Daubechies family.

Control Subject c1346plas Table 5.2(c) shows the results for this subject. All feature extraction methods perform similarly, at about 50% accuracy. This suggests that the classifiers were unable to learn anything from the data set.

Control Subject c1350plas Table 5.2(d) shows the results for subject c1350plas. No significant difference is seen between the different feature extraction methods.

(a) Subject c1339plas

	mean	median	std. dev	p-val AR	p-val best
match	51.73%	53.09%	22.12%	0.83	-
bior44	51.32%	51.85%	35.88%	0.89	0.94
db2	50.43%	50.00%	37.30%	0.99	0.82
AR	50.33%	51.23%	44.72%	-	0.83
db25	50.00%	48.77%	39.50%	0.97	0.77
db8	49.34%	48.15%	45.42%	0.90	0.72

(b) Subject c1344plas

	mean	median	std. dev	p-val AR	p-val best
db8	72.61%	81.48%	22.11%	< 0.05	-
db2	71.11%	79.01%	21.99%	0.10	0.71
db25	69.24%	75.31%	20.50%	0.21	0.39
match	67.16%	72.22%	16.02%	0.42	0.12
bior44	65.45%	66.05%	18.65%	0.74	0.06
AR	64.14%	68.52%	23.93%	-	< 0.05

(c) Subject c1346plas

	mean	median	std. dev	p-val AR	p-val best
AR	50.43%	51.23%	45.03%	-	-
db2	50.27%	50.62%	47.32%	0.98	0.98
match	50.21%	53.70%	47.32%	0.98	0.98
db8	49.96%	51.23%	48.96%	0.96	0.96
db25	49.92%	48.15%	49.05%	0.95	0.95
bior44	49.90%	46.30%	47.21%	0.95	0.95

(d) Subject c1350plas

	mean	median	std. dev	p-val AR	p-val best
db25	57.84%	63.58%	25.42%	0.76	-
match	57.80%	60.49%	17.49%	0.74	0.99
db2	57.70%	60.49%	23.69%	0.77	0.97
db8	57.28%	62.35%	25.69%	0.84	0.91
AR	56.26%	61.11%	30.70%	-	0.76
bior44	54.55%	57.41%	27.10%	0.75	0.49

Table 5.2: Results by feature extraction method, control subjects.

Stroke Subject s1331plas Table 5.3(a) shows the results for subject s1331plas. No significant difference is seen between the different feature extraction methods.

Stroke Subject s1332plas Table 5.3(b) shows the results for this subject. No significant difference is seen between the different feature extraction methods, though Daubechies wavelets seem to perform better than AR processing. Db2 processing shows a nearly 56% accuracy versus slightly below 50% for AR, but the p-value is 0.25 so the difference cannot be said to be significant.

Stroke Subject s1333plas Table 5.3(c) shows the results for this subject. Like for subject s1332, an improvement is seen using Daubechies wavelets, but it is above the $p = 0.05$ level.

(a) Subject s1331plas

	mean	**median**	**std. dev**	**p-val AR**	**p-val best**
match	55.91%	58.02%	14.04%	0.40	-
db8	54.26%	53.09%	24.34%	0.60	0.65
db25	52.96%	51.23%	23.69%	0.74	0.41
bior44	52.82%	48.77%	26.09%	0.77	0.42
db2	51.19%	53.70%	31.26%	0.96	0.29
AR	50.82%	57.41%	44.59%	-	0.40

(b) Subject s1332plas

	mean	**median**	**std. dev**	**p-val AR**	**p-val best**
db2	56.91%	59.26%	19.95%	0.25	-
db8	55.84%	58.02%	22.71%	0.34	0.78
db25	54.88%	61.11%	22.65%	0.42	0.60
match	54.73%	55.56%	16.90%	0.41	0.52
bior44	52.72%	55.56%	30.20%	0.66	0.37
AR	49.61%	49.38%	44.59%	-	0.25

(c) Subject s1333plas

	mean	**median**	**std. dev**	**p-val AR**	**p-val best**
db8	60.76%	63.58%	16.97%	0.20	-
db25	60.27%	64.20%	17.20%	0.24	0.87
match	58.05%	55.56%	12.40%	0.47	0.32
bior44	57.20%	59.88%	20.17%	0.64	0.30
db2	55.37%	56.17%	22.05%	0.94	0.14
AR	54.98%	56.17%	30.17%	-	0.20

Table 5.3: Results by feature extraction method, stroke subjects.

5.4 Accuracies When Using Clinical Classifier With Fixed Weights

This section examines the performance of the clinical classifier, with AR feature extraction, if the same weights are used for all subjects. Only data from channel CP3 is used. This channel is chosen because it is directly over the motor strip, and so it would be expected to be most active during our task. For autoregressive processing, only the 9-12 Hz frequency bin feature is given a nonzero weight. For wavelet processing, the alpha band is given twice the weight of the beta and gamma bands, as in the previous section.

The purpose of this section is to determine if choosing channel weights manually is in fact helpful, or if it is better to simply use the channel closest to the motor area of the brain.

Table 5.4 shows that there is very little difference between these accuracies and those of the previous section. The lowest p-value is 0.64, suggesting that there is very little difference and it may not be worthwhile to manually set classifier weights when AR feature extraction is used.

	mean	**median**	**std. dev**	**p-val base**
Control Subject c1339plas	50.64%	46.91%	40.58%	0.97
Control Subject c1344plas	63.33%	66.67%	23.78%	0.85
Control Subject c1346plas	50.43%	51.23%	45.03%	1.00
Control Subject c1350plas	55.78%	55.56%	30.96%	0.93
Stroke Subject s1331plas	54.12%	58.02%	31.06%	0.64
Stroke Subject s1332plas	49.61%	49.38%	44.59%	1.00
Stroke Subject s1333plas	54.32%	61.11%	31.36%	0.91

Table 5.4: Accuracies for clinical classifiers using fixed weights for all trials.

5.5 Support Vector Machines vs. Clinical Classifier

This section investigates whether there is a benefit to allowing a machine learning technique like SVMs to choose weights automatically for all features. In other words, the SVM is responsible for setting the weights for each feature. For each feature extraction method, two SVMs were trained: one on the data from all channels, and one on the data from channel CP3 only. The results from these machines are shown with the results from the two clinical classifiers discussed in the previous two sections. The results of the SVM classifier are compared to the results of the two clinical classifiers with t-tests.

Significant differences were found for three subjects: control subject c1350plas and stroke subjects s1331plas and s1333plas. SVMs using data from all channels achieved a higher classification accuracy for these subjects, indicating that there was activity occurring in multiple areas of these subjects' brains.

Additionally, a significant difference between the clinical classifier and the clinical classifier with fixed weights was not found for any feature extraction method for any subject except stroke subject s1331plas. The clinical classifier limited to channel CP3 performs significantly better than the regular clinical classifier for db2 and db8 wavelet feature extraction.

Control Subject c1339plas Table 5.5 shows the results for control subject c1339plas. There is no clear difference between any processing types.

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	53.42%	56.17%	22.86%	0.63	0.64
SVM Linear	52.49%	51.23%	13.09%	0.72	0.74
Clinical Classifier, CP3 Only	50.64%	46.91%	40.58%	0.97	-
Clinical Classifier	50.33%	51.23%	44.72%	-	0.97

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	53.37%	53.09%	12.10%	0.67	0.71
Clinical Classifier, CP3 Only	51.69%	49.38%	32.88%	0.95	-
SVM Linear, CP3 Only	51.50%	51.85%	20.23%	0.97	0.97
Clinical Classifier	51.32%	51.85%	35.88%	-	0.95

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	57.02%	60.49%	15.83%	0.21	0.43
SVM Linear, CP3 Only	54.73%	56.17%	21.31%	0.44	0.82
Clinical Classifier, CP3 Only	53.70%	50.00%	27.87%	0.59	-
Clinical Classifier	50.43%	50.00%	37.30%	-	0.59

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	56.87%	58.02%	26.85%	0.27	0.60
SVM Linear, CP3 Only	54.49%	55.56%	20.92%	0.43	0.93
Clinical Classifier, CP3 Only	54.03%	55.56%	31.41%	0.51	-
Clinical Classifier	49.34%	48.15%	45.42%	-	0.51

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	55.64%	55.56%	19.91%	0.33	0.81
Clinical Classifier, CP3 Only	54.65%	55.56%	24.72%	0.44	-
SVM Linear, CP3 Only	54.30%	53.09%	22.97%	0.47	0.94
Clinical Classifier	50.00%	48.77%	39.50%	-	0.44

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	53.93%	53.09%	8.65%	0.47	0.52
SVM Linear, CP3 Only	52.51%	51.85%	15.55%	0.82	0.97
Clinical Classifier, CP3 Only	52.39%	50.62%	16.17%	0.85	-
Clinical Classifier	51.73%	53.09%	22.12%	-	0.85

Table 5.5: Classification rates by classifier type, c1339plas

Control Subject c1344plas Table 5.6 shows the results for control subject c1344plas. There is no clear difference between any processing types, despite the subject's relatively high classification rates. The likely cause of this is that all movement-related information for this subject is contained in the data from channel CP3.

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	69.38%	75.31%	17.68%	0.17	0.12
Clinical Classifier	64.14%	68.52%	23.93%	-	0.85
SVM Linear	63.52%	66.67%	19.71%	0.88	0.96
Clinical Classifier, CP3 Only	63.33%	66.67%	23.78%	0.85	-

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	68.83%	73.46%	17.00%	0.30	0.30
Clinical Classifier, CP3 Only	65.45%	66.05%	18.65%	1.00	-
Clinical Classifier	65.45%	66.05%	18.65%	-	1.00
SVM Linear	58.52%	67.28%	39.66%	0.22	0.22

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	71.60%	79.63%	21.82%	0.90	0.90
Clinical Classifier, CP3 Only	71.11%	79.01%	21.99%	1.00	-
Clinical Classifier	71.11%	79.01%	21.99%	-	1.00
SVM Linear	66.58%	75.93%	28.95%	0.34	0.34

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	74.05%	76.54%	16.70%	0.69	0.69
SVM Linear, CP3 Only	72.67%	80.86%	21.04%	0.99	0.99
Clinical Classifier, CP3 Only	72.61%	81.48%	22.11%	1.00	-
Clinical Classifier	72.61%	81.48%	22.11%	-	1.00

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	70.62%	76.54%	18.92%	0.70	0.70
SVM Linear	69.26%	70.99%	14.88%	0.99	0.99
Clinical Classifier, CP3 Only	69.24%	75.31%	20.50%	1.00	-
Clinical Classifier	69.24%	75.31%	20.50%	-	1.00

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	69.67%	75.31%	15.76%	0.39	0.39
SVM Linear, CP3 Only	67.20%	72.22%	15.78%	0.99	0.99
Clinical Classifier, CP3 Only	67.16%	72.22%	16.02%	1.00	-
Clinical Classifier	67.16%	72.22%	16.02%	-	1.00

Table 5.6: Classification rates by classifier type, c1344plas

Control Subject c1346plas Table 5.7 shows the results for control subject c1346plas. No difference is apparent between any processing types.

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	50.72%	49.38%	37.65%	0.97	0.97
Clinical Classifier, CP3 Only	50.43%	51.23%	45.03%	1.00	-
Clinical Classifier	50.43%	51.23%	45.03%	-	1.00
SVM Linear	48.87%	50.00%	19.67%	0.81	0.81

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	50.33%	50.62%	31.38%	0.95	0.95
Clinical Classifier, CP3 Only	49.90%	46.30%	47.21%	1.00	-
Clinical Classifier	49.90%	46.30%	47.21%	-	1.00
SVM Linear	48.87%	48.15%	16.07%	0.87	0.87

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	50.37%	56.17%	44.71%	0.99	0.97
Clinical Classifier	50.27%	50.62%	47.32%	-	0.98
Clinical Classifier, CP3 Only	50.04%	50.62%	49.15%	0.98	-
SVM Linear	48.23%	47.53%	18.21%	0.76	0.79

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	50.33%	54.32%	46.98%	0.97	0.97
Clinical Classifier, CP3 Only	49.96%	51.23%	48.96%	1.00	-
Clinical Classifier	49.96%	51.23%	48.96%	-	1.00
SVM Linear	48.91%	50.00%	15.94%	0.87	0.87

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
Clinical Classifier, CP3 Only	49.92%	48.15%	49.05%	1.00	-
Clinical Classifier	49.92%	48.15%	49.05%	-	1.00
SVM Linear, CP3 Only	49.61%	57.41%	34.01%	0.97	0.97
SVM Linear	49.38%	52.47%	32.48%	0.94	0.94

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
Clinical Classifier, CP3 Only	50.21%	53.70%	47.32%	1.00	-
Clinical Classifier	50.21%	53.70%	47.32%	-	1.00
SVM Linear, CP3 Only	49.73%	51.85%	24.82%	0.95	0.95
SVM Linear	47.06%	48.77%	20.19%	0.64	0.64

Table 5.7: Classification rates by classifier type, c1346plas

Control Subject c1350plas Table 5.8 shows the results for control subject c1350plas. The SVM which uses all channels shows a significant improvement over the clinical linear classifier for all feature extraction methods.

(a) accuracies for AR signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	65.06%	65.43%	10.06%	< 0.05	< 0.05
SVM Linear, CP3 Only	58.87%	59.26%	21.59%	0.59	0.53
Clinical Classifier	56.26%	61.11%	30.70%	-	0.93
Clinical Classifier, CP3 Only	55.78%	55.56%	30.96%	0.93	-

(b) accuracies for bior44 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	65.82%	66.67%	14.09%	< 0.05	< 0.05
Clinical Classifier, CP3 Only	55.33%	58.64%	26.85%	0.87	-
SVM Linear, CP3 Only	54.73%	56.17%	25.09%	0.97	0.90
Clinical Classifier	54.55%	57.41%	27.10%	-	0.87

(c) accuracies for db2 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	73.97%	74.07%	14.49%	< 0.05	< 0.05
SVM Linear, CP3 Only	60.02%	62.35%	17.70%	0.54	0.54
Clinical Classifier, CP3 Only	57.70%	60.49%	23.69%	1.00	-
Clinical Classifier	57.70%	60.49%	23.69%	-	1.00

(d) accuracies for db8 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	75.06%	75.31%	14.77%	< 0.05	< 0.05
SVM Linear, CP3 Only	61.81%	64.20%	17.11%	0.26	0.08
Clinical Classifier	57.28%	62.35%	25.69%	-	0.55
Clinical Classifier, CP3 Only	54.34%	58.64%	28.36%	0.55	-

(e) accuracies for db25 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	73.44%	72.22%	15.24%	< 0.05	< 0.05
SVM Linear, CP3 Only	61.77%	64.20%	20.70%	0.36	0.25
Clinical Classifier	57.84%	63.58%	25.42%	-	0.85
Clinical Classifier, CP3 Only	57.00%	59.26%	24.42%	0.85	-

(f) accuracies for match signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	66.11%	66.67%	11.55%	< 0.05	< 0.05
SVM Linear, CP3 Only	59.16%	61.11%	17.94%	0.68	0.98
Clinical Classifier, CP3 Only	59.07%	62.35%	16.89%	0.69	-
Clinical Classifier	57.80%	60.49%	17.49%	-	0.69

Table 5.8: Classification rates by classifier type, c1350plas

Stroke Subject s1331plas Table 5.9 shows the results for stroke subject s1331plas. Both SVMs show a significant improvement over the clinical classifier for all feature extraction methods except for match filtering. For db2 and db8 wavelets, the clinical classifier limited to channel CP3 performed significantly better than the baseline clinical classification.

(a) accuracies for AR signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear, CP3 Only	65.10%	69.14%	19.62%	< 0.05	< 0.05
SVM Linear	63.97%	66.67%	12.99%	< 0.05	< 0.05
Clinical Classifier, CP3 Only	54.12%	58.02%	31.06%	0.64	-
Clinical Classifier	50.82%	57.41%	44.59%	-	0.64

(b) accuracies for bior44 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	63.15%	62.96%	10.39%	< 0.05	0.16
SVM Linear, CP3 Only	60.86%	63.58%	16.33%	< 0.05	0.54
Clinical Classifier, CP3 Only	58.70%	62.35%	21.96%	0.18	-
Clinical Classifier	52.82%	48.77%	26.09%	-	0.18

(c) accuracies for db2 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	68.54%	68.52%	20.58%	< 0.05	0.10
SVM Linear, CP3 Only	64.61%	65.43%	17.53%	< 0.05	0.52
Clinical Classifier, CP3 Only	62.41%	64.20%	19.89%	< 0.05	-
Clinical Classifier	51.19%	53.70%	31.26%	-	< 0.05

(d) accuracies for db8 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	67.57%	72.22%	20.79%	< 0.05	0.16
SVM Linear, CP3 Only	64.47%	61.73%	17.73%	< 0.05	0.54
Clinical Classifier, CP3 Only	62.35%	64.20%	19.80%	< 0.05	-
Clinical Classifier	54.26%	53.09%	24.34%	-	< 0.05

(e) accuracies for db25 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	68.85%	72.22%	18.00%	< 0.05	< 0.05
SVM Linear, CP3 Only	62.39%	62.96%	16.99%	< 0.05	0.35
Clinical Classifier, CP3 Only	59.16%	62.96%	20.61%	0.13	-
Clinical Classifier	52.96%	51.23%	23.69%	-	0.13

(f) accuracies for match signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	59.34%	59.26%	12.00%	0.15	0.99
Clinical Classifier, CP3 Only	59.30%	60.49%	15.27%	0.21	-
SVM Linear, CP3 Only	58.66%	59.26%	13.77%	0.28	0.81
Clinical Classifier	55.91%	58.02%	14.04%	-	0.21

Table 5.9: Classification rates by classifier type, s1331plas

Stroke Subject s1332plas Table 5.10 shows the results for stroke subject s1332plas. The SVMs appear to be an improvement over the clinical classifiers, but the difference falls short of being significant.

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	59.09%	62.96%	21.59%	0.14	0.14
SVM Linear	57.30%	57.41%	10.22%	0.20	0.20
Clinical Classifier, CP3 Only	49.61%	49.38%	44.59%	1.00	-
Clinical Classifier	49.61%	49.38%	44.59%	-	1.00

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	56.26%	56.79%	9.23%	0.39	0.39
SVM Linear, CP3 Only	54.07%	59.26%	21.54%	0.78	0.78
Clinical Classifier, CP3 Only	52.72%	55.56%	30.20%	1.00	-
Clinical Classifier	52.72%	55.56%	30.20%	-	1.00

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	61.15%	62.35%	12.94%	0.17	0.17
SVM Linear, CP3 Only	58.42%	61.11%	17.49%	0.66	0.66
Clinical Classifier, CP3 Only	56.91%	59.26%	19.95%	1.00	-
Clinical Classifier	56.91%	59.26%	19.95%	-	1.00

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	59.44%	59.26%	11.36%	0.27	0.27
SVM Linear, CP3 Only	57.22%	58.02%	20.42%	0.73	0.73
Clinical Classifier, CP3 Only	55.84%	58.02%	22.71%	1.00	-
Clinical Classifier	55.84%	58.02%	22.71%	-	1.00

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear	60.00%	60.49%	10.88%	0.12	0.12
SVM Linear, CP3 Only	57.02%	59.88%	21.65%	0.60	0.60
Clinical Classifier, CP3 Only	54.88%	61.11%	22.65%	1.00	-
Clinical Classifier	54.88%	61.11%	22.65%	-	1.00

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val Clin.	p-val Clin. CP3
SVM Linear, CP3 Only	54.79%	55.56%	16.30%	0.98	0.98
Clinical Classifier, CP3 Only	54.73%	55.56%	16.90%	1.00	-
Clinical Classifier	54.73%	55.56%	16.90%	-	1.00
SVM Linear	53.99%	54.32%	10.74%	0.78	0.78

Table 5.10: Classification rates by classifier type, s1332plas

Stroke Subject s1333plas Table 5.11 shows the results for stroke subject s1333plas. No significant difference is apparent for any feature extraction method except for db2 processing, for which SVM processing with all channels shows a significant improvement at the $p = 0.05$ level.

(a) accuracies for AR signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear, CP3 Only	58.50%	60.49%	19.21%	0.45	0.38
SVM Linear	56.75%	56.79%	12.15%	0.67	0.58
Clinical Classifier	54.98%	56.17%	30.17%	-	0.91
Clinical Classifier, CP3 Only	54.32%	61.11%	31.36%	0.91	-

(b) accuracies for bior44 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	61.38%	61.73%	15.18%	0.20	0.20
Clinical Classifier	57.20%	59.88%	20.17%	-	0.97
SVM Linear, CP3 Only	57.18%	57.41%	21.52%	1.00	0.97
Clinical Classifier, CP3 Only	57.06%	55.56%	21.05%	0.97	-

(c) accuracies for db2 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	64.16%	66.05%	14.40%	< 0.05	0.32
Clinical Classifier, CP3 Only	61.13%	64.81%	18.53%	0.12	-
SVM Linear, CP3 Only	60.19%	65.43%	19.54%	0.21	0.79
Clinical Classifier	55.37%	56.17%	22.05%	-	0.12

(d) accuracies for db8 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	62.10%	62.96%	13.31%	0.63	0.72
Clinical Classifier, CP3 Only	60.99%	65.43%	19.97%	0.95	-
Clinical Classifier	60.76%	63.58%	16.97%	-	0.95
SVM Linear, CP3 Only	57.20%	58.64%	20.16%	0.30	0.30

(e) accuracies for db25 signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
SVM Linear	60.68%	61.11%	14.60%	0.89	0.97
Clinical Classifier, CP3 Only	60.56%	63.58%	18.78%	0.93	-
Clinical Classifier	60.27%	64.20%	17.20%	-	0.93
SVM Linear, CP3 Only	53.48%	54.32%	41.45%	0.24	0.23

(f) accuracies for match signal processing, all trials

	mean	**median**	**std. dev**	**p-val Clin.**	**p-val Clin. CP3**
Clinical Classifier	58.05%	55.56%	12.40%	-	0.80
Clinical Classifier, CP3 Only	57.41%	59.26%	14.67%	0.80	-
SVM Linear	56.91%	56.17%	16.62%	0.67	0.86
SVM Linear, CP3 Only	56.48%	60.49%	30.40%	0.71	0.83

Table 5.11: Classification rates by classifier type, s1333plas

5.6 Linear and Nonlinear SVM Kernels

To investigate the performance of nonlinear SVM kernels, SVMs using the three nonlinear kernels were trained and tested, and their results compared against those of SVMs with linear kernels. No differences were found. Full results are given in Appendix 7.1.

5.7 Linear SVMs With Data Restricted to Channel Subsets

A likely explanation for the fact that SVMs have a higher classification rate than the clinical classifier for some subjects is the fact that the SVM uses data from many features, while the clinical classifier is limited to only those features that were *a priori* designated as the most important. In order to test whether this improvement was due to SVMs finding brain activity in nonmotor regions, SVMs were trained and tested on various channel subsets. These subsets are:

- Channel CP3 only
- "Small Left" Channels: CP3 & C3.
- "Medium Left" Channels: CP3, C3, CP1, C1, CPZ, CZ
- "Large Left" Channels: All channels in the center strip or left of it
- "Right" Channels: All channels not in the "large left" set
- All channels

Significant differences between the results for various channel sets are seen for subjects c1344plas, c1350plas, s1331plas, and s1333plas. The differences are generally small in terms of classification percentages. For c1344plas, all channel sets which

did not include the right-side channels performed about equally. For c1350plas, the channel sets with a larger number of channels performed better than those with fewer. s1331plas and 1333plas show few significant differences, though large channel sets perform better than smaller. Subject s1332plas shows no difference in the results of any channel set for any feature extraction method, suggesting that the signal for this subject was widely distributed across a large number of electrodes and may have been due to contamination by EMG or other noise.

These results suggest that SVMs are effective at ignoring irrelevant data for most subjects. Certain subjects perform better when right-side channels are excluded from the dataset, suggesting that it may be beneficial to exclude channels that are known to be irrelevant. However, there is no evidence that more specific feature selection is beneficial.

Control Subject c1339plas No significant difference was seen in the classification rates for different subsets of channels for this subject. This is likely due to the fact that no strong control signal was present in the subject's EEG. The results are shown in Table 5.12.

(a) accuracies for all channel sets, AR signal processing

	mean	median	std. dev	p-val all chan.	p-val best
CP3 Channel	53.42%	56.17%	22.86%	0.79	-
Small Left Channels	52.90%	54.32%	23.55%	0.91	0.90
All Channels	52.49%	51.23%	13.09%	-	0.79
Right Channels	52.02%	52.47%	9.59%	0.82	0.66
Medium Left Channels	51.98%	52.47%	12.92%	0.83	0.67
Large Left Channels	51.19%	50.62%	14.34%	0.61	0.52

(b) accuracies for all channel sets, bior44 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	53.44%	54.32%	10.00%	0.98	-
All Channels	53.37%	53.09%	12.10%	-	0.98
Medium Left Channels	51.79%	51.23%	12.35%	0.48	0.42
Right Channels	51.63%	51.23%	14.08%	0.47	0.42
CP3 Channel	51.50%	51.85%	20.23%	0.54	0.51
Small Left Channels	51.44%	50.62%	28.33%	0.63	0.61

(c) accuracies for all channel sets, db2 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	57.02%	60.49%	15.83%	-	-
Medium Left Channels	56.44%	56.79%	13.96%	0.83	0.83
CP3 Channel	54.73%	56.17%	21.31%	0.51	0.51
Small Left Channels	54.26%	54.32%	22.77%	0.44	0.44
Large Left Channels	54.18%	54.32%	19.27%	0.38	0.38
Right Channels	53.81%	53.70%	21.07%	0.35	0.35

(d) accuracies for all channel sets, db8 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	57.59%	58.02%	14.67%	0.86	-
All Channels	56.87%	58.02%	26.85%	-	0.86
Medium Left Channels	55.16%	55.56%	12.47%	0.66	0.33
Right Channels	54.79%	55.56%	21.64%	0.64	0.41
CP3 Channel	54.49%	55.56%	20.92%	0.59	0.35
Small Left Channels	54.26%	55.56%	18.11%	0.53	0.27

(e) accuracies for all channel sets, db25 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	56.01%	59.88%	16.34%	0.91	-
All Channels	55.64%	55.56%	19.91%	-	0.91
Right Channels	54.88%	54.94%	18.77%	0.83	0.73
Small Left Channels	54.51%	54.94%	22.39%	0.77	0.68
CP3 Channel	54.30%	53.09%	22.97%	0.73	0.64
Medium Left Channels	53.48%	55.56%	13.25%	0.49	0.35

(f) accuracies for all channel sets, match signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	53.93%	53.09%	8.65%	-	-
Large Left Channels	53.85%	54.32%	8.70%	0.96	0.96
Right Channels	53.35%	55.56%	13.36%	0.78	0.78
Small Left Channels	52.72%	54.32%	9.74%	0.47	0.47
CP3 Channel	52.51%	51.85%	15.55%	0.54	0.54
Medium Left Channels	52.33%	52.47%	8.34%	0.30	0.30

Table 5.12: SVM linear classification for different subsets of channels, subject c1339plas

Control Subject c1344plas For this subject, the classification rate was significantly lower for the data from the channels on the right side of the head. Channel subsets which included the "correct" channels, i.e., the channels over the left-side motor strip, are statistically indistinguishable. The results are shown in Table 5.13.

(a) accuracies for all channel sets, AR signal processing

	mean	median	std. dev	p-val all chan.	p-val best
CP3 Channel	69.38%	75.31%	17.68%	0.09	-
Small Left Channels	68.66%	73.46%	17.39%	0.13	0.82
Medium Left Channels	67.61%	72.22%	14.76%	0.20	0.55
Large Left Channels	65.35%	66.67%	13.51%	0.55	0.16
All Channels	63.52%	66.67%	19.71%	-	0.09
Right Channels	56.67%	57.41%	10.51%	< 0.05	< 0.05

(b) accuracies for all channel sets, bior44 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
CP3 Channel	68.83%	73.46%	17.00%	0.07	-
Medium Left Channels	68.56%	74.69%	16.53%	0.07	0.93
Small Left Channels	68.27%	72.22%	17.69%	0.08	0.86
Large Left Channels	66.77%	70.37%	16.40%	0.14	0.50
All Channels	58.52%	67.28%	39.66%	-	0.07
Right Channels	57.67%	58.02%	9.84%	0.87	< 0.05

(c) accuracies for all channel sets, db2 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	73.13%	75.93%	17.87%	0.14	-
Medium Left Channels	72.61%	77.78%	19.48%	0.18	0.88
Small Left Channels	72.30%	80.25%	21.67%	0.22	0.82
CP3 Channel	71.60%	79.63%	21.82%	0.29	0.68
All Channels	66.58%	75.93%	28.95%	-	0.14
Right Channels	58.40%	61.11%	29.42%	0.13	< 0.05

(d) accuracies for all channel sets, db8 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	74.05%	76.54%	16.70%	-	-
Large Left Channels	73.97%	76.54%	15.70%	0.98	0.98
Medium Left Channels	73.58%	79.01%	18.99%	0.88	0.88
Small Left Channels	73.37%	80.86%	20.75%	0.84	0.84
CP3 Channel	72.67%	80.86%	21.04%	0.69	0.69
Right Channels	58.23%	64.20%	35.80%	< 0.05	< 0.05

(e) accuracies for all channel sets, db25 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	70.78%	75.31%	17.72%	0.61	-
Medium Left Channels	70.76%	75.31%	17.70%	0.62	0.99
CP3 Channel	70.62%	76.54%	18.92%	0.66	0.96
Small Left Channels	70.51%	77.78%	19.18%	0.69	0.94
All Channels	69.26%	70.99%	14.88%	-	0.61
Right Channels	61.83%	63.58%	18.58%	< 0.05	< 0.05

(f) accuracies for all channel sets, match signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	69.67%	75.31%	15.76%	-	-
Large Left Channels	68.09%	72.84%	14.70%	0.57	0.57
Medium Left Channels	67.55%	72.84%	15.64%	0.46	0.46
Small Left Channels	67.24%	71.60%	15.74%	0.40	0.40
CP3 Channel	67.20%	72.22%	15.78%	0.39	0.39
Right Channels	60.95%	61.73%	14.36%	< 0.05	< 0.05

Table 5.13: SVM linear classification for different subsets of channels, subject c1344plas

Control Subject c1346plas No significant difference between channel subsets were apparent for this subject. The results are shown in Table 5.14.

(a) accuracies for all channel sets, AR signal processing

	mean	median	std. dev	p-val all chan.	p-val best
CP3 Channel	50.72%	49.38%	37.65%	0.74	-
Large Left Channels	50.51%	48.15%	21.01%	0.66	0.97
Small Left Channels	49.67%	46.91%	21.29%	0.83	0.85
Medium Left Channels	49.16%	43.83%	23.27%	0.94	0.78
All Channels	48.87%	50.00%	19.67%	-	0.74
Right Channels	47.74%	46.30%	17.36%	0.74	0.58

(b) accuracies for all channel sets, bior44 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
CP3 Channel	50.33%	50.62%	31.38%	0.75	-
All Channels	48.87%	48.15%	16.07%	-	0.75
Medium Left Channels	48.72%	43.21%	24.97%	0.97	0.76
Large Left Channels	48.52%	49.38%	15.93%	0.90	0.69
Small Left Channels	47.82%	43.21%	28.81%	0.81	0.65
Right Channels	46.67%	46.30%	15.96%	0.45	0.42

(c) accuracies for all channel sets, db2 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
CP3 Channel	50.37%	56.17%	44.71%	0.73	-
Large Left Channels	49.28%	47.53%	17.91%	0.75	0.86
Medium Left Channels	48.27%	45.68%	25.94%	0.99	0.75
All Channels	48.23%	47.53%	18.21%	-	0.73
Small Left Channels	48.15%	46.91%	31.12%	0.99	0.75
Right Channels	47.49%	50.62%	21.76%	0.84	0.65

(d) accuracies for all channel sets, db8 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
CP3 Channel	50.33%	54.32%	46.98%	0.82	-
Large Left Channels	49.65%	47.53%	19.89%	0.82	0.92
Right Channels	49.44%	50.00%	23.26%	0.88	0.90
All Channels	48.91%	50.00%	15.94%	-	0.82
Small Left Channels	47.94%	43.21%	24.63%	0.80	0.73
Medium Left Channels	47.33%	44.44%	29.69%	0.72	0.68

(e) accuracies for all channel sets, db25 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	50.58%	51.85%	20.79%	0.81	-
CP3 Channel	49.61%	57.41%	34.01%	0.97	0.85
All Channels	49.38%	52.47%	32.48%	-	0.81
Small Left Channels	48.50%	48.15%	30.57%	0.88	0.66
Right Channels	47.84%	45.06%	19.33%	0.75	0.46
Medium Left Channels	47.72%	43.21%	26.36%	0.76	0.51

(f) accuracies for all channel sets, match signal processing

	mean	median	std. dev	p-val all chan.	p-val best
CP3 Channel	49.73%	51.85%	24.82%	0.52	-
Medium Left Channels	48.81%	49.38%	21.26%	0.64	0.83
Large Left Channels	48.09%	51.23%	20.27%	0.78	0.69
Small Left Channels	47.65%	48.15%	10.63%	0.84	0.55
All Channels	47.06%	48.77%	20.19%	-	0.52
Right Channels	47.00%	46.30%	20.88%	0.99	0.51

Table 5.14: SVM linear classification for different subsets of channels, subject c1346plas

Control Subject c1350plas For wavelet feature extraction, a significant improvement is seen for this subject when using all channels, rather than any smaller subsets, meaning that there was activity in several channels. The results are shown in Table 5.15.

(a) accuracies for all channel sets, AR signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	65.06%	65.43%	10.06%	-	-
Large Left Channels	62.76%	63.58%	10.76%	0.23	0.23
Medium Left Channels	61.91%	66.05%	19.13%	0.26	0.26
Small Left Channels	60.31%	62.96%	23.41%	0.15	0.15
CP3 Channel	58.87%	59.26%	21.59%	< 0.05	< 0.05
Right Channels	58.31%	59.26%	9.75%	< 0.05	< 0.05

(b) accuracies for all channel sets, bior44 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	65.82%	66.67%	14.09%	-	-
Large Left Channels	63.72%	64.81%	14.37%	0.42	0.42
Right Channels	60.78%	61.11%	12.67%	< 0.05	< 0.05
Medium Left Channels	58.50%	64.81%	23.41%	< 0.05	< 0.05
Small Left Channels	55.62%	59.88%	24.08%	< 0.05	< 0.05
CP3 Channel	54.73%	56.17%	25.09%	< 0.05	< 0.05

(c) accuracies for all channel sets, db2 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	73.97%	74.07%	14.49%	-	-
Large Left Channels	69.55%	74.69%	22.25%	0.20	0.20
Right Channels	65.58%	68.52%	17.56%	< 0.05	< 0.05
Medium Left Channels	64.30%	70.37%	23.31%	< 0.05	< 0.05
Small Left Channels	60.84%	64.20%	22.48%	< 0.05	< 0.05
CP3 Channel	60.02%	62.35%	17.70%	< 0.05	< 0.05

(d) accuracies for all channel sets, db8 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	75.06%	75.31%	14.77%	-	-
Large Left Channels	70.82%	71.60%	16.64%	0.14	0.14
Right Channels	67.65%	66.67%	16.30%	< 0.05	< 0.05
Medium Left Channels	67.04%	72.84%	20.65%	< 0.05	< 0.05
Small Left Channels	62.96%	66.67%	20.25%	< 0.05	< 0.05
CP3 Channel	61.81%	64.20%	17.11%	< 0.05	< 0.05

(e) accuracies for all channel sets, db25 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	73.44%	72.22%	15.24%	-	-
Large Left Channels	67.57%	70.37%	20.47%	0.08	0.08
Right Channels	67.49%	69.75%	19.93%	0.07	0.07
Medium Left Channels	65.21%	67.90%	17.99%	< 0.05	< 0.05
Small Left Channels	62.65%	64.81%	20.42%	< 0.05	< 0.05
CP3 Channel	61.77%	64.20%	20.70%	< 0.05	< 0.05

(f) accuracies for all channel sets, match signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	66.11%	66.67%	11.55%	-	-
Large Left Channels	64.71%	66.05%	11.80%	0.51	0.51
Medium Left Channels	59.79%	65.43%	17.15%	< 0.05	< 0.05
CP3 Channel	59.16%	61.11%	17.94%	< 0.05	< 0.05
Small Left Channels	58.64%	61.73%	18.48%	< 0.05	< 0.05
Right Channels	56.71%	58.02%	9.11%	< 0.05	< 0.05

Table 5.15: SVM linear classification for different subsets of channels, subject c1350plas

Stroke Subject s1331plas No clear improvement is seen for this subject, as seen in Table 5.16. Smaller channel sets tend to do worse than larger ones when using wavelet feature extraction, but no significant difference seems to exist when using autoregressive or mu-matched feature extraction.

(a) accuracies for all channel sets, AR signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Right Channels	66.63%	70.99%	14.99%	0.30	-
Medium Left Channels	66.46%	67.28%	15.81%	0.35	0.95
CP3 Channel	65.10%	69.14%	19.62%	0.71	0.63
Small Left Channels	64.16%	65.43%	17.29%	0.95	0.41
All Channels	63.97%	66.67%	12.99%	-	0.30
Large Left Channels	62.35%	64.81%	12.28%	0.48	0.09

(b) accuracies for all channel sets, bior44 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	65.14%	65.43%	10.21%	0.29	-
Medium Left Channels	65.02%	66.05%	11.71%	0.36	0.95
All Channels	63.15%	62.96%	10.39%	-	0.29
Right Channels	61.48%	61.73%	13.93%	0.46	0.10
CP3 Channel	60.86%	63.58%	16.33%	0.36	0.09
Small Left Channels	60.19%	61.11%	16.65%	0.24	0.05

(c) accuracies for all channel sets, db2 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	70.21%	71.60%	11.96%	0.59	-
Medium Left Channels	70.21%	69.14%	15.50%	0.62	1.00
All Channels	68.54%	68.52%	20.58%	-	0.59
Right Channels	67.33%	64.81%	21.85%	0.75	0.37
Small Left Channels	64.90%	66.67%	16.82%	0.29	< 0.05
CP3 Channel	64.61%	65.43%	17.53%	0.26	< 0.05

(d) accuracies for all channel sets, db8 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Medium Left Channels	69.90%	71.60%	15.65%	0.49	-
Large Left Channels	69.63%	69.14%	11.66%	0.51	0.92
Right Channels	67.80%	68.52%	20.91%	0.95	0.53
All Channels	67.57%	72.22%	20.79%	-	0.49
CP3 Channel	64.47%	61.73%	17.73%	0.38	0.08
Small Left Channels	64.40%	65.43%	16.57%	0.36	0.06

(e) accuracies for all channel sets, db25 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Medium Left Channels	68.85%	69.75%	14.20%	1.00	-
All Channels	68.85%	72.22%	18.00%	-	1.00
Large Left Channels	68.27%	68.52%	12.79%	0.84	0.82
Right Channels	64.98%	66.67%	19.07%	0.26	0.21
CP3 Channel	62.39%	62.96%	16.99%	< 0.05	< 0.05
Small Left Channels	62.00%	64.20%	16.86%	< 0.05	< 0.05

(f) accuracies for all channel sets, match signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	59.47%	59.26%	10.19%	0.95	-
All Channels	59.34%	59.26%	12.00%	-	0.95
CP3 Channel	58.66%	59.26%	13.77%	0.77	0.72
Small Left Channels	58.42%	60.49%	14.35%	0.70	0.65
Medium Left Channels	58.19%	59.88%	12.56%	0.61	0.54
Right Channels	57.39%	58.02%	8.63%	0.31	0.23

Table 5.16: SVM linear classification for different subsets of channels, subject s1331plas

Stroke Subject s1332plas The results for subject s1332plas are seen in Table 5.17. No significant difference exists in the classification rates for different channel subsets.

(a) accuracies for all channel sets, AR signal processing

	mean	median	std. dev	p-val all chan.	p-val best
CP3 Channel	59.09%	62.96%	21.59%	0.56	-
Large Left Channels	58.58%	58.64%	11.24%	0.52	0.87
Medium Left Channels	58.48%	59.26%	12.26%	0.57	0.85
Small Left Channels	57.98%	60.49%	19.60%	0.81	0.77
All Channels	57.30%	57.41%	10.22%	-	0.56
Right Channels	55.04%	55.56%	10.55%	0.24	0.19

(b) accuracies for all channel sets, bior44 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	56.52%	57.41%	9.74%	0.88	-
All Channels	56.26%	56.79%	9.23%	-	0.88
Small Left Channels	55.16%	54.94%	17.53%	0.67	0.60
Medium Left Channels	54.94%	55.56%	12.95%	0.52	0.45
Right Channels	54.22%	54.32%	11.43%	0.29	0.24
CP3 Channel	54.07%	59.26%	21.54%	0.47	0.42

(c) accuracies for all channel sets, db2 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	61.15%	62.35%	12.94%	-	-
Large Left Channels	60.33%	60.49%	12.94%	0.73	0.73
Medium Left Channels	59.14%	59.88%	12.18%	0.38	0.38
CP3 Channel	58.42%	61.11%	17.49%	0.33	0.33
Small Left Channels	57.82%	56.79%	15.62%	0.21	0.21
Right Channels	57.65%	59.26%	12.24%	0.13	0.13

(d) accuracies for all channel sets, db8 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	60.02%	61.73%	12.52%	0.79	-
All Channels	59.44%	59.26%	11.36%	-	0.79
Medium Left Channels	58.68%	61.11%	13.03%	0.73	0.57
Small Left Channels	58.31%	62.35%	17.99%	0.68	0.55
CP3 Channel	57.22%	58.02%	20.42%	0.46	0.37
Right Channels	56.83%	54.94%	11.24%	0.21	0.14

(e) accuracies for all channel sets, db25 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	60.10%	60.49%	11.96%	0.96	-
All Channels	60.00%	60.49%	10.88%	-	0.96
Medium Left Channels	57.98%	59.88%	13.57%	0.37	0.37
CP3 Channel	57.02%	59.88%	21.65%	0.34	0.34
Right Channels	56.85%	58.02%	11.20%	0.12	0.13
Small Left Channels	56.77%	58.02%	18.27%	0.24	0.24

(f) accuracies for all channel sets, match signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	55.39%	56.17%	10.64%	0.47	-
CP3 Channel	54.79%	55.56%	16.30%	0.75	0.81
Medium Left Channels	54.65%	56.17%	10.66%	0.74	0.70
Small Left Channels	54.49%	55.56%	14.22%	0.83	0.69
All Channels	53.99%	54.32%	10.74%	-	0.47
Right Channels	53.13%	56.17%	16.23%	0.73	0.37

Table 5.17: SVM linear classification for different subsets of channels, subject s1332plas

Stroke Subject s1333plas The results for subject s1333plas are seen in Table 5.18. The results are similar to those of subject s1331plas, in that larger channel sets have better classification rates than smaller ones for wavelet feature extraction, but not for AR and match feature extraction.

(a) accuracies for all channel sets, AR signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	58.99%	59.26%	10.49%	0.28	-
Medium Left Channels	58.99%	59.26%	17.20%	0.41	1.00
Small Left Channels	58.64%	60.49%	17.37%	0.49	0.89
CP3 Channel	58.50%	60.49%	19.21%	0.55	0.86
All Channels	56.75%	56.79%	12.15%	-	0.28
Right Channels	54.98%	55.56%	10.41%	0.39	< 0.05

(b) accuracies for all channel sets, bior44 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	61.38%	61.73%	15.18%	-	-
Large Left Channels	59.65%	61.11%	11.25%	0.48	0.48
Right Channels	58.07%	58.02%	12.13%	0.19	0.19
CP3 Channel	57.18%	57.41%	21.52%	0.22	0.22
Small Left Channels	57.08%	57.41%	17.67%	0.16	0.16
Medium Left Channels	56.67%	58.64%	14.80%	0.09	0.09

(c) accuracies for all channel sets, db2 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	64.16%	66.05%	14.40%	-	-
Large Left Channels	63.46%	64.81%	17.62%	0.81	0.81
Medium Left Channels	60.43%	64.20%	16.42%	0.19	0.19
CP3 Channel	60.19%	65.43%	19.54%	0.21	0.21
Small Left Channels	59.94%	62.96%	21.69%	0.21	0.21
Right Channels	58.29%	61.73%	22.73%	0.09	0.09

(d) accuracies for all channel sets, db8 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
Large Left Channels	62.55%	62.96%	14.85%	0.86	-
All Channels	62.10%	62.96%	13.31%	-	0.86
Medium Left Channels	59.77%	60.49%	13.60%	0.35	0.29
Small Left Channels	59.40%	63.58%	16.97%	0.33	0.28
CP3 Channel	57.20%	58.64%	20.16%	0.12	0.10
Right Channels	56.77%	58.02%	23.26%	0.13	0.11

(e) accuracies for all channel sets, db25 signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	60.68%	61.11%	14.60%	-	-
Large Left Channels	60.60%	61.11%	19.32%	0.98	0.98
Medium Left Channels	58.42%	57.41%	22.39%	0.51	0.51
Small Left Channels	56.40%	57.41%	32.18%	0.35	0.35
Right Channels	56.30%	56.79%	28.32%	0.29	0.29
CP3 Channel	53.48%	54.32%	41.45%	0.21	0.21

(f) accuracies for all channel sets, match signal processing

	mean	median	std. dev	p-val all chan.	p-val best
All Channels	56.91%	56.17%	16.62%	-	-
Small Left Channels	56.89%	62.96%	27.50%	1.00	1.00
CP3 Channel	56.48%	60.49%	30.40%	0.92	0.92
Large Left Channels	56.40%	57.41%	12.48%	0.85	0.85
Right Channels	54.94%	55.56%	16.02%	0.51	0.51
Medium Left Channels	54.81%	54.94%	11.18%	0.42	0.42

Table 5.18: SVM linear classification for different subsets of channels, subject s1333plas

5.8 Success Rates

The previous sections have all evaluated the performance of classification methods in terms of classification accuracy. While this is an important consideration, a BCI trial is only successful if the subject moves the cursor to hit the appropriate target. This section attempts to correlate classification accuracy to target hit rates.

Since the data analyzed in this study were collected in screening sessions with 3-second target presentations and no cursor movement displayed to the subject, the target hit rate cannot be directly calculated. Instead, a synthetic "success rate" was calculated. This was done by calculating the cursor position for each sample, and finding the minimum and maximum cursor position. The cursor position was reset to zero at the beginning of each trial, and moved an amount equal to the decision value at each timestep. An activation trial was counted as a success if the maximum cursor position were greater than the absolute value of the minimum cursor position, and vice versa for relaxation trials. In other words, if the cursor position were closer to the correct target than the incorrect target, then there exists some value of gain for which the cursor would have hit the target.

Success rates were calculated for each method tested in Section 5.7. The correlation coefficient of each method's mean classification accuracy and success rate, and the p-value of the no-correlation hypothesis, were calculated by the least squares method. These values are shown in Table 5.19. The correlation coefficients are rather high, ranging from a low of 0.5326 to a high of 0.8040. The p-values of the no-correlation hypotheses are negligible for all subjects. The success rates are shown in Appendix 7.2.

Success rates seem to be relatively high. The success rate of a method is often higher than the classification accuracy for that method, and small increases in classification accuracy can have large effects on success rates. For example, for AR feature extraction and clinical classification, subject c1350plas has a 56.40% classification

Subject	Corr. Coef.	P-Val.
c1339plas	0.6871	0.0000
c1344plas	0.6356	0.0000
c1346plas	0.5326	0.0003
c1350plas	0.7510	0.0000
s1331plas	0.6718	0.0000
s1332plas	0.8040	0.0000
s1333plas	0.6781	0.0000

Table 5.19: Correlation coefficients of classification rates to success rates and P-values of the no-correlation hypotheses.

rate and a 63.33% success rate. For AR feature extraction and SVM classification using data from all channels, the classification rate is 65.06% and the success rate is 93.33% This suggests that relatively minor improvements in classification can have a dramatic effect on BCI performance.

Chapter 6

Discussion

This section describes the main findings of this study and the ways in which they extend the existing literature. The limitations of these findings are discussed and recommendations are given for further studies.

6.1 Findings

The main findings of this study are as follows.

First, when using the clinical classifier, a statistically significant difference ($p < 0.05$) difference was found, for one of seven subjects, between the classification rates given by standard autoregressive feature extraction and 8th order Daubechies wavelet feature extraction. However, the p-values of between db8 wavelets and the other wavelet feature extraction methods, as well as mu-matched filtering, were greater than 0.05 (Table 5.2(b)). The p-value of the comparisons between db8 wavelet feature extraction and mu-matched feature extraction is 0.12, and it is 0.06 for the comparison between db8 and bior44 wavelet feature extraction. This makes it likely that Daubechies wavelets all perform similarly at extracting mu waves from this particular subject's EEG, and are superior to autoregressive filtering, Biorthogonal 4/4 wavelets, and mu-matched filtering for this subject. Although that is the likeliest

explanation, it cannot be unequivocally proven from this data. No statistically significant difference between feature extraction methods was seen for six of the seven subjects. Previous studies [20, 12, 14] found wavelets to be an effective tool for extracting information from EEG

Second, for three of the seven subjects, a statistically significant difference was seen between clinical classification and classification with a support vector machine using a linear kernel. This could not be reliably improved by training the SVMs on various subsets of channels, with the exception that most subjects performed significantly worse when SVMs were trained on only the right-side channels.

Third, no difference was found in the classification results of SVMs with linear and nonlinear kernels. This supports the conclusion of Garrett, *et al.* who found only a minor difference between linear and nonlinear classification methods [11].

Lastly, a high correlation was found between classification rates and successful cursor movement. No studies were found in the existing literature measuring this correlation.

6.2 Limitations

A major limitation of this study is the small number of subjects. This made it problematic to average results across subjects, since there was a wide variation in results from subject to subject. Having data from a larger pool of subjects would allow firmer conclusions to be drawn regarding the effectiveness of the classification strategies. As it is, the best that can be said is that it appears that SVM classification and wavelet feature extraction may both be beneficial for BCI applications.

Another limitation of this study is the fact that each data sample's label is assigned based on what target was shown to the subject during data collection. In other words, the subject is assumed to be performing the correct action (by performing a motor

action or imagining it when the upper target is shown, or relaxing when the lower target is shown) at all times. This cannot be true for 100% of samples, but there is no basis for evaluating each sample and discarding those for which it is not true.

Furthermore, only minimal denoising was done, limited to CAR spatial processing to reduce noise common to all channels. No provision was made to detect eye blinks or EMG contamination in EEG. These strategies were not pursued because it is difficult to detect EMG contamination in online trials, and the intention of this study was to improve EEG classification for online BCI processing.

Additionally, the "success rate" measure of Chapter 5.5.8 is an entirely synthetic measure. It is unknown if the high success rates would be duplicated in training session trials, where the subject has 30 seconds to attempt to hit the target with a cursor.

6.3 Conclusion

Daubechies family wavelets appear to be at least as effective at extracting motor-related information from EEG as autoregressive filtering methods. Mu-matched filtering could not be demonstrated to be significantly better than autoregressive feature extraction.

6.4 Suggestions for Future Work

All classification accuracies in this study were calculated offline. In order to conclusively demonstrate the suitability of the methods analyzed in this study, their online performance must be evaluated. A study should be done using wavelet and SVM modules in BCI2000 in order to measure target hit rates for each method.

Chapter 7

Appendix

7.1 Linear and Nonlinear SVM Kernels

This section shows the classification results for linear and nonlinear SVM kernels. No difference in classification accuracy is seen.

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	55.10%	56.17%	17.42%	0.35
SVM Polynomial	54.81%	56.79%	17.10%	0.40
SVM Sigmoid	54.42%	56.17%	19.48%	0.52
SVM Linear	52.49%	51.23%	13.09%	-

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	54.16%	56.17%	12.99%	0.73
SVM Linear	53.37%	53.09%	12.10%	-
SVM Sigmoid	53.15%	51.85%	13.85%	0.92
SVM Polynomial	53.13%	53.09%	19.62%	0.93

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	57.02%	60.49%	15.83%	-
SVM RBF	55.14%	55.56%	18.50%	0.55
SVM Polynomial	54.88%	60.49%	29.31%	0.62
SVM Sigmoid	54.71%	58.02%	22.60%	0.52

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	56.87%	58.02%	26.85%	-
SVM RBF	56.69%	55.56%	13.65%	0.96
SVM Sigmoid	56.67%	59.26%	16.13%	0.96
SVM Polynomial	55.00%	56.79%	22.47%	0.68

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	57.86%	59.88%	19.00%	0.53
SVM Sigmoid	56.44%	55.56%	23.82%	0.84
SVM Linear	55.64%	55.56%	19.91%	-
SVM Polynomial	55.37%	51.85%	29.78%	0.95

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	53.93%	53.09%	8.65%	-
SVM RBF	53.81%	54.32%	11.57%	0.95
SVM Sigmoid	53.70%	54.32%	13.71%	0.91
SVM Polynomial	50.33%	53.09%	48.20%	0.57

Table 7.1: Classification rates by classifier type, c1339plas

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	66.95%	74.69%	22.14%	0.37
SVM Sigmoid	65.19%	69.75%	26.31%	0.70
SVM Linear	63.52%	66.67%	19.71%	-
SVM Polynomial	62.84%	66.67%	19.91%	0.85

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	65.33%	67.90%	28.35%	0.28
SVM Sigmoid	64.55%	66.05%	28.54%	0.34
SVM Polynomial	60.99%	64.20%	17.06%	0.66
SVM Linear	58.52%	67.28%	39.66%	-

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	69.75%	80.86%	25.90%	0.53
SVM Sigmoid	68.81%	77.16%	26.22%	0.66
SVM Linear	66.58%	75.93%	28.95%	-
SVM Polynomial	65.19%	66.67%	23.04%	0.77

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	74.05%	76.54%	16.70%	-
SVM RBF	71.69%	79.01%	23.25%	0.52
SVM Sigmoid	69.71%	77.78%	25.31%	0.27
SVM Polynomial	69.42%	74.07%	22.33%	0.20

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	69.26%	70.99%	14.88%	-
SVM RBF	69.05%	76.54%	23.99%	0.96
SVM Polynomial	68.85%	70.37%	18.69%	0.89
SVM Sigmoid	68.42%	75.31%	24.40%	0.82

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	69.92%	76.54%	18.08%	0.94
SVM Linear	69.67%	75.31%	15.76%	-
SVM Sigmoid	69.57%	76.54%	19.45%	0.97
SVM Polynomial	53.97%	55.56%	37.06%	< 0.05

Table 7.2: Classification rates by classifier type, c1344plas

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	49.59%	45.68%	27.69%	0.87
SVM Sigmoid	49.49%	48.77%	33.72%	0.90
SVM Polynomial	49.09%	41.98%	26.22%	0.96
SVM Linear	48.87%	50.00%	19.67%	-

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	48.87%	48.15%	16.07%	-
SVM Sigmoid	47.70%	40.74%	34.51%	0.81
SVM RBF	47.35%	38.27%	30.69%	0.73
SVM Polynomial	47.02%	40.74%	27.82%	0.66

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	48.23%	47.53%	18.21%	-
SVM RBF	47.14%	43.21%	31.98%	0.82
SVM Sigmoid	47.02%	38.89%	34.29%	0.81
SVM Polynomial	46.21%	43.21%	28.45%	0.64

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	48.91%	50.00%	15.94%	-
SVM RBF	47.16%	41.36%	32.05%	0.71
SVM Polynomial	46.75%	43.83%	29.42%	0.62
SVM Sigmoid	46.28%	38.27%	34.87%	0.60

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	49.38%	52.47%	32.48%	-
SVM RBF	48.79%	51.85%	23.74%	0.91
SVM Polynomial	47.45%	48.15%	22.88%	0.71
SVM Sigmoid	47.16%	44.44%	28.70%	0.69

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	47.06%	48.77%	20.19%	-
SVM Polynomial	46.87%	47.53%	20.32%	0.96
SVM RBF	46.73%	44.44%	25.01%	0.94
SVM Sigmoid	46.52%	39.51%	26.45%	0.90

Table 7.3: Classification rates by classifier type, c1346plas

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	67.10%	70.37%	14.66%	0.38
SVM Linear	65.06%	65.43%	10.06%	-
SVM Polynomial	57.98%	61.11%	29.25%	0.08
SVM Sigmoid	56.83%	56.17%	35.14%	0.08

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	65.82%	66.67%	14.09%	-
SVM RBF	64.65%	70.99%	21.37%	0.72
SVM Sigmoid	62.49%	65.43%	28.65%	0.42
SVM Polynomial	58.91%	64.81%	27.92%	0.09

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	73.97%	74.07%	14.49%	-
SVM RBF	73.09%	75.31%	17.85%	0.77
SVM Sigmoid	72.26%	77.16%	19.94%	0.59
SVM Polynomial	66.07%	67.90%	20.00%	< 0.05

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	75.06%	75.31%	14.77%	-
SVM RBF	72.86%	77.16%	20.61%	0.50
SVM Sigmoid	71.60%	77.78%	21.86%	0.31
SVM Polynomial	66.73%	74.07%	23.19%	< 0.05

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	73.44%	72.22%	15.24%	-
SVM RBF	72.65%	80.25%	21.41%	0.82
SVM Sigmoid	70.74%	77.78%	25.04%	0.48
SVM Polynomial	66.42%	71.60%	24.89%	0.07

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	66.11%	66.67%	11.55%	-
SVM RBF	65.45%	67.90%	12.23%	0.76
SVM Sigmoid	64.61%	67.90%	13.39%	0.51
SVM Polynomial	57.35%	55.56%	25.12%	< 0.05

Table 7.4: Classification rates by classifier type, c1350plas

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	68.97%	74.07%	18.59%	0.09
SVM Polynomial	68.05%	73.46%	21.01%	0.20
SVM Sigmoid	66.93%	68.52%	23.50%	0.39
SVM Linear	63.97%	66.67%	12.99%	-

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Sigmoid	66.01%	69.14%	13.40%	0.19
SVM RBF	65.58%	67.28%	11.20%	0.22
SVM Polynomial	64.84%	66.67%	14.22%	0.46
SVM Linear	63.15%	62.96%	10.39%	-

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Sigmoid	72.94%	72.22%	17.07%	0.20
SVM RBF	71.56%	72.22%	20.40%	0.42
SVM Linear	68.54%	68.52%	20.58%	-
SVM Polynomial	68.48%	70.37%	24.29%	0.99

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	71.30%	72.84%	19.95%	0.32
SVM Sigmoid	70.88%	72.84%	15.37%	0.32
SVM Polynomial	70.74%	72.84%	23.50%	0.44
SVM Linear	67.57%	72.22%	20.79%	-

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	70.33%	74.69%	21.03%	0.68
SVM Sigmoid	70.33%	74.07%	19.07%	0.66
SVM Linear	68.85%	72.22%	18.00%	-
SVM Polynomial	68.85%	69.75%	24.15%	1.00

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Sigmoid	59.42%	58.02%	10.70%	0.97
SVM Linear	59.34%	59.26%	12.00%	-
SVM RBF	59.32%	59.26%	12.31%	0.99
SVM Polynomial	54.71%	53.70%	36.03%	0.35

Table 7.5: Classification rates by classifier type, s1331plas

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Polynomial	58.17%	62.96%	24.60%	0.80
SVM RBF	58.02%	65.43%	25.05%	0.84
SVM Sigmoid	57.67%	70.37%	31.77%	0.93
SVM Linear	57.30%	57.41%	10.22%	-

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	56.26%	56.79%	9.23%	-
SVM RBF	54.65%	54.94%	14.92%	0.48
SVM Sigmoid	53.66%	59.26%	26.66%	0.48
SVM Polynomial	52.82%	50.62%	13.53%	0.11

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	61.15%	62.35%	12.94%	-
SVM RBF	58.05%	58.64%	13.34%	0.20
SVM Sigmoid	57.61%	66.05%	22.01%	0.29
SVM Polynomial	56.17%	56.79%	15.00%	0.05

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	59.44%	59.26%	11.36%	-
SVM RBF	57.53%	59.26%	13.18%	0.40
SVM Polynomial	56.91%	57.41%	14.71%	0.29
SVM Sigmoid	55.72%	62.35%	29.83%	0.37

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	60.00%	60.49%	10.88%	-
SVM RBF	57.57%	60.49%	14.58%	0.30
SVM Sigmoid	56.19%	67.28%	27.93%	0.33
SVM Polynomial	56.07%	58.64%	14.83%	0.10

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	54.59%	55.56%	14.81%	0.80
SVM Linear	53.99%	54.32%	10.74%	-
SVM Sigmoid	53.27%	53.70%	23.46%	0.83
SVM Polynomial	52.33%	53.09%	28.31%	0.67

Table 7.6: Classification rates by classifier type, s1332plas

(a) accuracies for AR signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	60.14%	62.35%	24.63%	0.34
SVM Polynomial	58.93%	57.41%	28.53%	0.59
SVM Linear	56.75%	56.79%	12.15%	-
SVM Sigmoid	56.28%	64.20%	38.52%	0.93

(b) accuracies for bior44 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	62.30%	62.96%	13.07%	0.72
SVM Sigmoid	61.73%	63.58%	11.11%	0.89
SVM Linear	61.38%	61.73%	15.18%	-
SVM Polynomial	60.49%	61.73%	11.77%	0.72

(c) accuracies for db2 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	64.16%	66.05%	14.40%	-
SVM Sigmoid	61.69%	65.43%	20.37%	0.44
SVM Polynomial	61.44%	59.26%	29.79%	0.53
SVM RBF	61.01%	64.81%	28.37%	0.44

(d) accuracies for db8 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM Linear	62.10%	62.96%	13.31%	-
SVM Sigmoid	59.01%	59.88%	15.94%	0.25
SVM RBF	57.74%	56.79%	29.50%	0.30
SVM Polynomial	54.26%	52.47%	25.51%	< 0.05

(e) accuracies for db25 signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	61.95%	64.20%	20.84%	0.70
SVM Sigmoid	61.32%	65.43%	15.71%	0.82
SVM Polynomial	60.95%	64.20%	28.32%	0.95
SVM Linear	60.68%	61.11%	14.60%	-

(f) accuracies for match signal processing, all trials

	mean	median	std. dev	p-val SVM linear
SVM RBF	57.30%	57.41%	19.27%	0.91
SVM Linear	56.91%	56.17%	16.62%	-
SVM Sigmoid	56.83%	59.88%	19.93%	0.98
SVM Polynomial	52.76%	54.94%	41.28%	0.47

Table 7.7: Classification rates by classifier type, s1333plas

7.2 Success Rates

The following tables show the success rates for each subject, calculated as described in Section 5.8.

	Mean Classification Rate	Success Rate
AR; clinical clsf.	50.33%	50.00%
AR; SVM, all	52.49%	53.33%
AR; SVM, large left	51.19%	58.33%
AR; SVM, med. left	51.98%	58.33%
AR; SVM, small left	52.90%	56.67%
AR; SVM, CP3	53.42%	63.33%
AR; SVM, right	52.02%	53.33%
match; clinical clsf.	51.73%	51.67%
match; SVM, all	53.93%	68.33%
match; SVM, large left	53.85%	63.33%
match; SVM, med. left	52.33%	63.33%
match; SVM, small left	52.72%	63.33%
match; SVM, CP3	52.51%	56.67%
match; SVM, right	53.35%	51.67%
db8; clinical clsf.	49.34%	50.00%
db8; SVM, all	56.87%	60.00%
db8; SVM, large left	57.59%	68.33%
db8; SVM, med. left	55.16%	70.00%
db8; SVM, small left	54.26%	68.33%
db8; SVM, CP3	54.49%	61.67%
db8; SVM, right	54.79%	55.00%

Table 7.8: Classification rates and success rates, subject c1339plas

	Mean Classification Rate	Success Rate
AR; clinical clsf.	64.14%	85.00%
AR; SVM, all	63.52%	76.67%
AR; SVM, large left	65.35%	80.00%
AR; SVM, med. left	67.61%	85.00%
AR; SVM, small left	68.66%	83.33%
AR; SVM, CP3	69.38%	86.67%
AR; SVM, right	56.67%	75.00%
match; clinical clsf.	67.16%	83.33%
match; SVM, all	69.67%	85.00%
match; SVM, large left	68.09%	83.33%
match; SVM, med. left	67.55%	81.67%
match; SVM, small left	67.24%	81.67%
match; SVM, CP3	67.20%	81.67%
match; SVM, right	60.95%	80.00%
db8; clinical clsf.	72.61%	78.33%
db8; SVM, all	74.05%	88.33%
db8; SVM, large left	73.97%	85.00%
db8; SVM, med. left	73.58%	85.00%
db8; SVM, small left	73.37%	83.33%
db8; SVM, CP3	72.67%	78.33%
db8; SVM, right	58.23%	55.00%

Table 7.9: Classification rates and success rates, subject c1344plas

	Mean Classification Rate	Success Rate
AR; clinical clsf.	52.45%	56.67%
AR; SVM, all	48.87%	50.00%
AR; SVM, large left	50.51%	43.33%
AR; SVM, med. left	49.16%	46.67%
AR; SVM, small left	49.67%	51.67%
AR; SVM, CP3	50.72%	45.00%
AR; SVM, right	47.74%	45.00%
match; clinical clsf.	50.37%	50.00%
match; SVM, all	47.06%	48.33%
match; SVM, large left	48.09%	50.00%
match; SVM, med. left	48.81%	43.33%
match; SVM, small left	47.65%	45.00%
match; SVM, CP3	49.73%	50.00%
match; SVM, right	47.00%	46.67%
db8; clinical clsf.	50.27%	50.00%
db8; SVM, all	48.91%	55.00%
db8; SVM, large left	49.65%	48.33%
db8; SVM, med. left	47.33%	43.33%
db8; SVM, small left	47.94%	43.33%
db8; SVM, CP3	50.33%	50.00%
db8; SVM, right	49.44%	51.67%

Table 7.10: Classification rates and success rates, subject c1346plas

	Mean Classification Rate	Success Rate
AR; clinical clsf.	56.40%	63.33%
AR; SVM, all	65.06%	93.33%
AR; SVM, large left	62.76%	83.33%
AR; SVM, med. left	61.91%	83.33%
AR; SVM, small left	60.31%	75.00%
AR; SVM, CP3	58.87%	73.33%
AR; SVM, right	58.31%	88.33%
match; clinical clsf.	59.07%	70.00%
match; SVM, all	66.11%	96.67%
match; SVM, large left	64.71%	95.00%
match; SVM, med. left	59.79%	83.33%
match; SVM, small left	58.64%	73.33%
match; SVM, CP3	59.16%	73.33%
match; SVM, right	56.71%	85.00%
db8; clinical clsf.	54.34%	55.00%
db8; SVM, all	75.06%	93.33%
db8; SVM, large left	70.82%	86.67%
db8; SVM, med. left	67.04%	86.67%
db8; SVM, small left	62.96%	80.00%
db8; SVM, CP3	61.81%	78.33%
db8; SVM, right	67.65%	85.00%

Table 7.11: Classification rates and success rates, subject c1350plas

	Mean Classification Rate	Success Rate
AR; clinical clsf.	50.39%	50.00%
AR; SVM, all	63.97%	83.33%
AR; SVM, large left	62.35%	80.00%
AR; SVM, med. left	66.46%	71.67%
AR; SVM, small left	64.16%	71.67%
AR; SVM, CP3	65.10%	70.00%
AR; SVM, right	66.63%	78.33%
match; clinical clsf.	50.82%	50.00%
match; SVM, all	59.34%	70.00%
match; SVM, large left	59.47%	70.00%
match; SVM, med. left	58.19%	60.00%
match; SVM, small left	58.42%	65.00%
match; SVM, CP3	58.66%	63.33%
match; SVM, right	57.39%	68.33%
db8; clinical clsf.	52.70%	51.67%
db8; SVM, all	67.57%	60.00%
db8; SVM, large left	69.63%	85.00%
db8; SVM, med. left	69.90%	75.00%
db8; SVM, small left	64.40%	70.00%
db8; SVM, CP3	64.47%	63.33%
db8; SVM, right	67.80%	61.67%

Table 7.12: Classification rates and success rates, subject s1331plas

	Mean Classification Rate	Success Rate
AR; clinical clsf.	49.61%	50.00%
AR; SVM, all	57.30%	76.67%
AR; SVM, large left	58.58%	76.67%
AR; SVM, med. left	58.48%	76.67%
AR; SVM, small left	57.98%	75.00%
AR; SVM, CP3	59.09%	73.33%
AR; SVM, right	55.04%	65.00%
match; clinical clsf.	54.73%	61.67%
match; SVM, all	53.99%	60.00%
match; SVM, large left	55.39%	65.00%
match; SVM, med. left	54.65%	68.33%
match; SVM, small left	54.49%	63.33%
match; SVM, CP3	54.79%	61.67%
match; SVM, right	53.13%	55.00%
db8; clinical clsf.	55.84%	61.67%
db8; SVM, all	59.44%	76.67%
db8; SVM, large left	60.02%	73.33%
db8; SVM, med. left	58.68%	78.33%
db8; SVM, small left	58.31%	68.33%
db8; SVM, CP3	57.22%	60.00%
db8; SVM, right	56.83%	73.33%

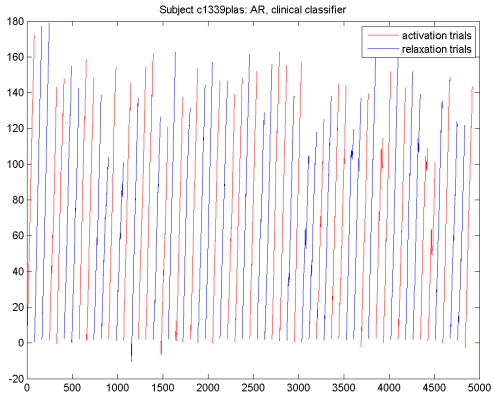
Table 7.13: Classification rates and success rates, subject s1332plas

	Mean Classification Rate	Success Rate
AR; clinical clsf.	52.28%	50.00%
AR; SVM, all	56.75%	66.67%
AR; SVM, large left	58.99%	75.00%
AR; SVM, med. left	58.99%	66.67%
AR; SVM, small left	58.64%	78.33%
AR; SVM, CP3	58.50%	73.33%
AR; SVM, right	54.98%	68.33%
match; clinical clsf.	53.58%	60.00%
match; SVM, all	56.91%	53.33%
match; SVM, large left	56.40%	61.67%
match; SVM, med. left	54.81%	60.00%
match; SVM, small left	56.89%	53.33%
match; SVM, CP3	56.48%	53.33%
match; SVM, right	54.94%	53.33%
db8; clinical clsf.	55.45%	68.33%
db8; SVM, all	62.10%	80.00%
db8; SVM, large left	62.55%	73.33%
db8; SVM, med. left	59.77%	73.33%
db8; SVM, small left	59.40%	70.00%
db8; SVM, CP3	57.20%	63.33%
db8; SVM, right	56.77%	56.67%

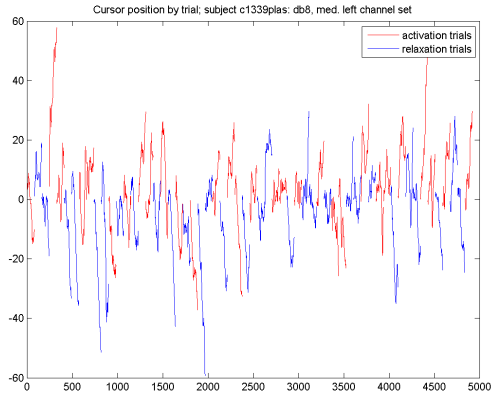
Table 7.14: Classification rates and success rates, subject s1333plas

7.3 Cursor Paths

The following plots illustrate the behavior of the cursor under selected processing methods. The cursor is moved as described in Section 5.8. Two plots are shown for each subject: the baseline method (AR / clinical classifier) and the method with the highest success rate. These plots demonstrate the difference in performance that could be expected in a BCI application by change of feature extraction and classification methods. A large difference in cursor movement is seen for certain subjects.

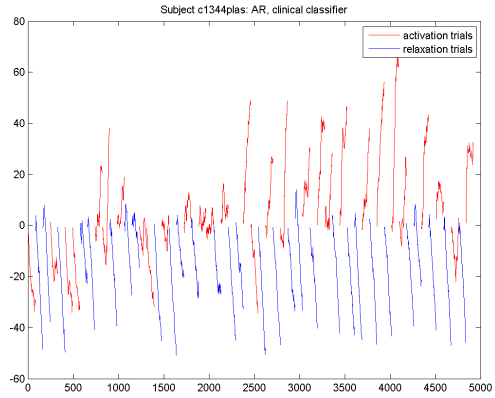


(a)

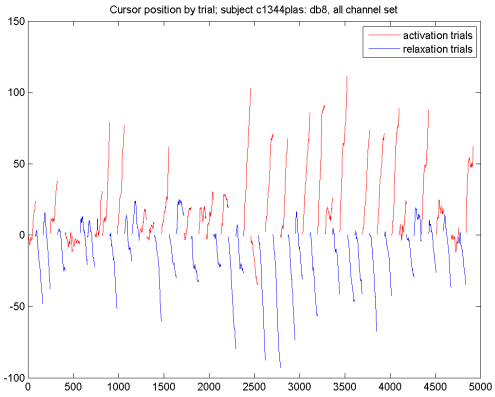


(b)

Figure 7.1: Cursor paths for subject c1339plas, AR feature extraction and clinical classification (a) and db8 wavelet feature extraction and SVM classification with the medium left channel set (b).

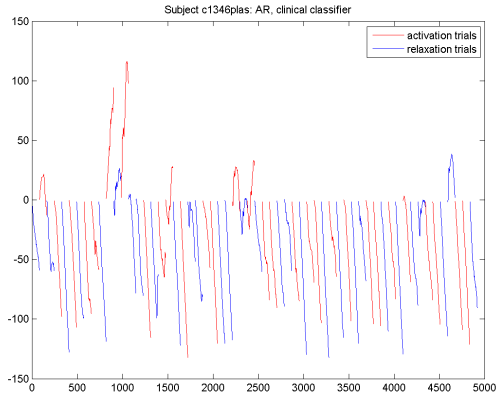


(a)

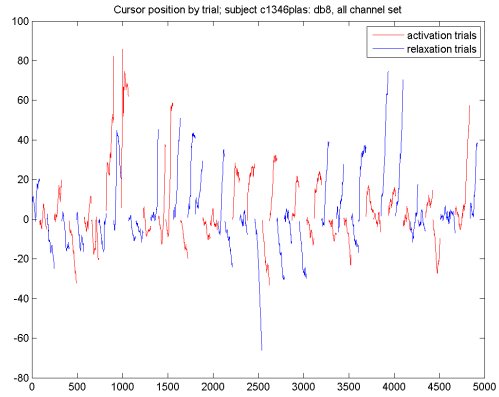


(b)

Figure 7.2: Cursor paths for subject c1344plas, AR feature extraction and clinical classification (a) and db8 wavelet feature extraction and SVM classification with all channels (b).

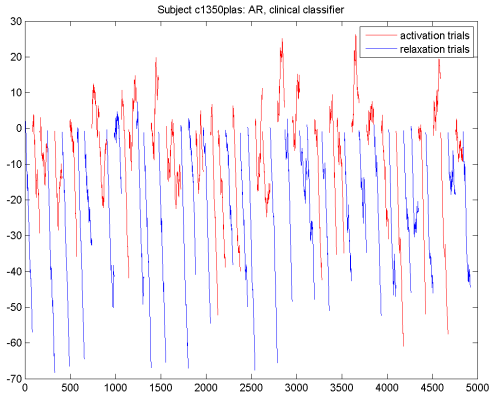


(a)

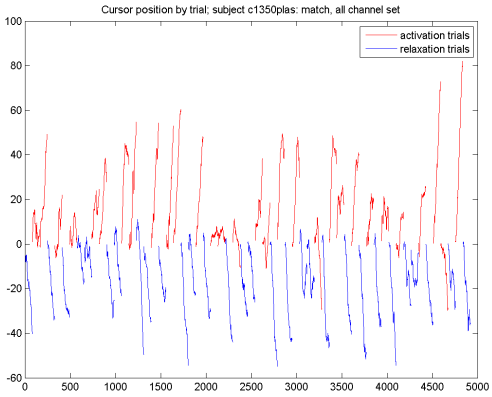


(b)

Figure 7.3: Cursor paths for subject c1346plas, AR feature extraction and clinical classification (a) and db8 wavelet feature extraction and SVM classification with all channels (b).

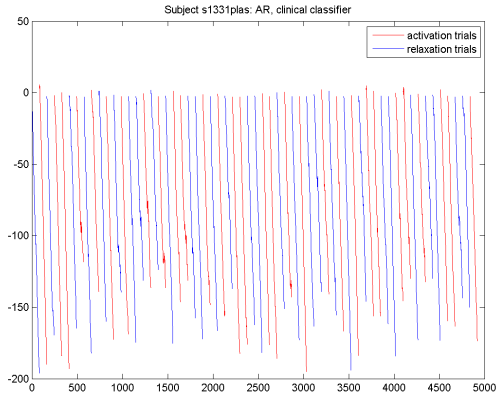


(a)

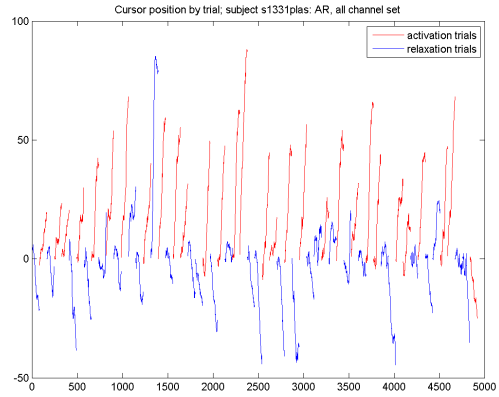


(b)

Figure 7.4: Cursor paths for subject c1350plas, AR feature extraction and clinical classification (a) and mu-matched feature extraction and SVM classification with all channels (b).

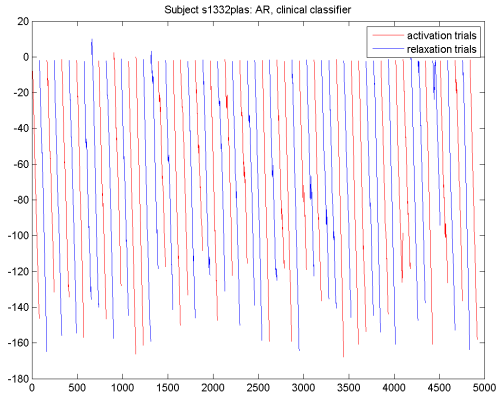


(a)

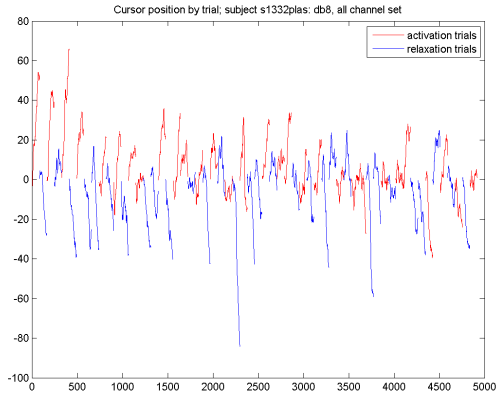


(b)

Figure 7.5: Cursor paths for subject s1331plas, AR feature extraction and clinical classification (a) and AR feature extraction and SVM classification with all channels (b).

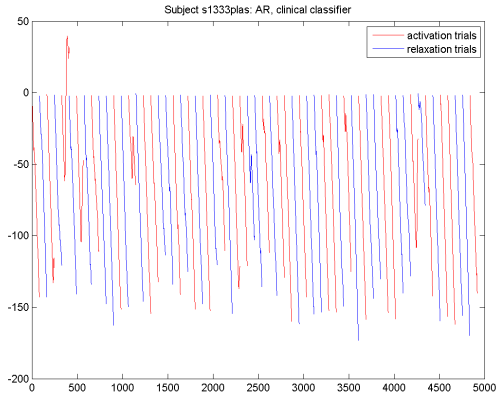


(a)

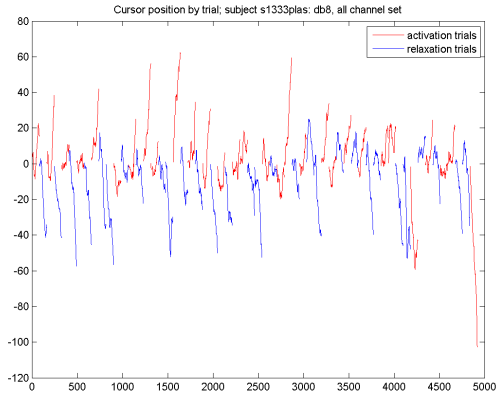


(b)

Figure 7.6: Cursor paths for subject s1332plas, AR feature extraction and clinical classification (a) and db8 wavelet feature extraction and SVM classification with all channels (b).



(a)



(b)

Figure 7.7: Cursor paths for subject s1333plas, AR feature extraction and clinical classification (a) and db8 wavelet feature extraction and SVM classification with all channels (b).

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