2011

Investigation of Variability in Cognitive State Assessment based on Electroencephalogram-derived Features

Samantha Lokelani Crossen
Wright State University

Investigation of Variability in Cognitive State Assessment based on Electroencephalogram-derived Features

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Engineering

By

SAMANTHA LOKELANI CROSSEN
B.S.B.E., Wright State University, 2009

2011
Wright State University

WRIGHT STATE UNIVERSITY

SCHOOL OF GRADUATE STUDIES

July 1, 2011

I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Samantha Lokelani Crossen ENTITLED Investigation of Variability in Cognitive State Assessment based on Electroencephalogram-derived Features BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Engineering.

Ping He, Ph.D.
Thesis Director

Thomas Hangartner, Ph.D., Chair
Department of Biomedical, Industrial and Human Factors Engineering

Committee on Final Examination

Ping He, Ph.D.

James Christensen, Ph.D.

Yan Liu, Ph.D.

Andrew Hsu, Ph.D.
Dean, Graduate School

Abstract

Crossen, Samantha Lokelani. M.S.Egr., Department of Biomedical, Industrial, and Human Factors Engineering, Wright State University, 2011. Investigation of Variability in Cognitive State Assessment based on Electroencephalogram-derived Features.

To implement adaptive aiding in modern aviation systems there is a need for accurate and reliable classification of cognitive workload. Using electroencephalogram (EEG)-derived features, it has been reported that an Artificial Neural Network (ANN) can achieve 95% or higher classification accuracy on the same day for an individual operator, but only 70% or less on a different day. To gain a further insight into this discrepancy, data from a previous study was utilized to study the classification variability. The EEG-derived features were first calculated by spectral power estimation. The variability was then analyzed by performing cognitive workload classification in which different methods of training and testing were used and different classifiers were implemented to compare classification accuracies. The classifiers include an ANN, Adaboost Algorithm, and a t-test method. The results show that when the ANN or Adaboost method is used, the amount of overlapping among training and testing data impacts the classification accuracy significantly. When there is no overlap, all classifiers can only achieve an accuracy of about 70%, with the Adaboost outperforming other classifiers slightly. By allowing some overlap, the accuracy of the ANN or Adaboost method increases significantly. It was concluded that the main source of the classification variability is the inherent variability of the EEG-derived features.

Table of Contents

List of Figures

List of Tables

Acknowledgments

First, I would like to thank Dr. Ping He for encouraging me to go onto graduate school and for always being very supportive throughout my graduate studies. I would like to express thanks to Dr. James Christensen and Dr. Yan Liu who are on my thesis committee. Both Dr. Christensen and Dr. Liu have been very helpful and have given me much advice regarding my thesis work. I would also like to thank Justin Estepp and Jason Monnin, whom I had the chance to work with at Wright-Patterson Air Force Base, for always being there to answer my questions and for all of the encouragement. I am very grateful for The Dayton Area Graduate Studies Institute (DAGSI) for the opportunity they have given me by funding my research.

I would like to thank my family and friends for always being there for me. I would like to especially thank my husband, Nick Klosterman, who has given me unending love and support. Finally, I would like to show much appreciation to John and Christine Crossen, my parents, who have made me who I am today and have given me the faith to conquer anything I put my mind to. Thank you everyone!

1. Introduction

Modern aviation systems are capable of loading their operators with high levels of cognitive demands and as these demands increase, the ability of an operator to successfully complete required tasks may diminish. If there is a method to classify the operator's state of cognitive workload, aviation systems may be able to adjust their demands to better facilitate the available cognitive capabilities of the operator. This entire process, referred to as adaptive aiding, will lead to increased operator performance [1,2]. Accurate and reliable assessment of the operator's cognitive state is, therefore, the key to successful implementation of adaptive automation. The application of inappropriate aiding, resultant from misclassification of cognitive state could result in further decreased task performance [2]. Similarly, excessive aiding could lead to inattentiveness, also leading to decreased performance. An ideal classification system would have a classification accuracy of 100%. Such a perfect classification may be difficult to achieve in real-world applications due to the inherent variability in human physiology measures, but accuracies of 95% or higher are highly desirable for real-world applications.

A number of different classifiers have been used to classify physiological data such as linear discriminant analysis (LDA), support vector machines (SVM), boosting algorithms and artificial neural networks (ANN) [3-6]. The ANN is a popular classifier for discriminating at least two levels of workload conditions and has been developed to classify operator's cognitive workload [6-8]. An ANN is simply a mathematical model with interconnected networks of simple processing elements. These elements can be classified as one of the following three: input, output, or hidden elements [3]. When used as a classifier of cognitive workload, the common inputs to the ANN are features derived from the operator's physiological measures such as an electroencephalogram (EEG) recorded from several electrode placement sites, blink rate, heart rate, and respiration rate. The physiological measure which has received much attention in classifying cognitive workload is the EEG-derived features.

The term electroencephalogram or EEG was introduced by the German psychiatrist Hans Berger, who was the first to systematically analyze the potential fluctuations recorded from the brain. The recorded fluctuating potentials represent a superposition of the volume-conductor fields produced by a variety of active neuronal current generators [9]. The sources generating the field potentials recorded at the scalp are a summation of neuronal elements with complex interconnections. Electrodes are placed on the scalp to measure the potential difference between an electrode and a distant reference electrode. These recordings demonstrate continuous oscillating electric activity within the brain with a magnitude in the range of 100 μV. The frequency range of an EEG signal is from DC to 100 Hz. Spectral power in the traditional clinical frequency bands (delta [0.5 – 3 Hz], theta [4 – 7 Hz], alpha [8 – 13 Hz], beta [14 – 30 Hz], and gamma [31 – 42 Hz]) have been used to analyze the cognitive state of an operator by using them as features to input into a classifier [7].

EEG signals change prominently between states of alertness, such as being awake or asleep. The EEG signals have been used in clinical settings for monitoring brain function in such studies as assessing sleep disorders [10] and in evaluating the level of awareness during administration of anesthesia [11]. These studies suggest that EEG signal measurements have a high sensitivity to alertness; therefore, EEG-derived features are used to classify cognitive workload. Gevins and Smith explored brain signals that are sensitive to variations in mental effort in a working memory study. It was reported that the magnitude of spectral power in the theta band was enhanced during difficult workload and the magnitude of spectral power in the alpha band was attenuated during difficult workload [12]. There have been other studies that have also found that the theta, alpha, beta and gamma bands are enhanced or attenuated during workload [13,14]. The enhancement or attenuation of the spectral power of EEG during working memory tasks provided the motivation to look at the spectral power of EEG during low and high workload tasks to determine an index of separability.

From the results of previous studies on spectral power of EEG, it has been shown that EEG signal changes are highly predictable during states of alertness [12-14]. Researchers at Wright-Patterson Air Force Base (WPAFB) have developed a three-layer artificial neural network[1] with backpropagation training to act as a classifier that uses EEG-derived features to differentiate between states where the operator is successfully completing assigned tasks and a cognitive overload condition where performance begins to negatively impact mission success [2]. To test the ANN as a classifier, a systematic lab study was conducted at WPAFB that involved 8 subjects, spread across 5 days, with 3 trials each day, each including 3 levels of task difficulty. Power of the EEG was used as features, which was derived by Fast Fourier Transform (FFT). It has been previously reported that classification accuracies of 95% or higher were shown to be achievable

[1] A three-layer artificial neural network contains an input layer, one hidden layer (with the same number of nodes as the input layer), and an output layer containing two nodes.

when classification strategies were specifically designed for an individual operator and tested on the same day [15]. More specifically, the data collected from a particular operator on a particular day were divided into three sets, a training data set, a validation set, and a test data set. A total of 105 features (obtained from 21 electrode sites using 5 frequency bands) were derived from the physiology measures and fed to the ANN for classification. The training data set was used to train the ANN by adjusting its weights and biases, with the validation data set used to check for overfitting. Once trained, the weights and biases of the network were fixed and the ANN acted as a pattern classifier. When it was tested using the test data set from the same operator on the same day, the accuracy of classification could reach 95% or higher. However, when the same trained ANN was tested using the data collected from another operator or from the same operator but on a different day, it was reported that the classification accuracy would drop greatly [15]. In order to achieve a higher accuracy, the ANN needs to be re-trained using the data collected from that individual operator or on that particular day. This change in the classification strategies, in order to maintain high classification accuracy, is referred to as day-to-day and individual variability, and is considered the main obstacle to the real-world application of the current classification system.

It is noticed that the day-to-day variability from the above study is manifested in the overall result of classification that includes an ANN classifier and the set of input features. Since the ANN is trained by a set of input features, the low classification accuracy could be the result of a change in the input features. In order to identify the source of the day-to-day variability, it was decided to directly examine the variability of each EEG-derived feature using the data collected in above-mentioned systematic study.

2. Materials and Methods

To examine classification variability, this study focuses on classifying cognitive workload for an individual subject within the same day; specifically, focusing on an individual subject and classifying workload between trials within the same day. The classifiers used in this study include an Artificial Neural Network (ANN), AdaBoost Algorithm, and a t-test method. Each classifier independently determines which EEG-derived features are salient. The ANN and AdaBoost Algorithm determine salient features to use for workload classification but are not transparent to the user. To classify cognitive workload using the t-test method, a t-test was performed to determine the saliency of specific EEG-derived features and these features were utilized to classify workload. A t-test assesses whether the means of two groups are statistically different from each other. The t-test values are used as a measure of the saliency of each of the EEG-derived features. By finding the most salient features that change significantly with workload, this could reduce the number of features needed and in turn reduce the amount of training data and will most likely reduce the time to train the classifier [15]. Considering t-test value analysis and different classifier methods, the final outcome is to find salient features with an effective classifier method.

2.1. Generation of the EEG Features

EEG features generated for this study were obtained from the systematic lab study discussed previously. The data set from the study was collected while study participants performed a variety of tasks using the Multi-Attribute Task Battery (MATB) interactive software developed by NASA [16]. The MATB software simulates tasks analogous to those a flight crewmember or operator would encounter and these tasks include monitoring, tracking, communication and resource allocation responsibilities that occur simultaneously in a continually changing environment. The demands of each task in MATB were varied so that three levels of difficulty were available. A total of 21 channels were recorded which include 19 channels of EEG at sites positioned according to the standard International 10-20 electrode system plus vertical and horizontal electrooculogram (VEOG and HEOG) [17]. VEOG and HEOG were recorded for artifact correction purposes. Peripheral measures such as eye blink, heart rate, and respiration intervals were also collected but will not be used in this study since the focus is on EEG-derive features. The data was originally sampled at 256 Hz and filtered from 0.05 – 100 Hz. The data was then down sampled to 128 Hz.

Table 1. Description of the six different randomized sequences of workload conditions.

Code of sequence	**Sequence of Workload**	**Time sequence for each workload level (seconds)**		
A	L-M-H	30-330	360-660	690-990
B	L-H-M	30-330	390-690	720-1020
C	M-L-H	30-330	360-660	720-1020
D	M-H-L	30-330	360-660	720-1020
E	H-L-M	30-330	390-690	720-1020
F	H-M-L	30-330	360-660	690-990

Data from the 8 subjects was collected in 5 days spread over the period of one month. The 5 days were separated by 1 day, 1 week, 3 weeks, and 4 weeks. In each of the 5 days, the subject completed 3 trials, each lasted about 17 minutes. During each trial, the subject was presented a randomized sequence of low, medium, and high workload conditions that lasted for 5 minutes each with ‘transition’ time between workload conditions (Table 1). This transition time consisted of 60 seconds between low/high and high/low conditions and 30 seconds between low/medium, medium/low, medium/high, and high/medium conditions. The data from the low and medium conditions were combined and designated as normal workload condition. Therefore, the output from a classification system would be a binary decision: normal workload or high workload condition. Before data was collected, all subjects were trained on the MATB tasks until performance parameters attained asymptote with minimal errors.

The electrooculogram (EOG) artifacts (electric noise produced by eye movement) in the original data were already removed using MANSCAN software. Spectral analysis was performed using a Fast Fourier Transform (FFT) to create EEG features for input into a classifier. To perform an FFT on continuous biomedical signals, segmentation is needed. Since the EEG signal does not have a natural zero period, a window function is used to segment the signal. Signal from each of the 19 EEG channels was segmented by using a hanning window function by two different methods. These methods included segmenting by using a 10-second window with a 9-second overlap between adjacent windows and by using a 5-second window with a 0-second overlap. From each segment (using both windowing methods), a FFT was performed. The mean log power in each of the five bands during each window, which was defined as a "feature", was then calculated: delta band (0.5 – 3 Hz), theta band (4 – 7 Hz), alpha band (8 – 12 Hz), beta band (13 – 30 Hz), and gamma band (31 – 42 Hz). The mean log power in the five frequency bands was used to obtain more of a normal distribution. Since there are a total of 19 channels at five frequency bands, there will be a total of 95 features at any moment, and the value of each feature is updated every one second or five seconds depending on the windowing method. For each of the 17-minute trials in which a 10-second window was used to calculate the features, there will be 600 exemplars for each feature during the normal workload condition (sample number N_N = 600), and 300 exemplars during the high workload condition (sample number N_H = 300). For each of the 17-minute trials in which a 5-second window was used to calculate the features, there will be 120 exemplars for each feature during the normal workload condition (sample number N_N = 120), and 60 exemplars during the high workload condition (sample number N_H = 60).

2.2. Use of T-test to Visualize Separability of Workload Conditions

If the value of a certain feature is highly correlated to the cognitive workload, it is a salient feature for classification of the cognitive workload. When an ANN is trained, the most salient features are automatically selected to associate with larger weights. However, the saliency of each feature is difficult to quantify and the process of selecting the most salient features is not visible to the user. With an understanding that there is an enhancement or attenuation of spectral power EEG during high workload conditions and by using statistical analysis, a method for quantifying the saliency of each individual feature is possible.

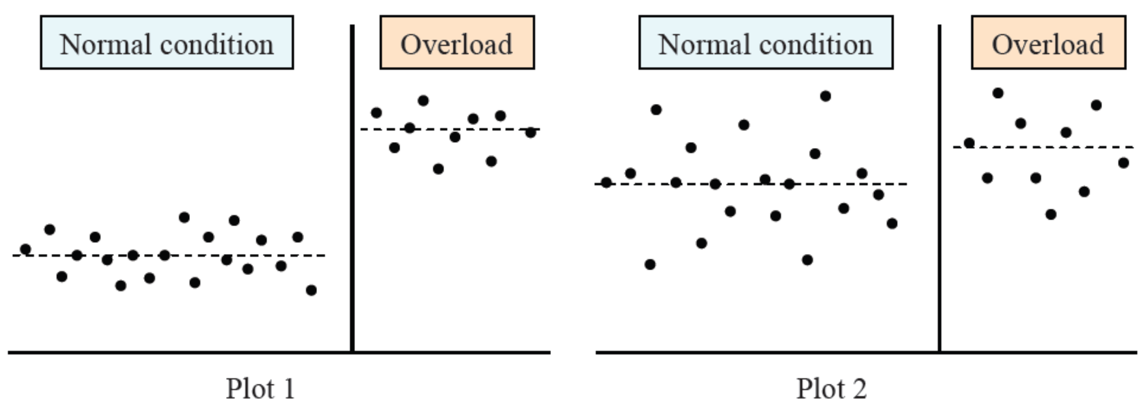

Figure 1. These are plots of normal and overload exemplars for a certain feature. Plot 1 displays a salient feature. Plot 2 displays a feature in which both workload conditions are inseparable.

If the 600 or 120 exemplars (sample number changes depending on windowing method) of a particular feature during the normal condition and 300 or 60 exemplars during the high or overload conditions are plotted, we may get the following two possible plots shown in Figure 1. From here on, these exemplars for high and normal workload conditions will be referred to as "feature values". In Plot 1, the feature values in the normal condition are significantly different from its value in the overload condition, so the feature is salient for the purpose of separating the two conditions. On the other hand, in Plot 2 the feature values in the two conditions are not significantly different, so the feature is unable to separate the two conditions. The value for each exemplar for a particular feature in the overload condition is denoted as A (i), for i = 1, 2, …, N_O, and its value for exemplars in the normal condition as B (i), for i = 1, 2, …, N_N. The t-test statistic can be defined as:

$$t = \frac{\bar{A} - \bar{B}}{S\sqrt{(\frac{1}{N_O} + \frac{1}{N_N})}} \qquad [1]$$

Where $\bar{A}$ is the mean of A (i) and $\bar{B}$ is the mean of B (i), and S is defined by:

$$S = \sqrt{\frac{\sum(A(i) - \bar{A})^2 + \sum(B(i) - \bar{B})^2}{N_O + N_N - 2}} \qquad [2]$$

The t-test statistic defined in Equation (1) is actually the test statistic for comparing two samples means (indicated in Figure 1, Plot 1 and Plot2, by the dashed lines). In the application of obtaining salient features, the absolute value of this t-test statistic is proportional to the saliency of the feature. Therefore, the t-test statistic value is used as an index of separability of normal workload conditions and high workload conditions in which the variability of the EEG-derived features may be visualized and the saliency of the EEG features can be obtained. After calculating the t-test value for each feature in each trial for each subject, the saliency of different features were compared and the features were ranked according to their saliency value determined from the t-test analysis (from high t-test values to low t-test values). The top ranked salient features are used as the input features for the t-test classification method.

2.3. Classification of Workload

The EEG-derived features are used to classify workload using different classifiers. The three different classifiers that were utilized are: artificial neural network (ANN), AdaBoost Algorithm, and a t-test classification method. More emphasis is placed on using the ANN and AdaBoost Algorithm to perform classification of cognitive workload. The ANN is composed of interconnected networks of simple processing elements, as described earlier, and once trained, the weights and biases of the network were fixed and the ANN acted as a pattern classifier. The AdaBoost (Adaptive Boosting) Algorithm is a boosting [2] algorithm that was introduced in 1995 [18]. The AdaBoost Algorithm generates a set of classifiers sequentially. A final classifier is formed using a weighted majority voting system: the weight of each classifier depends on its performance on the training set used to build it [19]. The AdaBoost requires a weak base learning algorithm or base classifier and in this study the weak base learning algorithm or base classifier used was a decision stump. A decision stump assigns a case a class label based on a single feature, so it can be considered as a decision tree with a single path. The t-test method utilizes the t-test values to classify workload and is described in further detail in

[2] Boosting is a general method for improving the accuracy of any given learning algorithm.

the results section. There are advantages and disadvantages to using t-test values and the mean power feature values to perform classification. The t-test classification method itself is transparent; it is a “linear” method that does not have the ability to use combined or joint features, which would be expected to result in low classification accuracies.

An assessment of the methods used for training and testing the classifiers was also performed. Different methods of training and testing were evaluated to see how classification accuracy is dependent upon the way that training and testing data are obtained. Here, the overlapping of samples for training and testing when using a 10-second window and 9-second overlap is emphasized. When training and testing come from the same trial and same day, there is a possibility that the samples in the training and testing data sets are not independent. When the training and testing samples are not independent, high classification accuracy is most likely to be achieved. By using a 5-second window with no overlap, the training and testing data sets are independent samples. The methods utilized to assess training and testing is as follows:

1. Guarantee of no overlapping within the training and testing data sets:
    - Same subject, same day training and testing (2 trials for training and 1 trial for testing).
2. Effect of overlapping within the training and testing data sets:
    - Same subject, same day training and testing (combine 3 trials and randomize, use 2/3 of randomized trials for training and the remaining 1/3 for testing).

New generated features have also been examined. The new features generated include the parameters obtained from autoregressive modeling and also power spectrum values obtained from the autoregressive modeling. This was performed to see if new features would improve the workload classification accuracies.

3. Experimental Results

The primary goal was to obtain salient features by performing statistical analysis to separate high workload from normal workload conditions. From the results, obtaining a set of salient features became inconclusive because of day-to-day and within-day variations in the EEG-derived features. Our secondary goal was to compare performance of the ANN, Adaboost Algorithm, and a t-test method that have been trained on all of the 95 EEG-derived features for each individual subjects using different windowing methods. It was found that high classification accuracy was dependent upon the methods of training and testing the classifier and also dependent upon if the testing data was independent from the training data or not. Both of these findings will be discussed further the following sections: statistical analysis results, classification of workload results, and results based on AR modeling.

3.1. Statistical Analysis Results

T-test analysis was used to compare the two sample means of normal and high workload conditions. A high t-test value was considered as a salient feature and represented the ability to separate high and normal workload conditions. By looking at the mean value of the feature values in the high workload condition and normal workload condition there is a possibility that high workload has a lower mean value than normal workload. In this case, the t-test value would have a negative value by using Equation 1; therefore, the absolute value of the t-test value is taken to determine the saliency of that feature. In order to visualize separability of the high and normal workloads, the feature values from the high, medium, and low workloads were plotted. From the plots, it was observed that in some cases the feature values corresponding to the high and normal workloads were indeed visually separable as seen in Figure 2, but in most cases the feature values from the high workload condition would overlap the feature values from the normal workload condition, as seen in Figure 3. These plots were generated for all subjects, all features, and all trial sessions.

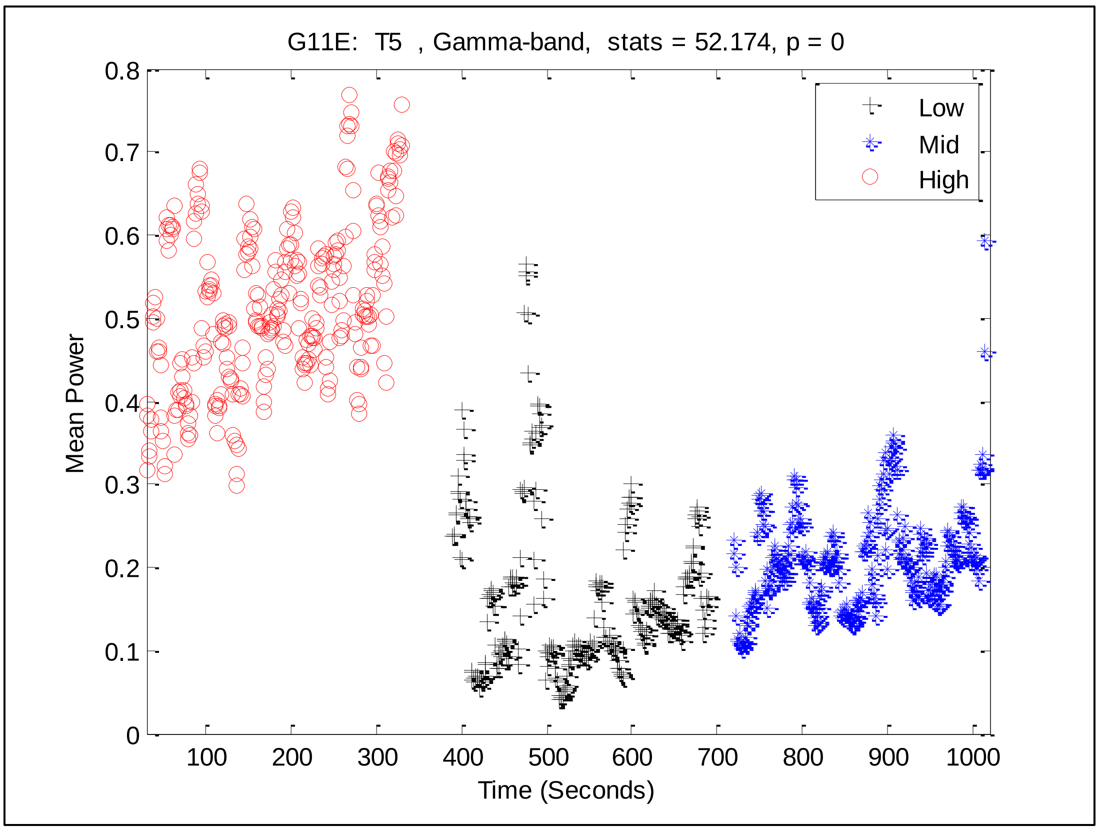

Figure 2. Here is a plot of feature values for the EEG feature T5 Gamma (Subject G, Day 1, Trial 1, and Sequence E) which visually shows the separability of high and normal workload conditions. The t-test value is 52.41. Therefore, this is considered salient feature.

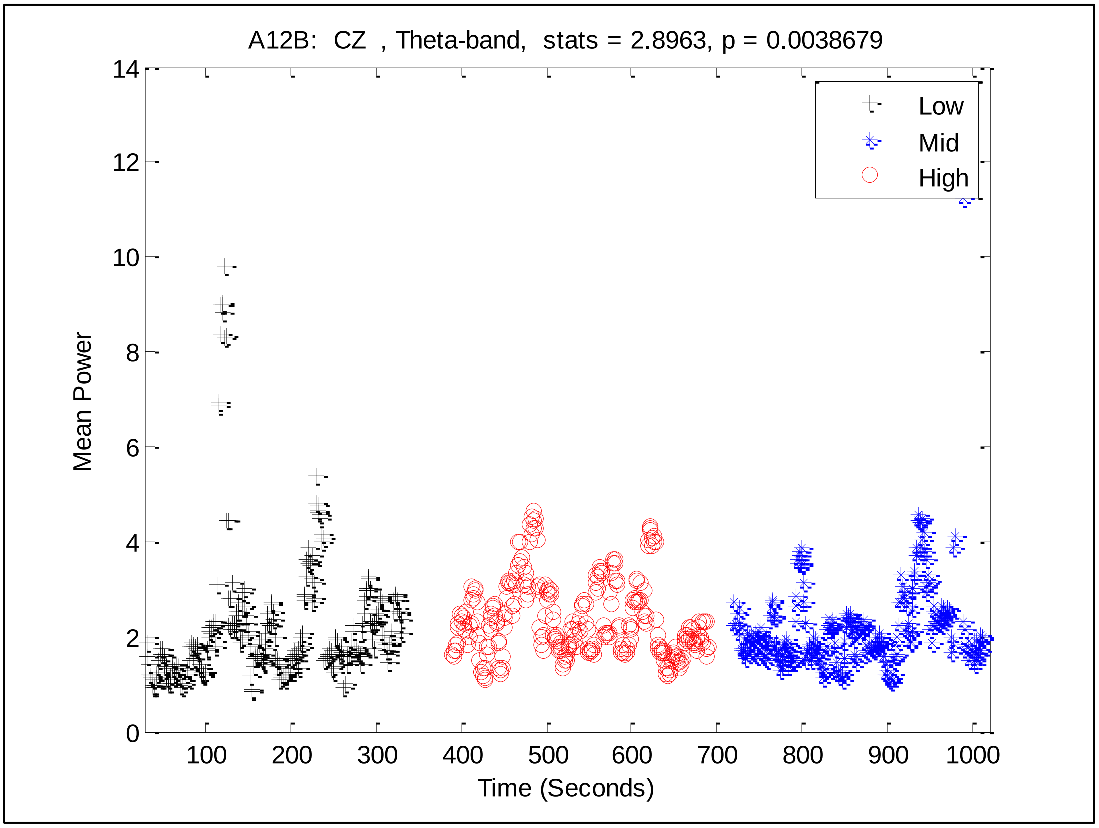

Figure 3. Here is a plot of feature values for the EEG feature CZ Theta (Subject A, Day 1, Trial 2, and Sequence B). The t-test value is 2.8963 and visually the high and normal workloads are not separable. Therefore, this is considered a non-salient feature.

It was also observed from these plots that the feature value data for any workload condition often contained outliners (narrow peaks in the plot from Figure 3). Therefore, in comparing the feature values of the two levels of workload, a t-test on the "medians" of the feature values of high and normal levels of workload was performed:

$$t = \frac{median(A(i)) - median\ (B\ (i))}{S\sqrt{(\frac{1}{N_O} + \frac{1}{N_N})}} \qquad [3]$$

Where, as before, the value for each exemplar for a particular feature in the overload condition is denoted as A (i), for i = 1, 2, …, N_O, and its value for exemplars in the normal condition as B (i), for i = 1, 2, …, N_N. The variables N_O and N_N are total sample numbers in each workload condition and S is defined by Equation 2. By evaluating the separability workloads by using the medians of the feature values, possible effects from outliers in the feature value data is reduced.

Table 2. The ranking of features by frequency of the feature being in the top ten features for each trial for every subject for the 10-second windowing method (left) and the 5-second windowing method (right).

Feature	Frequency
O1 Gamma	38
FP2 Beta	37
CZ Theta	34
O2 Gamma	30
FP1 Beta	28
O1 Alpha	28
O1 Beta	28
FP1 Gamma	25
O1 Theta	25
FP2 Gamma	23

Feature	Frequency
O1 Alpha	61
O2 Alpha	57
T4 Alpha	56
C3 Alpha	55
CZ Alpha	52
C4 Alpha	52
P4 Alpha	51
T5 Alpha	49
PZ Alpha	48
T3 Alpha	46

Based on the magnitude of the above t-test value, a rank of the 95 EEG features for each trial for each subject was generated. A t-test value was obtained for every subject for each of the 15 trials completed and t-test value tables were produced to obtain saliency rank of EEG features (Appendix B and Appendix C). The top ten ranked features for each subject for each of the 15 trials (total of 1200 “top-ranked” features) were combined and used to find the features that occurred most frequently to acquire a “general” ranking for the most salient features across subjects, days, and trials (Table 2). From the ranking using the 10-second windowing method, features in the beta and gamma bands occurred more frequently in the top ten ranked features for each trial.

From the ranking using the 5-second windowing method, features in only the alpha band occurred more frequently in the top ten ranked features for each trial. The difference between the two ranks can be attributed to the different window lengths used. The window used in spectral power estimation creates a spectral average that reduces the variance in the spectral power estimation; therefore, using a larger window reduces that amount of variance. Also, the overlapping used in the 10-second window method creates a great amount of segments which further reduces variance.

Table 3. The ranking of features by frequency of the feature being in the top ten ranked features for each trial for Subject B using the 10-second windowing method (left) and the 5-second windowing method (right).

Subject B			
Feature		**Frequency**	**Percent**
PZ	Gamma	11	7.3
O1	Gamma	10	6.7
T5	Gamma	9	6.0
P4	Gamma	9	6.0
T6	Gamma	8	5.3
O2	Gamma	8	5.3
P3	Gamma	6	4.0
C3	Beta	5	3.3
FP1	Beta	4	2.7
FP1	Gamma	4	2.7

Subject B			
Feature		**Frequency**	**Percent**
T5	Alpha	13	8.7
CZ	Alpha	11	7.3
PZ	Alpha	11	7.3
P4	Alpha	11	7.3
T4	Alpha	10	6.7
T6	Alpha	10	6.7
P3	Alpha	10	6.7
O1	Alpha	10	6.7
C3	Alpha	9	6.0
F4	Alpha	8	5.3

Given that the focus of this study is day-to-day and within trial variability, the most frequent top-ranked EEG-derived features for each individual subjects was additionally obtained. As an example, Table 3 shows the top ten ranked features for Subject B across days and trials using the two different windowing methods. The EEG-derived feature PZ Gamma is the top ranked feature for the 10-second windowing method. The feature PZ Gamma occurred 11 times within the 150 “top-ranked” features (5 Days x 3 Trials x 10 Top Ranked Features) which is only 7.3 % occurrence. Subject B was considered the best subject in regards to the top feature having the highest occurrence value for both windowing methods (10-second window and 5-second window). Thus, from the top ten ranked features, variability of the EEG-derived features is seen across days and across trials for each individual subject.

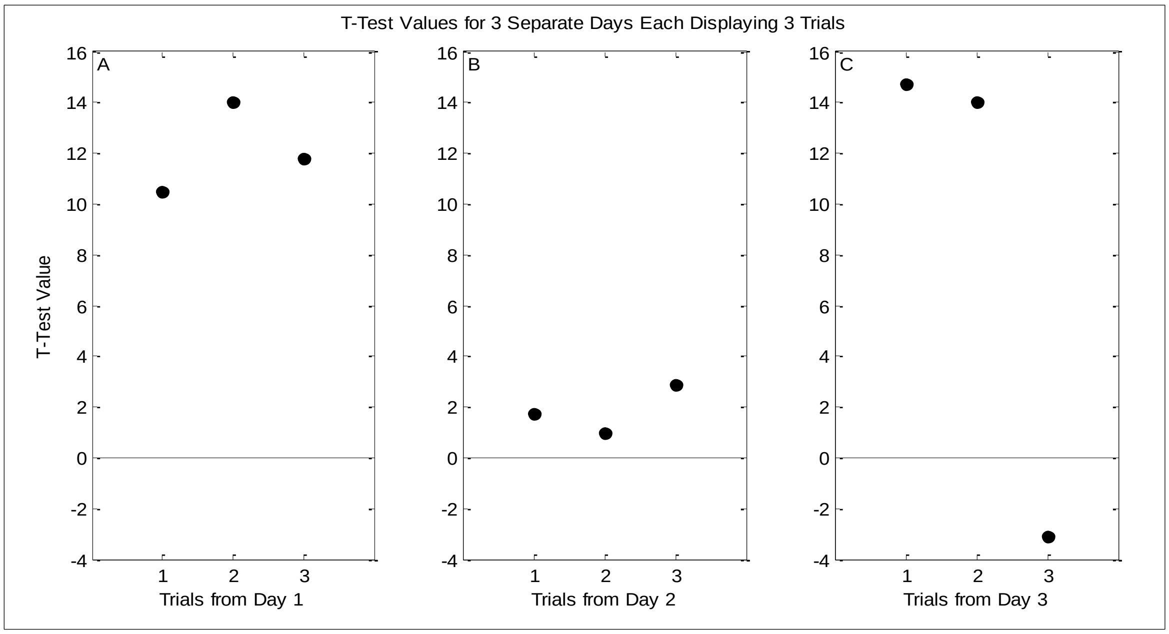

Figure 4. This is a visual display of within day variability and reversal of workloads.

Analyzing the t-test values and rank of features provided a more careful examination to the claim that same day classification has high classification accuracies. From analyzing the t-test values from day-to-day and trial-to-trial, variability in the t-test value was noticed. This variability is a reversal of high and normal workloads. For example, in one particular trial the median value of high workload was higher than low workload and in a second particular trial (from the same day) the median value of high workload was lower than that of low workload. This suggests that the spectral power of EEG for a particular feature may be attenuated during difficult workload for one trial and then enhanced during difficult workload for a different trial. So, not only is there a day-to-day variation which has been claimed by previous studies for an individual subject, but there is noticeable within-day variation also. A visual of within-day variation can be seen in Figure 4. In this figure, all three plots show the t-test values for three trials of one particular day. The first plot shows all three trials have high t-test values and are all positive; this represents a stable and salient feature. The second plot shows all three trials have low t-test values and are all positive; this represents a stable feature but not a salient feature because of the low value of the t-test. The third plot shows two trials have very high t-test values but the third trial has a low, negative value (which means there was a reversal of high and normal workload); this feature is neither stable nor salient. From the t-test analysis, most of the subject's features exhibited behavior seen in the second and third plots of Figure 4.

After discovering this within-day variation, it was decided to look further into this variation and for each specific EEG feature, the t-test values from the 10-second windowing method were plotted for each trial and each day into a single plot (Figure 5 and Figure 6). Within these plots, the day-to-day variation along with within-day variation could be observed. Throughout the analysis, it was found that mostly all features showed signs of t-test values changing from positive values to negative values between trials and days, which allow one to conclude that there is a reversal of high workload and normal workload. This finding suggests that these features are not salient. For each subject, the plots were analyzed to find the features that were consistently positive or negative and are listed in Table 4. From the list of features that are consistent in terms of t-test values, it was noticed that the alpha and theta features overlap between subjects for being consistently positive or negative.

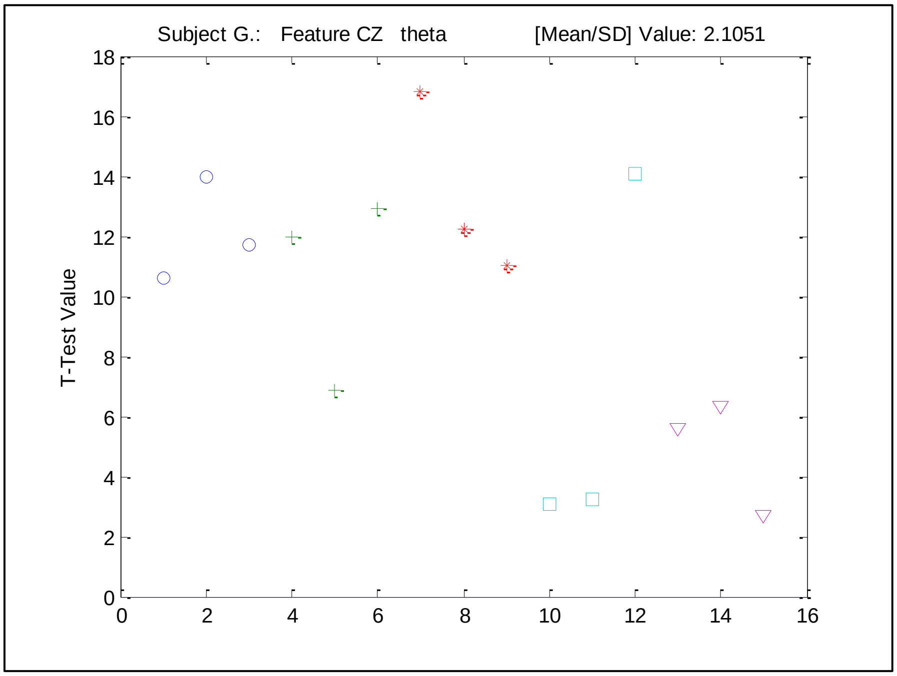

Figure 5. Here is an example of the EEG feature CZ Theta from Subject G that shows to be consistent across all 15 sessions. That is, for each of the 5 days and 3 trials, the median value for high workload was greater than the median value of normal workload.

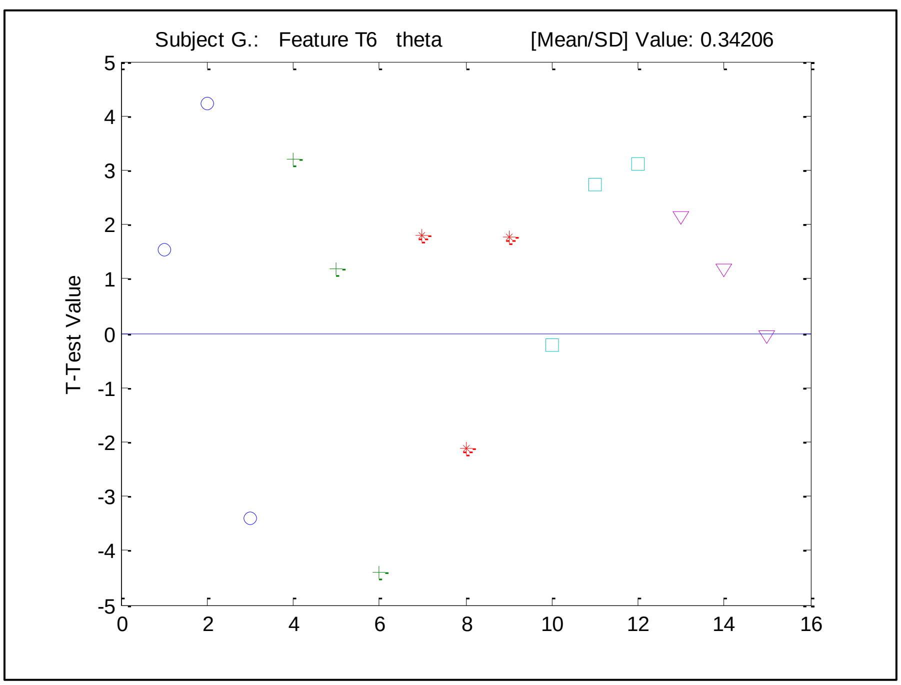

Figure 6. Here is an example of an inconsistent feature, PZ Alpha, from Subject G. This would not be considered a salient feature.

Table 4. List of features that have consistently positive or negative t-test values analyzed from the t-test value plots for the 10-second windowing method.

A	**B**	**C**	**D**	**E**	**F**	**G**	**H**
None	FP1 - Beta	FZ - Beta	C3 - Alpha	FZ- Theta	None	CZ - Theta	C3 - Alpha
	FP2 - Beta	F4 - Alpha	C4 - Alpha	C3 - Theta		C4 - Theta	C3 - Beta
	FP2 - Gamma	C3 - Alpha	P3 - Alpha	CZ - Theta		PZ - Theta	
	C3 - Theta	CZ - Alpha	P4 - Alpha	C4 - Theta		O1 - Theta	
	PZ - Gamma	C4 - Alpha		P3 - Delta			
	P4 - Gamma	PZ - Alpha		PZ - Alpha			
		P4 - Alpha		P4 - Alpha			
				O1 - Theta			

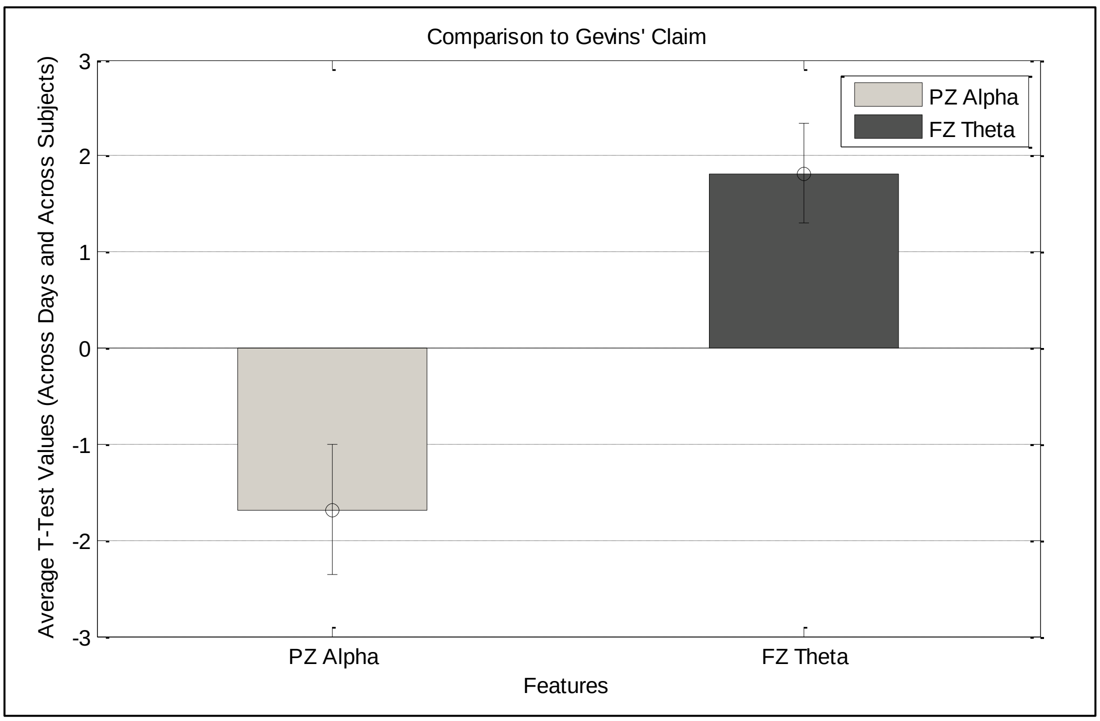

Figure 7. Here is a plot to compare to Gevin's claim. After averaging the t-test values across days and across subject it was found that PZ Alpha is attenuated and FZ Theta is enhanced during difficult workloads.

It was interesting that there was a great amount of features in the alpha and theta bands that remained consistently positive or negative across subjects (Table 4). There were also beta and gamma bands that remained consistent. To compare to the study by Gevins and Smith, the t-test values were averaged across days and subjects for the features PZ Alpha and FZ Theta. The average t-test value for PZ Alpha was -1.69 with a standard error of 0.68 and the average t-test value for FZ Theta was 1.82 with a standard error of 0.51 (Figure 7). So these results do support the claim that PZ Alpha is attenuated during high workload levels and FZ Theta is enhanced during high workload levels. Although, considering the overlap of feature values (Figure 3) and the inconsistency of the t-test values across trials and days (Figure 6), the question is whether they should be considered salient.

3.2. Workload Classification Results

The observation of within-day variation led to two different derived methods for classification of workload. First, two trials on the same day were combined for training and validating the classifier and the remaining third trial on that day was used for testing. From this method of training and testing a classifier (a guarantee of no overlapping within the training and testing data sets), low classification accuracy was observed by all of the classifiers with the Adaboost Algorithm to some extent outperforming the other classifiers. In the second method (the effect of overlapping within the training and testing data sets), data from all three trials were combined. Two-thirds of the combined data randomly selected was used for training and validating the classifier and the remaining one-third of the combined data was used for testing. By using this method, the classification accuracies obtained from using the t-test classification method increased from an average classification accuracy of 60% (Method 1) to an average of 68% (Method 2). So by using the second method there was not a significant increase in classification accuracy from using the t-test classification method. Using the second method, high classification accuracy was obtained by the ANN and AdaBoost Algorithm, and the accuracy values are compatible with that reported by Russell on the same day and same individual [15]. Considering the second method (the effect of overlapping within the training and testing data sets), another process of training and testing the classifier was developed to analyze the effect of overlap on classification accuracies. This process used two trials and varied amounts of data from the third trial to use for training. First, every other feature value in the third trial was used to combine with two trials from the same day for training, therefore, the training data was updated every 1 second (considering the 10-second windowing method, the value of each EEG-derived feature is updated every 1-second because of the 9-second overlap). Next, the training data was updated every two seconds by taking an exemplar for training after every two feature values.

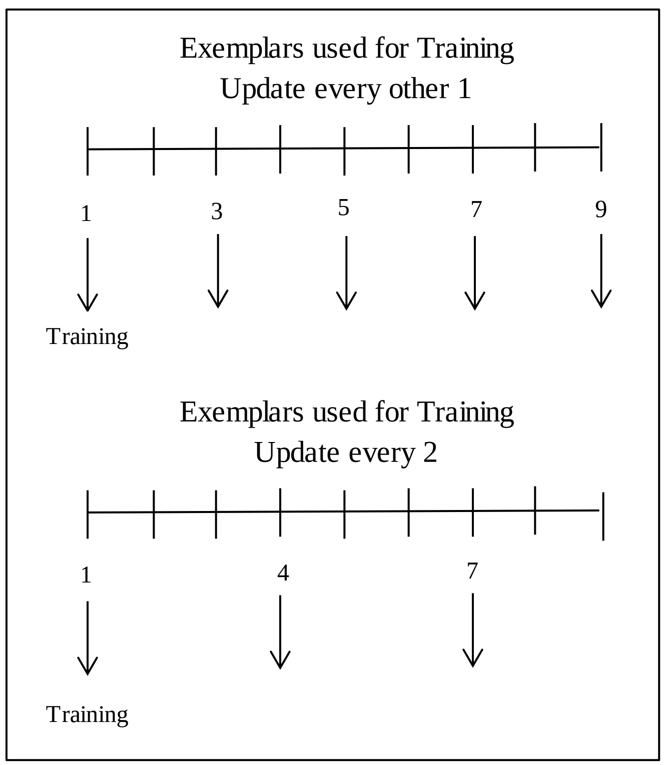

Figure 8. Display of how exemplars are divided into training and test data sets to analyze the dependency of overlap in the training and test data sets.

A visual of how data from the third trial is taken for training can been seen in Figure 8. As the number of feature values between samples taken for training increased (less chance of overlap in the training and test data sets), the classification accuracies decreased (Figure 9). This suggested that indeed classification accuracy is dependent upon the possible "overlap" of feature data in the training and test data sets.

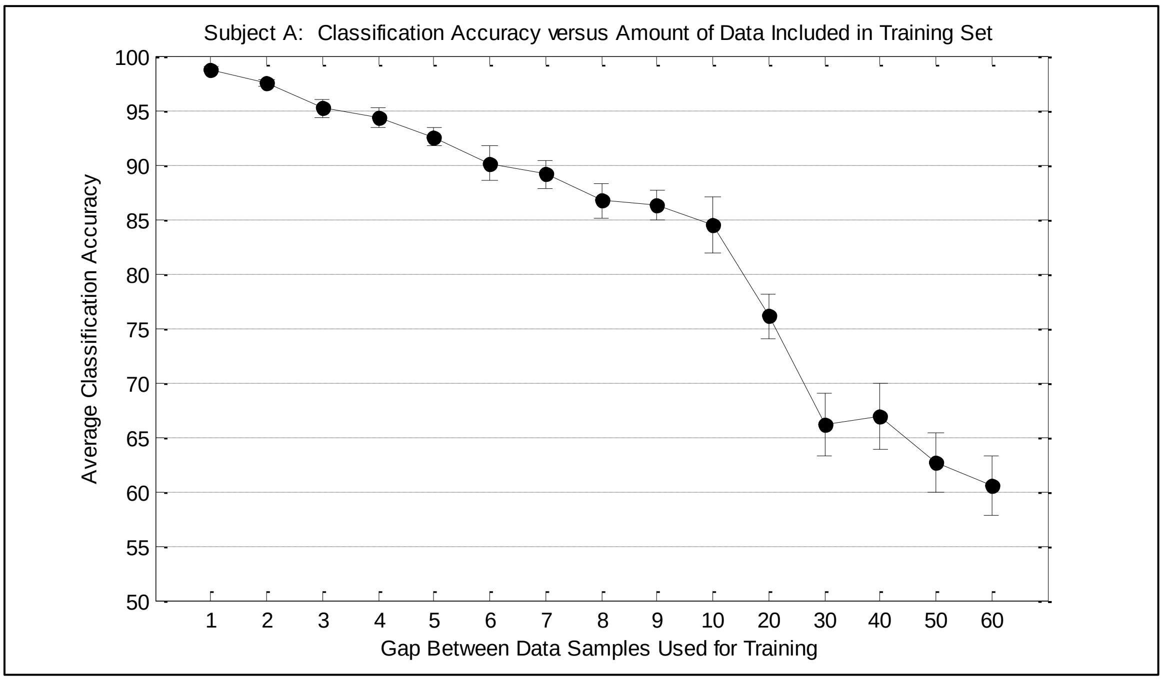

Figure 9. This is a plot of average classification accuracy with standard error bars versus the amount of data included in the training data set.

Knowing that there might be dependence within the training and test data sets, it was suggested to use a 5-second window with no overlap while doing spectral analysis. This way there was a guarantee of no overlapping within the training and test data sets. This pre-processing method was used to re-test the second "training and testing" method in which all three trials were combined and then split into separate training and test data sets. When using a 10-second window with 9-second overlap high classification accuracy was obtained but when using a 5-second window with no overlap it would result in low classification accuracy (Table 5 and Table 6). Therefore, the result of the 5-second window with no overlap method suggests that the training and test data sets were not completely independent.

The t-test classification method utilizes the salient feature determined by t-test values to classify workload. To classify workload using the t-test values, the top ten ranked features' of the training data were used for the different classification methods. In the features' mean power plots, similar to the plots shown in Figures 2 and 3, a threshold was developed between the high and normal workloads. The threshold was calculated as follows:

$$Threshold = \frac{median\big(A(i)\big) - median(B(i))}{2} + median\big(B(i)\big) \qquad [4]$$

Where, as before, the value for each exemplar for a particular feature in the overload condition is denoted as A (i), for i = 1, 2, …, N_O, and its value for exemplars in the normal condition as B (i), for i = 1, 2, …, $N_{N.}$ The variables N_O and N_N are total sample numbers in each workload condition. This threshold was used to compare to the mean power feature value for each 10 second segment (by using the 10-second windowing method) in the test data set to determine whether it was high or normal workload based on the threshold value. If the 10 second segment was indeed high workload (or normal workload), then the classification for this segment was "correct", otherwise, the classification for this segment was "incorrect." The above process was applied to each 10-second segment. A detailed description of the t-test classification method can be seen in Appendix D. The percentage of correct classification was then determined to compare to the ANN and AdaBoost Algorithm.

The t-test classification method was only performed using a 10-second window because this is the windowing method that was performed first and since the results were not as satisfactory as the ANN and AdaBoost Method, the t-test method was not used for the 5-second windowing method. Seen by the results, the classification accuracies from the t-test classification method are not as good as the ANN or AdaBoost Algorithm (Table 5). These results are somewhat expected since the ANN can use joint features as the t-test method only considers each feature separately and the AdaBoost Algorithm is a very powerful machine learning algorithm.

Table 5. This table contains classification accuracies from three different classifiers by using a 10-second window with a 9-second overlap when performing spectral power estimation.

Comparison of Classification Methods (Processed with 10 Second Window)			
	ANN Avg. C.A.	***AdaBoost Avg. C.A.***	***T-Test Method C.A.***
Method 1 (No Overlap)	61.38 ± 13.48	67.77 ± 10.55	60.54 ± 12.51
Method 2 (Overlap)	98.84 ± 0.81	98.63 ± 1.22	68.75 ± 6.17

Table 6. This table contains classification accuracies from three different classifiers by using a 5-second window with no overlap when performing spectral power estimation.

Comparison of Classification Methods (Processed with 5 Second Window)			
	ANN Avg. C.A.	***AdaBoost Avg. C.A.***	***T-Test Method C.A.***
Method 1 (No Overlap)	60.72 ± 13.02	64.52 ± 10.51	X
Method 2 (No Overlap)	76.42 ± 8.59	78.26 ± 7.90	X

From the results obtained by the different windowing methods, 10-second window with a 9-second overlap versus 5-second window with no overlap, it is difficult to exactly determine if the significant decrease in classification accuracy by using Method 2 (combine all 3 trials from the same day, randomize and use 2/3 for training and the remaining 1/3 for testing) was a result from the guarantee of no overlap in the training and test data set or if the decrease was from the reduction in window length when performing spectral power estimation. The purpose of windowing the data while performing spectral estimation is to smooth or average the data in the frequency domain to reduce variance. A wider length window gives a better frequency resolution. Therefore, to determine whether the decrease in classification accuracy was a result of a decrease in the length of the window or if it was from no overlap in the training and test data sets, a window of 5 seconds with 4 second overlap was used to compare to the 5 second window with no overlap by using Method 2 to train and test the classifier. The results can be seen in Table 7. The classification accuracies from using a 5-second window with a 4-second overlap was still significantly higher than the classification accuracies from using a 5-second window with no overlap. These results suggest that the classifiers are sensitive to the overlap of data in the training and test data sets.

Table 7. This table contains classification accuracies from the ANN and AdaBoost Algorithm for using two different windowing methods.

Method 2		
	ANN Avg. C.A.	***AdaBoost Avg. C.A.***
5 Second Window with 4 Second Overlap	93.74 ± 2.57	92.55 ± 3.93
5 Second Window with No Overlap	76.42 ± 8.59	78.26 ± 7.90

3.3. Classification of Workload based on Two Features

From the study performed by Gevins and Smith, it was found that the features PZ Alpha and FZ Theta were stable enough to determine workload [12]. From the t-test analysis, it was seen that some Alpha and Theta bands were considered to have consistent t-test values across trials, which is no sign of reversal in workloads (Table 4). A saliency rank of features (Table 2) was obtained in which the feature PZ Alpha was listed but it cannot be concluded that the top ranked features are "salient" features since workload classification accuracy is so low, around 70%. Therefore, it was decided to perform the t-test classification method using only two features suggested by Gevins and Smith instead of the top ten ranked features (ranked by the absolute value of the t-test value). By doing this, the classification accuracies were comparable to the previous methods but it was noticed that the standard deviation was lower (Table 8).

Table 8. Average classification accuracies with standard deviations for each Subject.

	T-test Method using top ten ranked features	**T-test using only PZ Alpha & FZ Theta**	**ANN**
A	46.13 ± 14.36	58.30 ± 7.57	51.48 ± 11.60
B	63.44 ± 13.67	60.11 ± 5.01	63.50 ± 10.11
C	62.78 ± 9.73	64.30 ± 5.64	59.76 ± 9.40
D	61.12 ± 7.11	60.36 ± 6.17	50.94 ± 9.07
E	64.20 ± 12.14	67.46 ± 3.44	75.97 ± 12.55
F	60.01 ± 11.65	62.15 ± 4.81	60.14 ± 12.20
G	67.42 ± 8.99	63.75 ± 4.79	71.34 ± 11.27
H	61.08 ± 9.53	62.32 ± 6.10	59.54 ± 12.01

3.4. Classification of Workload based on AR Modeling Results

Most of workload classification studies use mean power of the five EEG bands as the features to feed into a classifier. In order to calculate the mean power, short-time Fourier Transform (FFT) is used which is a common power spectral estimation method and was the method used in this study. Since the FFT method requires a large amount of data for appropriate frequency resolution, it is applied to windowed data sets. It is well-known that window-based power spectrum calculation has many problems such as spectral leakage [20-22].

An alternative method for calculating power spectrum is based on autoregressive (AR) modeling which does not use windowing methods and can reduce spectral leakage and improve frequency resolution [22]. It has been reported that AR power spectrums display the frequency content of signals more clearly than FFT power spectrums and the results from AR spectrums can be used for clinical diagnosis, for example, epilepsy [21,22]. Using AR modeling, there are two approaches that can be considered for workload classification:

1. Use AR parameters to calculate the power spectrum and calculate mean power of the five EEG bands to obtain similar features as before to input into a classifier.
2. Directly use the AR parameters as features to input into a classifer.

To calcuate the AR parameters, the function "arburg" in Matlab was used. This function estimates the AR parameters via Burg's method where a 10th order AR model was utilized. Considering the first approach, 95 features will be generated as before with the FFT method. For the second approach, since a 10th order model was used, there will be ten AR parameters for each EEG channel which results in 190 features. To train and test the classifiers Method 2 (combine all 3 trials from the same day, randomize and use 2/3 for training and the remaining 1/3 for testing) was used and the results can be seen in Table 9 and Table 10. The new features generated by AR modeling did not significantly improve workload classification accuracy.

Table 9. Comparison of classification accuracies from the t-test classification method depending on method of processing input features.

T-Test Classification Method	
Input Features	***Average Classification Accuracy***
Window-based Spectral Analysis	60.10 ± 12.43
AR Spectral Analysis	60.75 ± 12.54

Table 10. Comparison of classification accuracies from the ANN classifier depending on the method of processing input features.

ANN Classifier	
Input Features	***Average Classification Accuracy***
Window-based Spectral Analysis	61.67 ± 13.35
AR Spectral Analysis	61.65 ± 13.52
AR Parameters	60.86 ± 13.18

4. Discussion

The two main observations from this study are as follows: (1) the observation of within-day variability by use of a t-test and (2) the improvement of classification accuracy when there is an overlapping of features in the training and test data sets. The within-day variability was quantified by t-test statistical analysis of the mean spectral power data of the EEG signal, while improvement of classification accuracy was found by workload classification pre-processing methods.

The main advantage of using a t-test is that it is a linear method that allows the user to visualize the saliency or separability of the high and normal workload conditions. From the t-test analysis, for most of the EEG-derived features, there was a significant overlap between the feature values of the two workload conditions. As a result, these features are not considered as salient features and are, therefore, not ideal for classifying the workload level. Through the examination of the fifteen t-test values of a particular EEG-derived feature for a particular subject (three trials per day, a total of five days), it was noticed that for many features, not only does the t-test value change across different days, but it also changes significantly across the three trials within the same day. The reason for the change in t-test value is not known. The change in t-test value could be either a result of the change in the median value of the distribution or a change in variance, therefore, future analysis needs to be performed to determine whether the median value or variance of each high and normal workload distributions are changing which causes a change in t-test value from trial-to-trial and day-to-day. Although, the finding that the t-test values changed within a single day led us to further explore the statement in Russell's report that "within-day classification accuracy was very high [15]." To examine this statement, different methods obtaining input features and different methods of training and testing the classifiers were devised.

Two methods of training and testing the classifiers were utilized. The first method used feature data from two trials for network training and validation, and then tested the trained classifier on the data from the third trial. This method does not include any data from the test trial for training. The second method combined feature data from all three trials; randomly selected 2/3 from the mixture for training and validation, and then tested on the remaining 1/3 data. In this method, the training set includes data from all trials. The results were very interesting: the second method produced very high classification accuracy (95 – 97%) but the first method in average produced a very low accuracy (50 – 65%). The second method for training and testing a classifier for workload classification produces high classification accuracies, but this method cannot be used in real-time applications: one can only use the past data to train a classifier and apply it to future acquired data. Also, while performing workload classification the features were made to be completely independent by processing the features with a 5-second window and no overlap. When performing classification using the 5-second window processed features, the classification accuracy is significantly degraded and this suggests inherent variability in the EEG-derived features. The ANN and AdaBoost Algorithm are both very powerful classifiers which are seen from our results. Both classifiers are sensitive to the overlapping of data in the training and test data sets and to data from the same trial producing high classification accuracies.

5. Conclusion

The classification accuracies of classifying cognitive workload did not meet the goal of 95% classification accuracy. From the results, a classification accuracy of 76-78% was achieved using Method 2 in which all trials were combined and randomized to obtain training and test data sets, however, this approach is not practical in real-time applications. Overall, a much clearer picture of the variability in cognitive state assessment has been created – that is the inherent variability in the feature values used in classification. It is possible that the current EEG features used for workload classification do not have enough information to classify workload or there is too great of a variability within-day and day-to-day to utilize these features for classification purposes. The results indicate that there is too much variation in the mean power of EEG across different subjects, different days of the same subject, or even different trials within the same day, and there is too much overlap between the values of this feature corresponding to the two levels of workload. As a result, the classification accuracy cannot be improved significantly even if one can find a more powerful classifier (to replace ANN, AdaBoost, etc.).

There are many new directions for physiology-based operator functional state assessment, a few of which is to investigate new features that will be more stable and more uniquely correlated with the workload level, improve current feature data input into the classifiers by normalization processes and find other classification methods. One method that is under serious consideration is to investigate the functional connectivity between different cortical activation sources reconstructed from high-density EEG. On the whole, this study is an improvement in the knowledge of brain function and is one step closer to finding a practical method for classification of workload in modern aircraft systems.

References

[1] G.F. Wilson, "An Analysis of mental workload in pilots during flight using multiple psychophsiological measures," *The International Journal of Aviations Psychology*, vol. 12, pp. 3-18, 2002.

[2] G.F. Wilson, "Pilot workload, operator functional state and adaptive aiding," *Operator Functional State*, 2003.

[3] P.L. Craven et al., "Cognitive Workload Gauge Development: Comparison of Real-time Classification Methods," in *Foundations of Augmented Cognition*. New York: Springer, 2006.

[4] D. Garrett, D.A. Peterson, C.W. Anderson, and M.H. Thaut, "Comparison of linear, nonlinear, and feature selection methods for EEG signal classification.," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, no. 2, pp. 141-144, 2003.

[5] S. Sun, C. Zhang, and D. Zhang, "An experimental evaluation of ensemble methods for EEG signal classification," *Pattern Recognition Letters*, vol. 28, pp. 2157-2163, 2007.

[6] T.I. Laine, K.W., Jr. Bauer, J.W. Lanning, C.A. Russell, and G.F. Wilson, "Selection of input features across subjects for classifying crewmember workload using artificial neural networks," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 32, pp. 691-704, 2002.

[7] G.F. Wilson and C.A. Russell, "Real-time assessment of mental workload using psychophysiological measures and artificial neural networks," *Human Factors*, no. 45, pp. 635-643, 2003.

[8] K.A. Greene et al., "Selection of psychophysiological features for classifying air traffic controller workload in neural networks," *Smart Engineering System Design*, vol. 2, pp. 315-330, 2000.

[9] John W. Clark, Jr., "The Origin of Biopotentials," in *Medical Instrumentation: Application and Design*, Third Edition ed., John G. Webster, Ed. United States: John Wiley & Sons, Inc., 1998, pp. 156-175.

[10] M.A. Carskadon and A. Rechtschaffen, "Monitoring and staging human sleep," in *Principles and Practice of Sleep Medicine*, 2nd ed. Philadelphia: W.B. Saunders & Co, 1989, pp. 943-960.

[11] E.R. John et al., "Invariant reversible QEEG effects of anesthetics," *Consciousness and Cognition*, vol. 10, pp. 165-183, 2001.

[12] Alan Gevins and Michael E. Smith, "Neurophysiological measures of cognitive workload during human-computer interaction," *Theoretical Issues in Ergonomics Science*, vol. 4, no. 1-2, pp. 113-131, 2003.

[13] C.J. Stam, "Brain dynamics in theta and alpha frequency bands and working memory performance in humans," *Neuroscience Letters*, vol. 286, pp. 115-118, 2000.

[14] G.F. Wilson, C.R. Swain, and P. Ullsperger, "EEG power changes during a multiple level memory retention task," *International Journal of Psychophysiology*, vol. 32, pp. 107-118, 1999.

[15] C.A. Russell, "Investigating the effects of day-to-day variations of psychophysiological measures in cognitive load classification," United States Air Force Research Laboratory, Technical Report 2002.

[16] J.R. Comstock and R.J. Arnegard, "The multi-attribute task battery for human operator workload and strategic behavior research," 1992.

[17] H.H. Jasper, "The ten-twenty electrode system of teh International Federation," *Clinical Neurophysiology*, vol. 10, pp. 371-375, 1958.

[18] Y. Freund and R.E. Schapire, "A Short Introduction to Boosting," vol. 14, no. 5, pp. 771-780, 1999.

[19] E. Bauer and R. Kohavi, "An Empirical Comparison of Voting Classification Algorithms: Bagging, Boosting, and Variants," *Machine Learning*, vol. 36, pp. 105-142, 1999.

[20] M. Akin and M.K. Kiymik, "Application of Periodogram and AR Spectral Analysis to EEG Signals," *Journal of Medical Systems*, vol. 24, no. 4, pp. 247-256, 2000.

[21] O. Faust, R.U. Acharya, A.R. Allen, and C.M. Lin, "Analysis of EEG signals during epileptic and alcoholic states using AR modeling techniques," *ITBM-RBM*, vol. 29, pp. 44-52, 2008.

[22] I. Guler, M.K. Kiymik, M. Akin, and A. Alkan, "AR spectral analysis of EEG signals by using maximum likelihood estimation," *Computers in Biology and Medicine*, vol. 31, pp. 441-450, 2001.

Appendix A – Acronyms and Symbols

LDA	Linear Discriminant Analysis
SVM	Support Vector Machine
ANN	Artificial Neural Network
EEG	Electroencephalogram
MATB	Multi-Attribute Task Battery
NASA	National Aeronautics and Space Administration
WPAFB	Wright-Patterson Air Force Base
EOG	Electrooculogram
FFT	Fast Fourier Transform
t	T-test statistic
$A(i)$	Feature values for overload condition
$B(i)$	Feature values for normal condition
$\bar{A}$	Mean of feature values for the overload condition
$\bar{B}$	Mean of feature values for the normal condition
N_O	Number of exemplars for overload condition
N_N	Number of exemplars for normal condition
S	Pooled variance
AR	Autoregressive

Appendix B – Tables including Feature Rank According to T-Test Statistic for 10-second window

Table A1. Feature rank according to t-test statistic for 10-second windowing method for all trials for Subject A.

	A11A		A12B		A13C		A21E		A22F	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O2 Alpha	-14.388	C4 Theta	10.722	FP2 Beta	-29.716	F4 Delta	-7.217	O1 Alpha	-13.702
2	O2 Gamma	-11.242	FP2 Beta	5.815	FP2 Gamma	-25.235	O2 Alpha	-6.801	O1 Beta	-12.347
3	O2 Beta	-10.467	PZ Theta	5.807	CZ Theta	17.114	FP2 Delta	-5.933	O1 Gamma	-12.119
4	FP2 Delta	9.623	P4 Theta	4.654	FP1 Beta	-16.286	T3 Alpha	-5.880	PZ Theta	-11.054
5	FP2 Beta	8.823	O1 Alpha	4.597	O1 Beta	11.707	C3 Alpha	-5.590	T5 Beta	-10.045
6	P4 Beta	-6.927	F4 Alpha	4.501	O1 Gamma	11.100	C3 Delta	-5.139	T5 Gamma	-9.876
7	PZ Beta	-6.771	O1 Gamma	4.050	CZ Delta	10.000	FP2 Alpha	-4.882	P3 Beta	-9.326
8	P4 Gamma	-6.195	CZ Beta	-3.789	F8 Beta	-9.820	P4 Delta	-4.818	P3 Gamma	-9.322
9	PZ Gamma	-5.267	T3 Delta	-3.545	FZ Alpha	9.731	FP1 Alpha	-4.735	PZ Beta	-8.854
10	CZ Beta	-5.154	O1 Beta	3.206	FP1 Gamma	-9.424	O1 Beta	4.676	T5 Alpha	-8.602

	A23E		A31B		A32A		A33E		A41C	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Alpha	-5.325	O2 Alpha	31.162	FP2 Beta	14.548	FP2 Beta	-28.544	O1 Alpha	18.903
2	O2 Delta	-4.753	O2 Beta	26.525	FP1 Beta	10.942	FP1 Beta	-13.562	O1 Beta	14.227
3	CZ Delta	-4.503	O1 Alpha	-26.322	F4 Alpha	8.658	FP2 Gamma	-13.263	O1 Gamma	11.359
4	O2 Beta	-4.424	O2 Gamma	21.923	FZ Alpha	8.014	O1 Alpha	12.751	O1 Theta	11.123
5	FZ Alpha	4.205	O1 Beta	-16.297	FP2 Gamma	7.724	F8 Delta	11.298	PZ Alpha	10.770
6	CZ Theta	3.581	O1 Gamma	-15.705	F4 Delta	7.649	O1 Beta	11.259	P3 Alpha	10.626
7	FP1 Gamma	3.377	FP2 Beta	14.088	CZ Theta	7.249	C3 Delta	10.657	P3 Beta	9.630
8	FP1 Delta	-3.231	CZ Theta	11.911	F4 Theta	6.409	O1 Gamma	9.940	P4 Alpha	8.469
9	O1 Gamma	-3.101	O2 Theta	11.249	O1 Alpha	5.616	F4 Delta	9.265	T5 Beta	7.766
10	C3 Theta	2.789	T5 Alpha	-9.783	CZ Alpha	5.177	T5 Alpha	9.050	P3 Gamma	7.727

	A42F		A43D		A51B		A52C		A53F	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Alpha	-14.118	O1 Beta	-7.588	O1 Alpha	-12.610	PZ Beta	11.418	T3 Alpha	-10.515
2	O1 Beta	-11.698	O1 Gamma	-7.173	O1 Beta	-10.087	CZ Beta	10.283	T5 Beta	-9.944
3	O1 Theta	-9.757	PZ Gamma	-6.424	CZ Theta	9.925	PZ Gamma	9.261	FP2 Beta	-9.683
4	O1 Gamma	-8.798	CZ Gamma	-5.913	O1 Gamma	-9.612	CZ Gamma	9.150	CZ Beta	-9.530
5	FP1 Delta	-7.378	O1 Alpha	-5.798	O2 Beta	-8.776	FZ Beta	9.079	T3 Beta	-9.389
6	T5 Beta	-7.046	P3 Beta	-5.426	O2 Alpha	-8.630	P3 Beta	8.802	FZ Beta	-8.940
7	T5 Gamma	-6.623	PZ Beta	-5.281	O2 Gamma	-7.192	T5 Beta	8.173	P3 Beta	-8.163
8	FP2 Beta	-5.936	P3 Gamma	-5.266	PZ Theta	5.568	P4 Beta	7.325	O1 Delta	-7.976
9	P3 Beta	-5.330	FZ Gamma	-5.129	F3 Delta	-5.456	FZ Alpha	7.096	PZ Beta	-7.410
10	O2 Theta	-5.281	CZ Beta	-4.668	P4 Delta	-4.793	P3 Gamma	7.093	T3 Gamma	-7.352

Table A2. Feature rank according to t-test statistic for 10-second windowing method for all trials for Subject B.

	B11E		B12F		B13D		B21B		B22A	
Rank	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**
1	FP1 Beta	15.755	FP2 Delta	10.971	O1 Gamma	17.946	PZ Gamma	19.386	PZ Delta	13.159
2	PZ Gamma	13.213	O2 Gamma	10.155	T5 Gamma	17.809	C3 Beta	-11.704	T4 Delta	10.876
3	FZ Delta	11.141	FP1 Delta	9.976	P3 Gamma	14.734	FP1 Gamma	9.749	C3 Alpha	-8.630
4	T5 Gamma	10.763	F4 Delta	-8.385	PZ Gamma	13.695	FZ Theta	9.371	T6 Delta	8.598
5	FP2 Beta	9.987	FP2 Beta	8.346	P4 Gamma	13.284	CZ Beta	-8.985	F8 Delta	8.402
6	P3 Gamma	9.833	C3 Beta	-7.803	FP1 Beta	13.129	O1 Gamma	8.352	C3 Beta	-6.530
7	P4 Gamma	9.667	CZ Delta	-7.468	FP2 Beta	11.771	CZ Theta	8.160	P4 Alpha	-6.519
8	FP2 Alpha	9.438	PZ Gamma	7.215	O2 Gamma	11.524	P3 Gamma	7.849	C4 Alpha	-6.348
9	FP1 Alpha	9.155	T3 Delta	-6.884	T6 Gamma	11.514	C3 Gamma	7.806	FP2 Alpha	5.947
10	FP1 Gamma	8.669	FP1 Beta	6.875	CZ Gamma	11.170	P4 Delta	7.303	FP1 Gamma	5.560

	B23E		B31C		B32F		B33D		B41B	
Rank	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**
1	FP2 Gamma	11.802	FZ Beta	13.926	C3 Delta	-11.867	F3 Delta	10.175	T5 Gamma	18.744
2	FP2 Beta	11.590	F4 Beta	13.810	P3 Delta	-11.770	C3 Theta	7.678	P3 Gamma	16.583
3	C3 Beta	-9.372	C4 Beta	13.127	O2 Delta	-11.200	T6 Gamma	7.381	F8 Gamma	16.454
4	FP2 Delta	7.946	T5 Beta	12.852	P4 Delta	-10.066	PZ Gamma	6.856	PZ Gamma	14.105
5	C3 Delta	-7.599	T6 Gamma	11.706	F3 Delta	-9.123	P4 Gamma	6.659	P4 Gamma	14.028
6	C3 Alpha	-7.241	P3 Delta	11.498	FZ Delta	-7.550	O1 Gamma	6.405	C4 Gamma	13.816
7	T5 Delta	-7.165	CZ Theta	11.348	PZ Delta	-7.460	FZ Gamma	6.171	O1 Gamma	13.178
8	O1 Gamma	6.820	T5 Gamma	11.213	T5 Delta	-6.128	CZ Gamma	6.107	CZ Gamma	13.158
9	O2 Gamma	6.800	F3 Beta	10.886	FP2 Delta	-6.065	O2 Theta	6.070	F4 Gamma	12.195
10	T3 Delta	-6.626	F4 Theta	10.716	PZ Alpha	5.708	T5 Gamma	5.898	T4 Gamma	12.146

	B42C		B43F		B51A		B52B		B53C	
Rank	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**
1	P4 Gamma	27.852	O2 Gamma	18.944	O1 Gamma	8.932	FP1 Gamma	12.514	O1 Gamma	20.125
2	T6 Gamma	27.174	T6 Gamma	18.128	T5 Gamma	7.998	O2 Gamma	12.394	T6 Gamma	19.764
3	O2 Gamma	26.203	O1 Gamma	16.162	T3 Gamma	7.454	T6 Gamma	11.160	O2 Gamma	18.912
4	T5 Gamma	25.449	F8 Gamma	-15.129	O1 Theta	7.299	O1 Gamma	10.740	P4 Gamma	17.679
5	P3 Gamma	24.868	P4 Gamma	13.494	F8 Delta	7.284	P4 Gamma	9.091	PZ Gamma	17.249
6	T4 Gamma	24.600	T5 Gamma	13.114	O2 Gamma	7.084	PZ Gamma	8.825	P3 Gamma	15.089
7	O1 Gamma	23.981	F8 Beta	-12.637	T6 Gamma	7.046	O1 Theta	8.445	CZ Theta	13.951
8	PZ Gamma	23.728	C3 Beta	-12.296	PZ Gamma	6.619	FP1 Beta	7.811	T5 Gamma	13.819
9	C4 Gamma	23.154	P4 Delta	-9.198	F7 Gamma	-6.328	O2 Theta	7.551	C3 Theta	12.718
10	F4 Gamma	22.782	PZ Gamma	9.119	P4 Gamma	6.300	O2 Beta	7.466	CZ Gamma	12.484

Table A3. Feature rank according to t-test statistic for 10-second windowing method for all trials for Subject C.

	C11B		C12A		C13E		C22F		C23D	
Rank	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**
1	FZ Alpha	-13.347	P3 Delta	-12.019	T3 Alpha	-11.143	O2 Theta	-12.199	C4 Theta	-4.856
2	P4 Alpha	-12.033	P3 Alpha	-7.490	P4 Theta	-9.970	F8 Theta	-9.770	T4 Beta	-3.834
3	P3 Alpha	-11.625	PZ Alpha	-7.290	P4 Alpha	-9.951	P4 Theta	-9.578	C4 Alpha	-3.335
4	T3 Alpha	-11.213	O1 Alpha	-6.193	PZ Theta	-8.779	O1 Theta	-9.563	T3 Beta	-3.303
5	PZ Alpha	-11.201	T4 Delta	-6.096	O1 Theta	-8.473	T4 Theta	-8.952	C3 Theta	-3.077
6	O1 Alpha	-11.197	C3 Delta	5.717	C4 Theta	-8.431	T3 Theta	-8.720	CZ Theta	-2.926
7	F4 Alpha	-11.174	O2 Alpha	-5.668	O2 Theta	-8.373	C4 Theta	-8.691	C4 Beta	-2.732
8	F3 Alpha	-10.907	T6 Delta	5.476	PZ Alpha	-8.156	PZ Theta	-8.553	C4 Delta	-2.719
9	CZ Alpha	-10.877	C3 Alpha	-5.450	P3 Alpha	-7.942	P3 Theta	-8.430	T4 Gamma	-2.701
10	C3 Alpha	-10.594	T3 Alpha	-5.327	P3 Theta	-7.887	T6 Theta	-8.262	T4 Alpha	-2.683

	C31B		C32C		C33F		C41A		C42B	
Rank	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**
1	CZ Alpha	-11.558	T4 Gamma	30.235	P4 Delta	-10.677	P4 Delta	16.112	P3 Theta	10.575
2	C4 Alpha	-10.575	FP2 Gamma	26.463	F4 Delta	-10.180	C4 Delta	8.085	PZ Theta	9.785
3	C3 Alpha	-10.016	FP2 Beta	23.973	T5 Beta	9.931	PZ Theta	8.041	P4 Theta	8.431
4	F8 Delta	9.673	FP1 Gamma	19.202	O2 Delta	-8.845	F4 Gamma	-7.158	T5 Theta	8.321
5	T4 Alpha	-9.149	T4 Beta	16.742	FP2 Beta	-8.090	P4 Theta	6.238	C3 Alpha	-8.306
6	T3 Alpha	-9.098	FP1 Beta	16.398	P3 Beta	7.647	CZ Beta	-5.961	O2 Theta	7.542
7	P4 Beta	-8.100	T3 Beta	15.698	O1 Beta	7.357	F4 Delta	5.762	CZ Theta	7.082
8	CZ Beta	-7.996	O1 Delta	15.697	FP2 Alpha	-6.955	P3 Theta	5.601	O1 Theta	6.903
9	FP2 Beta	7.830	T3 Gamma	12.755	C4 Alpha	-6.047	C3 Gamma	-5.471	CZ Alpha	-6.621
10	CZ Theta	7.649	P3 Theta	10.398	T4 Beta	-5.857	P3 Gamma	-5.432	FZ Alpha	-6.057

	C43C		C51E		C52F		C53D	
Rank	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**	**Features**	**T-Test Value**
1	PZ Delta	14.574	P4 Alpha	-12.774	T5 Gamma	20.149	FP1 Gamma	9.487
2	C4 Delta	14.373	O1 Theta	-12.730	P3 Gamma	17.489	C4 Alpha	-7.983
3	T4 Delta	12.739	C4 Alpha	-12.137	FZ Alpha	-14.754	PZ Delta	-7.954
4	O2 Delta	11.815	T3 Theta	-10.473	O2 Gamma	14.701	P4 Alpha	-7.297
5	F4 Delta	11.035	CZ Alpha	-10.313	O1 Gamma	13.955	PZ Alpha	-7.082
6	FP2 Gamma	9.114	C3 Theta	-10.096	CZ Alpha	-13.527	P3 Alpha	-6.829
7	FP2 Delta	8.927	P3 Alpha	-9.979	C3 Alpha	-13.403	O1 Alpha	-6.370
8	O1 Delta	8.371	FP2 Alpha	-9.938	F3 Alpha	-13.221	FP1 Beta	6.317
9	FP2 Beta	8.126	PZ Alpha	-9.661	FP1 Alpha	-12.916	F3 Theta	6.092
10	O1 Alpha	7.700	O2 Alpha	-9.515	T3 Gamma	12.647	T3 Alpha	-6.061

Table A4. Feature rank according to t-test statistic for 10-second windowing method for all trials for Subject D.

	D11C		D13D		D21B		D22C		D23F	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	P3 Alpha	-9.626	T4 Gamma	-21.807	P4 Gamma	-8.277	FP1 Beta	11.115	FP2 Beta	-10.614
2	CZ Alpha	-9.547	P4 Beta	-21.048	T6 Gamma	-8.050	FP1 Gamma	6.735	P3 Delta	-8.854
3	PZ Alpha	-9.238	P4 Gamma	-20.927	P4 Beta	-7.688	O1 Alpha	-6.404	FP1 Beta	-8.826
4	P4 Alpha	-7.852	CZ Beta	-20.275	FZ Gamma	-7.646	O2 Alpha	-5.832	FP1 Alpha	-8.269
5	PZ Gamma	-7.722	T3 Beta	-20.154	F8 Theta	-7.587	FP2 Beta	5.694	FP2 Gamma	-7.392
6	FP1 Alpha	-7.530	PZ Beta	-20.087	F8 Delta	-7.447	PZ Alpha	-4.657	FP2 Alpha	-7.010
7	FP1 Beta	-7.524	T4 Beta	-20.074	CZ Gamma	-7.165	P3 Delta	4.640	CZ Alpha	-6.387
8	CZ Gamma	-7.352	FZ Gamma	-19.096	F8 Gamma	-7.124	T6 Theta	4.562	FP1 Gamma	-6.158
9	FZ Alpha	-7.319	CZ Gamma	-19.043	CZ Beta	-7.083	FZ Theta	4.547	PZ Alpha	-6.134
10	P4 Gamma	-6.877	T6 Beta	-18.676	PZ Beta	-7.039	O1 Theta	-4.398	O1 Alpha	-5.722

	D31A		D32B		D33C		D41E		D42F	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	F7 Delta	8.016	P3 Alpha	-12.218	T4 Beta	-11.473	O1 Alpha	-11.341	F3 Alpha	-13.628
2	FP2 Alpha	6.057	FP2 Alpha	-12.149	O2 Gamma	-11.349	F3 Alpha	-10.293	T5 Gamma	-12.950
3	T3 Theta	-5.025	T6 Alpha	-11.839	P4 Beta	-11.014	FZ Alpha	-9.840	T6 Alpha	-12.085
4	P3 Alpha	-4.844	P4 Alpha	-11.216	P4 Gamma	-10.663	P3 Alpha	-9.018	CZ Alpha	-11.947
5	T5 Alpha	-4.838	PZ Alpha	-10.327	T6 Gamma	-10.567	T5 Alpha	-8.928	P3 Alpha	-11.710
6	FP1 Theta	4.704	FP1 Alpha	-10.307	PZ Gamma	-10.315	FP2 Alpha	-8.714	O1 Alpha	-11.648
7	CZ Delta	4.417	T5 Alpha	-9.349	O2 Beta	-10.194	PZ Theta	-8.703	FZ Alpha	-11.558
8	F7 Beta	-4.385	CZ Alpha	-8.970	T4 Gamma	-10.167	C3 Alpha	-8.552	C3 Alpha	-11.531
9	FP1 Alpha	4.317	FP2 Beta	-8.907	T6 Beta	-10.051	CZ Alpha	-8.524	T5 Alpha	-11.448
10	F4 Theta	4.183	C4 Alpha	-8.482	PZ Beta	-9.960	PZ Alpha	-8.368	F7 Gamma	-11.263

	D43D		D51B		D52A		D53E	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T4 Gamma	11.603	T4 Gamma	-7.549	C3 Delta	9.522	T4 Beta	-13.473
2	T4 Beta	11.000	F8 Delta	-7.205	T3 Delta	6.669	P4 Gamma	-12.962
3	T4 Theta	9.697	T4 Beta	-6.941	T5 Delta	6.355	T4 Gamma	-12.244
4	FZ Theta	9.678	P3 Gamma	-6.737	FP1 Beta	5.423	P4 Beta	-11.330
5	T4 Alpha	8.157	T5 Gamma	-6.040	F7 Delta	5.070	PZ Gamma	-11.251
6	F4 Theta	7.896	PZ Theta	-5.402	FP1 Gamma	4.760	PZ Beta	-11.036
7	P4 Theta	7.453	T3 Alpha	-5.293	F8 Delta	4.480	T6 Beta	-10.719
8	O1 Alpha	-6.602	C3 Gamma	-5.291	FZ Delta	4.419	CZ Beta	-10.469
9	F8 Alpha	6.379	C3 Beta	-5.271	T5 Alpha	4.228	T6 Gamma	-10.391
10	F8 Theta	5.582	P3 Beta	-5.257	PZ Gamma	-3.922	CZ Gamma	-10.225

Table A5. Feature rank according to t-test statistic for 10-second windowing method for all trials for Subject E.

	E11B		E12C		E13F		E21A		E22B	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	PZ Theta	10.386	FP1 Delta	-11.033	CZ Beta	-11.700	O2 Theta	13.055	C4 Alpha	12.626
2	O1 Theta	9.364	FP2 Delta	-10.846	C3 Beta	-10.499	CZ Theta	12.172	O2 Theta	11.406
3	O2 Theta	8.690	T4 Alpha	-8.534	F8 Delta	-10.311	C4 Theta	10.671	F7 Delta	-7.947
4	P4 Theta	8.471	F3 Theta	6.950	O2 Gamma	-9.559	PZ Theta	9.707	T4 Delta	-7.031
5	CZ Theta	8.271	FZ Theta	6.924	T3 Alpha	-9.015	C3 Theta	9.658	C4 Delta	-6.634
6	P3 Theta	7.287	P4 Alpha	-6.880	F3 Beta	-8.535	F8 Delta	9.039	PZ Delta	-6.459
7	C3 Theta	6.792	PZ Beta	-6.611	PZ Beta	-8.485	O1 Theta	8.770	P3 Delta	-6.382
8	F8 Delta	-5.818	F4 Theta	5.781	C4 Delta	-8.330	T6 Delta	8.253	T6 Delta	-6.163
9	C4 Theta	5.799	F7 Delta	-5.759	F3 Alpha	-8.285	FZ Theta	8.014	O1 Theta	5.819
10	FZ Theta	5.081	F4 Delta	-5.555	P4 Delta	-8.259	F3 Theta	7.878	C3 Theta	5.746

	E23C		E32B		E33C		E41B		E42A	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O2 Theta	14.924	P4 Theta	8.544	F8 Gamma	12.741	T3 Gamma	24.387	T3 Gamma	38.854
2	O1 Theta	14.497	O2 Theta	8.448	F8 Beta	9.255	T3 Beta	19.078	T3 Beta	33.874
3	O1 Gamma	10.763	O1 Theta	6.934	FP2 Gamma	9.022	O2 Gamma	17.640	T5 Gamma	26.509
4	FZ Alpha	-10.499	PZ Theta	6.428	F7 Gamma	9.001	O2 Beta	14.856	O1 Gamma	22.333
5	FP2 Alpha	-9.032	CZ Theta	4.596	FP1 Gamma	8.928	O1 Beta	13.710	O1 Beta	19.395
6	T6 Alpha	-8.571	C4 Theta	3.535	P4 Alpha	-8.041	O2 Delta	-12.615	T5 Beta	18.140
7	F3 Alpha	-8.505	F7 Gamma	3.319	C3 Gamma	7.513	T3 Alpha	12.088	T4 Gamma	17.416
8	F4 Alpha	-8.429	C3 Theta	2.878	O1 Theta	7.373	CZ Theta	11.594	O2 Gamma	16.161
9	CZ Alpha	-7.684	FZ Theta	2.501	F7 Beta	6.877	O1 Gamma	10.914	T4 Beta	15.522
10	CZ Theta	7.641	P3 Theta	2.461	C4 Alpha	-6.462	T5 Beta	10.618	PZ Gamma	14.603

	E43E		E51C		E52F		E53D	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Gamma	33.694	O2 Alpha	-11.723	O1 Gamma	18.588	O1 Gamma	16.507
2	O1 Beta	29.693	P4 Alpha	-11.490	O1 Theta	17.568	P4 Theta	10.604
3	T5 Beta	27.143	O1 Alpha	-10.139	C4 Alpha	17.301	O1 Beta	9.872
4	T4 Beta	26.887	F3 Alpha	-9.695	T4 Gamma	16.945	T3 Gamma	9.715
5	T6 Beta	25.279	O1 Beta	-9.479	O1 Beta	14.630	PZ Theta	9.568
6	T4 Gamma	24.966	FZ Alpha	-9.248	C3 Theta	14.527	O2 Gamma	9.353
7	T6 Gamma	22.290	CZ Delta	-9.248	T4 Beta	14.396	CZ Theta	9.137
8	T5 Gamma	21.906	T6 Delta	-9.120	C4 Theta	14.301	CZ Alpha	-8.738
9	P4 Gamma	16.513	FP1 Alpha	-8.702	CZ Theta	14.148	T6 Alpha	-8.618
10	F3 Delta	-14.344	C3 Delta	-8.355	O2 Theta	14.044	T3 Beta	8.506

Table A6. Feature rank according to t-test statistic for 10-second windowing method for all trials for Subject F.

Rank	F12C		F13F		F21E		F22F		F23D	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	F7 Delta	14.347	O1 Alpha	22.171	O2 Beta	22.740	CZ Alpha	17.022	O2 Alpha	12.626
2	F4 Delta	13.872	O2 Alpha	21.024	O2 Gamma	21.669	O2 Alpha	15.370	PZ Theta	12.371
3	O2 Beta	13.821	O2 Gamma	20.105	O2 Alpha	15.870	C4 Alpha	13.283	C4 Alpha	12.326
4	O2 Gamma	12.140	O2 Beta	19.311	C4 Alpha	11.908	F4 Alpha	13.074	C4 Theta	12.306
5	O2 Alpha	10.879	C4 Alpha	18.246	CZ Alpha	9.080	FZ Alpha	11.233	P4 Theta	10.153
6	P4 Beta	9.809	O1 Beta	16.797	O1 Alpha	8.670	F7 Delta	-7.135	CZ Theta	9.542
7	PZ Delta	9.549	O1 Gamma	15.647	C4 Delta	-6.909	CZ Theta	6.827	C3 Theta	8.407
8	T6 Gamma	9.546	F4 Alpha	14.887	F4 Alpha	5.920	F7 Beta	-6.387	FP1 Delta	-7.868
9	F7 Theta	9.425	CZ Alpha	12.206	PZ Alpha	5.798	FZ Delta	-6.061	P4 Alpha	7.657
10	PZ Beta	9.326	PZ Alpha	12.197	P4 Alpha	5.688	C4 Theta	6.031	F3 Delta	-7.581

Rank	F31B		F32A		F33E		F41C		F42F	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Gamma	16.240	T3 Beta	-23.020	O1 Alpha	-15.981	T4 Delta	12.999	FP1 Beta	41.671
2	O1 Beta	12.981	T3 Gamma	-21.820	O1 Beta	-14.456	PZ Delta	12.138	FP2 Beta	40.184
3	O2 Beta	12.240	T3 Alpha	-13.663	O2 Beta	-13.743	FP2 Beta	-12.101	FP2 Gamma	38.481
4	O1 Alpha	10.818	T5 Theta	-12.554	O1 Gamma	-13.670	O2 Delta	12.034	FP1 Gamma	36.874
5	O2 Gamma	9.663	C3 Gamma	-10.611	O2 Gamma	-11.989	CZ Delta	11.646	FP1 Alpha	14.640
6	T3 Beta	-9.443	F4 Alpha	-10.460	T3 Beta	-11.487	O2 Gamma	11.158	FP2 Alpha	12.978
7	F3 Alpha	-7.409	F7 Beta	-10.308	O2 Alpha	-11.018	T6 Theta	11.116	T4 Alpha	-10.888
8	T3 Gamma	-7.026	FZ Theta	-9.936	T3 Gamma	-10.746	C4 Delta	10.422	CZ Beta	-8.662
9	T3 Delta	-6.684	F3 Theta	-9.629	P3 Beta	-10.623	T3 Delta	9.757	T4 Beta	-8.288
10	F7 Gamma	-5.975	F3 Beta	-9.380	T4 Beta	-10.143	O2 Beta	9.553	T3 Delta	-7.803

Rank	F43D		F51B		F52C		F53F	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T3 Gamma	7.916	O2 Alpha	8.306	FP2 Beta	22.049	O2 Beta	16.512
2	FZ Alpha	7.320	F7 Beta	-8.109	FP1 Beta	16.863	O2 Gamma	15.922
3	T3 Beta	6.961	F7 Alpha	-8.050	FP2 Gamma	12.042	O2 Alpha	14.695
4	FP2 Delta	-6.149	T3 Beta	-7.842	FP1 Gamma	11.893	P4 Gamma	14.032
5	F4 Alpha	5.417	O2 Beta	7.575	F3 Delta	-7.151	PZ Beta	12.829
6	O2 Gamma	4.921	T3 Gamma	-7.571	FZ Gamma	-5.601	P4 Beta	12.649
7	CZ Alpha	4.825	C3 Beta	-7.085	CZ Gamma	-5.004	T6 Gamma	12.385
8	O2 Theta	-4.301	T4 Beta	-6.932	F7 Beta	-4.590	O1 Beta	10.887
9	O1 Theta	-4.279	FZ Beta	-6.772	F4 Delta	-4.534	PZ Gamma	10.257
10	FP1 Beta	4.157	F8 Beta	-6.626	F4 Beta	-4.511	CZ Beta	8.909

Table A7. Feature rank according to t-test statistic for 10-second windowing method for all trials for Subject G.

Rank	G11E		G12F		G13D		G21B		G22A	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T5 Gamma	52.174	T5 Beta	55.489	FP2 Beta	-30.260	O1 Theta	13.140	FP2 Beta	-15.623
2	T5 Beta	40.369	T5 Gamma	44.050	FP2 Gamma	-23.415	CZ Theta	11.991	FP2 Gamma	-11.515
3	T6 Gamma	31.171	T6 Beta	40.492	T4 Gamma	-15.889	O2 Theta	10.442	T3 Gamma	-10.564
4	FP2 Beta	-29.560	T6 Gamma	36.226	FP1 Beta	-14.738	CZ Beta	-10.187	P4 Delta	-10.128
5	FP2 Gamma	-21.804	T4 Gamma	31.559	FP1 Gamma	-13.718	FP2 Gamma	-10.167	FZ Alpha	7.587
6	T6 Beta	20.383	T4 Beta	31.186	CZ Beta	-13.306	FP2 Beta	-9.684	FZ Theta	7.562
7	FP1 Beta	-13.290	P4 Gamma	27.232	T4 Beta	-12.481	C3 Theta	9.443	F3 Theta	7.327
8	C3 Theta	12.551	O2 Gamma	27.047	T3 Beta	-11.804	P3 Theta	8.729	T3 Beta	-7.104
9	T3 Gamma	12.504	O1 Gamma	25.269	CZ Theta	11.688	C4 Theta	8.120	C4 Theta	7.000
10	CZ Theta	10.605	P4 Beta	22.614	T3 Gamma	-11.547	P4 Delta	-7.500	C3 Theta	6.995

Rank	G23E		G31C		G32F		G33D		G41B	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	CZ Theta	12.916	FP2 Beta	-38.535	FP2 Beta	18.718	O1 Theta	12.187	T6 Gamma	31.811
2	T4 Delta	-12.676	FP2 Gamma	-30.830	FP2 Gamma	13.490	C4 Theta	11.959	T5 Gamma	27.406
3	F3 Theta	12.393	CZ Theta	16.838	T4 Beta	13.249	CZ Theta	11.024	T6 Beta	24.559
4	F4 Theta	10.547	PZ Theta	15.822	CZ Theta	12.253	C3 Theta	10.875	T5 Beta	23.011
5	CZ Delta	-9.990	FP1 Gamma	-15.601	C3 Theta	11.038	P3 Theta	8.919	F8 Beta	-22.313
6	C3 Theta	9.935	O1 Theta	15.275	FZ Theta	10.331	F4 Theta	8.738	FP2 Beta	-21.502
7	PZ Delta	-8.966	FP1 Beta	-15.250	O1 Theta	9.595	FZ Theta	8.409	FP2 Gamma	-17.526
8	T3 Beta	7.670	O2 Theta	15.168	F3 Theta	9.087	T3 Theta	8.094	F8 Gamma	-15.325
9	C4 Theta	7.289	C4 Theta	15.071	F4 Theta	8.905	PZ Theta	7.799	P4 Alpha	8.005
10	FP2 Beta	-6.887	T3 Beta	-14.128	FP1 Delta	-8.608	F7 Theta	7.631	P3 Alpha	7.011

Rank	G42C		G43F		G51A		G52B		G53C	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Gamma	13.687	FP2 Beta	-24.087	O2 Gamma	14.530	O1 Theta	11.687	F8 Gamma	-13.849
2	PZ Gamma	12.105	FP2 Gamma	-19.149	O2 Beta	13.074	FP1 Beta	-7.460	F8 Alpha	-13.502
3	O2 Gamma	11.548	CZ Theta	14.084	O2 Alpha	11.513	FP2 Gamma	-6.701	T3 Gamma	11.903
4	P3 Beta	11.522	T6 Beta	13.474	O1 Theta	10.781	CZ Theta	6.329	FP1 Gamma	-11.578
5	O1 Beta	10.655	FZ Theta	12.879	FP1 Beta	-10.346	FP1 Gamma	-6.214	F3 Gamma	-10.513
6	FP2 Beta	-10.384	T6 Gamma	12.576	PZ Theta	9.178	P4 Theta	5.756	F4 Gamma	-10.344
7	P3 Gamma	9.879	F4 Beta	-11.174	O2 Theta	8.684	FP2 Delta	-5.722	FZ Gamma	-9.910
8	O2 Theta	9.021	C4 Theta	10.693	CZ Beta	-8.266	PZ Theta	5.592	F4 Beta	-9.878
9	CZ Gamma	8.888	F4 Gamma	-10.582	FP2 Beta	-7.770	PZ Alpha	5.577	P3 Gamma	-9.306
10	T5 Beta	8.879	O1 Theta	10.516	P3 Theta	7.063	FZ Alpha	5.521	F8 Beta	-8.405

Table A8. Feature rank according to t-test statistic for 10-second windowing method for all trials for Subject H.

	H11B		H12A		H13E		H21C		H22F	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	FP1 Beta	21.817	C4 Beta	-15.048	O1 Gamma	39.528	FP1 Beta	-25.373	FP1 Beta	30.315
2	FP1 Gamma	17.828	O1 Gamma	12.857	O1 Beta	38.417	FP2 Beta	-22.261	FP1 Gamma	22.122
3	FP2 Beta	13.716	F4 Beta	-11.417	O2 Beta	36.683	O1 Gamma	18.635	FP2 Beta	21.536
4	FP1 Alpha	13.459	O1 Beta	10.788	O2 Gamma	35.634	C4 Alpha	-16.536	C4 Alpha	11.241
5	FP2 Gamma	12.077	FZ Beta	-9.194	FP1 Beta	21.768	FP1 Gamma	-16.428	FP2 Gamma	11.051
6	P3 Beta	-11.548	P4 Alpha	-9.193	FP2 Beta	19.462	O1 Beta	14.672	C3 Alpha	-9.683
7	CZ Beta	-11.331	C4 Alpha	-9.072	P4 Gamma	15.325	FP2 Gamma	-14.213	PZ Alpha	-8.599
8	T5 Beta	-11.230	T5 Delta	8.691	FP2 Gamma	15.263	C4 Beta	-13.679	P3 Delta	-8.365
9	C3 Beta	-10.571	T4 Alpha	-8.562	T6 Gamma	15.053	T4 Alpha	-12.582	P3 Alpha	-8.272
10	F7 Delta	-9.326	CZ Beta	-8.523	FP1 Gamma	14.984	F8 Beta	-11.555	F3 Alpha	-8.143

	H23D		H31B		H32C		H33F		H41A	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Alpha	-9.059	CZ Alpha	-12.557	FP1 Delta	10.046	CZ Beta	-10.359	O1 Gamma	19.728
2	CZ Theta	9.043	P4 Alpha	-9.444	FP2 Delta	9.084	T3 Alpha	-9.904	O1 Beta	16.928
3	F4 Delta	-8.678	C3 Alpha	-8.815	FP1 Beta	9.057	FZ Gamma	-9.503	CZ Theta	16.348
4	C3 Theta	8.362	FZ Alpha	-8.731	O1 Alpha	-7.495	F3 Gamma	-9.265	P4 Theta	15.226
5	O2 Alpha	-7.491	F3 Alpha	-8.479	F7 Theta	-6.426	CZ Gamma	-9.147	O2 Theta	14.041
6	F3 Delta	-6.192	FZ Delta	-8.399	C3 Theta	5.546	C4 Beta	-8.957	O2 Beta	13.269
7	T5 Alpha	-5.264	T4 Alpha	-7.599	T3 Alpha	-5.435	FZ Beta	-8.874	O1 Alpha	13.230
8	P3 Alpha	-5.122	PZ Alpha	-6.977	T3 Gamma	-5.394	C3 Beta	-8.797	T5 Gamma	13.227
9	C4 Alpha	-5.012	C4 Alpha	-6.901	T6 Delta	5.197	FP1 Gamma	-8.720	PZ Theta	11.648
10	C3 Beta	-4.978	F4 Alpha	-6.714	T6 Theta	5.090	P3 Gamma	-8.245	C3 Theta	10.962

	H42B		H43C		H51E		H52F		H53D	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Delta	10.523	O1 Beta	21.825	C4 Beta	-10.726	C4 Beta	-12.180	C4 Beta	-9.910
2	T6 Delta	9.837	O1 Gamma	21.752	FP1 Beta	-9.624	C3 Beta	-11.592	C3 Beta	-9.195
3	O2 Delta	9.191	O1 Delta	21.401	F8 Delta	-9.238	O1 Beta	-10.483	PZ Beta	-8.974
4	FP1 Beta	8.249	O2 Beta	20.329	C3 Beta	-8.551	CZ Beta	-8.936	CZ Theta	7.994
5	CZ Theta	6.422	O2 Gamma	18.711	P3 Alpha	-7.279	P3 Alpha	-8.612	P3 Beta	-7.961
6	F7 Alpha	-6.380	O1 Alpha	18.321	FZ Beta	-7.237	T5 Beta	-8.560	C3 Theta	7.944
7	F3 Alpha	-6.260	O2 Alpha	17.450	FP1 Gamma	-7.175	P3 Beta	-8.506	CZ Beta	-7.737
8	T3 Beta	-6.074	O1 Theta	17.173	T4 Delta	-7.048	O1 Gamma	-8.438	PZ Gamma	-7.407
9	T3 Alpha	-6.047	FZ Alpha	13.228	T6 Beta	-6.792	T5 Alpha	-8.211	P3 Gamma	-7.155
10	FP1 Gamma	5.804	FZ Theta	10.678	CZ Beta	-6.454	T6 Delta	-8.087	T5 Gamma	-7.027

Appendix C - Tables including Feature Rank According to T-Test Statistic for 5-second window

Table A9. Feature rank according to t-test statistic for 5-second windowing method for all trials for Subject A.

	A11A		A12B		A13C		A21E		A22F	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O2 Gamma	-8.813	C3 Delta	-4.461	FP2 Beta	-11.969	T4 Delta	-5.821	O1 Gamma	-11.293
2	O2 Beta	-6.948	T5 Delta	-4.391	FP2 Gamma	-10.746	P4 Delta	-4.799	O1 Beta	-11.213
3	O2 Alpha	-6.312	F7 Gamma	-3.406	FP1 Beta	-6.328	FP2 Delta	-4.741	P3 Delta	-9.844
4	FP1 Delta	-5.562	C4 Theta	3.194	O1 Beta	4.795	F4 Delta	-4.511	O1 Alpha	-9.701
5	FP2 Beta	4.660	F7 Delta	-3.029	CZ Delta	4.705	O2 Delta	-3.941	PZ Delta	-8.401
6	P4 Gamma	-4.651	P3 Delta	-2.820	F3 Theta	4.581	T3 Delta	-3.911	F7 Delta	-8.084
7	PZ Beta	-4.616	P4 Theta	2.780	FP1 Gamma	-4.546	F8 Beta	3.808	T5 Gamma	-8.052
8	FP2 Delta	4.438	F7 Beta	-2.577	F8 Beta	-4.526	T3 Alpha	-3.498	F7 Gamma	-7.654
9	FZ Delta	-3.912	T5 Theta	-2.552	F7 Gamma	-4.365	C3 Delta	-3.471	P3 Gamma	-7.346
10	CZ Delta	-3.902	CZ Delta	-2.526	O1 Gamma	4.325	CZ Beta	-3.195	T5 Beta	-7.132

	A23E		A31B		A32A		A33E		A41C	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T3 Beta	2.930	O1 Gamma	-17.883	FP2 Beta	8.964	FP2 Beta	-13.953	O1 Beta	9.987
2	F4 Delta	-2.772	O1 Beta	-17.329	FP2 Gamma	6.802	FP2 Gamma	-11.436	O1 Gamma	9.249
3	CZ Delta	-2.736	O1 Alpha	-15.634	F7 Delta	-6.625	C3 Delta	10.489	O1 Alpha	9.020
4	T3 Gamma	2.627	O2 Beta	14.897	T6 Gamma	5.584	FZ Delta	8.705	T5 Gamma	7.784
5	O2 Delta	-2.611	O2 Alpha	14.851	FP1 Beta	5.319	O2 Delta	8.432	T5 Beta	7.704
6	C4 Delta	-2.490	T5 Gamma	-13.720	F4 Gamma	4.433	FP1 Beta	-8.344	P3 Gamma	6.339
7	FP1 Gamma	2.401	O2 Gamma	13.636	FZ Gamma	4.414	T5 Delta	8.302	O1 Theta	6.244
8	O1 Alpha	-2.320	T5 Beta	-12.625	T6 Beta	4.413	F7 Gamma	-6.478	F8 Delta	5.925
9	FP1 Delta	-2.273	P3 Gamma	-9.745	CZ Gamma	4.351	F4 Delta	6.468	P3 Beta	5.884
10	F7 Delta	-2.251	P3 Beta	-8.380	F4 Alpha	4.348	F8 Delta	6.257	F4 Delta	4.508

	A42F		A43D		A51B		A52C		A53F	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Delta	-9.755	CZ Gamma	-7.204	O1 Beta	-6.277	FZ Gamma	7.264	O1 Delta	-11.693
2	O1 Beta	-7.384	C3 Gamma	-7.033	O1 Gamma	-5.684	CZ Gamma	6.895	F8 Delta	-8.377
3	O2 Delta	-7.332	T5 Beta	-7.008	O1 Delta	-5.312	P4 Delta	-6.453	O2 Delta	-6.954
4	T5 Gamma	-7.224	PZ Gamma	-6.681	O2 Gamma	-5.291	T4 Gamma	6.277	F7 Delta	-6.346
5	T5 Beta	-7.221	T3 Gamma	-6.634	P4 Delta	-5.198	T5 Beta	6.182	PZ Delta	-6.248
6	F7 Delta	-7.136	T5 Gamma	-6.558	O1 Alpha	-5.023	T3 Gamma	6.016	T4 Delta	-5.679
7	FP2 Gamma	-6.934	P3 Gamma	-6.511	O2 Beta	-5.001	C3 Gamma	5.953	T3 Delta	-5.668
8	T3 Beta	-6.906	T3 Beta	-6.335	C4 Delta	-4.752	CZ Beta	5.907	P3 Delta	-5.446
9	T6 Delta	-6.742	P3 Beta	-6.323	CZ Theta	4.426	PZ Gamma	5.777	T5 Delta	-5.313
10	O1 Gamma	-6.731	CZ Beta	-6.058	P3 Delta	-4.102	C3 Beta	5.692	T3 Gamma	-5.273

Table A10. Feature rank according to t-test statistic for 5-second windowing method for all trials for Subject B.

Rank	B11E		B12F		B13D		B21B		B22A	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	PZ Gamma	4.717	C3 Beta	-5.258	T5 Gamma	7.639	PZ Gamma	6.589	T4 Delta	6.200
2	P3 Gamma	4.655	PZ Gamma	5.163	O1 Gamma	7.625	P3 Gamma	5.128	PZ Delta	6.171
3	T5 Gamma	4.545	T6 Gamma	4.952	PZ Gamma	6.371	T5 Gamma	4.755	CZ Delta	5.720
4	T6 Delta	4.472	T3 Gamma	4.767	CZ Gamma	6.077	P4 Delta	4.664	F8 Delta	5.662
5	FP1 Beta	4.367	T4 Gamma	4.501	T4 Gamma	5.886	CZ Theta	4.644	FZ Delta	4.846
6	C3 Beta	-4.358	CZ Gamma	4.407	P3 Gamma	5.882	O1 Gamma	4.403	F4 Delta	4.164
7	F4 Gamma	-4.194	O2 Gamma	4.326	F4 Gamma	5.664	C3 Gamma	4.322	T6 Delta	4.063
8	T4 Gamma	3.694	P4 Gamma	4.106	P4 Gamma	5.586	C3 Beta	-4.263	O2 Delta	3.917
9	CZ Gamma	3.681	C4 Gamma	4.021	T3 Gamma	5.480	F7 Delta	4.147	C3 Beta	-3.572
10	FP2 Beta	3.668	P3 Gamma	3.977	FZ Gamma	5.100	P3 Theta	4.139	F3 Delta	3.325

Rank	B23E		B31C		B32F		B33D		B41B	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	C3 Beta	-5.054	C4 Gamma	7.468	FZ Delta	-7.766	T4 Gamma	5.509	T5 Gamma	6.984
2	T3 Gamma	-4.843	T5 Delta	7.288	P3 Delta	-7.219	F3 Delta	5.226	T4 Gamma	5.785
3	P3 Delta	-4.703	F4 Gamma	7.032	C3 Delta	-7.166	T6 Gamma	5.202	F8 Gamma	5.504
4	T5 Delta	-4.676	T5 Gamma	6.939	F3 Delta	-7.037	P4 Gamma	5.132	P3 Gamma	5.290
5	P4 Delta	-4.147	T6 Gamma	6.362	P4 Delta	-6.694	T5 Gamma	4.335	O1 Gamma	4.675
6	O1 Gamma	4.023	C4 Alpha	5.904	PZ Delta	-6.619	C4 Gamma	4.263	F4 Gamma	4.581
7	T3 Delta	-3.969	CZ Delta	5.416	CZ Delta	-6.381	CZ Gamma	4.253	P4 Gamma	4.193
8	FP2 Gamma	3.896	F4 Beta	5.218	T5 Delta	-6.269	PZ Gamma	3.817	C4 Gamma	4.150
9	CZ Delta	-3.807	CZ Theta	5.048	C4 Delta	-6.069	F4 Gamma	3.741	PZ Gamma	4.085
10	FP2 Beta	3.579	FZ Delta	4.904	O2 Delta	-5.029	O1 Gamma	3.627	T6 Gamma	3.707

Rank	B42C		B43F		B51A		B52B		B53C	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T5 Gamma	11.093	O2 Gamma	7.251	T6 Gamma	5.621	C3 Gamma	6.041	O1 Gamma	7.865
2	O1 Gamma	10.386	T6 Gamma	6.620	T5 Gamma	5.277	FP1 Gamma	5.259	T6 Gamma	7.505
3	O2 Gamma	10.229	F8 Gamma	-6.222	T4 Gamma	5.059	O2 Gamma	5.093	P3 Gamma	7.301
4	T6 Gamma	10.203	O1 Gamma	5.545	T3 Gamma	4.821	T4 Gamma	4.696	PZ Gamma	7.081
5	P3 Gamma	8.810	T5 Gamma	5.131	O1 Gamma	4.792	O1 Gamma	4.665	T5 Gamma	7.062
6	P4 Gamma	8.629	F7 Beta	-4.763	FZ Gamma	4.743	F3 Gamma	4.384	O2 Gamma	6.849
7	T4 Gamma	8.619	C3 Beta	-4.748	F4 Gamma	4.393	P3 Gamma	4.228	T4 Gamma	6.808
8	F4 Gamma	8.514	F7 Gamma	-4.439	P4 Gamma	4.122	FZ Gamma	4.165	FZ Gamma	6.584
9	PZ Gamma	7.678	P4 Gamma	4.159	C3 Gamma	4.118	T5 Gamma	4.055	P4 Gamma	6.540
10	C4 Gamma	7.479	C4 Delta	-4.078	PZ Gamma	3.746	CZ Gamma	3.972	CZ Gamma	6.198

Table A11. Feature rank according to t-test statistic for 5-second windowing method for all trials for Subject C.

Rank	C11B		C12A		C13E		C22F		C23D	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	CZ Alpha	-6.400	P3 Delta	-8.130	T3 Delta	-9.183	C4 Delta	-8.678	T4 Gamma	-9.763
2	FZ Alpha	-6.154	O1 Delta	-6.319	T6 Delta	-8.743	P4 Delta	-8.256	C4 Gamma	-9.431
3	T3 Alpha	-6.012	F7 Gamma	5.455	C4 Gamma	-8.219	T4 Delta	-7.740	T3 Gamma	-7.982
4	F4 Alpha	-5.933	F7 Beta	4.877	C3 Delta	-7.796	CZ Delta	-7.478	T6 Gamma	-6.936
5	O2 Alpha	-5.790	T4 Delta	-4.708	F7 Delta	-6.762	F4 Delta	-7.009	CZ Gamma	-6.857
6	C3 Alpha	-5.359	P3 Alpha	-4.047	T4 Gamma	-6.219	PZ Alpha	-6.861	P4 Gamma	-6.822
7	P3 Alpha	-5.188	C3 Delta	3.524	PZ Alpha	-5.943	P3 Alpha	-6.332	P3 Gamma	-6.768
8	PZ Alpha	-5.157	O2 Delta	-3.403	C4 Alpha	-5.796	P4 Alpha	-6.328	F4 Gamma	-6.679
9	F3 Alpha	-4.929	O1 Alpha	-3.335	F8 Delta	-5.795	T6 Delta	-6.157	T4 Beta	-6.602
10	P4 Alpha	-4.869	O2 Alpha	-3.278	P4 Alpha	-5.674	C4 Alpha	-6.156	T5 Gamma	-6.582

Rank	C31B		C32C		C33F		C41A		C42B	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T3 Alpha	-5.054	T4 Gamma	12.761	P4 Delta	-7.864	P4 Delta	6.151	T5 Gamma	4.716
2	F4 Delta	-4.108	FP2 Gamma	10.752	F4 Delta	-6.484	F4 Gamma	-5.102	PZ Theta	4.337
3	CZ Alpha	-4.080	T4 Beta	10.144	FP2 Beta	-5.934	F3 Gamma	-4.496	CZ Delta	-3.978
4	P4 Beta	-4.061	FP2 Beta	9.566	T5 Beta	5.729	C3 Gamma	-4.487	F3 Delta	-3.873
5	T4 Delta	-3.778	FP1 Gamma	7.721	O2 Delta	-5.158	P3 Gamma	-4.254	P4 Delta	-3.756
6	T3 Gamma	-3.563	O1 Delta	7.260	FP2 Gamma	-4.806	CZ Gamma	-4.109	P3 Theta	3.544
7	F3 Delta	-3.527	FP1 Beta	6.988	F8 Delta	-4.317	T3 Gamma	-4.042	FP1 Beta	3.500
8	C3 Alpha	-3.519	T3 Beta	5.823	O1 Beta	3.832	PZ Beta	-3.750	F8 Delta	3.431
9	C4 Alpha	-3.390	T3 Gamma	5.208	O1 Gamma	3.803	P4 Gamma	-3.738	T6 Theta	3.254
10	CZ Delta	3.344	PZ Delta	4.809	PZ Delta	-3.789	C4 Alpha	-3.698	C3 Theta	3.207

Rank	C43C		C51E		C52F		C53D	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	FP2 Delta	6.780	C4 Alpha	-5.280	T5 Gamma	10.772	FP1 Gamma	6.072
2	PZ Delta	6.701	O1 Theta	-5.106	O2 Gamma	8.430	C4 Alpha	-4.183
3	O1 Delta	6.455	P3 Alpha	-4.980	O1 Gamma	8.153	C3 Delta	-3.708
4	O1 Gamma	-5.749	C3 Alpha	-4.905	P3 Gamma	7.459	O1 Delta	-3.284
5	T4 Delta	5.664	P4 Alpha	-4.887	CZ Alpha	-6.506	P4 Alpha	-3.088
6	O2 Gamma	-5.546	CZ Alpha	-4.876	C4 Alpha	-6.453	F3 Beta	-3.049
7	C4 Delta	5.424	O1 Alpha	-4.671	T3 Gamma	6.338	FZ Delta	-2.983
8	FP2 Gamma	5.359	FP2 Alpha	-4.449	PZ Alpha	-5.758	T5 Delta	2.929
9	T4 Gamma	-5.134	O2 Alpha	-4.406	PZ Gamma	5.460	FP1 Beta	2.884
10	T3 Delta	5.131	O2 Theta	-4.401	C3 Alpha	-5.322	O1 Alpha	-2.796

Table A12. Feature rank according to t-test statistic for 5-second windowing method for all trials for Subject D.

	D11C		D13D		D21B		D22C		D23F	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Delta	6.705	T4 Gamma	-17.124	F8 Gamma	-11.544	T6 Beta	-4.233	P3 Delta	-8.852
2	PZ Delta	5.974	T4 Beta	-16.034	F8 Beta	-10.396	P3 Delta	4.062	FP1 Delta	-7.264
3	F3 Gamma	-5.869	C4 Gamma	-15.703	T4 Gamma	-10.004	PZ Delta	-3.864	T5 Delta	-6.753
4	F3 Beta	-5.585	FZ Gamma	-15.098	F4 Gamma	-9.795	O2 Delta	-3.828	T6 Delta	-6.408
5	T5 Gamma	-5.559	CZ Gamma	-15.002	T3 Gamma	-9.778	T6 Gamma	-3.814	C3 Delta	-6.406
6	P3 Alpha	-5.424	P4 Gamma	-14.417	C4 Gamma	-8.865	O2 Beta	-3.568	FP2 Delta	-5.818
7	CZ Gamma	-5.371	C4 Beta	-14.237	FZ Gamma	-8.775	F4 Delta	3.320	FP2 Gamma	-5.500
8	FZ Gamma	-5.214	F4 Gamma	-14.082	T4 Beta	-8.386	FP1 Beta	3.008	FP2 Beta	-5.451
9	FP1 Gamma	-5.186	F8 Gamma	-13.999	CZ Gamma	-8.120	O2 Alpha	-2.872	F3 Delta	-5.359
10	P4 Alpha	-5.137	F8 Beta	-13.438	T3 Beta	-7.916	FP1 Gamma	2.872	T4 Delta	-5.266

	D31A		D32B		D33C		D41E		D42F	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	F7 Delta	7.377	FP2 Gamma	-6.523	O2 Gamma	-6.989	P4 Gamma	-9.780	F3 Delta	-13.730
2	FP2 Delta	5.761	T6 Delta	-6.230	FZ Gamma	-6.848	T4 Gamma	-9.309	F7 Delta	-11.040
3	O2 Delta	5.360	FP2 Beta	-6.057	O2 Beta	-6.726	PZ Gamma	-8.971	FZ Delta	-10.496
4	CZ Delta	5.333	FP1 Alpha	-5.959	CZ Gamma	-6.709	O1 Gamma	-8.599	T4 Delta	-9.697
5	C4 Delta	4.973	C4 Alpha	-5.824	PZ Beta	-6.700	T5 Gamma	-8.560	O2 Theta	9.520
6	P3 Delta	4.323	P3 Alpha	-5.704	PZ Gamma	-6.661	CZ Gamma	-8.478	FP2 Delta	-9.471
7	F4 Delta	4.314	FP1 Gamma	-5.547	T6 Gamma	-6.649	T6 Gamma	-8.403	C3 Delta	-8.881
8	O1 Delta	3.923	FP1 Beta	-5.502	P4 Gamma	-6.496	T4 Beta	-8.307	FZ Gamma	-8.667
9	P4 Delta	3.792	P4 Alpha	-5.430	O1 Gamma	-6.450	C4 Gamma	-8.234	CZ Gamma	-8.645
10	FZ Delta	3.349	T6 Alpha	-5.372	O1 Beta	-6.421	T5 Beta	-8.166	F3 Gamma	-8.261

	D43D		D51B		D52A		D53E	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T4 Beta	6.441	F8 Delta	-7.159	T3 Delta	5.691	T4 Gamma	-9.557
2	T4 Gamma	6.017	T4 Gamma	-7.149	C3 Delta	4.400	PZ Gamma	-9.171
3	F8 Beta	5.185	T4 Beta	-6.228	FZ Delta	4.208	P4 Gamma	-9.022
4	F8 Gamma	4.609	C3 Alpha	-4.729	O1 Delta	4.040	T4 Beta	-8.632
5	FZ Delta	-4.436	O1 Delta	4.492	T4 Gamma	-3.524	CZ Gamma	-8.500
6	F3 Delta	-4.337	T4 Alpha	-4.252	T5 Delta	3.240	P3 Gamma	-8.265
7	T4 Theta	4.204	F4 Beta	-4.126	T4 Beta	-3.147	PZ Beta	-8.028
8	T4 Alpha	4.153	T3 Alpha	-3.931	T6 Delta	3.146	C4 Gamma	-7.455
9	F8 Alpha	4.116	FZ Gamma	-3.525	FP1 Gamma	2.754	O1 Gamma	-7.393
10	F8 Theta	3.865	FZ Beta	-3.352	FP1 Beta	2.681	P3 Beta	-7.081

Table A13. Feature rank according to t-test statistic for 5-second windowing method for all trials for Subject E.

	E11B		E12C		E13F		E21A		E22B	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	P4 Delta	-6.691	FP1 Delta	-5.731	T3 Gamma	-9.489	T3 Gamma	6.558	T4 Delta	-8.208
2	O2 Delta	-5.341	FP2 Delta	-5.068	F3 Gamma	-8.947	T4 Gamma	6.014	PZ Delta	-6.686
3	F8 Delta	-4.971	T4 Gamma	-4.751	C3 Gamma	-8.915	T4 Delta	6.006	T6 Delta	-5.620
4	O1 Theta	4.759	F7 Delta	-4.349	C3 Beta	-8.771	F8 Delta	5.792	P3 Delta	-5.290
5	T3 Delta	-4.717	F4 Delta	-3.960	T3 Beta	-8.317	T6 Delta	5.661	C4 Alpha	5.212
6	PZ Theta	4.328	T4 Beta	-3.498	F7 Beta	-8.207	T3 Beta	4.980	T5 Delta	-5.135
7	PZ Delta	-4.324	C4 Delta	-3.385	F7 Gamma	-8.105	F7 Gamma	-4.867	O1 Beta	4.891
8	P4 Theta	4.266	C3 Alpha	-3.331	F3 Beta	-7.091	F7 Beta	-4.327	F8 Delta	-4.606
9	C4 Theta	4.257	C4 Gamma	-3.095	T3 Alpha	-6.205	O2 Theta	4.298	O1 Gamma	4.462
10	O2 Theta	4.154	O2 Delta	3.007	P4 Delta	-6.109	F4 Delta	4.187	C4 Delta	-4.272

	E23C		E32B		E33C		E41B		E42A	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	F7 Delta	-5.863	O2 Theta	4.000	F7 Gamma	10.977	T3 Gamma	11.216	T3 Beta	15.107
2	FZ Alpha	-4.945	F7 Gamma	3.752	F8 Gamma	10.724	T3 Beta	10.995	T3 Gamma	13.336
3	F7 Gamma	-4.495	CZ Theta	3.269	C3 Gamma	10.039	O1 Beta	6.822	T5 Gamma	12.275
4	O1 Gamma	4.432	PZ Theta	3.110	F3 Gamma	9.303	O2 Gamma	6.637	T5 Beta	11.367
5	FP1 Beta	-4.247	F7 Beta	3.058	F7 Beta	9.079	O2 Beta	6.484	T4 Gamma	9.000
6	T3 Gamma	-4.213	C4 Delta	-2.968	FZ Gamma	8.364	T5 Beta	6.365	P3 Gamma	8.971
7	F3 Alpha	-4.207	F3 Gamma	2.963	F8 Beta	8.338	T5 Gamma	5.686	T4 Beta	8.885
8	FP1 Gamma	-4.185	O1 Gamma	2.941	FP1 Gamma	8.073	O2 Delta	-4.897	PZ Gamma	8.429
9	F4 Alpha	-4.162	C3 Delta	-2.851	T3 Gamma	8.059	FP2 Delta	4.474	O1 Gamma	7.737
10	O2 Theta	4.153	O2 Gamma	2.780	FP2 Gamma	8.017	FP1 Delta	4.287	O2 Gamma	6.976

	E43E		E51C		E52F		E53D	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T4 Beta	14.608	C3 Delta	-10.343	T4 Gamma	9.361	F8 Gamma	-6.800
2	T4 Gamma	13.938	T3 Delta	-7.747	O1 Gamma	9.085	O1 Gamma	6.727
3	T5 Beta	13.242	T4 Delta	-7.376	T4 Beta	8.139	T3 Beta	6.272
4	T5 Gamma	12.228	T6 Delta	-6.711	O2 Delta	-7.278	F7 Gamma	-6.200
5	T6 Beta	11.674	CZ Delta	-6.489	PZ Delta	-7.192	T3 Gamma	6.136
6	T6 Gamma	11.110	F3 Alpha	-5.602	T4 Delta	-6.873	F8 Beta	-5.607
7	O1 Beta	9.689	CZ Beta	-4.774	O1 Beta	6.817	F4 Gamma	-5.154
8	O1 Gamma	9.555	P3 Delta	-4.638	F3 Gamma	-6.786	C3 Gamma	-5.123
9	T3 Gamma	9.347	FP1 Alpha	-4.591	C4 Alpha	6.580	F7 Beta	-5.085
10	T3 Beta	9.155	P4 Delta	-4.428	F8 Delta	-6.562	O2 Gamma	4.936

Table A14. Feature rank according to t-test statistic for 5-second windowing method for all trials for Subject F.

Rank	F12C		F13F		F21E		F22F		F23D	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	F7 Delta	11.112	O1 Alpha	10.539	O2 Gamma	10.532	O2 Beta	8.694	F7 Gamma	-8.782
2	F4 Delta	6.716	PZ Beta	10.521	O2 Beta	10.119	O2 Alpha	8.030	F7 Beta	-8.324
3	T6 Delta	5.524	P4 Beta	10.076	O2 Alpha	7.475	O2 Gamma	7.492	T6 Delta	-7.349
4	F7 Theta	5.433	T6 Beta	9.927	O1 Gamma	5.596	F3 Delta	-6.825	F7 Alpha	-5.702
5	F3 Delta	5.409	O2 Alpha	9.667	O1 Beta	5.351	F4 Alpha	6.764	C4 Alpha	5.432
6	O2 Gamma	4.968	T6 Gamma	9.636	P4 Gamma	5.166	F7 Beta	-6.726	F3 Beta	-5.248
7	PZ Beta	4.906	O2 Beta	9.415	T6 Gamma	5.124	CZ Alpha	6.589	O2 Alpha	5.111
8	O2 Beta	4.605	PZ Gamma	9.178	O1 Alpha	4.417	C4 Alpha	6.111	FP1 Delta	-5.043
9	P4 Gamma	4.569	O1 Beta	9.043	F7 Beta	-4.152	F3 Gamma	-5.827	T5 Delta	-5.030
10	O2 Alpha	4.554	P4 Gamma	8.971	C4 Alpha	4.002	PZ Delta	-5.507	F3 Gamma	-4.974

Rank	F31B		F32A		F33E		F41C		F42F	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	O1 Beta	7.330	T3 Beta	-12.354	O1 Beta	-7.855	O2 Delta	10.145	FP1 Beta	18.133
2	O1 Gamma	6.848	T3 Gamma	-11.536	O1 Gamma	-7.394	T4 Delta	10.139	FP2 Beta	18.011
3	T3 Gamma	-5.813	F7 Beta	-10.333	T3 Gamma	-7.393	PZ Delta	9.898	FP2 Gamma	17.123
4	T3 Beta	-5.349	C3 Beta	-10.006	T3 Beta	-7.098	C4 Delta	9.327	FP1 Gamma	15.857
5	T3 Delta	-4.843	C3 Gamma	-9.806	O1 Alpha	-6.431	CZ Delta	8.086	T4 Gamma	-10.353
6	O1 Alpha	4.834	F3 Beta	-9.317	O2 Beta	-5.259	O2 Gamma	7.970	C3 Gamma	-10.114
7	O2 Beta	4.679	F3 Gamma	-8.577	O1 Delta	-5.145	O1 Delta	7.734	C4 Gamma	-9.641
8	C3 Beta	-4.386	T4 Gamma	-8.394	O2 Gamma	-4.982	P3 Delta	7.733	T4 Beta	-9.615
9	O2 Gamma	4.347	F7 Gamma	-8.121	T5 Gamma	-4.920	F8 Delta	7.691	F8 Gamma	-8.553
10	F7 Gamma	-3.952	T4 Beta	-7.958	F4 Delta	-4.898	T3 Delta	6.884	FP2 Alpha	8.448

Rank	F43D		F51B		F52C		F53F	
	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T3 Beta	4.423	T3 Gamma	-6.134	FP2 Beta	10.428	T6 Gamma	9.436
2	FP2 Delta	-4.147	T3 Beta	-5.416	T3 Delta	-8.535	O2 Beta	9.323
3	T3 Gamma	3.540	C3 Delta	4.998	C4 Delta	-8.407	T6 Beta	8.832
4	F3 Delta	-3.485	T4 Beta	-4.601	T4 Delta	-8.326	O2 Gamma	8.132
5	T3 Alpha	3.267	O2 Gamma	4.419	PZ Delta	-7.958	O1 Beta	7.887
6	F8 Delta	-3.107	C3 Gamma	-4.319	F4 Delta	-7.385	P4 Gamma	7.563
7	FP1 Gamma	3.104	F4 Delta	4.102	T5 Delta	-7.383	P4 Beta	7.420
8	C3 Gamma	2.672	T4 Gamma	-3.997	FP2 Gamma	7.373	P3 Beta	7.056
9	O2 Theta	-2.622	O1 Alpha	3.754	FP1 Beta	7.209	PZ Beta	7.045
10	T3 Delta	-2.616	CZ Delta	3.586	P4 Delta	-6.988	T4 Gamma	7.004

Table A15. Feature rank according to t-test statistic for 5-second windowing method for all trials for Subject G.

	G11E		G12F		G13D		G21B		G22A	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T5 Gamma	15.086	T5 Beta	18.716	FP2 Beta	-12.113	T4 Delta	-5.897	FP2 Beta	-9.080
2	T5 Beta	14.645	T5 Gamma	17.446	T4 Gamma	-11.712	T5 Gamma	5.548	P4 Delta	-8.052
3	FP2 Beta	-13.393	T6 Beta	17.392	FP2 Gamma	-10.202	FP2 Gamma	-5.116	FP2 Gamma	-6.219
4	T6 Gamma	11.105	T6 Gamma	17.000	T3 Gamma	-8.313	T6 Gamma	4.763	T6 Delta	-5.788
5	FP2 Gamma	-9.933	T4 Beta	12.761	T4 Beta	-8.118	O1 Theta	4.350	T3 Gamma	-5.597
6	FP1 Beta	-9.528	T4 Gamma	11.915	T3 Beta	-7.297	CZ Theta	4.219	T4 Delta	-5.493
7	T6 Beta	9.091	O2 Gamma	11.506	FP1 Gamma	-6.443	T5 Beta	4.199	T3 Beta	-5.101
8	FP1 Gamma	-8.325	F8 Gamma	-11.317	C3 Gamma	-5.852	CZ Beta	-4.083	F7 Gamma	4.615
9	T3 Gamma	7.197	P4 Gamma	11.192	CZ Beta	-5.827	P4 Delta	-3.991	F7 Beta	3.966
10	T3 Beta	5.052	O1 Gamma	10.823	C3 Beta	-5.648	C3 Gamma	-3.695	FZ Theta	3.867

	G23E		G31C		G32F		G33D		G41B	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T4 Delta	-8.312	FP2 Beta	-20.704	O2 Delta	-7.702	T5 Delta	-6.344	T6 Gamma	12.669
2	PZ Delta	-6.513	FP2 Gamma	-15.824	FP1 Delta	-7.480	F8 Delta	6.080	T5 Gamma	12.182
3	CZ Delta	-6.100	T3 Gamma	-10.902	T5 Gamma	7.321	C4 Theta	4.800	F8 Beta	-10.405
4	F8 Delta	-5.265	T3 Beta	-9.831	T6 Gamma	7.309	C3 Theta	4.371	T6 Beta	10.149
5	O1 Delta	-4.292	T4 Gamma	-9.577	T5 Delta	-7.218	C4 Beta	-3.960	T5 Beta	9.507
6	F4 Delta	-4.155	C3 Gamma	-9.347	P3 Delta	-6.995	F4 Theta	3.696	F8 Gamma	-9.115
7	T5 Gamma	4.001	T4 Beta	-8.096	T5 Beta	6.823	O2 Delta	-3.682	FP2 Beta	-8.311
8	C3 Theta	3.912	F4 Gamma	-7.356	T4 Gamma	6.606	O1 Theta	3.625	FP2 Gamma	-6.005
9	T3 Gamma	3.907	FP1 Gamma	-6.896	T4 Beta	6.577	FZ Theta	3.614	CZ Delta	-4.801
10	T6 Gamma	3.809	CZ Theta	6.799	PZ Delta	-5.857	FP2 Beta	-3.185	P4 Delta	-4.559

	G42C		G43F		G51A		G52B		G53C	
Rank	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value	Features	T-Test Value
1	T5 Gamma	8.491	FP2 Beta	-10.269	T4 Gamma	-6.138	P3 Delta	-6.262	O2 Gamma	-12.117
2	PZ Gamma	8.299	T6 Gamma	9.432	T3 Gamma	-5.346	FZ Delta	-5.859	F4 Gamma	-10.325
3	O2 Gamma	7.836	T6 Beta	8.597	FP1 Beta	-4.968	FP1 Delta	-5.246	F3 Gamma	-10.092
4	T6 Gamma	7.475	FP2 Gamma	-8.207	FP1 Gamma	-4.733	T3 Delta	-4.658	F7 Gamma	-9.619
5	T5 Beta	7.460	C3 Gamma	-7.849	C4 Gamma	-4.460	T4 Delta	-4.447	C4 Gamma	-9.110
6	O1 Gamma	7.319	F4 Gamma	-7.096	F4 Gamma	-4.064	PZ Delta	-4.378	F8 Gamma	-9.052
7	P4 Gamma	7.071	C4 Gamma	-6.561	F8 Delta	-3.775	FP2 Delta	-4.363	FZ Gamma	-8.834
8	FZ Gamma	6.931	CZ Theta	5.821	FP2 Beta	-3.660	C4 Delta	-3.833	P4 Gamma	-8.422
9	P3 Gamma	6.779	C4 Theta	5.318	F4 Delta	-3.654	C3 Delta	-3.566	P3 Gamma	-8.315
10	F7 Gamma	6.611	F7 Gamma	-4.824	O2 Gamma	3.630	F7 Gamma	3.563	C3 Gamma	-7.757

Table A16. Feature rank according to t-test statistic for 5-second windowing method for all trials for Subject H.

Rank	H11B Features	H11B T-Test Value	H12A Features	H12A T-Test Value	H13E Features	H13E T-Test Value	H21C Features	H21C T-Test Value	H22F Features	H22F T-Test Value
1	FP1 Gamma	6.741	O1 Gamma	6.777	O1 Gamma	13.435	FP1 Beta	-13.540	FP1 Beta	12.544
2	FP1 Beta	6.484	C4 Alpha	-6.070	O1 Beta	12.046	FP2 Beta	-11.896	FP1 Gamma	10.025
3	F7 Delta	-5.556	P4 Alpha	-6.025	O2 Beta	11.473	FP2 Gamma	-10.244	FP2 Beta	9.550
4	FP2 Beta	5.263	C4 Beta	-5.687	O2 Gamma	10.145	FP1 Gamma	-10.031	FP2 Gamma	7.675
5	FP1 Alpha	4.586	O1 Beta	4.794	FP2 Beta	7.439	O1 Gamma	8.130	O1 Delta	-6.439
6	P3 Beta	-4.522	F4 Beta	-4.171	FP1 Beta	7.197	C4 Alpha	-7.476	C4 Alpha	6.348
7	FP2 Gamma	4.299	PZ Alpha	-3.978	FP2 Gamma	6.658	C4 Delta	6.850	P3 Delta	-6.256
8	F8 Gamma	3.823	T5 Delta	3.939	FP1 Gamma	6.466	F8 Beta	-6.603	O2 Beta	5.978
9	C3 Beta	-3.806	T4 Alpha	-3.926	FP1 Alpha	5.910	PZ Delta	6.146	O2 Gamma	5.562
10	CZ Beta	-3.396	F8 Beta	-3.708	T5 Gamma	5.882	C4 Beta	-6.011	T6 Delta	-4.783

Rank	H23D Features	H23D T-Test Value	H31B Features	H31B T-Test Value	H32C Features	H32C T-Test Value	H33F Features	H33F T-Test Value	H41A Features	H41A T-Test Value
1	F4 Delta	-6.277	F4 Delta	-7.046	T6 Delta	7.516	F3 Delta	4.446	O1 Beta	6.284
2	F3 Delta	-4.705	T6 Delta	-6.579	FP2 Delta	4.931	T3 Gamma	-4.385	O1 Gamma	6.113
3	CZ Delta	-3.906	F8 Delta	-6.511	FP1 Delta	4.490	C3 Beta	-4.381	F8 Delta	5.840
4	FZ Delta	-3.382	T4 Delta	-6.350	O2 Delta	4.026	T3 Beta	-4.333	T5 Gamma	5.298
5	C3 Beta	-3.378	C4 Delta	-5.836	C3 Delta	3.521	CZ Beta	-4.307	O2 Beta	4.935
6	T4 Delta	-3.365	C3 Delta	-5.809	T4 Delta	3.520	T3 Alpha	-4.004	O2 Delta	4.840
7	O1 Alpha	-3.151	FZ Delta	-5.160	PZ Delta	3.185	C3 Gamma	-3.746	T6 Theta	4.656
8	CZ Beta	-3.082	CZ Alpha	-5.038	T3 Gamma	-3.134	C3 Alpha	-3.680	CZ Theta	4.274
9	F3 Beta	-2.946	P4 Alpha	-4.343	C4 Beta	-3.118	F3 Beta	-3.644	O1 Alpha	4.149
10	F8 Gamma	-2.939	T4 Alpha	-4.243	FP1 Beta	2.808	P3 Gamma	-3.317	O2 Theta	4.118

Rank	H42B Features	H42B T-Test Value	H43C Features	H43C T-Test Value	H51E Features	H51E T-Test Value	H52F Features	H52F T-Test Value	H53D Features	H53D T-Test Value
1	O1 Delta	6.519	O1 Beta	8.877	O1 Delta	-8.638	T6 Delta	-8.921	C3 Beta	-5.161
2	O2 Delta	6.424	O1 Gamma	8.029	T4 Delta	-7.364	F8 Delta	-8.319	T6 Delta	-4.455
3	PZ Delta	5.255	O2 Alpha	7.516	C3 Delta	-7.054	C4 Delta	-7.352	P3 Beta	-4.254
4	P3 Delta	5.142	O1 Delta	7.281	F8 Delta	-6.469	T4 Delta	-6.634	T4 Delta	-4.236
5	F7 Beta	-4.937	O2 Beta	6.258	T5 Delta	-5.659	F7 Delta	-5.619	CZ Beta	-4.081
6	FP1 Beta	4.667	O1 Alpha	5.851	T3 Delta	-5.601	P4 Delta	-5.467	O2 Delta	-3.909
7	F7 Alpha	-4.564	O2 Gamma	5.084	FP1 Beta	-4.921	C4 Beta	-5.356	FP1 Delta	-3.894
8	F7 Gamma	-4.432	P4 Delta	-5.048	FP1 Gamma	-4.747	C3 Beta	-5.014	C4 Beta	-3.608
9	FP2 Delta	4.315	O1 Theta	4.994	C4 Beta	-4.364	P3 Beta	-4.247	PZ Gamma	-3.581
10	C4 Delta	4.263	FZ Delta	4.975	P4 Delta	-4.254	T5 Beta	-4.202	F7 Delta	-3.414

Appendix D - Steps to Perform Classification of Workload by T-Test Values

1. Run MATLAB code that combines two of the trials for one day. Develop a threshold between the high workload and normal workload (ex. $\frac{H}{L}$ or $\frac{L}{H}$). Also, produce a ranking of the features from the two trials.
2. Run MATLAB code that uses data from one trial (the third trial not used in step 1). Analyze one ten second segment for one feature and determine whether it is high workload or normal workload based on the threshold determined from step 1.
3. Perform step 2 for the top ten ranked features obtained in step 1 (Table A17).

Table A17. This is the process to implement the t-test classification method.

Feature	Threshold Value	10 Second Segment (H or N dependent on threshold value)
F1	High if > 0.8 Low if <0.8	H
F2	High if <1.2 Low if >1.2	H
↓	↓	↓
F10	High if <2 Low if >2	N

4. The ten second segments that were determined as "high" are given the value "1 x a^{N-1}" where "N" is the rank of the feature and "a" is a weighted value between 0.5~0.9 (to be determined). For those segments that were determined as "normal" are given the value "-1 x a^{N-1}".
5. (still work on a particular segment of 10-second) Sum all of the weighted values for the top ten features. If that summed value is positive (or negative), then it is classified as High Workload (or Normal Workload). If this 10-second segment

is indeed High Workload (or Normal Workload), then the classification for this segment is Correct, otherwise, the classification for this segment is Incorrect.

6. The above process will be applied to each 10-second segment; each of them will either be Correct or Incorrect. The percentage of correct classification for trial #3 can then be determined (total # of correct)/(total # of correct + total # of incorrect)
7. Compare this percentage with the classification accuracies from the ANN.