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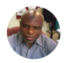
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# Evaluating the Effectiveness of Time-Domain Features for Motor Imagery Movements using SVM

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*Abstract*— **Motor imagery electroencephalogram signals are the only bio-signals that enable locked-in patients, who have lost control over every motor output, to communicate with and control their surroundings. Brain Machine Interface is collaboration between a human and machines, which translates brain waves to desired, understandable commands for a machine. Classification of motor imagery tasks for BMIs is the crucial part. Classification accuracy not only depends on how accurate and robust the classifier is; it is also about data. For well separated data, classifiers such as kernel SVM can handle classification and deliver acceptable results. If a feature provides large interclass difference for different classes, immunity to random noise and chaotic behavior of EEG signal is rationally conformed, which means the applied feature is suitable for classifying EEG signals. In this work, in order to have less computational complexity, time-domain algorithms are employed to motor imagery signals. Extracted features are: Mean Absolute Value, Maximum peak value, Simple Square Integral, Willison Amplitude, and Waveform Length. Support Vector Machine with polynomial kernel is applied for classification of four different classes of data. The obtained results show that these features have acceptable, distinct values for different these four motor imagery tasks. Maximum classification accuracy belongs to contribution of Willison amplitude as feature and SVM as classifier, with 95.1 percentages accuracy. Where, the lowest is the contribution of Waveform Length and SVM with 31.67 percentages classification accuracy.**

*Keywords- **Brain-machine Interface; Electroencephalogram; Feature extraction; Motor imagery; Support Vector Machine.***

## I. INTRODUCTION

It is more than a decade that Brain Machine Interface (BMI) has attracted notable attention. BMI is a direct link between brain and an external device aiming to control and manipulate surrounding or to be used as a communication medium. The idea of direct brain-computer communication was introduced by Vidal [1]. Brain waves and its electrical activities for this purpose are mainly recorded in form of electroencephalogram (EEG).

To design a system that translates brain waves to desired commands, EEG signal should be processed. Signal processing is known to be the core stage. EEG signals are one of the most challenging bio-signals in term of processing due to their nature. These signals are recognized by their poor signal to noise ratio and their high dimensionality. Moreover, their non-stationary characteristic and rapid variation over time and over sessions of recording poses as real difficulties. Different preprocessing and processing methods have been proposed and evaluated for improving the performance of devices dealing with EEG signals [2].

Preprocessing mostly consists of noise reduction and segmentation and processing is normally feature extraction and either classification or regression. However, in many researches, dimension reduction has been mentioned as a necessary part for more effective processing [3].

Feature extraction is to highlight the properties of signal, belong to one class, which makes it distinct from the other signal. Numbers of different algorithms in different dimensions, with variety of complexity, and efficiency have been suggested for motor imagery EEG signals. Existing features in literature cover time-domain, frequency-domain, and time-frequency domain [4-5-6].

After feature extraction, there could be another stage before classification, called feature selection or dimension reduction. If the numbers of features are too many to be processed, or in case, many of extracted features are redundant or not enough discriminant, dimension reduction and feature selection are the suggested solutions.

Many researches have been conducted with aim of developing algorithms, capable of selecting the most discriminant data, which help classifiers to have better performances and deliver more accurate results [7].

For motor imagery data, classifiers try to identify and differentiate different patterns of brain activities [8]. Hence, a BMI system can be considered as pattern recognition system partly [3][9-10]. Performance of pattern recognition systems directly depends on the effectiveness of the extracted feature and classification algorithms. Evidently, any improvements in these algorithms, greatly improve the performance of the BMI system.

The organization of this paper is as follows. In section II, methods and materials of this work including EEG signal acquisition, feature extraction, and classification are explained. Results and discussion are presented in section three. Finally, conclusion and future work are described in section four.

## II. Methods And Materials

### A. General Block Diagram

The procedure of this work is demonstrated as below.

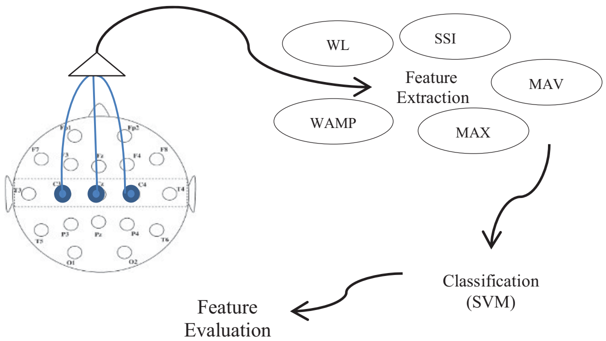


Figure1.The Whole Procedure

As portrayed in figure1, EEG signals were captured through three mono-polar recording channels, namely $C_3$, $C_4$, and $C_z$ according to International 10-20 system. Then, they were amplified and got prepared prior to processing. After that, five time-domain feature extraction methods were applied to the data separately, in order to highlight the different properties of the recorded EEG signals. Next, SVM algorithm was trained with the feature values to do the classification of four motor imagery movements. At last, the effectiveness of each feature was assessed based on the recognition accuracy ratio.

### B. EEG Acquisition

Data was collected from fifteen healthy, mentally sane people of which six of them are female. Subjects were in the range of 20 to 36 years old and all of them were university students. EEG signals were recorded via g.tec equipment, which is known to be one of the most accurate with high resolution devices available for recording bio-signals [11]. Subjects were asked to constantly think about the movement of their right hand, left hand, movement of their tongue in the right side and in their left side of their mouth. There was no actual movement during recording sessions and subjects merely did the thinking and imagining the related movements. In the recording environment only intense sound disturbances were avoided.

Three electrodes named as $C_3$, $C_4$, $C_z$ were located on the subject's scalp based on the international10-20 electrode placement system. These three electrodes cover the motor cortex area or the parietal lobe which is responsible for integrating sensory information from various parts of the body. Functions of the parietal lobe include information processing, movement, spatial orientation, speech, visual perception, recognition, perception of stimuli, pain and touch sensation and cognition. The figure below, figure 2, depicts the spectrum activity of one of the subjects during imagination of the movement of his tongue in the left side of his mouth.

Four different mental tasks of EEG data are acquired in this work. There has been no use of bio feedbacks to help subjects to perform these thinking tasks better; As it has been mentioned in several papers that biofeedback can be a remarkable aid for subjects to exhibit their performance better [12-13-14-15-16].

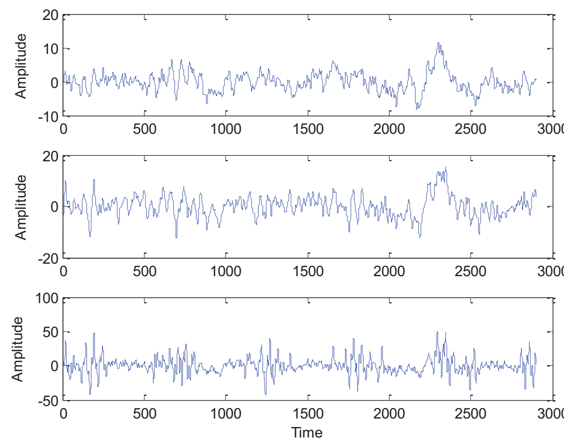


Figure3. EEG Signal recorded of Channel $C_3$ (up) Channel $C_4$ (middle) channel $C_z$ (down) while imagination of tongue movement to the left side.

Each record took one minute and imagination of each movement is recorded three times. Each acquired signal is divided to hundred segments. Segments do not have any overlap and each segment's length is two hundred fifty six milliseconds.

### C. Feature Extraction

Five afore mentioned time domain features were examined for EEG data in this work. Thereafter, Support Vector Machine (SVM) is applied to data to evaluate the efficiency of mentioned features.

From each segment one feature value is extracted. Rationally, from the whole signal hundred values as feature value are obtained. Each class has three related signals which are acquired from three mentioned channels, $C_3$, $C_4$, $C_z$, figure 3.

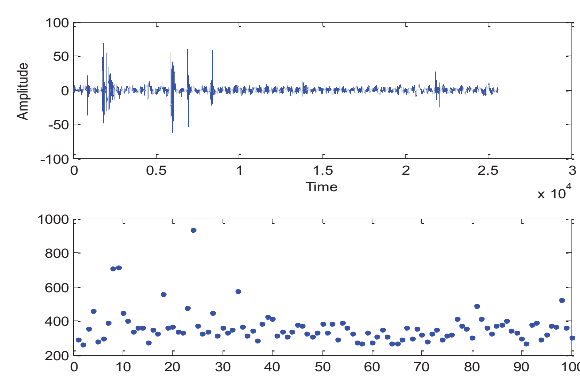


Figure 4.Channel $C_3$ signal of left tongue movement (up) and related MAV extracted feature (down)

Applied features are as follows:

*1) Mean Absolute Value*

Estimates the mean absolute value of each segment by adding the absolute value of all the values $x_i$ and dividing it by the length of the segment so that:

$$MAV_K = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (1)$$

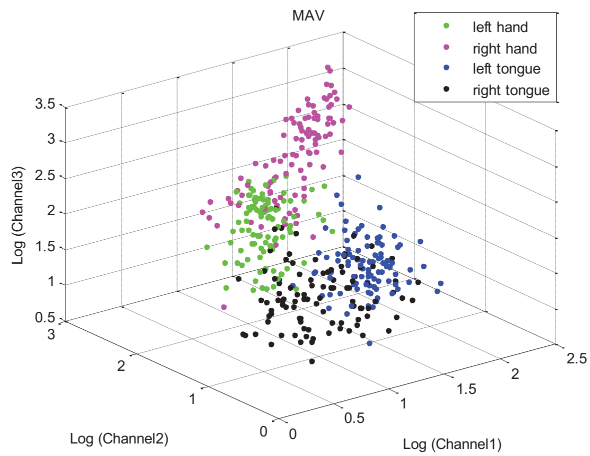


Figure5. Distribution of MAV in the feature space

*2) Maximum Value*

Maximum peak value refers to the maximum absolute value of each considered segment, that is:

$$x_k = \max|x_i| \quad (2)$$

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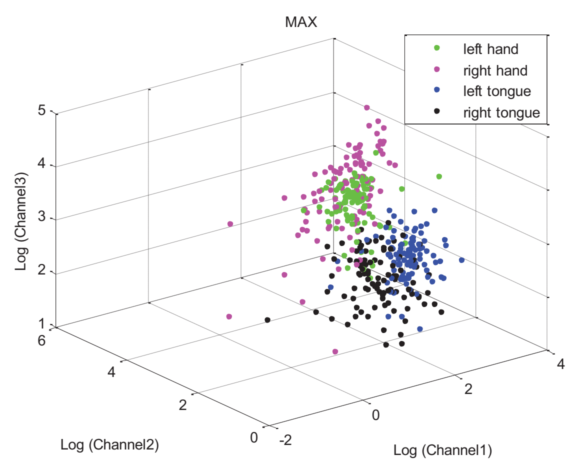


Figure6. Distribution of MAX in the feature space

*3) Simple Square Integral*

Simple Square Integral calculates the energy of EEG signal according to:

$$SSI_K = \sum_{i=0}^{N}(|x_i^2|) \quad (3)$$

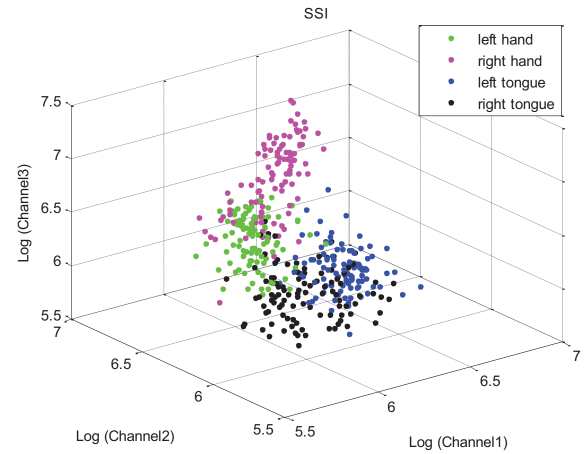


Figure7. Distribution of SSI in the feature space

*4) Willison Amplitude*

Willison Amplitude counts the number of times that absolute value of difference between EEG signal amplitude of two consecutive samples exceeds a predetermined threshold value.

$$WAMP_K = \sum_{i=1}^{N-1} f(|x_i - x_{i+1}|) \quad (4)$$

$$f(x) = \begin{cases} 1 & x > \varepsilon \\ 0 & otherwise \end{cases}$$

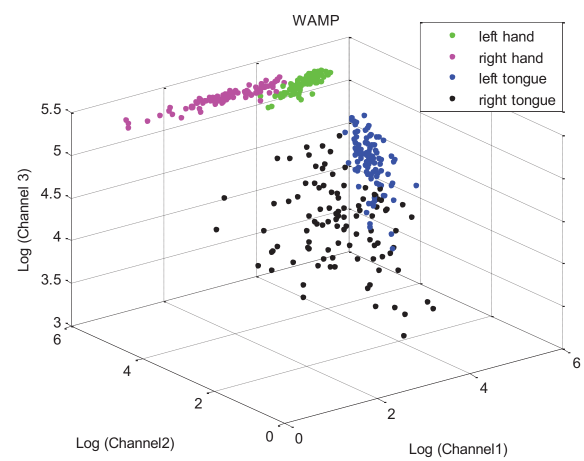


Figure8. Distribution of WAMP in the feature space

5) *Waveform length*

Waveform Length is the cumulative length of the waveform over the segment. It indicates a measure of waveform amplitude, frequency and duration all within a single parameter.

$$WL_k = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \quad (5)$$

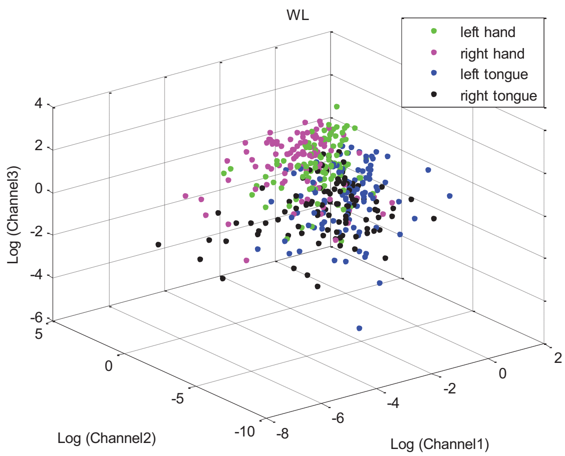


Figure9. Distribution of WL in the feature space

In all the mentioned equations, N: is the length of segment, k: is the current segment, $X_i$: is the current point of signal, and i: is the index of current point.

*D. Classification*

SVM uses discriminant hyperplanes to identify different classes. Selected hyperplanes are those that maximize the margins. With small increase of the classifier's complexity, linear SVM can make nonlinear decision boundaries by using "kernel trick". Generally, it is done by mapping the data to another space, mostly of much higher dimensionality, with help of kernel function. In our work, polynomial kernel function has been applied, as in many cases it had similar results with Gaussian SVM but for some feature-subject it carried out better results.

## III. RESULTS AND DISCUSION

Five time domain features have been tested for fifteen healthy subjects, including nine males and six females. EEG is a highly subject-specific signal, which is clear from the results shown in the Table1, as different features carried out different results for each subject. For example, the fourth feature has the best result for subject one. Although, it is not a satisfying feature for subject fourteen. More or less similar outcomes are obtained for the other subjects.

Table 1 shows the classification accuracy obtained from the classifier by applying mentioned features for each subject. In order to have more accurate results, each class of data was processed five times. Each time test data and training data were different sets of data compare to other times. Therefore, for each subject-method we obtained five different classification accuracy values. The value presented in table 1 for each subject-method is actually the mean value of these five times assessment. Mean value and standard deviation for each feature is also presented.

Small standard deviation indicates that regardless of feature ability in distinction, it could perform in a nearly constant manner for different EEG signals. On the contrary, a large standard deviation exhibits that feature is not robust and it face difficulties in dealing with chaotic behavior of EEG signal. Therefore, it is not reliable. Finally, the best feature is the one with the highest mean value and smallest standard deviation value.

Values with one star in Table 1 are the minimum classification accuracy and those with two stars are maximum accuracy obtained by the applied mentioned feature. Subject two tends to have some interesting results, as it could reach a quite high accuracy for WAMP; while it has the almost lowest for both MAV and SSI. Subject nine has two of highest accuracy obtained for MAV and SSI when it could deliver just reasonable classification accuracy for WAMP compare to the others WAMP results. A very interesting point to be mentioned here is that each method performed the best for one subject and the worst for another subject, which also shows that how unpredictable EEG signal is.

| SUBJECTS | MAV | MAX | SSI | WAMP | WL |
|---|---|---|---|---|---|
| Subject 1 | 64.99 | 34.83* | 63.99 | 86.62 | 31.67* |
| Subject 2 | 58.15* | 35.83 | 58.82 | 92.5 | 62.98 |
| Subject 3 | 89 | 69.83 | 89.15 | 81.4 | 60.32 |
| Subject 4 | 62.49 | 75.16** | 62.67 | 80.37 | 56.83 |
| Subject 5 | 74.34 | 63 | 73.6 | 95.1** | 56.7 |
| Subject 6 | 88.5 | 57.49 | 88.15 | 81.32 | 68.52** |
| Subject 7 | 74.68 | 38.16 | 75.15 | 90.7 | 48.3 |
| Subject 8 | 68.15 | 47.48 | 69.39 | 79.82 | 43.62 |
| Subject 9 | 92.64** | 57.84 | 90.67** | 80.86 | 48.49 |
| Subject 10 | 78.47 | 39.7 | 76.6 | 83.2 | 46.5 |
| Subject 11 | 74.49 | 46.64 | 72 | 86.15 | 49.15 |
| Subject 12 | 62.65 | 39.83 | 56.67* | 86.1 | 45.67 |
| Subject 13 | 67.32 | 46.47 | 66.16 | 78.33 | 39.67 |
| Subject 14 | 77.83 | 55.6 | 79.5 | 69.5* | 55.5 |
| Subject 15 | 61 | 46.16 | 59.7 | 80.82 | 53 |
| ***Mean*** | *68.66* | *46.94* | *66.80* | *80.18* | *48.6* |
| ***STD*** | *10.84* | *12.43* | *11.16* | *6.33* | *9.45* |
| ***Minimum*** | *58.15* | *34.83* | *56.67* | *69.5* | *31.67* |
| ***Maximum*** | *92.64* | *75.16* | *90.67* | *95.1* | *68.52* |

Table 1: classification accuracy, mean value and standard deviation of five features using SVM

## IV. Conclusion and Future Work

Feature extraction is to highlight important data and eliminate redundant data. It is a transformation of raw signal to feature vector. This transformation causes dimensionality reduction which speeds up classification process. Feature selection can even help more, as it chooses the best subset of original feature vector. The best collection of subsets is the one that minimize the probability of misclassification. In this work, SVM with fix parameters was applied for classification, in order to have a fair assessment to judge the effectiveness of features. Further work can be selecting two or more of these features and trying feature selection methods. Another possibility is to examine fusion classifier with these time-domain features, for the best possible result.

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