EEG Feature Selection for Thought Driven Robots using Evolutionary Algorithms

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***Abstract*— Machine control using electroencephalography (EEG) based brain computer interfaces (BCI) has been extensively researched in the past decade. However, research is often based on event bound methods such as motor imagery. Despite being useful in medical applications, even bound methods limit users' operational capability while performing BCI control. To alleviate the said limitation, we explore a robot control framework based on abstract thought. Abstract thought in this context is defined as conscious mental tasks that are not bound with any particular event or bodily movement. This paper presents an initial step in the framework, which is a methodology for optimal feature selection for abstract thought EEG data classification. The presented method contains 2 steps: 1) generational Genetic Algorithm (GA) based feature selection, and, 2) EEG data classification using selected features. The presented method was implemented on an EEG dataset acquired from a consumer grade EEG device. Abstract thought EEG data were collected for three actions pertaining to robot control; 1) "rest", 2) "move forward", and, 3) "turn left". The presented method was compared to EEG classification without any feature selection. Experimental results showed that the presented method outperformed the method without feature selection for all the tested classifiers with a 10% or higher improvement in classification accuracy.**

Keywords—Brain Computer Interfaces; Classification; Artificial Neural Networks; Genetic Algorithms

I. INTRODUCTION

Brain Computer Interfaces (BCI) are human-machine systems in which commands are interpreted solely from a user's measured brain activity [1], [2]. This activity can be collected in a myriad of ways, including measuring the electric field (EEG) or the magnetic field (MEG) of the brain, functional magnetic resonance imaging (fMRI), and functional near-field infrared spectroscopy (fNIRS) [3]. For practical research, EEG signals have been the preferred method of measurement due to low cost, ease of use, and minimal technical requirements [4], [5]. Furthermore, the extensive and ongoing research in EEG based BCI, as well as current technological developments, have yielded the development of low cost consumer grade EEG devices that can be used in the implementation of EEG-BCI systems [6], [7], [8]. One promising application of EEG-BCI is using EEG signals as mental commands for robot control [1], [3]. Robot control through EEG-BCI systems has been shown to be usable in different domains including medical applications, entertainment, manufacturing and security [2], [3], [10].

For EEG-BCI systems, researchers often base their models on methods that are bound to particular events [11], [2], [12]. Two popular examples are motor imagery and P300 Event Related Potential (ERP) [11], [12]. In motor imagery, the subject imagines raising their right/left hand without any corresponding physical movement [11], [2], and in P300 ERP a subject's mental reaction to various visual stimuli is measured [12]. Both these methods are very useful in various medical applications [3], [2], however they rely on EEG patterns that could easily be replicated during daily activity, which limits the operational capability of the user. For example, if left/right arm motor imagery is used to classify two tasks, any action requiring the subject to move their arms while using the EEG-BCI device could result in the system wrongly registering the resulting EEG pattern as a mental command. As such, these systems rely on the assumption that the EEG-BCI system will only be used while the user is not moving the body part outside of performing the tasks assigned to the device. In an effort to overcome this limitation, a method for robot control using conscious mental tasks that do not originate from bodily movement (i.e. motor imagery or ERP) or thought processes that might arise from daily activity (e.g. math problems, word/letter composition, etc.) is explored. These specific, recreate-able mental tasks are referred to as abstract thought in authors' work and in this paper.

As shown in previous work by the authors, abstract thought classification for BCI based robot control is a difficult task [1], [13], especially when using low cost consumer grade EEG devices for data acquisition. Consumer grade, commercial-off-the-shelf EEG devices are used in this work due to their ease of use and ease of acquisition. Though the consumer grade products are cheap and easy to use, they sacrifice the high accuracy of clinical models. Therefore, in order to make these commercial devices practically viable, highly robust and accurate algorithms are needed. Data preprocessing and feature selection are extremely crucial steps in EEG-BCI systems since EEG signals are shown to have low signal to noise ratio and to be high dimensional [4], [13]. This paper focuses on the step of feature selection.

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Feature selection is the process of finding the most discriminating properties of a data set, while keeping the total loss of information as low as possible [14]. Various methods of achieving this have been discussed in literature and it has been shown that feature selection can support the performance of EEG-BCI systems. In [15], [16] and [17] the authors use Genetic Algorithms for finding the optimal feature set from EEG data. Common Spatial Patterns were used as features in [18] and [19] in order to find the maximum variance in signals between multiple classes. In [20] and [21], extracted parameters via Autoregressive (AR) modeling are used as features. Other algorithms seen include Principal Component Analysis (PCA) [22], Neuro-fuzzy optimal feature selection [23], signal processing methods [24] and other evolutionary methods [25], [26]. In the interest of brevity, all the methods are not elaborated upon, more details can be found in [27].

The literature survey showed that feature selection has the capability of improving the performance of EEG-BCI applications. Therefore, this paper presents a methodology for selecting the set of optimal features from EEG data for improving the performance of abstract thought driven robot control. The presented methodology views the feature selection process as an optimization problem and uses the well documented and proven global optimization capabilities of Genetic Algorithms (GAs). GAs were used because it has been shown that GAs can be used successfully in feature selection methodologies in general and specifically in EEG-BCI applications as well [15]-[17]. During the evolutionary process of GAs, the strength of each candidate solution is calculated using a classification algorithm. Once the features were identified, final classification is carried out using a different classification algorithm. The presented method was implemented on an abstract thought EEG data set acquired using a consumer grade EEG device. The data set comprised of three thought patters pertaining to robot control: 1) "Rest", 2) "Move Forward", and, 3) "Turn Left". The results of the presented method were compared against EEG classification without feature classification. Several classifiers were tested for performing the final classification.

The rest of the paper is organized as follows. Section II provides an overview of the algorithms that are being used for the presented feature selection methodology. Section III elaborates the presented feature selection method. Section IV presents the specifics of implementation for the presented method. Section V presents the conducted experiments and the obtained experimental results and finally Section VI concludes the paper.

Genetic Algorithm

1: Initialize the population with random solutions (individuals)
2: Evaluate population (Calculate fitness of each individual)
3: Repeat until termination criterion is met
- **3.1:** Select parents (Selection)
- **3.2:** Recombination pairs of parents for new offspring (Crossover)
- **3.3:** Mutate offspring (Mutation)
- **3.4:** Evaluate new population

Fig. 1 Pseudo-code of the Genetic Algorithm (GA).

II. GENETIC ALGORITHMS

This section provides a brief introduction on Genetic Algorithms (GAs).

GAs are a type of evolutionary algorithms. Evolutionary algorithms are inspired by Darwin's theory of evolution [28]. GAs simulate biological evolution and it has been shown that they can be used for global optimization [28]. In order to encode the optimization problem in an evolutionary form, a set of candidate solutions to the problem are encoded in individuals. The set of individuals is called a population, or generation. For each generation, the strength of each individual in the population, called fitness, is calculated using a fitness function. The fitness is a measure of how well the candidate solution encoded by the individual performs with respect to the optimization problem. The GA attempts to maximize the fitness of individuals in the population.

The initial population is generated by randomly generating individuals. Then, using the individuals of the current generation, the next generation is generated by using evolutionary operators. The evolutionary operators are selection, mutation, crossover/recombination and elitism.

Selection is the process of choosing individuals from the current generation that will be used as parents to produce offspring for the next generation. Two main methods are used in literature for selection: tournament selection and roulette wheel selection. Once the parents are selected, crossover/recombination is used to generate new offspring. The most used crossover methods are one point, two point and uniform crossover. The crossover operation is important in the optimization process to avoid being stuck at local optima. The mutation operation is used to perform small random changes in the offspring to introduce random variations into the next population. Finally, the elitism operation makes one or more copies of the individual with the best fitness in the current population and moves them over to the next generation without any change. The purpose of elitism is to ensure that the best fitness of the next generation is at least as good as the best fitness of the current generation.

This evolutionary process is carried out for a predefined set of generations or until the best fitness of population reaches an equilibrium. The average fitness of the population and the best fitness of the population is kept track of throughout the process. Then, the best individual (the individual with highest fitness) in the final population is considered as the optimal solution for the problem. Fig. 1 shows the pseudocode of a GA.

III. Optimal Feature Selection for Abstract Thought Based Robot Control

This section elaborates the presented methodology of optimal feature selection for abstract thought based robot control. Fig. 2 shows the process of the presented method.

A. Data Acquisition

The first step of the presented method is data acquisition. EEG data for T number of actions are acquired from a non-invasive EEG measuring device with multiple sensors. Thus, the dimensionality (number of features) of the dataset is governed by the number of sensors that the device consists of. Therefore, a data record that is acquired at time *t,* from an EEG device with M number of sensors a data record with M features can be expressed as:

$$d_t = \{S_1^t, S_2^t, ..., S_M^t\} \tag{1}$$

where S_i^t is the value of the i^{th} sensor at time *t*.

Data acquired from the EEG device are the electrical activity of the brain. I.e., voltage value from each electrode is acquired at a given timestamp (S_i^t values in Eq. (1)). Features can be created from the electrical data by performing different preprocessing operations such as time-frequency analysis [13]. In the work presented in this paper, for the purpose of demonstrating the methodology of feature selection, features are considered to be the raw voltage values read in from the sensors. Therefore, using the presented methodology, the optimal set of sensors that results in the best classification accuracy is selected. It has to be noted that the presented methodology can be extended to select features of different types that are acquired from different signal processing techniques.

B. Encoding the Problem

For selecting the optimal subset of the M features, an optimization problem is solved. The global optimization capabilities of Genetic Algorithms (GA) are used for solving the optimization problem. As mentioned, each EEG data record that is acquired from a device with M sensors contains M number of features. Once the data are acquired, the data are encoded to be applied to the GA. As mentioned before, in GAs, candidate solutions are encoded as an individual and a population of individuals is created. For each generation a new population is created.

In the problem of finding the optimal subset for improved classification accuracy, a candidate solution is some subset of sensors. Therefore, a candidate solution for the problem can be expressed as,

$$f_s^n = \{f_1, f_2, ..., f_n\} \tag{2}$$

where f_s^n is a subset of features with n features where $n \le M$. For the initial generation of the GA, candidate solutions are randomly generated for different values of *n.* For the purpose of encoding the solutions with equal size, a fixed length binary string is used for representing a solution. The binary string

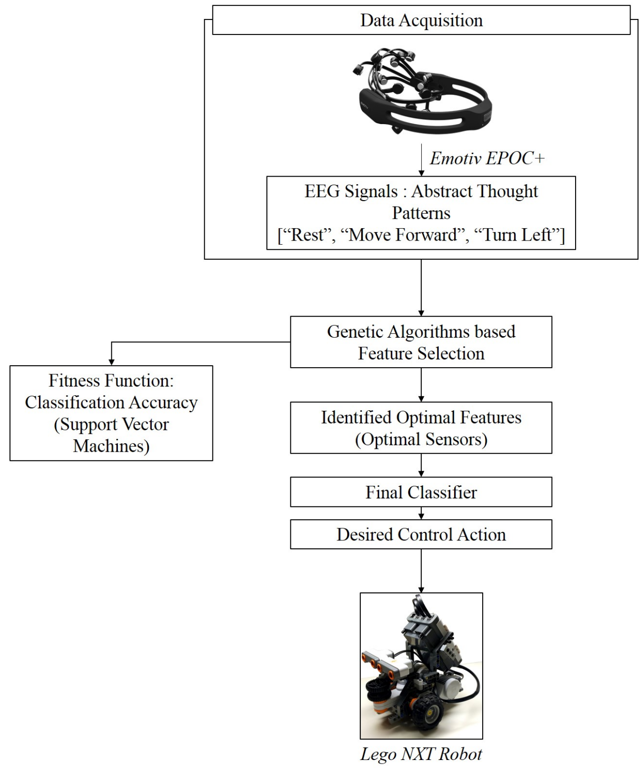

Fig. 2: Abstract thought driven robot control framework

consists of M bits, one bit assigned to each feature. If a feature is selected in a particular candidate solution, the bit pertaining to that feature will be set to "1" and "0" otherwise. For instance, where M is 10 and for a candidate solution where sensors 1, 2 and 5 are selected, the individual representing the candidate solution will be written as "1100100000". The initial population is created with P number of randomly created individuals.

C. Fitness Calculation

As mentioned in Section II, in a genetic algorithm the "goodness" of each individual is evaluated for each generation. For each generation, each individual is evaluated to acquire the measure of goodness, or the fitness. In the presented problem of finding optimal features for improved classification, the fitness of an individual should be related to the classification accuracy that can be achieved with the selected features. Therefore, in order to evaluate an individual, each individual, the EEG data classification process is carried out to obtain the classification accuracies. I.e. the chosen classification algorithm uses data only from the selected features as inputs to perform the classification. Therefore, the evolutionary process in the GA will attempt at maximizing the classification accuracy through the optimization process.

D. Evolutionary Process

Once the initial generation is created and fitness is calculated for all the individuals, the evolutionary process is carried out to solve the optimization problem. In the evolutionary process, a new generation is created at each iteration. With each iteration, it attempts to increase the average fitness of the population and the fitness of the best individual of the population. The individuals for the new generation is created by using the crossover/recombination operator. In crossover, two parents are combined to produce one or two children. As mentioned, the crossover operation can be perform in several methods. In this paper, uniform crossover is performed. In uniform crossover, the two parents are mixed to produce two children subject to a crossover rate. I.e. if the crossover rate is 50%, one child is created with 50% random bits from parent 1 and 50% random bits from parent 2. The unused bits from the two parents are used to make up the other child.

The parents are selected for recombination using the selection operation. There are several methods existing in literature to perform the selection. This paper utilizes the tournament selection methodology. In tournament selection, a predefined number of individuals, called the tournament size, are picked at random. The winner of the tournament is the individual with the highest fitness out of the picked individuals. Tournament selection process is carried out twice to select the two parents for one crossover operation. Once the new generation is populated with children, random mutations are introduced to the children subject to a mutation rate. This step is carried out to introduce random variations into the new generation. Mutation is implemented in this work by changing the values of random bits in randomly selected children. In addition to selection, crossover and mutation operations, the evolutionary process includes the elitism operation as well. The elitism operator retains a copy of the best individual of the current generation in the new generation. This operation is carried out to make sure that the best individual of the new generation is at least as good as the best individual of the previous generation.

As mentioned, the evolutionary process is carried out for a predefined number of iterations. Once the evolutionary process is complete, the best individual of the final generation represents the subset of features that provides best classification accuracy for the presented dataset in he given number of iterations. Therefore, the dimensions that are selected in the individual are the optimal features for classification.

Therefore, data from the selected features are sent as the inputs to the final classifier. Even though classification was performed for fitness classification, another classification process is carried out to acquire the final classification accuracy. Then, the EEG data classification is performed by the classifier using only the selected features. This step is included in the method to demonstrate that different classification processes can be carried out to improve classification accuracies after identifying the optimal dimensions. Theoretically, any classification algorithm can be used to perform the classification using the selected features.

IV. Implementation and Experimental Setup

This section elaborates the implementation specifics of the presented method. This section first presents the implementation of the data acquisition methodology and elaborates the data set. Then, the section details the specifics of implementing the method presented in Section III.

TABLE I. IMPLEMENTATION DETAILS OF THE GENETIC ALGORITHM

Algorithm	Generational Genetic Algorithm
Population size	100
Selection method	Tournament Selection with a Tournament size of 5
Elitism	2 Copies of the best individual retained
Crossover method	Uniform Crossover
Crossover rate	50%
Mutation method	Randomly swapping values in dimensions with a probability of 0.1
Mutation rate	20%

A. Data Acquisition

In this paper, EEG data were acquired through the use of an Emotiv EPOC+ Neuroheadset, a low cost, commercial-off-the-shelf, non-invasive, wireless EEG headset for BCI applications [6]. The EPOC+ was chosen due to its low cost, ease of use in a research setting, and because it has been shown to have excellent performance and reliability when compared with other high grade research level equipment [28], [30].

The Emotiv EPOC+ measures the users' brain activity via 14 EEG channel sensors, plus two CMS/DRL reference sensors, placed on the scalp. The sensors are positioned according to the international 10-20 system [30] (see Fig 3).

In order to provide guidance and visual stimulus, a simple Graphical User Interface (GUI) was created. The GUI was designed to be as simple as possible in order to minimize distractions for the subject, as well as reduce any unwanted ocular artifacts. The GUI cycled through words/phrases which prompted the subject to perform the desired mental task. Each subject was sat in front of a computer running the GUI and was asked to perform each task in the order that they appeared on the screen. Each task was recorded for 20 seconds each, and the task set was repeated 5 times per session for as many sessions as the user could complete.

For purposes of proof-of-concept and demonstration of the methodology, data acquired from a single user were used in the classification process. However, multiple data collection runs were carried out for the same individual. The used individual was a male graduate student. As mentioned before, data were acquired for three abstract thought patterns: "Rest", "Move forward", and "Turn left". The desired thought pattern was recorded when the data acquisition was performed. The complete dataset consisted of 50700 data records and 60% data were used for training and 40% for testing.

The data used in this study were the raw voltage values acquired from the 14 electrodes in the Emotiv EPOC+. I.e. the feature selection is carried out on the raw voltage values and no preprocessing techniques are applied on the data. No preprocessing is carried out because the emphasis in this work

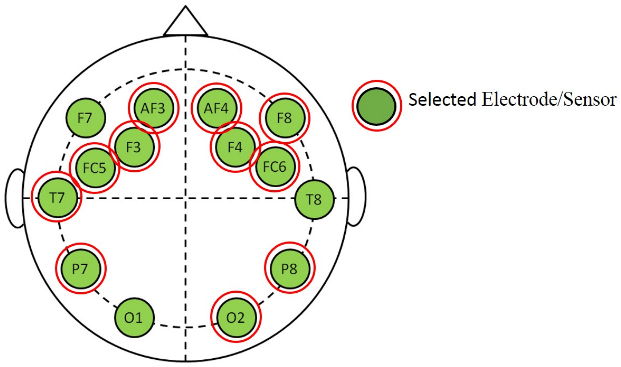

Fig. 3: Selected Electrodes by the Genetic Algorithms and their placement on the scalp according to the 10-20 international system

is on demonstrating the importance of feature selection. The input data are the voltage values and the output is the thought pattern label which is recorded at the time of data acquisition.

B. *Implementation of Optimal Feature Selection*

In implementing the method, data from 14 sensors were used. Therefoare, number of sensors M in eq. (1) was set to 14. Data were acquired for performing three actions pertaining to robot control. I.e. number T from Section III was set to three. Actions that users were instructed to perform were "Move forward", "Turn left" and "Rest". These actions were chosen so that it could be directly translated to robot control.

In order to perform the evolutionary feature selection, a generational GA was implemented. As mentioned in Section III, the GA was implemented with individuals encoding candidate solutions in a binary string. The length of the binary string was equal to the number of dimensions/ features in the data. Therefore, the length of the binary string was set to 14. A population was considered to have 100 individuals. The evolutionary operations of elitism, selection, mutation and crossover were implemented for the generational GA. More details about the GA implementation is given in Table I.

As mentioned in Section III, the fitness of each individual is evaluated at each iteration from the classification results. The fitness was calculated using the following function.

$$F_i = \left(\frac{Accuracy + \sum_{t=1}^{3} PR_t}{4} \right) \tag{3}$$

Where, F_i is the fitness of the i^{th} individual, *Accuracy* is the classification accuracy of the used classifier. PR_t is the Precision for the t^{th} action/class. Accuracy of the classifier can be calculated as,

$$Accuracy = \frac{Correctly\_classified\_records}{All\_testing\_records} \times 100\% \tag{4}$$

TABLE II. CLASSIFCATION RESULTS

	NB		ANN		SVM	
	GA based FS (%)	No FS (%)	GA based FS (%)	No FS (%)	GA based FS (%)	No FS (%)
Accuracy	**49.81**	36.78	**49.64**	38.40	**50.15**	38.94
Precision "Rest"	**48.92**	36.24	**49.21**	37.0	**49.79**	37.78
Precision "Forward"	**100**	**100**	**100**	**100**	**100**	**100**
Precision "Left"	**100**	**100**	**100**	**100**	**100**	**100**

TABLE III. SELECTED ELECTRODES FROM THE GA

Selected Electors
AF3, F3, FC5, T7, P7, O2, P8, FC6, F4, F8, AF4

Precision (PR) for a class (Class A) is the probability of a instance being classified correctly as Class A, given that it is classified as Class A. PR was included in the fitness function to prevent the classification from favoring a more prominent class to improve accuracy in a skewed dataset. For a particular class, PR can be calculated as follows.

$$PR_A = \frac{Correctly\_classified\_as\_A}{All\_records\_classified\_as\_A} \times 100\% \tag{5}$$

In order to keep in the same order of magnitude as the classification accuracy, the PRs were considered as a percentage in the fitness function given in eq. (5).

At each iteration, to calculate the fitness of each individual, the classification was performed using a Support Vector Machine (SVM). A Radial Basis Function (RBF) kernel with a penalty parameter 1.0 was used for the SVM. In order to extend the SVM to a multiclass problem, one-vs-one classification methodology was used.

In order to analyze the effectiveness of the presented methodology across classifiers, the final classifiers were used for performing the final classification was investigated using three classifiers as the final classifier. The classifiers selected were Artificial Neural Networks [31], SVMs and Naïve Bayes [32]. It has to be noted that, even though different classifiers were experimented for performing the final classification, SVMs were used for fitness calculation in the feature selection process.

V. Experimental Results

This section presents the experiments that were carried out and the results obtained from the experiments. The presented selection methodology was compared against EEG classification without any dimensionality selection.

As the first experiment, the presented GA based feature selection methodology was compared to a classification without any feature selection. The comparison was made with respect to classification accuracies and precision rates for all the three classes. In order to investigate the effectiveness of feature selection across classifiers, the experiment was carried out using three classifiers. However, the classifier used for obtaining the fitness of individuals in the GA training process was kept as SVM to keep the feature selection process identical across classifiers.

The purpose of the study was to investigate the effectiveness of using feature selection in performing the thought pattern classification for robot control. Therefore, data were not preprocessed before classification. When studying the effectiveness of the method, comparison between the accuracies between the presented method and the method feature selection is emphasized, rather than the accuracies themselves. I.e. The emphasis is not on the fact that accuracy values are usable for robot control or not, but on the fact whether the accuracies are improved by performing the GA based feature selection. Once the optimal feature set is identified, different methodologies can be carried out to improve classification accuracies. One such methodology was presented in authors' previous work [13].

Table II summarizes the results obtained in the experiment. It can be seen that the presented methodology for feature selection outperforms a methodology without feature selection. Further, the analysis across the three classifiers showed that the feature selection improves the classification results regardless of the classifier used. An improvement of 10.2% or higher was shown across all the classifiers. Further, it was shown that the SVM performed the best out of the three classifiers tested. Given more data from different users, this potentially can change. However, it was noticed that the results were heavily skewed towards the class "Rest". Even though the precision for "Left" and "Forward" were 100%, it can be seen that most of those records were misclassified as "Rest". Therefore, the accuracy for "Rest" and the overall accuracy is low.

When the data for "Rest" were acquired, the user wasn't instructed to think of any particular abstract thought. I.e. any inconsistent thought pattern that were thought of by the user at the "Rest" portion of the data collection was labeled as "Rest". Therefore, there is a high probability that data for "Rest" has no consistent pattern affiliated to it. Therefore, patterns similar to "left" and "Forward" can be included in "Rest". Therefore, when performing data acquisition, it is important to assign a consistent thought pattern to "Rest" as well.

Table III lists the electrodes that were selected by the GA as the sensors that yield the best classification accuracy for the given dataset of abstract thought patterns. Fig. 3 shows the electrode placement according to the international 10-20 system and distinguishes the placement of the selected sensors.

As mentioned before, the classification results are low even after the feature selection process. It has been shown in author's previous work that using abstract thought as opposed to methods like motor imagery is a difficult task. Therefore, the classification algorithms should be improved to improve the classification after the optimal feature selection methodology. As mentioned, previous work of authors for classification [13], can be used as one potential method to achieve better classification. In order to improve classification accuracies so that it is viable for robot control, other preprocessing techniques and augmentation of classification algorithms should be carried out alongside the feature selection.

VI. CONCLUSIONS

This paper presented an initial step of a EEG-BCI based robot control framework which uses abstract thought as opposed to even driven methods such as motor imagery. Feature selection was the presented initial step in this paper. The feature selection process was viewed as an optimization problem. The presented method utilized the global optimization capabilities of GAs to find the optimal features. The raw voltage values acquired from the electrodes were considered as input data. Therefore, optimal features were the optimal electrodes to use for the classification. The method was tested on an EEG dataset comprising of three thought patterns: "Rest", "Forward" and "Left". The presented feature selection methodology based classification was compared to classification without any feature selection. Three different classifiers were used for both methods. For every classifier, the presented method outperformed the method without feature selection with an improvement of 10% or higher. However, it was noticed that the classification accuracy for "Rest" was significantly lower than the other two actions. It should be noted that the presented methodology utilized the raw signals from the electrodes without any preprocessing. Hence all the classification accuracies are less than adequate. The purpose of the study was to investigate the usefulness of the feature selection methodology for the given application. As future work, different preprocessing techniques will be used for noise reduction and time-frequency analysis of signals. Then the presented feature selection methodology would be extended for identifying the optimal set of noise reduced features. For example, if time-frequency analysis is performed using methods such as Fast Fourier analysis or Wavelet transform, this feature selection methodology could be used to identify the optimal frequency bands or wavelet coefficients that result in the highest classification accuracy. Further, the method should be tested for data acquired from more users for multiple runs to acquire more generalized results.

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