EEG classification for BCI using genetic algorithm and k-fold cross validation

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Brain-Computer Interfaces (BCIs) have become popular in the last years and are used for several applications in human-computer interfaces including attention and workload measures as well as for direct control of objects. In this paper an electroencephalography (EEG) signal classification approach is applied for BCI. In this paper an approach based on genetic algorithm and k-fold cross validation is suggested for the EEG signal de-noising problem in motor imagery BCI. In order to evaluate the influence of the proposed feature extraction and feature selection approach on the accuracy of EEG signal classification five classification algorithms are adopted that are selected based on their performance in solving signal processing problems: Logistic Regression, K-neighbors, Support Vector Classifier (SVC) with Linear Regression, SVC with Radial Basis Function (RBF) Regression and Gaussian Training Classifier. The experimental results on Electrocorticography (ECoG) mental dataset for motor imagery BCI show that the classification accuracy can be improved by use of the suggested utilization of and k-fold cross validation at the feature extraction stage and genetic algorithm at the feature selection stage and the additional computational overhead is not significant.

Keywords – brain computer interface, electro-encephalography, feature extraction, feature selection, genetic algorithm, k-fold cross validation

BCI класификации, използващи генетичен алгоритъм и k-fold кръстосана валидация (Ивайло Е. Ивайлов). *Мозъчно-компютърните интерфейси стават все по-популярни през последните години. Изследователите използват тази технология за няколко типа приложения, включително приложения за привличане на внимание и натоварване, но също така и за директен контрол на обекти с помощта на BCI. В статията е представен подход за класификация на електроенцефалографски сигнали, базиран на използване на генетични алгоритми и k-кратна валидация за извличане и избор на признаци с цел подобряване на точността на класификацията. За да се оцени влиянието на предложеният подход върху точността на класификацията на ЕЕГ сигнали са използвани пет класификационни алгоритма, избрани поради ефективност им при обработка на сигнали: когистична регресия, класификация с K-съседи, класификация с опорни вектори и линейна регресия, класификация с опорни вектори и регресия с радиална базисна функция и класификатор на Гаусово обучение. Експерименталните резултати, получени за обучаващи електрокортикографски (ECoG) ментални данни показват, че точността на класификацията може да се подобри чрез използване на предложения подход с използване и k-кратно кръстосано валидиране на етапа на извличане на характеристика и генетичен алгоритъм на етапа на избор на характеристика, при това допълнителните изчислителни ресурси са несъществени спрямо подорението на точнсотта на класификацията.*

Lis of used abbreviations

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
BCI	Brain-Computer Interface
BPNN	Back-Propagation Neural Networks
BPSO	Binary Particle Swarm Optimization
BPSO-CSP	Binary Particle Swarm Optimization-Common Spatial Pattern
COP	Constraint Optimization Problems
CSP	Common Spatial Pattern
ECoG	Electrocorticography
EEG	Electroencephalography
FBCSP	Filter Bank Common Spatial Pattern
GA	Genetic Algorithm
GNMM	Genetic Neural Mathematic Method

ISAGA	Improved Simulated Annealing Genetic Algorithm
LDA	Latent Dirichlet Allocation
MCSP	Multi-channel Common Spatial Pattern
MLDW-PSO	Multi-stage Linearly-Decreasing Inertia Weight-Particle Swarm Optimization
MLP	Multilayer Perceptron
MLP-ABC	Multilayer Perceptron-Artificial Bee Colony
MOPSO	Multi-Objective Particle Swarm Optimization
PSD	Power Spectrum Density
PSO	Particle Swarm Optimization
RBF	Radial Basis Function
SVC	Support Vector Classifier
SVM	Support Vector Machine
WT	Wavelet Transform

Introduction

A brain-computer interface (BCI) can be characterized as a framework that interprets mind action examples of a human and translates them into messages or orders for an intuitive application in human-computer interfaces [1]. A human cerebrum action is estimated utilizing electro-encephalography (EEG) signals and motor imagery actions are used for different machine control operations. For example, an EEG based BCI can empower a human to move a cursor on a monitor by envisioning left or right hand movements. As they make computer control conceivable with no actual activity, EEG-based BCIs guarantee to alter numerous applications' zones and thus remarkably empower seriously motor-impaired humans and allow them to control assistive innovations, for example text input frameworks or wheelchairs [1]. They can be also utilized as recovery gadgets for stroke patients as new gaming input gadgets or used to plan versatile human-computer interfaces that can respond to the human psychological states.

To utilize a BCI, two stages are usually required: (1) an offline preparing stage during which the framework is aligned and (2) an operational online stage wherein the framework can perceive mind action designs and make an interpretation of them into machine commands. An online BCI framework involves a closed loop that start with the human providing a particular EEG signal (for example utilizing engine symbolism) and these EEG signals being estimated. At that point, EEG signals are normally preprocessed utilizing different spatial channels, outliers are removed from the signal and features are extracted. The extracted EEG features are then grouped prior to being converted into an order for a BCI application and before input is given to the humans to educate them if a particular mental order is perceived [1].

A metaheuristic frameworks are widely used approach for mathematical optimization that can be applied to discover, create, select and apply heuristics that may give an adequately decent answer for an optimization problem, particularly in cases of fragmented or uncertain data are available or when a calculation limit should be applied. Metaheuristics are successfully applied to hard optimization problems in cases the search space of the possible solutions doesn't allow exhaustive search to be applied. By utilizing guided heuristic search of the solution space the metaheuristics algorithms are very useful for combinatorial optimization problems [1].

Compared with other optimization techniques and approaches, metaheuristics do not ensure that a global optimal solution will be found but rather provide near-optimal solution for a limited computational time. Various metaheuristic algorithms employ different stochastic improvements and thus the solution provided is subject to randomness applied in the optimization procedure [1]. In combinatorial optimization problems through exploration of huge number of possible solutions metaheuristics can regularly discover good solution of the problem in hand with less computational efforts than improvement based approaches, iterative techniques, or basic heuristics. Metaheuristic-based approaches are usually classified into two main categories based on the number of solutions that are improved during the heuristic search: population based that utilize swarm intelligence approaches for heuristic improvement of many solutions in search of the optimal one, and trajectory-based algorithms that focus on improvement of a single solution by adopting heuristic based local search techniques. Genetic algorithms (GA) are one of the widely used metaheuristics for solving optimization problems that are based on the natural evolution process and exploit "survival of the fittest" principle.

Both feature selection and classification stages are very important and influence the results of the successful application of EEG signals in BCI [1]. Most brain-computer interfaces (BCIs) use the electroencephalogram (EEG) to measure brain activity. Alternatively, the electrocorticogram (ECoG) can be used, which provides better signal quality, but requires the implantation of subdural electrodes. Considering recent advances in signal processing, one might argue that employing modern spatial filters that can considerably improve signal quality and therefore the utility of EEG (as compared to ECoG), renders the ECoG unnecessary for BCIs [2]. In this paper an approach based on k-fold cross validation and genetic algorithm is suggested for the EEG signal de-noising problem in motor imagery BCI. In order to evaluate the influence of the proposed feature extraction and feature selection approach on the accuracy of EEG signal classification five classification algorithms are adopted that are selected based on their performance in solving signal and image processing problems.

Related work

Various researchers have used metaheuristics in order to improve the results of BCI applications. In [5] genetic algorithm is applied to find the optimum combination of feature extraction methods and classifiers in BCI applications. GA is used in [6] for automatic feature extraction in P300 signal detection problem applied for BCI. Integration of fuzzy classification with particle swarm optimization (PSO) is utilized in [7]. In [8] a novel technique for feature selection in BCI based on PSO and hybrid PSO is suggested. Heuristic algorithms are used in [9] to find a reasonable combination of weights and biases as well as of an appropriate architecture of multi-layered perceptron (MLP) neural networks utilized for BCI classification. A hybrid PSO-GA approach is used for feature selection in [10]. In an improved simulated annealing genetic algorithm (ISAGA) approach is used for feature selection of EEG signal. Incremental quantum PSO optimization algorithm is suggested in [12] for incremental classification of EEG data stream. GA is applied in [13] for feature reduction of EEG signals in mental task classification. Artificial Bee Colony (ABC) metaheuristics is used to select features from the BCI feature combination in [14] and the selected sub-features are classified by Support Vector Machine (SVM). In [15] binary PSO (BPSO) based channel selection of EEG signals is applied and its application to speller systems is presented. Common Spatial Pattern (CSP) and BPSO are used in combination to select the best frequency band because of their high performances in feature extraction of EEG signals and evolutional search respectively. In the BPSO-CSP algorithm each particle consists of 10 components, corresponding to one sub-band of the broad frequency band. Thereby each particle represents a combination of selected sub-bands and thus is a potential solution to the frequency band selection. Depending on the number solution representation one or several sub-bands may be selected by each particle. The covariance matrices of filtered EEG data are first calculated in each chosen sub-band and then aggregated. The CSP algorithm is then applied to the aggregated covariance matrix in order to extract spatial features. Finally, LDA classifier is used for the extracted features. In [17] genetic neural mathematic method (GNMM) method is applied to the EEG channel selection and classification problems. In [18] P300 signals are detected by employing Power Spectrum Density (PSD) for feature extraction and MLP-ABC scheme as a classifier. Artificial neural networks and PSO designed in a hybrid structure are used in [19] for diagnosis of epilepsy patients via EEG signals. Five metaheuristic algorithms are adopted to find the optimal wavelet transform (WT) parameters for the EEG signal denoising problem in [3]. In [20] a modified PSO with multi-stage linearly-decreasing inertia weight strategy (MLDW-PSO) based feature selection is proposed to select the most informative weighted features in an effective way. Swarm intelligence algorithms are suggested in [21] as a reliable method for the optimization of EEG signals for the improvement of the performance of the brain interfaces based on stable states visual events. A novel signal processing stage comprised of Filter Bank Common Spatial Pattern (FBCSP) for feature extraction, PSO for feature selection and LDA for classification is implemented as part of a BCI system in [22]. Walsh-Hadamard transform is applied for feature extraction and feature selection is based on BPSO in [23] and the feature classification uses MLP with back propagation training algorithm and Levenberg-Marquardt training algorithm. In [24] a novel application of a multi-objective particle swarm optimization (MOPSO) is suggested to solve the problem of effective channel selection for BCI systems. Multi-channel common spatial pattern (MCSP) is proposed to extract the features in [25] and two novel channel selection approaches are used to compromise between the optimal channels number and classification accuracy. A methodology for the automatic detection of normal, epilepsy and brain death from recorded EEG signals collected from clinic is proposed in [26]. Discrete WT is applied for feature extraction and error back propagation NN optimized by PSO is used for classification of neurological disorders. Simple BPNN has several drawbacks which mainly include large time duration during EEG signal classification that is removed by the utilization of PSO. A mental task classification algorithm using hybrid approach with PSO and recurrent neural network is suggested in [27]. Features are extracted from EEG signals that are recorded during five mental tasks, namely baseline–resting, mathematical multiplication, geometric figure rotation, letter composing and visual counting. The features are used by the neural network to classify different combinations of two mental tasks. The output of the BCI could be used with some translation schemes like Morse code or as two way movement control of a device as well as serve as communication or control channel for paralyzed patients with motor impairments. In [28] an optimization based on PSO, Ant Colony Optimization (ACO), GA and differential evolution algorithms is used in order to generate an optimum subset of features that improves the identification of features of EEG signals. Spectral Density of Power, Spectral Coherence methods and the computational cost between these algorithms are presented as measure of comparison.

EEG classification using genetic algorithm and k-fold cross-validation

In this paper an approach for BCI classification of EEG data using genetic algorithm and k-fold cross-validation is suggested. The general EEG data processing pipeline is shown on fig. 1. At the first stage feature extraction of the raw EEG data is based on k-fold cross validation. The second stage uses GA for feature selection and finally at the third stage five classification algorithms are used and experimentally evaluated: Logistic Regression, K-neighbors, Support Vector Classifier (SVC) with Linear Regression, SVC with Radial Basis Function (RBF) Regression and Gaussian Training Classifier. The classification algorithms are carefully selected based on their good performance in solving various signal and image processing problems [3].

K-fold cross validation for feature extraction

Cross-validation is a resampling method used to assess models on a restricted information test. The approach uses single parameter k referring to the number of groups that a given data sample is to be split into.

Cross-validation is primarily used in applied machine learning to estimate the accuracy of a machine learning model on unseen data. That is to use a limited sample in order to estimate how the model is expected to perform in general when used to make predictions on data not used during the training of the model. The popularity of k-fold cross validation is due to it is simple and generally results are less biased or less optimistic estimate of the model is given than other approaches as simple train/test split.

The general k-fold cross validation procedure is shown in Algorithm 1.

At the first step each observation in the data sample is assigned to an individual group and stays in that group for the duration of the procedure thus each sample is used in the hold out set 1 time and used to train the model k–1 times.

Algorithm 1 K-fold cross validation pseudo-code

```
1: Shuffle the dataset randomly
2: Split the dataset into k groups
3: for each unique group:
4:      Take the group as a hold out or test data set
5:      Take the remaining groups as a training data set
6:      Fit a model on the training set and evaluate it on
        the test set
7:      Retain the evaluation score and discard
        the model
8: Summarize the skill of the model using the sample
   of model evaluation scores
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In order to apply k-fold cross validation at the feature extraction stage of EEG classification the input EEG data signal is segmented into small overlapping regions and then randomly split into training and validation sets.

Genetic algorithm for feature selection

GA is a population based metaheuristics based on the metaphor of the natural phenomenon of Darwin evolution theory.

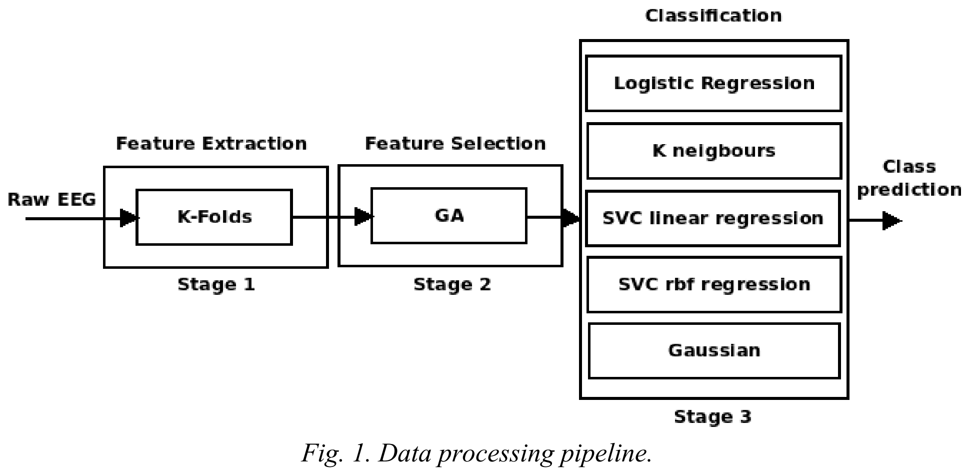

Fig. 1. Data processing pipeline.

GA procedure starts with a set of many solutions of the problem in hand with each solution being a vector of decision variables and each decision variable having a specific range of values. In the evolution context the set of solutions is equivalent to a population, each solution is analogous to a chromosome, each decision variable is analogous to a gene and each value of the decision variables is analogous to an allele [3].

In order to apply GA to constraint optimization problems (COP) both the objective function and the problem representation must be properly adjusted together with parameter tuning. GA typically has a set of parameters, including the size of the population P_{size}, the number of generations P_{no}, the crossover rate $P_{crossover}$ and the mutation rate $P_{mutation}$. In order to build an efficient and robust GA the parameter settings of each COP must be closely examined.

Algorithm 2 shows the high-level schematic pseudo-code of GA that starts with a population of candidate solutions X_{chrom}, where X_{chrom} is an augmented matrix of size $P_{size} \times N$ and N is the number of decision variables in each solution.

Algorithm 2 Genetic Algorithm pseudo-code

1: X_{chrom} ← Generate Initial Population
2: Evaluate(X_{chrom})
3: **while** (Stopping criterion is not met) **do**
4: $X_{chrom'}$ ← Selection(X_{chrom})
5: $X_{chrom''}$ ← Crossover($X_{chrom'}$)
6: $X_{chrom'''}$ ← Mutation($X_{chrom''}$)
7: Evaluate($X_{chrom'''}$)
8: X_{chrom} ← Replacement($X_{chrom'''} \cup X_{chrom}$)
9: **end while**

Initially, the population X_{chrom} is filled with random candidate solutions across the problem search space, that is:

$$X_{chrom} = X_{chrom^1}, X_{chrom^2}, \dots, X_{chrom^{Psize}} \quad (1)$$

Each candidate solution $X_{chrom'}$ is evaluated based on an objective function. The improvement loop in GA (Algorithm 1, line 3 to 9) repeats the following steps until a termination criterion is met: select the parents (new population $X_{chrom'}$) that will be used to generate the next population which will pairwise crossover with a probability of $P_{crossover}$ to come up with a new population $X_{chrom''}$. Afterward, each pairwise solution will be checked if it must be mutated with probability $P_{mutation}$ to come up with $X_{chrom'''}$. The new population will be reevaluated and the $X_{chrom'''}$ will be substituted with the population X_{chrom} based on a selection method. This procedure is followed to determine whether the offspring are fit or not. The GA procedure is repeated several times until an optimal solution is reached [3].

In order to apply GA at the feature selection stage of the EEG data classification, the data obtained after the feature extraction stage are represented as an individual with chromosomes that corresponds to the EEG data.

Experimental results

In order to experimentally evaluate the performance of the suggested approach for EEG data classification using 2-fold cross validation at the feature selection stage and genetic algorithm at the feature selection stage with five different classification algorithms EEG data for 2-class motor imagery classification is based on BCI competition III dataset I [29]. The dataset is provided by University of Tübingen, Germany, Institute of Medical Psychology and Behavioral Neurobiology, Max-Planck-Institute for Biological Cybernetics, Tübingen, Germany and Universität Bonn, Germany and comprises ECoG recordings from the same subject and with the same task but as two different sessions on two different days with about one week in between [30]. During the BCI experiment a subject had to perform imagined movements of either the left small finger or the tongue. The time series of the electrical brain activity is picked up during these trials using a 8x8 ECoG platinum electrode grid which is placed on the contralateral (right) motor cortex. All recordings are performed with a sampling rate of 1000 Hz and after amplification the recorded potentials are stored as microvolt values. Every trial consists of either an imagined tongue or an imagined finger movement and is recorded for 3 seconds duration. To avoid visually evoked potentials being reflected by the data the recording intervals start at 0.5 seconds after the visual cue has ended. A labeled training data set of ECoG recordings from the first session consists of two parts: (i) the brain activity during 278 trials stored in a 3D matrix named using the following format: [trials x electrode channels x samples of time series], and (ii) the labels of the 278 trials stored as a vector of –1/1 values.

For the experimental evaluation of the EEG mental data classification, the implementation of the data processing pipeline is based on Python 3.8.3 and the experiments are carried out using Jupyter notebook under Linux Fedora 33, 64 bit, kernel 5.9 on a machine equipped with Intel 12X Core I7-8750H, 2.20 GHZ, 16 GB RAM. Due to large size of the dataset the experimental evaluation is based on 25% of the data.

The accuracy of the classification is measured using several metrics: precision, recall, f1-score and support:

- Precision is calculated as ratio of system generated results that correctly predicted positive observations (True Positives) to the system's total predicted positive observations, both correct (True Positives) and incorrect (False Positives):

(2) $$Precision = \frac{TP}{TP+FP}$$

- Recall is calculated as ratio of system generated results that correctly predicted positive observations (True Positives) to all observations in the actual malignant class (Actual Positives):

(3) $$Recall = \frac{TP}{TP+FN}$$

- F1-score is the weighted average of the precision and the recall and therefore this score takes both False Positives and False Negatives into account to strike a balance between precision and recall:

(4) $$F1 - score = \frac{2*(Recall*Precision)}{Recall+Precision}$$

- Support is the number of samples of the true response that lie in the relevant class.
- Accuracy is the most intuitive performance measure calculated as ratio of the true classified observations over the total number of observations:

(5) $$Accuracy = \frac{TP+TN}{TP+FP+FN+TN}$$

- Macro average metrics is calculated for each label as unweighted mean.
- Weighted average is the average weighted by support of each label, i.e. the number of true instances for each label.

In order to apply GA at the feature selection stage of the EEG data classification the following parameters are used: population size 300, number of generations 1000, mutation rate 0.5.

The results of the classification accuracy for the EEG data classification with or without utilization of GA and 2-fold cross validation as feature detector and feature selector are given in Table 1 and on Fig. 3.

The execution time of the EEG classification using the five selected classifiers with and without utilization of GA and 2-fold cross validation is shown in Table 2.

The results from the experimental evaluation on the test set for the K-neighbors classifier are given in Table 3 while the results of the SVC RBF Regression classifier on the test dataset using GA and 2-fold cross validation give precision 0.72 and 0.60 for the two labels.

The comparison of the results show that the use of GA for feature selection improves the classification accuracy and the improvement is between 2 to 9 % for each of classification algorithms. The most significant influence of GA based feature selection is observed for the Logistic Regression, SVC Linear Regression and Gaussian Classification, but the overall classification accuracy of Gaussian Classification is quite low compared to the other classification algorithms. The best accuracy is achieved using SVC Linear Regression and Logistic Regression classifiers with GA based feature selection, 0.99 and 0.94 respectively.

On the other side, a comparison of the execution time of each of the classifiers is given in Table. 2. The results show that for all of the five classification techniques the use of GA and 2-fold cross validation requires more time, as can be expected, and the slowdown of the processing is between 1 and 22%, the smallest for K-neighbors classifier and the biggest for Logistic Regression. The fastest processing time is measured using SVC RBF Regression classifier and K-neighbors is the slowest classification technique used for EEG data classification. The best overall performance in terms of both accuracy and execution time is observed for SVC Linear Regression classifier.

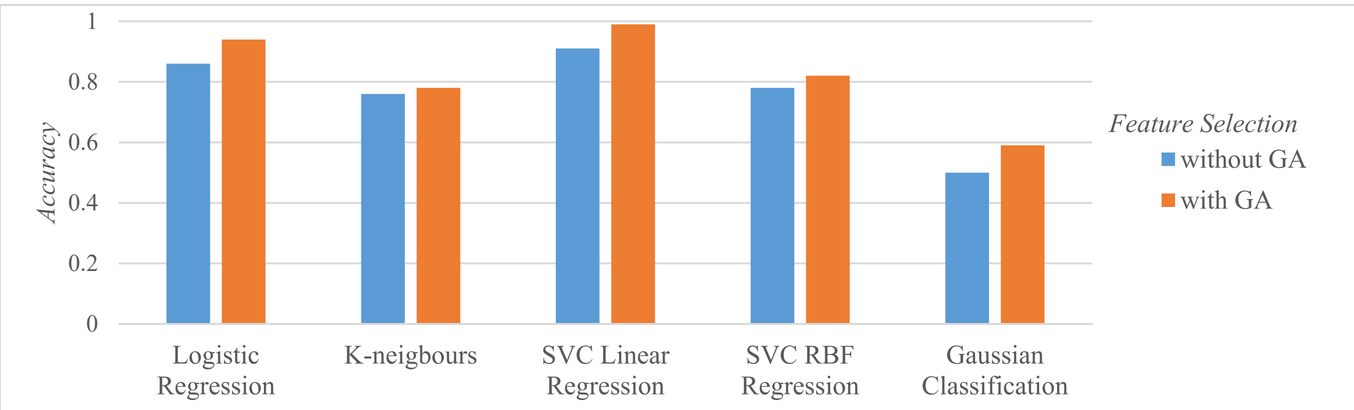

Fig. 3. Classification accuracy with and without feature selection using Genetic Algorithm.

Table 1

Accuracy of the classification with and without feature selection using Genetic Algorithm

Classifier	Training Accuracy	
	without GA	with GA
Logistic Regression	0.86	0.94
K-neighbours	0.76	0.78
SVC Linear Regression	0.91	0.99
SVC RBF Regression	0.78	0.82
Gaussian Classification	0.50	0.59

Table 2

Execution time of the EEG classification

Classifier	Execution time [ms]	
	without GA	with GA
Logistic Regression	51.4	66.1
K-neighbours	771	779
SVC Linear Regression	2.48	2.65
SVC RBF Regression	1.06	1.09
Gaussian Classification	14.1	16.4

Table 3

Accuracy metrics

	Precision	Recall	F1-score	Support
Label (–1)	0.69	0.61	0.65	134
Label (+1)	0.49	0.57	0.53	87
Accuracy			0.60	221
Macro avg	0.59	0.59	0.59	221
Weighted avg	0.61	0.60	0.60	221

Conclusion

In this paper an approach based on genetic algorithm and 2-fold cross validation is suggested for the EEG signal de-noising problem in motor imagery BCI. In order to evaluate the influence of the proposed feature extraction and feature selection approach on the accuracy of EEG signal classification five classification algorithms are experimentally evaluated: Logistic Regression, K-neighbors, Support Vector Classifier (SVC) with Linear Regression, SVC with Radial Basis Function (RBF) Regression and Gaussian Training Classifier. The experimental results show that the classification accuracy can be improved by use of the suggested utilization of 2-fold cross validation at the feature extraction stage and genetic algorithm at the feature selection stage and the additional computational overhead is not significant. EEG data processing based on 2-fold cross validation, genetic algorithm and SVC Linear Regression classifier provides best training and test accuracy improving the accuracy by 8% with only 6% overhead of the execution time.

As a future work more robust feature extraction approach can be also adopted to handle data de-noising in the EEG data processing pipeline for motor imagery BCI. Additionally, the suggested processing model can be also applied on different data sessions to assess its ability to generalize to other data.

Acknowledgements

The work presented in the paper is supported by research grant 202ПД0001-09 financed by the Research and Development Sector of TU-Sofia.

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Received on: 29.03.2021