Chapter 12
Comparison of Classification Methods for EEG Signals of Real and Imaginary Motion

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Abstract The classification of EEG signals provides an important element of brain-computer interface (BCI) applications, underlying an efficient interaction between a human and a computer application. The BCI applications can be especially useful for people with disabilities. Numerous experiments aim at recognition of motion intent of left or right hand being useful for locked-in-state or paralyzed subjects in controlling computer applications. The chapter presents an experimental study of several methods for real motion and motion intent classification (rest/upper/lower limbs motion, and rest/left/right hand motion). First, our approach to EEG recordings segmentation and feature extraction is presented. Then, 5 classifiers (Naïve Bayes, Decision Trees, Random Forest, Nearest-Neighbors NNge, Rough Set classifier) are trained and tested using examples from an open database. Feature subsets are selected for consecutive classification experiments, reducing the number of required EEG electrodes. Methods comparison and obtained results are presented, and a study of features feeding the classifiers is provided. Differences among participating subjects and accuracies for real and imaginary motion are discussed. It is shown that though classification accuracy varies from person to person, it could exceed 80% for some classifiers.

Keywords Motion intent classification · EEG signal analysis · Rough sets

12.1 Introduction

The classification of EEG signals is an important part of the brain-computer inter-face (BCI) application. It is required for the method to be highly accurate to maintain an efficient interaction between a human and a computer application [6, 15]. Applying a dedicated method of signal processing to EEG recordings allows for determining emotional states, mental conditions, and motion intents. Numerous experiments of imaginary motion recognition deal with unilateral, i.e. of left or right, hand motion. Such a classification is useful for locked-in-state or paralyzed subjects, thus it can be applied successfully to controlling computer applications [3, 11, 23–26, 31, 32, 52] or a wheelchair [7, 12] and communicating with locked-in patients and diagnosis of coma patients [8].

The motion intent classification can be performed in a synchronous or an asynchronous mode. The former method uses a visual cue, e.g. an icon on the screen flashing in timed intervals, and then verifies user's focus by means of the P300 potential induced in a reaction to this visual event [4, 5, 16, 33]. The latter approach is suited for self-paced interaction, but it requires a method of distinction between a resting and acting, in the latter case determining the type of the action [10, 40, 56]. The asynchronous approach is evaluated in our work, since the classification of left and right, and up and down motion intents and real motions is performed by various decision algorithms.

The main principle for detection and classification of imaginary motor activity in brain-computer interfaces is based on an observation that the real and imaginary motions involve similar neural activity of the brain [26]. It is indicated by an alpha wave signal power decrease in a motor cortex in a hemisphere contra-lateral to the movement side [25, 26, 31], usually registered by C_3 and C_4 channels [39, 43, 57]. It is related to a phenomena of event-related desynchronization (ERD) [20, 29, 58]. Such an activity can be detected and classified by various approaches.

Siuly et al. [42] employed a conjunction of an optimal allocation system and two-class Naïve Bayes classifier in the process of recognizing hand and foot movements. Data was partitioned in such a way that right hand movements were analyzed along with the right foot (first set) movements and left hand movements were analyzed also with right foot movements (second set). Left foot movements were not performed in the experiment. The global average accuracy over 10 folds, for the first and the second set, equalled to 96.36 and to 91.97%, respectively. The authors claimed to obtain the higher accuracy for the two-class Naïve Bayes classifier than for the Least Squares Support Vector Machine (LS-SVM), both cross-correlation (CC) and clustering technique (CT) based, examined in their earlier works [41, 59].

Schwarz et al. [38] aimed at developing BCI system that generates control signals for users with severe motor impairments, based on EEG signals processed using filter-bank common spatial patterns (fbCSP) and then classified with Random Forest which is a type of a random tree classifier, applied to experiments presented in their paper. In their experiments users were asked to perform right hand and feet motor imagination for 5 seconds according to the cue on the screen. For imagined right hand movement, each user was instructed to imagine sustained squeezing of a training ball. For motor imagery of both feet, the user was instructed to imagine repeated plantar flexion of both feet. The median accuracy of 81.4% over the feedback period (presenting information to the user about the motion intention) was achieved.

Kayikcioglu et al. [21] compared performance of k-NN , Multiple Layer Perceptron, which is a type of Artificial Neural Network tested herein, and SVM with RBF kernel. Training datasets were created based on one-channel EEG signal. The authors claim that the best accuracy was obtained for k-NN classifier but the presentation of the results is vague, thus not convincing.

Beside observing ERD occurrences, the motion intent classification is performed by: Linear Discriminant Analysis (LDA) [22, 31, 32, 58], k-means clustering and Principal Component Analysis (PCA) [48], or Regularised Fisher's Discriminant (RFD) [51]. The work presented in this chapter is inspired by previous results in applying Rough Set classifier of the real and imaginary motion activity over large database of 106 persons performing real and imaginary motion, resulting in accuracy exceeding 80%, and in some cases up to 100% [44, 45]. The main goal of this research is to determine the best method of signal classification, by applying selected classifiers, relatively simple and straightforward to use for practical applications. Another goal was to determine the impact of reducing the EEG signal representation on the accuracy: first by using a larger set of features (615), and then by limiting this amount of features (to 120 and to 50).

Despite the observed advancements in EEG classification there still remains a considerable group of users (15–30%) being "illiterate" in the Brain-Computer-Interfaces, thus unable to perform recognisable mental actions in a repeated manner. The exact reason is still unknown but the problem was formulated and studied [9, 53]. In this research there are subjects with relatively high and satisfactory results but the same methods yield poor results for other group of persons. The personal differences are discussed in Sect. 12.4.

The reminder of this chapter is structured as follows: Sect. 12.2 describes EEG signals preprocessing and feature extraction, Sect. 12.3 contains details of classifiers setup. Results are presented in Sects. 12.4, and 12.5 provides conclusions.

12.2 EEG Signal Parameterisation

EEG signals are parameterized in frequency bands associated experimentally with mental and physical conditions [55]. Following frequency ranges and their most popular interpretations are used: delta (2–4 Hz, consciousness and attention), theta (4–7 Hz, perceiving, remembering, navigation efforts) and alpha (8–15 Hz, thinking, focus, and attention), beta (conscious focus, memory, problem solving, information processing, 15–29 Hz), and gamma (learning, binding senses, critical thinking 30–59 Hz). Electrodes are positioned over crucial brain regions, and thus can be used for assessing activity of motor cortex, facilitating motion intent classification [1].

Recordings of EEG are polluted with various artifacts, originating from eye blinks, movement, and heartbeat. Dedicated methods were developed for detecting artifacts, filtering and improving signal quality. A Signal-Space Projection (SSP) [19, 50, 58], involving spatial decomposition of the EEG signals is used for determining contaminated samples. Such an artifact repeatedly originates from a given location, e.g. from eye muscles and is being recorded with distinct characteristics, amplitudes, and phases, thus the artifact pattern can be detected and filtered out. Signal quality improvements are also achieved by Independent Component Analysis (ICA) [19, 20, 50, 53].

The research approach presented in this chapter assumes an usage of Hilbert transform of the signal and of several parametrization methods based on envelope, power, and signal statistics, as well as a classification based on dedicated, carefully examined and trained classifiers. For those experiments a large EEG database was used: EEG Motor Movement/Imagery Dataset [14], collected with BCI2000 system [2, 37] and published by PhysioNet [14]. This database includes 106 persons and exceeds the amount of data collected by Authors themselves up to date, thus is more suitable for training and examining classification methods over a large population, facilitating also comparisons with research of others.

The dataset contains recordings of 4 tasks:

- A real movement of left-right hand,
- B real movement of upper-lower limbs,
- C imaginary movement of left-right hand,
- D imaginary movement of upper-lower limbs.

Sixty four electrodes were used located according to the 10–20 standard, with sampling rate 160 Sa/s, and timestamps denoting start and end of particular movement and one of 3 classes: rest, left/up, right/down. Among the available channels, only 21 were used, obtained from motor cortex: $FC_{Z,1,2,3,4,5,6}$, $C_{Z,1,2,3,4,5,6}$, $CP_{Z,1,2,3,4,5,6}$ (Fig. 12.1).

All 21 signals were processed in a similar manner, decomposed into the time-frequency domain (TF): delta (2–4 Hz), theta (4–7 Hz), alpha (8–15 Hz), beta (15–29 Hz), and gamma (30–59 Hz). Subsequently, each subband's envelope was obtained by Hilbert transform [27], reflecting activity in the given frequency band. This dataset was pre-processed employing the Brainstorm software, where segmentation and filtration of signals were performed [47]. Finally, 615 various features of envelopes were extracted. Authors of this chapter proposed a parametrization of envelopes of band-filtered signals. Consequently, 5 frequency subbands for each of 21 sensors, are parametrized as follows:

1. For a particular subband $j = \{delta, \ldots, gamma\}$ from a sensor $k = \{FC_1, \ldots, CP_6\}$, 5 activity features are extracted, reflecting the activity in the particular brain region: the sum of squared samples of the signal envelope (12.1), mean (12.2), variance (12.3), minimum (12.4), and maximum of signal envelope values (12.5),

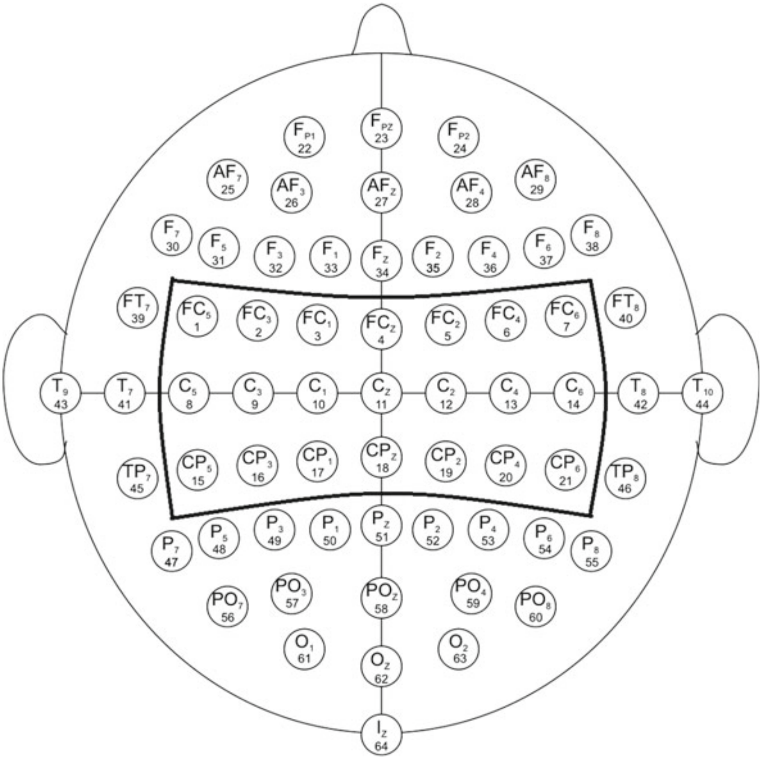

Fig. 12.1 A top view of a human head with electrodes in 10–20 setup, motor cortex channels in central region marked (*Source* [14])

2. For all 9 pairs of symmetrically positioned electrodes kL and kR (e.g. $kL = C_1$, and $kR = C_2$) the signal envelopes differences are calculated and summed up (12.6), to reflect asymmetry in hemispheres activity while performing unilateral motion:

$$SqSum_{j,k} = \sum_{i=1}^{N} \Big(e_{j,k}[i] \Big)^2, \tag{12.1}$$

$$Mean_{j,k} = \frac{1}{N} \sum_{i=1}^{N} \Big(e_{j,k}[i] \Big), \tag{12.2}$$

$$Var_{j,k} = \frac{1}{N} \sum_{i=1}^{N} \Big(e_{j,k}[i] - Mean_{j,k} \Big)^2, \tag{12.3}$$

$$Min_{j,k} = min(e_{j,k}[i]), \tag{12.4}$$

$$Max_{j,k} = max(e_{j,k}[i]), \tag{12.5}$$

$$SumDiff_{j,kL,kR} = \sum_{i=1}^{N} \Big(e_{j,kL}[i] - e_{j,kR}[i] \Big), \tag{12.6}$$

where, $e_{j,k}[i]$ is an envelope of the signal from particular subband j of electrode k and has length of N samples.

As a result there are 615 features extracted for every task. The result decision table includes also task number, person number and decision (T0, T1 or T2).

The multidimensional problem of classifying EEG signal is not straightforward, because personal biological and neurological features significantly influence values of registered signals and extracted features. In the following data classification (Sect. 12.3) every person is treated separately, thus for every task a new classifier is created with a different subset of useful and informative features.

EEG classification is hampered by personal biological and neurological differences, or other characteristics influencing EEG signal quality and features. Therefore each person is treated as individual classification case, and thus customized classifiers are created.

12.3 Data Classification Method

Data classification was performed in WEKA software package offering various data mining techniques [54], and in R programming environment [13] with RoughSets package [35].

All methods were applied in a 10 cross-validation runs, with a training and testing sets selected randomly in a 65/35 ratio split. These sets contain 1228 and 662 signals for a single person performing a particular task of 3 different action classes (rest, up/left motion, and down/right motion). The process is repeated for 106 persons, achieved average classification accuracy records are collected. In the described research three variants of features sets **P** were examined:

1. $\mathbf{P}_{615}$ with all 615 features.
2. $\mathbf{P}_{50}$ with features being the most frequently used in Rough Set classification rules from the first variant [44, 45]. Reducts from all iterations of given classification scenarios were analyzed for frequency of features and top 50 were used instead of 615 to repeat this experiment (Table 12.1). Other features appear in less than 3% of rules often matching only a single person, therefore are discarded to reduce overfitting. By this approach it is verified if a limited number of features is sufficient for accurate description of classes differences. Rough Set was used as a baseline, because of high accuracy achieved in previous experiments with this method [44, 45].
3. $\mathbf{P}_{C_3C_4}$ with 120 features obtained only from signals from electrodes C_3 and C_4, as these were reported by other research to be the most significant for motion

Table 12.1 Top 50 features for classification rules in Rough Set method. A number of rules including the feature is provided. The set is used for other classifier in this chapter, denoted as $\mathbf{P}_{50}$

Attribute	No. of appear.	Attribute	No. of appear.	Attribute	No. of appear.
Var_{theta,FC_Z}	420	Max_{gamma,C_3}	279	Var_{theta,FC_6}	253
Min_{delta,C_1}	409	Min_{delta,C_5}	277	Max_{beta,C_4}	252
Min_{delta,FC_5}	389	Sum_{theta,FC_3}	277	Max_{gamma,FC_2}	250
$Mean_{gamma,C_6}$	388	Min_{delta,FC_3}	276	Min_{delta,CP_4}	248
Sum_{alpha,CP_4}	378	Var_{gamma,C_6}	275	Min_{delta,CP_Z}	248
Min_{delta,FC_Z}	367	Min_{beta,C_1}	274	Max_{theta,FC_1}	246
$Mean_{delta,FC_5}$	340	Min_{delta,FC_2}	273	Sum_{beta,FC_2}	246
Min_{delta,C_4}	337	Sum_{beta,FC_4}	272	Max_{gamma,C_1}	245
Max_{beta,C_1}	327	Sum_{gamma,FC_5}	269	Sum_{alpha,CP_2}	244
Min_{delta,CP_5}	326	Min_{delta,C_3}	268	Sum_{gamma,C_4}	239
Sum_{delta,FC_6}	316	Var_{beta,C_Z}	268	Max_{gamma,FC_5}	238
Var_{theta,CP_2}	310	Min_{gamma,C_4}	260	Min_{delta,CP_3}	238
Var_{alpha,FC_Z}	304	Sum_{theta,FC_Z}	259	Var_{theta,CP_1}	236
Sum_{gamma,FC_1}	299	Var_{alpha,FC_3}	259	$Mean_{theta,FC_3}$	231
Var_{theta,CP_6}	290	Max_{gamma,FC_Z}	258	Max_{alpha,FC_6}	229
Min_{delta,CP_2}	288	Var_{theta,C_4}	258	Var_{theta,C_Z}	229
Min_{delta,C_6}	284	Min_{delta,FC_4}	254		

classification [25, 31, 43], for verifying if limiting the region of interest to two regions on motor cortex decreases accuracy.

Five classification methods were chosen. Each have own parameters, and to determine the best setup a training-testing cycle with cross-validation was repeated with automatic changes of parameters from an arbitrary defined values sets (Table 12.2). As a result, for each classifier the best configuration was identified for $\mathbf{P}_{615}$, $\mathbf{P}_{50}$ and $\mathbf{P}_{C_3C_4}$ and then used for subsequent experiments. Following methods were used:

- Naïve Bayes (NB). Naïve Bayes method uses numeric estimator with precision values chosen based on analysis of the training data [18]. A supervised discretization was applied, converting numeric attributes to nominal ones.
- Classifier trees (J48). A pruned C4.5 decision tree was applied [34], with adjusted confidence factor used for pruning C, and a minimum number of instances for a leaf M. C was selected from a set $\{2^{-5}, 2^{-4}, \ldots, 2^{-1}\}$, M:$\{2^1, 2^2, \ldots, 2^5\}$.
- Random Forest (RF). This method constructs I random trees considering K randomly selected attributes at each node. Pruning is not performed. I and K were from a set $\{2^3, \ldots, 2^7\}$.
- Nearest-Neighbors (NNge). An algorithm of Nearest-neighbors using non-nested generalized exemplars (hyperrectangles, reflecting if-then rules) was used [28, 36]. The method uses G attempts for generalization, and a number of folder for mutual information I. G and I were from a set $\{2^0, \ldots, 2^6\}$.

Table 12.2 Classifiers parameters resulting with the highest classification accuracy for three used features sets

Classifier	Features set $\mathbf{P}_{615}$	Features set $\mathbf{P}_{50}$	Features set $\mathbf{P}_{C_3 C_4}$
NB	Not applicable	Not applicable	Not applicable
J48	C = 0.03125, M = 16	C = 0.03125, M = 16	C = 0.03125, M = 16
RF	I = 64, K = 64	I = 64, K = 32	I = 64, K = 16
NNge	G = 8, I = 2	G = 8, I = 8	G = 8, I = 4
RS	Not applicable	Not applicable	Not applicable

- Rough Set classifier (RS). A method applying Pawlak's Rough Set theory [30, 35] was employed to classification. It applies maximum discernibility method for data discretization and it selects a minimal set of attributes (a reduct) maintaining discernibility between different classes, by applying greedy heuristic algorithm [17, 45, 46]. A reduct is finally used to generate decision rules describing objects of the testing set, and applying these to the testing set.

12.4 Classification Results

Classification accuracies obtained for 106 persons by the best configuration of selected 5 classifiers are shown below as box-whiskers plots [49] (Fig. 12.2).

It can be observed that Rough Sets (RS) are significantly more accurate in classification than other methods. Random Forest (RF) is the second, but the advantage over Naïve Bayes (NB), J48 and Nearest-Neighbors (NNge) is not statistically significant. Nearest-Neighbors is usually the worst. There are a few cases of very high accuracy exceeding 90%, but also a few persons' actions were impossible to classify (observed accuracy lower than 33% is interpreted as random classification).

In each case the imaginary motion classification (task B and D) is not as accurate as classification of the real motion (task A and C). This can be justified by inability to perform a task restricted to only mental activity in a repeated manner, or subjects' fatigue, incorrect positioning of electrodes, or even BCI illiteracy. Classification of real upper/lower limbs movement (task C) is the easiest one for every method.

It can be observed that applying $\mathbf{P}_{615}$ to classification (Fig. 12.2) generally yields better results than limited features sets $\mathbf{P}_{50}$ or $\mathbf{P}_{C_3 C_4}$ (Fig. 12.3 and 12.4). The accuracy decrease of ca. 5%.

Personal differences must be taken into account in application of EEG classification, as our experiments show some individuals perform the best, and other the worst repeatedly. For example, the subject S004 from the database was the highest ranked in 103 cases of 192 classification attempts, followed by S072 being the top ranked in 26, and S022 in 19 cases. The worst performing subjects were: S031 in 15, S098 in 13, S047 in 12, S021 in 11, and S109 in 11 cases of 192 attempts. Subjects

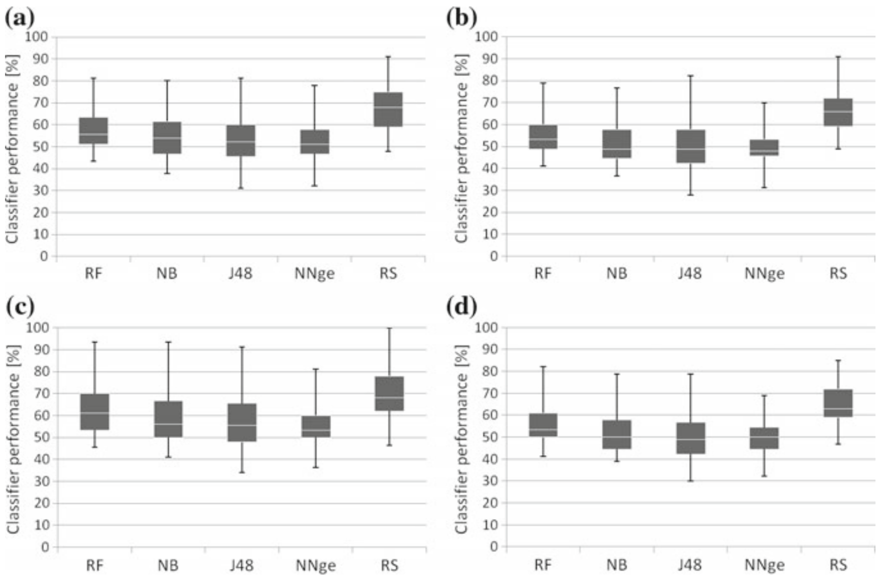

Fig. 12.2 Classification performance in 10 cross validation runs of selected classifiers for feature set $\mathbf{P}_{615}$: (a)–(d) tasks A–D respectively

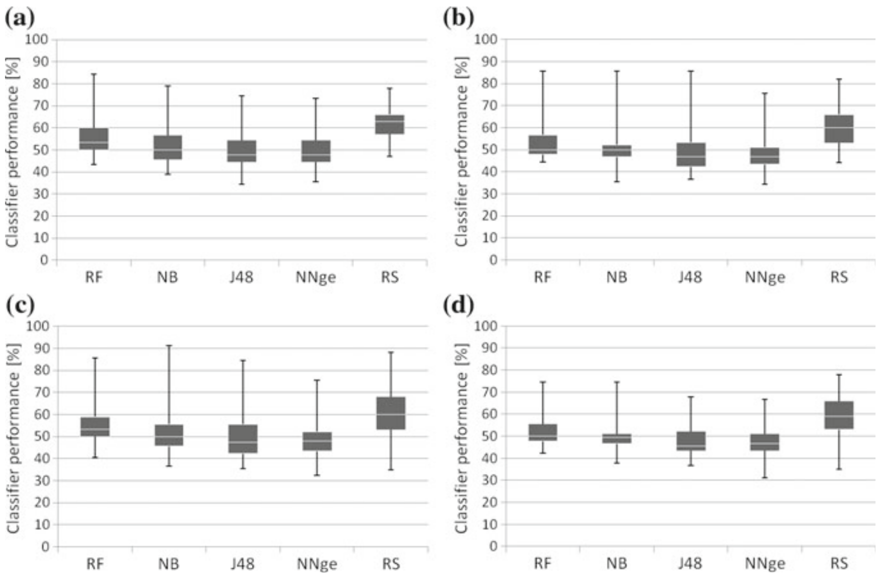

Fig. 12.3 Classification performance in 10 cross validation runs of selected classifiers for feature set $\mathbf{P}_{50}$: (a)–(d) tasks A–D respectively

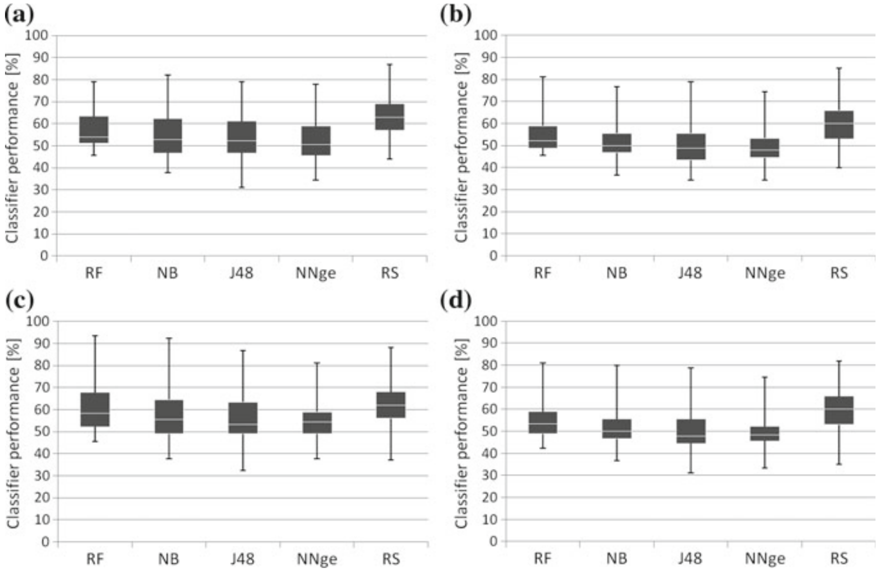

Fig. 12.4 Classification performance in 10 cross validation runs of selected classifiers for feature set $\mathbf{P}_{C_3C_4}$: (a)–(d) tasks A–D respectively

are anonymous and no personal details are provided, so actual physical difference between them cannot be determined.

12.5 Conclusions

A method of EEG signal pre-processing, parametrization, and classification with selected 5 classifiers was presented. Among applied methods Rough Sets (RS) and Random Forest (RF) achieved the highest accuracy, with the Rough Set (RS) significantly outperforming other methods.

The presented procedure can be employed in a simple interface involving motion classification by EEG signals analysis. It opens a possibility to develop accurate and responsive computer applications to be interacted by intents of rest, left, right, up, and down motion. These five binary input controls are sufficient to perform complex actions such as navigating, confirming or rejecting options in a graphical user interface.

For each person the training and classification process must be repeated, because each case could differ, albeit slightly, with electrodes placements, signal registration conditions, hair and skin characteristics, varying level of stress and fatigue, varying manner of performing the imaginary motion, etc.

Subjects were anonymous, so their physical differences are unknown, but large discrepancy in classification accuracy was observed, probably impossible to be overcome. Still, it must be yet determined whether satisfactory accuracy can be achieved by applying processing and classification of signals from non-invasive registration of brain activity through the skull and the scalp.

The results presented in this chapter were achieved without a necessity to apply complex methods such as ICA or SSP described in literature, and blink and heartbeat artefacts elimination or signal improvements methods were not employed. Therefore main strength of the approach is its simplicity, and confirmed high accuracy, possible to achieve provided the person is able to perform defined actions in a repeated manner.

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