Comparative Analysis of Feature Extraction Techniques in Motor Imagery EEG Signal Classification

Chapter · January 2018

DOI: 10.1007/978-981-10-5828-8_8

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Abstract Hand movement (both physical and imaginary) is linked to the motor cortex region of human brain. This paper aims to compare the left–right hand movement classification performance of different classifiers with respect to different feature extraction techniques. We have deployed four types of feature extraction techniques—wavelet-based energy–entropy, wavelet-based root mean square, power spectral density-based average power, and power spectral density-based band power. Elliptic bandpass filters are used to discard noise and to extract alpha and beta rhythm which corresponds to limb movement. The classifiers used are Bayesian logistic regression, naive Bayes, logistic, variants of support vector machine, and variants of multilayered perceptron. Classifier performance is evaluated using area under ROC curve, recall, precision, and accuracy.

Keywords EEG · BCI · Motor imagery · Signal processing
Feature extraction · Classification · ROC · Sensitivity · Precision

1 Introduction

Human activities especially limb movements and thoughts are controlled by brain. Each and every activity exhibits a different signature encoded in microvolt electric signal generated inside the brain. This signal can be measured in many ways. One such way is *electroencephalography* which is widely used due to its noninvasiveness,

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A.K. Somani et al. (eds.), *Proceedings of First International Conference on Smart System, Innovations and Computing*, Smart Innovation, Systems and Technologies 79, https://doi.org/10.1007/978-981-10-5828-8_8

portability, and cost-effectiveness. In this method, electrodes are placed in different regions on the scalp of the human brain. The spatial positioning of the electrodes is done according to International 10−20 system [25]. The signal obtained in this procedure is known as *encephalogram (EEG)* [4].

Now let us understand the brain activities during hand movement. Right portion of human body is controlled by left hemisphere of human brain and vice versa. So right hand movement can be detected through the EEG activity reading in C3 electrode which is placed in the motor cortex region of left hemisphere and the opposite is also true; left hand movement is connected to the C4 electrode in motor cortex region of right hemisphere of human brain and so left hand movement can be detected through the EEG activity reading in C4 electrode. It is generally agreed that out of all the brain rhythms, only alpha and beta bands are sufficient to distinguish the type of hand movement [13]. Existing literature also states that, during right hand movement, the alpha band in $C3$ will be diminished and beta band will be increased. The common understanding is that alpha band signifies relaxed state of human brain, whereas beta band suggests muscle movements [19, 23, 27].

In this paper, we experiment with different feature extraction and classification techniques on EEG data for imagined hand movement. Raw EEG signal is very noise prone. So we first de-noise the signal using digital filters. Then we generate feature vectors from the filtered signal with the help of multiple feature extraction techniques. Finally, a variety of classifiers are run on the feature vectors to build left–right hand movement prediction model. We measure and report the performance of the classifiers.

Paper organization: This paper is divided into five sections. Section 1 is the overview of EEG-based motor imagery classification. Section 2 briefly describes related work, problem statement, and our contribution. Data preparation and feature extraction techniques used in the study are explained in Sect. 3. Section 4 presents results and discussion. Finally, we conclude our work in Sect. 5.

2 Related Works, Problem Statement, and Contributions

A. Related works on feature extraction: Classification of EEG signals has attracted a lot of attention from scientists and engineers working in theoretical and applied neuro-computing due to its tremendous potential in understanding the basic brain functions and its applications in medical field, gaming, virtual reality, etc. We focus on the techniques used for feature extraction and classification of motor imagery. A brief overview of related work on various feature extraction techniques is provided in Table 1.

B. Problem statement: Given a dataset of motor imagery EEG signals known to contain left hand or right hand movements, our goal is to identify which set of features lead us to better left–right hand movement classification. The prominent questions that we encounter in this paper are as follows:

Table 1 Related work on feature extraction

Sl. No.	Feature extraction techniques	References
1	Fast fourier transformation (FFT)	[5, 15]
2	Short-time fourier transformation (STFT)	[22, 26]
3	Power spectral density (PSD)	[3, 6, 7, 24]
4	Discrete wavelet transform (DST)	[2, 7, 17, 18]
5	Continuous wavelet transform (CWT)	[22]
6	Band power	[7, 16]

1. Which features of EEG data should be used for classification?
2. Given these features, which classifiers should be used?

C. Contributions: We conducted experiments to answer the questions posed in the previous section. Our major contributions from the study are as follows:

1. We found that wavelet-based features are best for EEG-type nonstationary signals.
2. We found logistic and linear Support Vector Machine (SVM1) are best performer classifiers.
3. We were able to characterize the performance of these classifiers on the data in a precise way using widely used metrics like recall, precision, and ROC.

3 Data Preparation and Feature Extraction

For our analysis, BCI competition II 2003 (dataset III) has been taken from the Department of Medical Informatics, Institute for Biomedical Engineering, University of Technology, Graz. The data has been used widely as a benchmark data in this field of EEG-based motor imagery classification problem [1].

A. Data Preprocessing: An elliptic bandpass filter is used to extract the frequency band of 0.5–30 Hz which covers both the alpha (8–12 Hz) and beta (18–25 Hz) bands. Also, we have used sampling frequency at 128 Hz.

B. Hardware and Software configuration: MATLAB $R2014a$ is used for feature extraction and WEKA 3.6 classification tool is used to classify the obtained feature vectors with an Intel Core i5 computer.

C. Feature Extraction Techniques used: From past literatures, we find various types of feature extraction techniques which were used for left–right hand movement classification. For comparison, all the popular and mostly used feature extraction techniques are employed in this paper and in addition their combinations are

Table 2 Details of feature sets used

Feature sets name	Actual extracted feature sets	Features length
Ap	Average power	4
Bp	Average band Power	4
EngEnt	Wavelet-based energy–entropy	4
RMS	Wavelet-based root mean square	2
BpAp	Combining (2) & (1)	8
EngEntAp	Combining (3) & (1)	8
EngEntBp	Combining (3) & (2)	8
EngEntRms	Combining (3) & (4)	6
RmsAp	Combining (4) & (1)	6
RmsBp	Combining (4) & (2)	4

also used to explore their discriminating effectiveness. These are the Power Spectral Density (PSD)-based average power (Ap), band power (Bp), wavelet-based energy–entropy (EngEnt), and RMS values (RMS). Detailed description of the feature extraction techniques can be found in our previous work in [8]. We provide in Table 2 a brief description of the feature sets used in our experiments. The maximum feature set length is eight and the minimum is two. In machine learning, feature set length is a critical performance parameter.

4 Results and Discussion

The primary purpose of the paper is to compare the performance of different feature sets and whether multiple classifiers behave consistently on the same feature set. In our previous works, it is observed that both the classifiers, support vector machine (SVM) and multilayered perceptron (MLP), perform better than other popular classifiers (e.g., Naive Bayes, Logistic, etc.) in motor imagery classification [8, 9, 11]. However, in this study, we have incorporated probabilistic to nonlinear classifiers so that in total, five primary types of classifiers with three variants of SVM and two variants of MLP (Table 3) are used. In Table 3, *C* and *Nu* are the regularization parameters, used to give relaxation to the training error in SVM. After reasonable tuning, the *C* value is taken as 1.0 and *Nu* value as 0.5. If this value is close to 0, it signifies a large margin, i.e., it simply ignores those points which are violating the margin constraint. On the other hand, high value indicates narrow margin where constraints are hard to ignore. The length of feature sets is the number of inputs in MLPs. The average of feature set length and class labels is used as number of hidden layers in our MLP variants.

In the past, many papers used the said feature extraction techniques separately. This paper uses most of the prominent extraction methods independently and in a

Table 3 Types and variants of classifiers

Classifiers	Variants	Kernel functions
Bayesian logistic regression	–	NA
Naive Bayes	–	NA
Logistic	–	NA
SVM1	C-SVC (C = 1.0)	Linear
SVM2	Nu-SVC (Nu = 0.5)	Linear
SVM3	Nu-SVC (Nu = 0.5)	Polynomial (degree = 3)
	Learning rate	Momentum
MLP1	0.3	0.20
MLP2	0.7	0.29

combined way. This provides a comparative analysis of the quality of the feature sets [10, 12, 14, 20]. It is well known in machine learning that the classification is as good as the data set is. Most of the modern-day classifiers are not robust and suffer data-dependent predictions. Now our feature extraction techniques are fundamentally based on two principles: one, wavelet-based and two, power-based. All types are explained in the earlier section of this paper. These are common digital signal processing (DSP) techniques widely discussed and explained in any book on DSP or in related papers [21].

So the power spectral-based feature extraction technique deals with the power distributions of alpha and beta bands. Again, average band power talks about the concentration of power for the individual bands. Our results obtained from power-based extraction methods are performing well in terms of our measures but they are not the best. The possible explanation could be the power exhibition for both the right and left hands are more or less same with minimal distinctive information. Another extraction principle is wavelet-based feature sets. Wavelet is most appropriate for any nonstationary signal like EEG. It considers both the frequency range and temporal range at the time of signal processing. Unlike power-based features, wavelet-based feature extraction techniques are applied on the filtered (0.5–30 Hz) EEG signal without considering the alpha and beta bands specifically. Wavelet-based energy–entropy provides the best consistent results irrespective of the classifiers. Another interesting finding is that wavelet-based RMS feature set with only two features gives performance as good as four energy–entropy features, particularly for the Naive Bayes, logistic, and SVM2 classifiers.

Except area under ROC, SVM with linear kernel outperforms others in all other performance measures. Energy–entropy combining with AP, BP, and RMS is also used as feature sets. It is suggested that the combined results do not include any additional distinctive features and thus give similar result what is demonstrated by the energy–entropy individually. However, energy–entropy with BP loses its significance in combination. RMS with other combinations is as good as RMS itself rather it loses in few cases. BLR, Naive Bayes, and logistic classifiers exhibit improvement

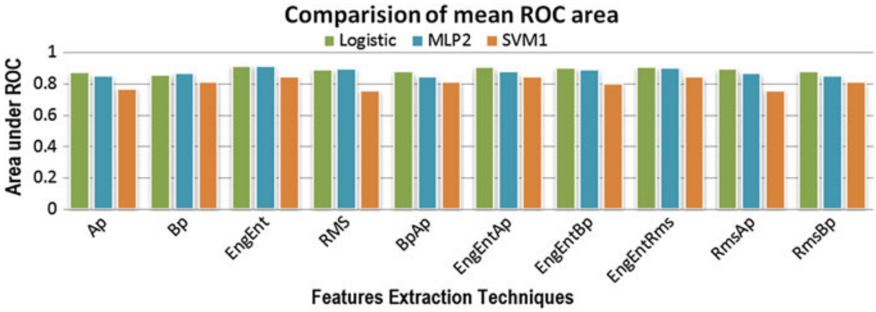

Fig. 1 ROC area chart for best three classifiers

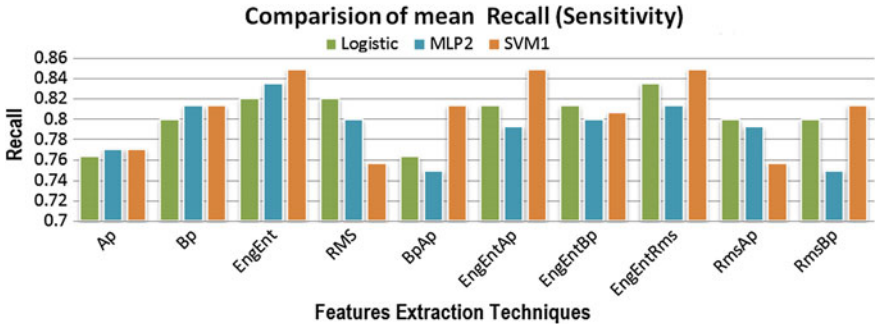

Fig. 2 Recall chart for best three classifiers

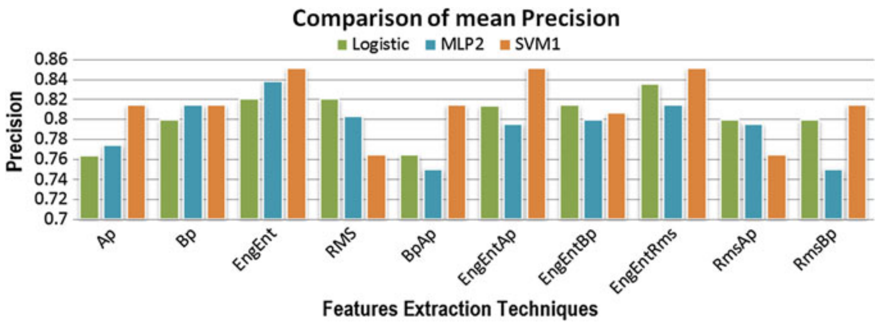

Fig. 3 Precision chart for best three classifiers

in performance when they use energy–entropy with RMS combination over energy–entropy or RMS independently.

In Table 4, the observations of our study are represented in a concise manner. Performances of all the classifiers as per the measures are given in the tabular formats in Tables 5, 6, 7, and 8 in Appendix A. Performance plots for best three classifiers (Logistic, MLP2, and SVM1) are shown in Figs. 1, 2, 3, and 4.

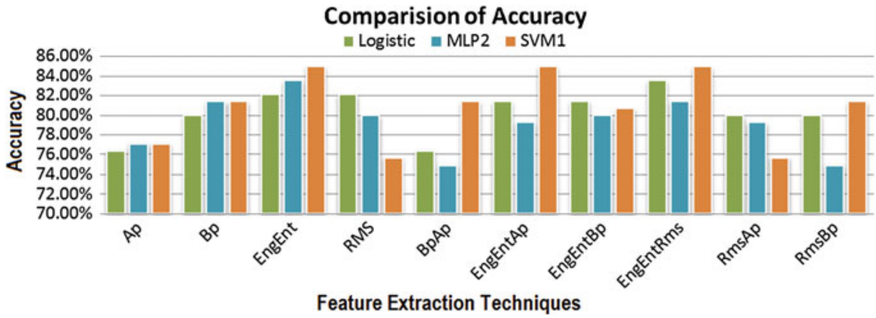

Fig. 4 Accuracy chart for best three classifiers

Table 4 Observations obtained from results

Sl. No.	Empirical findings	Significance
1	Logistic gives highest ROC area and MLP2 gives second highest ROC area	1. Large area under ROC ensures higher degree of confidence in the prediction model
2	SVM1 provides best sensitivity, precision, and accuracy	1. It indicates the quality of prediction (test) is consistent
3	Wavelet-based energy–entropy features perform better than other feature sets	1. It gives same results as its combination with others. Sometimes even better than its combinations 2. No information gain by adding the average power and average band power as additional features
4	RMS gives competitive results to energy–entropy	1. Having feature set length of two, it has as good discriminating information as others 2. Moreover, wavelet-based variants comprise more distinctive information over features obtained from power spectral-based variants on alpha and beta bands

5 Conclusion

In this paper, we have used and discussed a variety of feature extraction techniques and their combinations. Summarizing our findings, we can state that the feature extraction technique based on joint time–frequency-based wavelet transform is the most suitable one for classification of EEG signals for left–right hand movement discrimination. However, our work is limited to offline analysis of EEG signals. In future, our focus will be on implementing the best extraction algorithms in real-time systems for brain-state discrimination.

Appendix: A

Table 5 Results based on ROC area

For ROC area (under the curve)								
	BLR	Naive Bayes	Logistic	MLP1	MLP2	SVM1	SVM2	SVM3
Ap	0.729	0.817	0.875	0.867	0.854	0.771	0.664	0.564
Bp	0.793	0.858	0.860	0.87	0.874	0.814	0.807	0.814
EngEnt	0.800	0.897	0.918	0.894	0.917	0.850	0.821	0.757
RMS	0.793	0.876	0.892	0.898	0.899	0.757	0.821	0.514
BpAp	0.793	0.885	0.880	0.869	0.848	0.814	0.807	0.814
EngEntAp	0.636	0.886	0.909	0.879	0.880	0.850	0.821	0.757
EngEntBp	0.786	0.883	0.906	0.874	0.896	0.807	0.807	0.814
EngEntRms	0.807	0.893	0.910	0.890	0.907	0.850	0.821	0.757
RmsAp	0.779	0.881	0.900	0.884	0.870	0.757	0.821	0.514
RmsBp	0.793	0.872	0.880	0.876	0.855	0.814	0.807	0.814

Table 6 Results based on sensitivity (recall)

For recall (sensitivity)								
	BLR	Naive Bayes	Logistic	MLP1	MLP2	SVM1	SVM2	SVM3
Ap	0.729	0.757	0.764	0.771	0.771	0.771	0.664	0.564
Bp	0.793	0.786	0.800	0.771	0.814	0.814	0.807	0.814
EngEnt	0.800	0.800	0.821	0.814	0.836	0.850	0.821	0.757
RMS	0.793	0.800	0.821	0.807	0.800	0.757	0.821	0.514
BpAp	0.793	0.771	0.764	0.779	0.75	0.814	0.807	0.814
EngEntAp	0.636	0.793	0.814	0.836	0.793	0.850	0.821	0.757
EngEntBp	0.786	0.793	0.814	0.786	0.800	0.807	0.807	0.814
EngEntRms	0.807	0.807	0.836	0.814	0.814	0.850	0.821	0.757
RmsAp	0.779	0.786	0.800	0.764	0.793	0.757	0.821	0.514
RmsBp	0.793	0.800	0.800	0.750	0.750	0.814	0.807	0.814

Table 7 Results based on precision

For mean precision								
	BLR	Naive Bayes	Logistic	MLP1	MLP2	SVM1	SVM2	SVM3
Ap	0.765	0.759	0.764	0.772	0.775	0.815	0.666	0.569
Bp	0.793	0.787	0.800	0.772	0.815	0.815	0.808	0.815
EngEnt	0.802	0.802	0.821	0.817	0.839	0.852	0.822	0.780
RMS	0.793	0.801	0.821	0.812	0.804	0.765	0.822	0.515
BpAp	0.793	0.772	0.765	0.779	0.751	0.815	0.808	0.815
EngEntAp	0.789	0.793	0.814	0.837	0.796	0.852	0.822	0.780
EngEntBp	0.786	0.793	0.815	0.786	0.800	0.807	0.809	0.817
EngEntRms	0.812	0.810	0.836	0.817	0.815	0.852	0.822	0.780
RmsAp	0.781	0.786	0.800	0.765	0.796	0.765	0.821	0.515
RmsBp	0.793	0.800	0.800	0.750	0.751	0.815	0.808	0.815

Table 8 Results based on accuracy

For accuracy (%)								
	BLR	Naive Bayes	Logistic	MLP1	MLP2	SVM1	SVM2	SVM3
Ap	72.86	75.71	76.43	77.14	77.14	77.14	66.43	56.43
Bp	79.29	78.57	80.00	77.14	81.43	81.43	80.71	81.43
EngEnt	80.00	80.00	82.14	81.43	83.57	85.00	82.14	75.71
RMS	79.29	80.00	82.14	80.71	80.00	75.71	82.14	51.43
BpAp	79.29	77.14	76.43	77.86	75	81.43	80.71	81.43
EngEntAp	63.57	79.29	81.43	83.57	79.29	85.00	82.14	75.71
EngEntBp	78.57	79.29	81.43	78.57	80.00	80.71	80.71	81.43
EngEntRms	80.71	80.71	83.57	81.43	81.43	85.00	82.14	75.71
RmsAp	77.86	78.57	80.00	76.43	79.29	75.71	82.14	51.43
RmsBp	79.29	80.00	80.00	75.00	75.00	81.43	80.71	81.00

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