Dagging Meta Classifiers with Support Vector Machine

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Abstract

Brain-Computer Interface (BCI) processes the brain signals into computer understandable signals which in turn are converted into control signals. Thus, BCI acts as a communication system between the brain and an external device. The brain signals are captured in the form of Electroencephalogram (EEG) and BCI system transforms it into control signals by extracting features, pattern recognition and classification. In this paper, the features from the EEG are extracted using Gaussian smoothened Fast Hartley Transform (GS-FHT) which computes the energies of different motor imagery. Dagging Meta classifiers are used with Support Vector Machine for classification of the extracted features. The proposed methodology was evaluated using publicly available BCI Competition dataset IVA. The evaluations of preprocessed signals show that the extracted features from EEG were interpretable and the classification accuracy obtained were satisfactory.

Key words - Data mining, Brain computer interface, Gaussian Fast Hartley transform, EEG

1. Introduction

BCI is an emerging technology, which enables the crippled people to communicate with the external world and helps their mobility through devices like mind controlled wheelchair. The changes in the brain signals are used as operative control signals using Electroencephalogram (EEG) based BCI. In analyzing the brain signals, Motor Imagery (MI) is the state during which the depiction of a particular motor action is internally reactivated within the working memory without any overt motor output. This is governed by the principles of motor control. Motor Imagery (MI) produces measurable potential changes in the EEG signals termed as Event-Related De-synchronization / synchronization (ERD/ERS) patterns.

The BCI translates the recorded brain signals for any motor related actions into input signals, by processing the signal and classifying the motor imagery. Various applications in neuroprosthetic are based on this motor imagery method. The BCI system detects the motor imagery changes and transforms them into a control signal which can, for example, be used to control an electric wheel chair.

Brain Computer Interface (BCI) is a communication system which links the human neural system and machine, aiming to communicate and control devices by mere "thinking" or brain activity [1]. As the BCI relies on the brain rather than the body for control and feedback, patients who suffer from severe motor impairments find it useful as an alternative form of communication and to control external devices with brain activity. The BCI is mainly used by disabled persons, for whom it helps to control devices such as artificial limbs, spelling devices, or environment control systems.

Brain Computer Interface aims at directly translating brain activities into sequences of control commands for an output device such as a computer application or neuroprosthesis by noninvasive or invasive approach [2]. Focus of BCI research and development is mainly on neuroprosthetic devices (devices using brain waves to initiate movement) which help to damaged hearing, sight and movement.

2. DATA SET

IV A dataset used in the brain computer interface competition provided by Intelligent Data Analysis Group. This data set consists of recordings from five healthy subjects who sat in a chair with arms resting on armrests. Visual cues indicated for 3.5 s which of the following 3 motor imageries the subject should perform: (L) *left* hand, (R) *right* hand, (F) right *foot*. The presentation of target cues was intermitted by periods of random length, 1.75 to 2.25 s, in which the subject could relax. Given are continuous signals of 118 EEG channels and markers that indicate the time points of 280 cues for each of the 5 subjects (*aa*, *al*, *av*, *aw*, *ay*). Subject aa was used in our study.

3.SIGNAL PRE-PROCESSING

The acquired EEG signal cannot be directly used as input for the output device in BCI. Since the recording sessions have different kinds of interference waveforms, these are termed as artifacts. The artifacts are, any recorded electrical potential, not originated in brain. The main sources of artifacts are:

- EEG equipment
- Electrical interference from external source other than subject and recording system
- The leads and the electrodes
- Normal electrical activity from the heart, eye blinking, eye movement of the subject

In case of visual inspections, the artifacts can be easily identified. But during automated analysis, the artifacts cause serious misclassification which considerably reduces the effectiveness of BCI system. So recognition and elimination of artifacts in real-time EEG is a must for the development of practical systems.

Earlier works have identified that the eye blinks and eyeball movements are the most severe artifacts. The eyeblink and eyeball movement cause changes in the potential field that affects the signals from the most frontal electrodes. Due to the artifact, high and low frequencies are induced depending on its duration and amplitude.

4. Experimental Results

Dagging:

This meta classifier [3] creates a number of disjoint, stratified folds out of the data and feeds each chunk of data to a copy of the supplied base classifier. Predictions are made via averaging, since all the generated base classifiers are put into the Vote meta classifier[4,5].Useful for base classifiers that are quadratic or worse in time behavior, regarding number of instances in the training data.

SMO

Sequential Minimal Optimization (SMO) [6] is a simple algorithm that can quickly solve the SVM QP problem without any extra matrix storage and without using numerical QP optimization. The advantage of SMO is its ability to solve the Lagrange multipliers analytically.

SMO is an iterative algorithm for solving the optimization problem. SMO breaks this problem into a series of smallest possible sub-problems, which are then solved analytically.

The algorithm proceeds as follows:

1. Find out a Lagrange multiplier x_1 that violates the Karush–Kuhn–Tucker (KKT) conditions for the optimization problem.
2. Pick a second multiplier x_2 and optimize the pair (x_1,x_2)
3. Repeat steps 1 and 2 until convergence.

SVM polykernel

Support Vector Machines

Support Vector Machines (SVM) [7,8,9] is a powerful, state-of-the-art algorithm with strong theoretical foundations based on the Vapnik-Chervonenkis theory. SVM has strong regularization properties. regularization refers to the generalization of the model to new data.SVM models have similar functional form to neural networks and radial basis functions, both popular data mining techniques. However, neither of these algorithms has the well-founded theoretical approach to regularization that forms the basis of SVM. The quality of generalization and ease of training of SVM is far beyond the capacities of these more traditional methods.

SVM can model complex, real-world problems such as text and image classification, hand-writing recognition, and bioinformatics and biosequence analysis.SVM performs well on data sets that have many attributes, even if there are very few cases on which to train the model. There is no upper limit on the number of attributes; the only constraints are those imposed by hardware. Traditional neural nets do not perform well under these circumstances.

SVM [10,11] classification is based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. SVM finds the vectors that define the separators giving the widest separation of classes.SVM classification supports both binary and multiclass targets.

Dagging with SMO using SVM polykernel

Correctly Classified Instances 164 66.129 %

Incorrectly Classified Instances 84 33.871 %

Kappa statistic	0.1209
Mean absolute error	0.4262
Root mean squared error	0.4871
Relative absolute error	93.0084 %
Root relative squared error	101.7885 %
Coverage of cases (0.95 level)	97.9839 %
Mean rel. region size (0.95 level)	97.379 %
Total Number of Instances	248

=== Detailed Accuracy By Class ===

TPRate	FPRate	Precision	Recall	F-Meas	ROCArea	PRC Area	Class
0.931	0.83	0.671	0.931	0.78	0.578	0.681	hand
0.17	0.069	0.577	0.17	0.263	0.578	0.439	foot

Weighted Avg.

0.661	0.56	0.638	0.661	0.597	0.578	0.595

=== Confusion Matrix ===

a	b	<-- classified as
149	11	a = hand
73	15	b = foot

Dagging with SMO using SVM RBF kernel

Correctly Classified Instances	160	64.5161%
Incorrectly Classified Instances	88	35.4839%
Kappa statistic		0
Mean absolute error		0.3556
Root mean squared error		0.5897
Relative absolute error		77.6097 %
Root relative squared error		123.2406 %
Coverage of cases (0.95 level)		68.1452 %
Mean rel. region size (0.95 level)		54.2339 %
Total Number of Instances		248

=== Detailed Accuracy By Class ===

TPRate	FPRate	Precision	Recall	F-Meas	ROCArea	PRC Area	Class
1	1	0.645	1	0.784	0.514	0.652	hand
0	0	0	0	0	0.514	0.369	foot

Weighted Avg.

0.645	0.645	0.416	0.645	0.506	0.514	0.551

=== Confusion Matrix ===

a	b	<-- classified as
160	0	a = hand
88	0	b = foot

5. Conclusion

The Brain Computer Interface System should learn to discriminate various patterns of brain signals accurately so that the user is able to perform different mental tasks. In this paper, Dagging Meta classifiers with Support Vector Machine for classification of the extracted features are investigated. Gaussian smoothened Fast Hartley Transform (GS-FHT) which computes the energies of different motor imagery is used for extracting features from the EEG. Dagging Meta classifier which forms a number of disjoint, stratified folds of the data and presents it to the supplied base classifiers. Dagging was used with SMO using SVM Polykernel and RBF Kernel. Classification accuracy of 66.13% was obtained. Further investigations need to be done to improve the classification accuracy by varying the SVM capacity and Gamma values of the Kernel.

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