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Detection of single-trial EEG of the neural correlates of familiar faces recognition using machine-learning algorithms

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ABSTRACT

We analyze Electroencephalograph EEG data with several classification algorithms to classify probe and irrelevant data. Out of eight algorithms, five foun to perform poorly: Decision Tree, Random Forest, Neural Network, SVM RBF and Adaboost, while KNN, SVM Linear and Naive Bayes Gaussian yielded satisfactorily. Analysis is carried with 14 different subjects. Various metrics like accuracy, precision and recall are calculated to establish best performing algorithms with Electroencephalogram EEG data. Further work is needed on this area by increasing the number of subjects and experiments, with an idea to eliminate inters subjective variability. Also, work on algorithms tuning for better mental states capturing.

Key words : EEG data, Machine learning, Kernels, KNN, SVM, Decision Tree, Random Forest, Neural Network, Adaboost and Naive Bayes, Kernels, Radial Basis Function, Sigmoid

1. INTRODUCTION

Capturing emotions of people play an important role in human communication and interaction. Recognizing the emotional states is very vital in natural f[1]orm of communication [1]. Capturing emotions and interaction between people and machines are very vital in brain computer interfaces. Having a reliable emotion capturing system is a must for effective human and machine communication. This can ensure acceptable capturing accuracy, robustness against any artifacts, and adaptability to practical scenarios.

There are three different engineering techniques for emotion detection and recognition. The first approach is the analysis of facial expressions and speech. The second type is based on the periphery physiological signals. This approach provides more detailed and complex information compared to the audio visual one. The third type is based on brain signals being recorded from central nervous system (CNS). Different types of approaches are used to read brain signals such as Electrocorticography (ECG), Electroencephalograph (EEG), and Functional Magnetic Resonance Imaging (FMRI). The most common used technique for recording brain signals is the EEG. EEG signals give more information about the emotional states. Studies show that EEG study for emotions received much attention. However, these approaches still suffer from some limitations. Different approaches based on machine learning have been developed to analyze EEG data on different application such as Brain Computer Interface (BCI) and Deception detection.

Machine learning approaches are good choice for analyzing the variability in EEG data [2]. These methods can be more effective for pre-processing and learning by classification and hence can be more efficient for brain computer interface BCI and capturing mental status. The training models can be created with least number of training subjects.

These learning techniques extract complex high dimensional variability and classify in a robust manner. Also, they offer great challenges from the viewpoint of a data analyst, and these are characterized by significant trial to trial and subject to subject variability. Real time signals are mostly high dimensional with few samples. With this limited samples models need to be fitted and need to address the signal-to noise ratio, which is unfavorable. Considering these variabilities, machine learning methods can be addressed as best choice of EEG brain data analysis.

2. MACHINE LEARNING METHODS

Empirical data modeling can be well applied to many of the medical and engineering applications [32]. This modeling uses the induction process for model building; further these models can be tested and observed for real time data. Observational data is considered as sample. Following are some of the well-known machine learning techniques that can be applied for analysis [3].

2.1 K Nearest Neighbor

KNN algorithm is one of the simple classification algorithms and it is one of the commonly used learning algorithms. KNN works with the assumption that samples of a dataset with similar properties exists in proximity. Unlabeled sample is labeled by locating k nearest samples and the most frequent class label is assigned to the unlabeled sample. KNN is also known as lazy learning algorithm and it is non-parametric. KNN doesn't make assumptions on the data distribution. Models are prepared from the data. This algorithm data points are classified into different classes to make prediction of the new class [4].

KNN Algorithm works with concept of feature similarity. How closely out of sample features matches training set,

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defines how data points are classified. Features of KNN include high accuracy, and it is versatile but computationally expensive with high memory requirements. As well, it is sensitive to irrelevant features and scale of data.

Euclidean distance metric is routinely applied for EEG data. Effectiveness of five distance metrics of k-NN: Manhattan, Euclidean, Minkowski, Chebychev and Hamming can give better accuracies. Distance metric has a significant effect on k-NN accuracy[4].

2.2 Support Vector Machine

Support Vector Machine is commonly used for classifying EEG Data [3]. SVMs are considered as supervised learning algorithms [5]. This is a prediction technique that maximizes predictive accuracy and avoids over fit to the data. It tries to maximize the distance between separating the elements of two different classes. Takes the data to bigger dimensional spaces and applies optimization theory.

Support Vector Machine (SVM) is commonly used for analyses of Electroencephalography (EEG) signals [3]. EEG signals are recorded with high dimensional space. Kernel functions will be more helpful for efficient implementation of non-linear mapping. SVM with different kernels is giving highest level of accuracies for EEG signals [3].

2.3 Decision Tree

Decision Tree is a basic learning algorithm and much used learning technique, this is also a supervised learning technique. This is a tree-based learning algorithm. This algorithm generates predictive models with good accuracy, stability and good interpretation. This technique cans also map and model non-linear relationships. It is adaptable at solving classification and regression problems. Decision trees work well with both categorical and continuous data problems. It divides the data into homogeneous sets with most significant splitter. Features of Decision tree include easy to understand, requires less data cleaning and are non-parametric [16].

A good decision tree structure-based classification and applied for classifying EEG data with self generated specific DTS by selecting most appropriate features. Survey shows that decision tree structure-based methods have been successfully applied to the EEG data sets and achieved better classification accuracy rates on the test data.

2.4 Random Forest

Random Forest is also one of the learning techniques with classification and regression using decision trees. RF is a collection of predictor trees. Every tree relies on the values of the vector independently with same distribution among all other trees. As the numbers of trees increase in the forest, the generalization errors converge. As the strength of trees and sub trees of the forest and relations among them. This technique also can be used for regression with training and testing datasets [13].

Survey shows that Random Forest is yielding better results with EEG data compared to other well-known learning algorithms. Pilot analysis with Random Forest has confirmed the superiority of Random Forest over others. It is giving better accuracy and identifies a distinctive correlation between beta and delta waves with respective states of brain.

2.5 Neural Network

Artificial Neural Network (ANN) is a learning process which simulates the nervous systems work. It is a network with large number layers consisting of interconnected nodes (neurons). ANNs learn by example. This technique applies the process of adjusting to the synaptic connections that exist between neurons [17] [31].

Work on artificial neural network started in 1943, initially a simple neural network model with electrical circuits was made. Then this model with remarkable ability started deriving meaning form complicated and imprecise data to learn the patterns. These models detect trends which complex to be noticed by humans and other computer techniques. Neural networks are compliments to other algorithmic approaches. Features of Neural Networks include massively parallel distributed structure, ability to learn and generalize.

Different techniques have been used to analyze and classify EEG signals such artificial neural network (ANN) and logistic regression (LR). Moreover, techniques such as Wavelet transform is used for exploring different characteristics of the signals such as trends, discontinuities and common patterns. It is observed from the studies that ANN based classifiers outperform their LR based counterparts .

2.6 AdaBoost

AdaBoost is a famous ensemble learning algorithm which is classification-based algorithm. This algorithm was first proposed by Freund and Schapire. AdbBoost works by comparing the decisions weights of all the poor (i.e. uncertain) classifiers; it uses majority voting technique to generate final output [8].

Boosting technique strategy converts weak learner to a strong learner. AdaBoost uses decision stamps. Nonetheless, these algorithms can take up both classification and regression problems. Other algorithms which are boosting based include Gradient tree boosting and XGBoost.

EEG signals can be captured and evaluated using different features of EEG, which are given as input vectors to AdaBoost. It is comparatively more accurate and fast compare to other algorithms.

2.7 Naive Bayes Guassian

Naive Bayes classification algorithm is once again for binary and multi class classification problems. It is probabilistic approach. Here attribute values are assumed to be conditional independent given the target values. This approach of learning performs well on real time data. This approach can be extended to real time scenarios with

Gaussian distribution, this is called Naïve Bayes Gaussian. This algorithm uses mean and standard deviation, probabilities for input values. This approach is scalable and efficient [9]

For EEG data analysis, the signal is decomposed into scales and statistical features are extracted with these scales. These the data with reduced features is given as an input to Naïve Bayes. The results with this algorithm are also much competitive and encouraging.

3. EXPERIMENTAL SETUP

The details the experiment was explained in [1]. However, the following subsections will briefly highlight the main steps followed to record EEG data.

Participants

Fourteen subjects (male and female) participated in the experiment.

Stimulus Presentation

Rapid Serial Visual Presentation was used to present stimuli. Stimuli were presented at rate of 133 millisecond. All stimuli were facer with size of 280*329 pixel grey phtographs.

Three different types of stimuli were displayed: (1) Probes: faces of famous people (5 faces of famous people) ; (2) Irrelevants: random faces that were unknown to the subjects (5 faces of unfamiliar people); (3) Target: an irrelevant face, but subjects were asked to report it at the end of each trial(i.e. that are task-relevant).

There total number of trials was 225; 75 trials for each type of stimuli: Target, Probe and Irrelvant. In other words, each type was displayed 75 times. The whole experiment consisted of 5 blocks; 45 trials in each block: 15 Target trials; 15 Probe trials; and 15 irrelevant trials. One item from each stimuli type (Target, Probe, Irrelevant) was presented in each block.

Experiment Tasks

At the beginning of the experiment, subjects were given a target face. Subjects were instructed to answer a question 'Did you see the Target face?'. This question was presented at the end of each trial. Subjects were asked to answer the question with 'Yes' or 'No' at the end of each trial. This Target face was comprised to force subjects to concentrate on the stimuli presentation. Subjects were not informed about the presentation time of the Probes.

Data acquisition and analyses

Electroencephalographic (EEG) data were recorded using a BioSemi ActiveTwo system. The recording was on the following scalp sites: P4, Oz, Fz, Cz, P3, Pz, A1 and A2 channels.

All trials of each condition: the Target, the Probe, and the Irrelevant were averaged to create the Event Related Potentials (ERPs). Each EEG trial was created by segmenting the data from a -100ms to 1200ms. All ERPs were time-locked to the beginning of a critical face. The grand-averaged ERPs of all conditions at Pz electrode is shown in figure 1.

As can be seen from figure 1, the target produced a large P300 (from 300ms to 800ms) because it was a task relevant. Our interest is to statistically compare between the ERPs data of the probe and irrelevant. As can be seen, the probe produced a negativity (from 300ms to 480ms) followed by a positive peak (from 480ms to 600ms), whereas there is no such negativity or positivity produced by the Irrelevant. The comparison was between the probe and irrelevant conditions. Figure 2 depicts the ERPs of all the fourteen subjects.

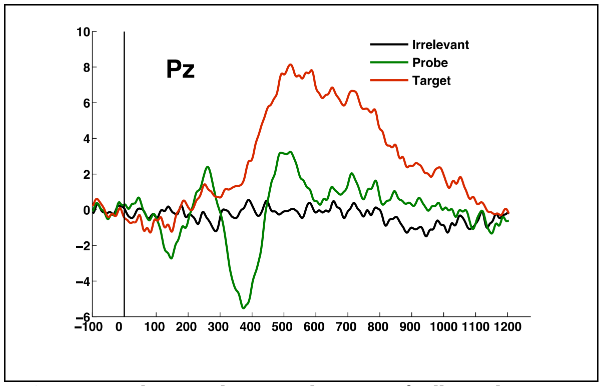

Figure 1: The grand-averaged ERPs of all conditions at Pz electrode. The target produced a large P300 (from 300ms to 800ms) because it was a task relevant. The goal is comparing between the green line (Probe) and the black line (irrelevant) ERPs. Note that, the probe produced a negativity (from 300ms to 480ms) followed by a positive peak (from 480ms to 600ms), whereas there is no such negativity or positivity produced by the Irrelevant.

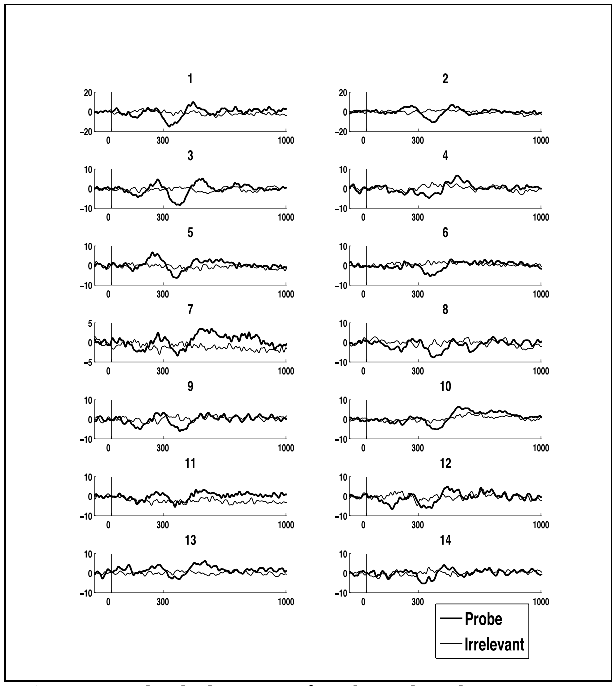

Figure 2: Individuals ERPs of probe and irrelevant ERPs 14 subjects). The irrelevant ERP is shown with the thinner line. The probe ERP is shown with the thicker line. As can be seen, most of the subjects produced a negative deflection which is followed by positivity one between 280ms and 650ms with respect to the beginning of the Probe. However, such pattern was not produced by the irrelevant.

Machine Learning Setup

Experiments are conducted with one of the best data analytics platform i.e scikit and with panda's libraries, implemented using python. Various performance measures like accuracy, precision, recall is used for performance measurements. In the present work best performing algorithms with best performance measures are considered for comparative algorithm analysis.

Machine algorithms are applied on the fourteen different sets of probe and irrelevant data sets of EEG signals. Experiments are carried in several stages. Initially training and testing datasets are prepared by dividing the datasets to 60-40. Algorithms are applied on individual data sets with default parameters. In further stages the data sets are merged keeping one set for testing and other remaining datasets merged for training. Results with merged dataset are analyzed to be better compared with individual data sets testing. Out of eight different algorithms the best performing algorithms are established for the present EEG data sets.

4. DISCUSSIONS AND RESULTS

For a more reliable learning and classification process, a training set and a test set are constructed for each subject. The training set is formed by combining all except one session of EEG data for emotional states. The test set is formed with one left over state sessions of EEG data. Classification performance is compared using spectrum across different subjects. Algorithms are like KNN, SVM, Decision Tree, Random Forest, Neural Network, Adaboost and Naive Bayes are applied to these feature data.

Predictive performances are estimated with metrics like accuracy, precision and racall. These metrics are calculated using the following formulas.

$$Accuracy = (TP+TN) / (P+N)$$

$$Precision = (TP) / (TP+FP)$$

$$Recall = (TP) / (P)$$

TP: true positives
FP: false positives
FN: false negatives
TN: true negatives
P = TP + FN
The total number of positive instances
N = FP + TN
The total number of negative instances

Classification performance with individual subjects are shown in Table 1. The classification results with merged subjects are presented in Table2, Table 3 and Table 4 with metrics accuracy, precision and recall respectively.

Table 1: Performance (Accuracy) of Algorithms

Subject	Algorithm Performance (Accuracy)							
	K N Neighbor	Support Vector Machine		Decision Tree	Radom Forest	Neural Network	AdaBoost	Naeive Bays Gaussian
		SVM Linear	SVM RBF					
1	0.65	0.71	0.47	0.47	0.59	0.65	0.76	0.74
2	0.62	0.75	0.38	0.38	0.65	0.67	0.76	0.67
3	0.72	0.76	0.45	0.45	0.71	0.72	0.76	0.74
4	0.50	0.52	0.47	0.47	0.42	0.57	0.52	0.53
5	0.51	0.56	0.46	0.46	0.53	0.56	0.54	0.58
6	0.66	0.63	0.44	0.44	0.56	0.51	0.56	0.66
7	0.64	0.56	0.46	0.46	0.56	0.63	0.59	0.63
8	0.55	0.52	0.45	0.45	0.58	0.52	0.53	0.53
9	0.53	0.49	0.42	0.42	0.47	0.63	0.56	0.58
10	0.67	0.75	0.45	0.45	0.50	0.53	0.72	0.57
11	0.56	0.58	0.42	0.42	0.60	0.44	0.54	0.60
12	0.67	0.66	0.45	0.45	0.47	0.53	0.66	0.57
13	0.59	0.63	0.42	0.42	0.63	0.61	0.61	0.54
14	0.51	0.63	0.42	0.42	0.66	0.56	0.58	0.66
Best	0.72	0.76	0.47	0.47	0.71	0.72	0.76	0.74

Table 2: Performance (Accuracy) of Algorithms with Merged Datasets

Subject	Algorithm Performance (Accuracy)							
	K N Neighbor	Support Vector Machine		Decision Tree	Radom Forest	Neural Network	AdaBoost	Naeive Bays Gaussian
		SVM Lineear	SVM RBF					
1	0.68	0.73	0.50	0.50	0.70	0.60	0.68	0.67
2	0.74	0.76	0.52	0.48	0.66	0.73	0.71	0.78
3	0.68	0.74	0.50	0.50	0.65	0.74	0.59	0.70
4	0.60	0.63	0.49	0.51	0.55	0.61	0.54	0.61
5	0.65	0.70	0.50	0.50	0.61	0.62	0.61	0.65
6	0.63	0.71	0.50	0.50	0.60	0.67	0.55	0.61
7	0.57	0.68	0.50	0.50	0.64	0.62	0.65	0.62
8	0.61	0.60	0.50	0.50	0.54	0.55	0.54	0.53
9	0.58	0.67	0.51	0.49	0.61	0.61	0.59	0.63
10	0.58	0.64	0.50	0.50	0.62	0.56	0.58	0.60
11	0.59	0.70	0.51	0.49	0.63	0.58	0.56	0.65
12	0.65	0.68	0.50	0.50	0.63	0.59	0.68	0.59
13	0.60	0.71	0.50	0.50	0.60	0.69	0.70	0.71
14	0.50	0.66	0.49	0.51	0.51	0.60	0.64	0.60
Best	0.74	0.76	0.52	0.51	0.70	0.74	0.71	0.78

Table 3: Performance (Precision) of Algorithms

Leave One Out Subject	Algorithim Performance (Average Precision)							
	K N Neighbor	Support Vector Machine		Decision Tree	Radom Forest	Neural Network	AdaBoost	Naeive Bays Gaussian
		SVM Linear	SVM RBF					
1	0.66	0.77	0.22	0.22	0.6	0.86	0.68	0.76
2	0.66	0.77	0.15	0.15	0.71	0.77	0.83	0.7
3	0.75	0.78	0.2	0.2	0.74	0.73	0.74	0.75
4	0.75	0.78	0.2	0.2	0.74	0.73	0.74	0.75
5	0.52	0.56	0.21	0.21	0.53	0.53	0.61	0.61
6	0.67	0.63	0.19	0.19	0.62	0.59	0.58	0.71
7	0.65	0.56	0.21	0.21	0.53	0.6	0.59	0.61
8	0.59	0.53	0.2	0.2	0.57	0.58	0.61	0.55
9	0.55	0.5	0.18	0.18	0.45	0.69	0.51	0.6
10	0.69	0.75	0.2	0.2	0.48	0.52	0.64	0.59
11	0.69	0.75	0.2	0.2	0.48	0.52	0.64	0.59
12	0.68	0.66	0.2	0.2	0.5	0.63	0.64	0.58
13	0.62	0.66	0.18	0.18	0.67	0.64	0.64	0.6
14	0.52	0.63	0.18	0.18	0.64	0.58	0.6	0.72
Best	0.75	0.78	0.22	0.22	0.74	0.86	0.83	0.76

Table 4: Performance (Recall) of Algorithms

Subject	Algorithm Performance (Average Recall)							
	K N Neighbor	Support Vector Machine		Decision Tree	Radom Forest	Neural Network	AdaBoost	Naeive Bays Gaussian
		SVM Linear	SVM RBF					
1	0.65	0.71	0.47	0.47	0.59	0.79	0.65	0.74
2	0.62	0.75	0.38	0.38	0.62	0.73	0.8	0.65
3	0.72	0.76	0.45	0.45	0.71	0.71	0.74	0.74
4	0.72	0.76	0.45	0.45	0.71	0.71	0.74	0.74
5	0.72	0.76	0.45	0.45	0.71	0.71	0.74	0.74
6	0.66	0.63	0.44	0.44	0.63	0.58	0.58	0.71
7	0.64	0.56	0.46	0.46	0.53	0.59	0.59	0.61
8	0.55	0.52	0.45	0.45	0.55	0.53	0.6	0.53
9	0.53	0.49	0.42	0.42	0.46	0.63	0.49	0.58
10	0.67	0.75	0.45	0.45	0.47	0.52	0.63	0.58
11	0.67	0.75	0.45	0.45	0.47	0.52	0.63	0.58
12	0.67	0.66	0.45	0.45	0.48	0.62	0.64	0.59
13	0.59	0.63	0.42	0.42	0.64	0.59	0.63	0.58
14	0.51	0.63	0.42	0.42	0.61	0.54	0.59	0.68
Best	0.72	0.76	0.47	0.47	0.71	0.79	0.80	0.74

5. CONCLUSION AND FUTURE WORK

The comparisons were based on accuracy; a comparative performance analysis is carried. It is can be observed from the results that SVM, KNN and Naive Bayes are better performing machine algorithms when applied on the fourteen different sets of probe and irrelevant data sets of EEG signals. Out of eight different algorithms the best performing algorithms are established for the present EEG data sets. These results are more improved with merged data sets of EEG data.

Analyzing highly robust and variable and noisy EEG signals is a big challenge. Advanced machine learning techniques and adaptive signal processing methods are addressing a lot to this. With these approaches one can go into insight for general mental state monitoring and brain computer interfacing. In the present work we have tried to present and establish the machine as the key approach.

The future research work on this area will be focused with increased the number of subjects and increased number of experiments, with an idea to eliminate inters subjective variability. Also, we can further work on algorithms tuning for better mental states capturing.

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