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Real-Time EEG Based Object Recognition

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Abstract— **A Brain Computer Interface (BCI) provides a communication path between human brain and the computer system. The major goal of BCI research is to develop a system that allows disabled people to communicate with other people, to control artificial limbs, or to control their environment. BCI is a challenging topic of computer vision research. It is extensively used by disabled people to communicate with other persons and helps to interact with the external environments. This paper provides an insight into object recognition by analyzing EEG signals in real-time. Three machine learning algorithms are implemented which are used for classification by supervised learning, namely Decision Trees, K-Nearest Neighbors and Support Vector Machine (SVM), multiple training sets and users are taken into account during the experiment and the efficiency of each algorithm is compared to suggest the best suited algorithm for this purpose.**

Index Terms— **Brain Computer Interface, Invasive and Non-Invasive, Electroencephalography (EEG), Emotive epoc, Decision Trees, K-Nearest Neighbors, Support Vector Machine (SVM), Object recognition, Supervised learning**

I. INTRODUCTION

BCIs started with *Hans Berger's* inventing of electrical activity of the human brain and the development of electroencephalography (EEG). In 1924 Berger recorded an EEG signals from a human brain for the first time. By analyzing EEG signals Berger was able to identify oscillatory activity in the brain, such as the alpha wave (8–12 Hz), also known as Berger's wave. EEGs permitted completely new possibilities for the research of human brain activities [1].

A BCI is a communication and control system that does not depend in any way on the brain's normal neuromuscular output channels, that is the user's intent is conveyed by brain signals (such as EEG) rather than by peripheral nerves and muscles, and these brain signals do not depend for their generation on neuromuscular activity. For example, in a natural system, a person will think of moving his arm, and the peripheral nerves and muscles decode these signals and his/her arm moves [2]. While in a BCI system, the user's arm maybe replaced by a robotic arm and the brain signals that are sent to move the arm, are decoded by the computer. As a communication and control system, a BCI establishes a real-time interaction between the user and the outside world. The user receives feedback reflecting the outcome of the BCI's operation, and that feedback can affect the user's subsequent intent and its expression in brain signals.

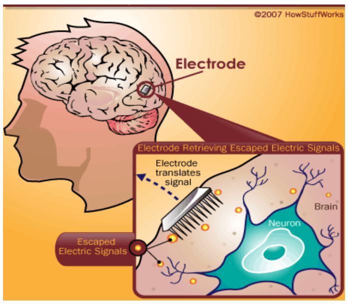

Fig 1. How BCIs work [Courtesy: HowStuffsWork.com]

The brain is a complex inter-connection of neurons, individual nerve cells that are connected to one another by dendrites and axons. Every time a person think, move, feel or remember something, the neurons are at work. That work is carried out by small electric signals that zip from neuron to neuron as fast as 250 mph [3]. The signals are generated by differences in electric potential carried by ions on the membrane of each neuron. Although the paths the signals take are insulated by something called myelin, some of the electric signal escapes. These signals are detected, interpreted and are used by a device of some kind as shown in fig 1.

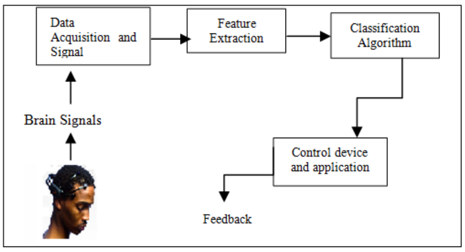

Fig 2. Representation of BCI

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Two main aspects of BCI are data acquisition and classification. Data Acquisition is done mainly by using a device that can record the brain signals. Devices that gather more information are more powerful and tend to give better results. The signals are then analyzed and features extraction algorithms are run on them. Classification algorithms are used to differentiate between the brain signals and map the signals to its actions. Classification of the brain signals has proved to be extremely difficult because commonality does not exist between each person. Therefore a customized profile needs to be created for each person, where he/she has to carry out independent training for each object. Finally the decoded signals are sent to other control devices and application which can use it as an input interface.

This paper presents a novel application of BCI, which is object recognition through real-time EEG, and implements various machine learning algorithms for the classification and identification of objects. The experiment is carried out using emotiv epoc device [4], and has been carried out by multiple users and each of the users has been tested with different sets of training data. The resultant efficiency of each implemented algorithm is compared to suggest the best suited algorithm for this purpose.

BCI has gained momentum and practical viability in the field of neuroprosthetics applications. A reliable system capable of recognizing various brain actions has many important applications. One of the main goals is to enable completely paralyzed patient to communicate with their environment [2].

II. EEG

Electroencephalography (EEG) is a type of non-invasive interface, which has high potential due to its fine temporal resolution, ease of use, portability and low set-up cost. A common method for designing BCI is to use EEG signals extracted during mental tasks [5], [6]. EEG is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. The EEG is modified by motor imagery and can be used by patients with severe motor impairments (e.g., late stage of amyotrophic lateral sclerosis) to communicate with their environment and to assist them. Such a direct connection between the brain and the computer is known as an EEG-based BCI. EEG-based BCI have become a hot spot in the study of neural engineering, rehabilitation, and brain science [1].

The EEG headset, as shown in fig 3, is EPOC headset manufactured by Emotiv Inc [4], [7]. It is used to read a person's brain waves from the surface of the scalp. The Research Edition SDK by Emotiv Systems includes a research headset: a 14 channel (plus CMS/DRL references, P3/P4 locations) high resolution, neuro-signal acquisition and processing wireless neuroheadset [7]. Channel names based on the International 10-20 locations are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 [7]. The Research Edition SDK also includes a proprietary software toolkit that exposes the APIs and detection libraries.

Fig 3. Subject wearing the Emotiv Epoc Headset

III. EXPERIMENTAL WORK

An experiment was conducted to test the efficiency of the recognition of objects using EEG signals. The experiment was conducted on 5 individuals 3 boys and 2 girls of the ages between 20 and 25, using an emotive epoc device to capture the brain signals. The users were asked to train the machine for a total of 100 training sets per object, and only then where the different classification methods tested for accuracy on the users.

Fig 4 shows the block diagram of the entire process beginning from data accusation via the EEG headset up till the results of the classification algorithm.

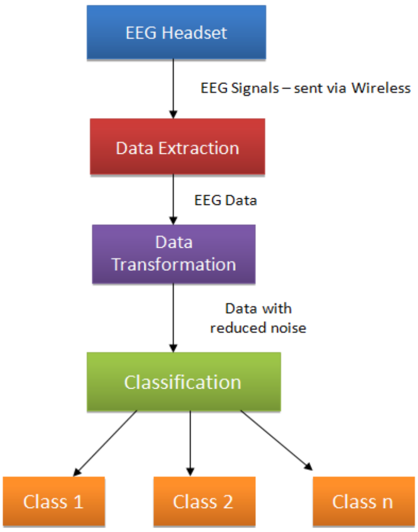

Fig 4. Block Diagram of the system

Emotive Neuroheadset

The device used in this project is the Emotiv EPOC neuroheadset. Emotiv EPOC is a high resolution, multi-channel, wireless neuroheadset. The device comes with the following gadgets: [7]

i. Headset Assembly with Rechargeable Lithium battery already installed
ii. USB Transceiver Dongle
iii. Hydration Sensor Pack with 16 Sensor Units
iv. Saline solution

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v. 50/60Hz 100-250 VAC Battery Charger (US customers)or USB charger (non-US customers)
vi. CD Installation Disk for Windows XP or Vista (only for EPOC consumer headset. SDKs are delivered electronically)

The EPOC uses a set of 14 sensors plus 2 references to tune into electric signals produced by the brain. It also has a two-axis gyro for detecting the head movements.

Data Acquisition

This is first step where electroencephalography (EEG) signals are obtained from the neuroheadset in the form of sensor readings and stored in a CSV file. The brain signals are extracted as EEG signals from the emotive epoc device. The Research Edition SDK includes a proprietary software toolkit that exposes the APIs to extract data in numerical form. It interfaces with the device and obtains the required sensor readings which can be subsequently processed. The CSV file contains 16 attributes each corresponding to the EEG signal for an electrode. The data is sampled for 4 seconds with the data rate of 118 values per second.

Fig 4, is a visualization of the EEG signal reading for electrode F5 for 3 different trials, while a user was thinking of an apple for 4 seconds (each color represents a different trial)

IV. EEG VISUALIZATIONS

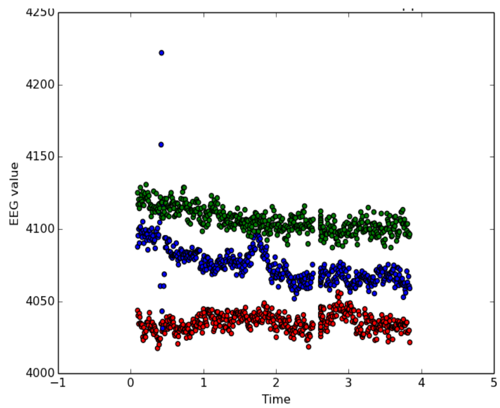

Fig 5. A plot of EEG for 3rd electrode in 3 trials (red, blue, green) for an apple fruit when the user saw an apple while wearing neuroheadset.

Training

This is the second step where each user trains the device for the first time he/she uses it before identification. The machine is trained for 100 training set reading for each object before any test of classification is carried out. The data obtained from the emotive epoc device which is stored in a CSV file is processed for data transformation by reducing dimensions and noise reduction. This is done by calculation the mean and standard deviations for each trials, only the mean reading for each electrode is used for processing this reduces the dimensions and also reduces the noise caused by the device. The reduced dimensions for the data lower the memory cost and the algorithm becomes faster. To ensure that a good data set is acquired, the process of training will be repeated for the same object multiple times with the same user as well as different users.

Classification

Machine learning concerns with the construction and study of systems that can learn from data. Machine learning focuses on prediction, based on known properties learned from the training data [8]. Supervised learning algorithms are trained on labeled examples, i.e., input where the desired output is known. For classification of data we are using supervised learning algorithm. The supervised learning algorithm attempts to generalize a function or mapping from inputs to outputs which can then be used speculatively to generate an output for previously unseen inputs.

1) Decision trees

Decision Trees (DTs) are a non-parametric supervised learning method used for the purpose of classification. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features [9]. It turns out that decision trees are an efficient way to classify the type of data is obtained from the emotive device. An optimized version of the Classification and Regression Trees (CART) algorithm is used to construct the decision trees and Gini Index is used for attribute selection. CART constructs binary trees using the feature and threshold that yield the largest information gain at each node. Since the EEG data is continuous-valued a split-point is selected as splitting criteria for the branches. Objects are classified by comparing the EEG values of electrodes with the split points as shown in fig 5.

To compute Gini impurity for a set of items, suppose i takes on values in {1, 2... m}, and let f_i be the fraction of items labeled with value i in the set [10].

$$I_G(f) = \sum_{i=1}^{m} f_i(1-f_i) = \sum_{i=1}^{m}(f_i - f_i^2) = \sum_{i=1}^{m} f_i - \sum_{i=1}^{m} f_i^2 = 1 - \sum_{i=1}^{m} f_i^2$$

Advantages:

- These trees are simple to understand and can also be visualized
- The cost of using the tree (i.e., predicting data) is logarithmic in the number of data points used to train the tree.
- Performs well even if its assumptions are somewhat violated by the true model from which the data were generated.

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Disadvantage:

- Decision-tree learners can create over-complex trees that do not generalize the data well
- Decision tree learners create biased trees if some classes dominate

Fig 6 shows the construction of a decision tree for classification of two objects namely food and mountain, where F5, T8, P7 represents various electrodes

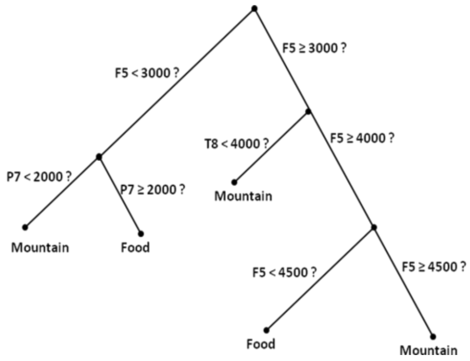

Fig 6. Decision Tree

2) K-Nearest Neighbors

Neighbors-based classification is a type of instance-based learning or non-generalizing learning [11]. Classification is computed from a simple majority vote of the nearest neighbors of each point. The nearest neighbor classification used uses uniform weights: that is, the value assigned to a query point is computed from a simple majority vote of the nearest neighbors. The 16 electrodes of the emotive device are each represented by a dimension; hence a 16 dimensional space is derived. Each training reading is plotted as a point in this space as shown in fig 7. The test reading is also plotted on the same plane, and its class is determined by the majority of the seven nearest plotted point in the space.

Advantage:

- Robust to noisy data
- Effective if training data is large

Disadvantage:

- Need to determine the value of k
- Computation cost is higher

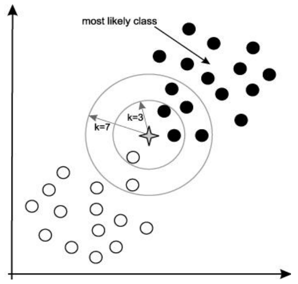

Fig 7. K-Nearest Neighbors Algorithm

3) Support Vector Machines

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns [12], used for classification and regression analysis. The 16 electrodes of the emotive device are each represented by a dimension; hence a 16 dimensional space is derived. Each training reading is plotted as a point in this space as shown in fig 8. If the different classes of points are linearly separable, linear kernel is used, else Radial Basis Function kernels is used to map samples into another dimensional space. The Maximum marginal hyper-plane is found that differentiates between the two classes and the test data is plotted next and compared to which class it belongs.

Given training vectors $x_i \in R^p$, i=1,..., n, in two classes, and a vector $y \in R^n$ such that $y_i \in \{1, -1\}$, SVC solves the following primal problem:

$$\min_{w,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1,n} \zeta_i$$

$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i,$$
$$\zeta_i \geq 0, i = 1, ..., n$$

Its dual is

$$\min_{\alpha} \frac{1}{2} \alpha^T Q \alpha - e^T \alpha$$
$$\text{subject to } y^T \alpha = 0$$
$$0 \leq \alpha_i \leq C, i = 1, ..., l$$

where e is the vector of all ones, $C > 0$ is the upper bound, Q is an *n* by *n* positive semidefinite matrix, $Q_{ij} \equiv K(x_i, x_j)$ and $\phi(x_i)^T \phi(x)$ is the kernel. Here training vectors are mapped into a higher (maybe infinite) dimensional space by the function ϕ.

The decision function is:

$$\operatorname{sgn}(\sum_{i=1}^{n} y_i \alpha_i K(x_i, x) + \rho)$$

Advantage:

- Effective in high dimensional spaces.
- Uses a subset of training points in the decision function (called support vectors), so it is also memory efficient.

Disadvantage:

- If the number of features is much greater than the number of samples, the method is likely to give poor performances

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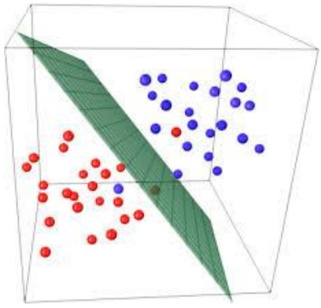

Fig 8. Support Vector Machines

V. RESULTS

The experiment was conducted to test the efficiency of object recognition using EEG signals. Accuracy here is defined as the amount of correct classification among a set of 100 tests. The experiment was conducted on 5 individuals 3 boys and 2 girls of the ages between 20 and 25. During the experiment the users were asked to train the machine for a total of 100 training sets per object, and only then where the different classification methods tested for accuracy on the users.

Testing K Nearest Neighbors to distinguish between 2 objects by providing a training set of 100 reading and running the test 100 times gives us an efficiency of 70% for accurate classification Fig 9.

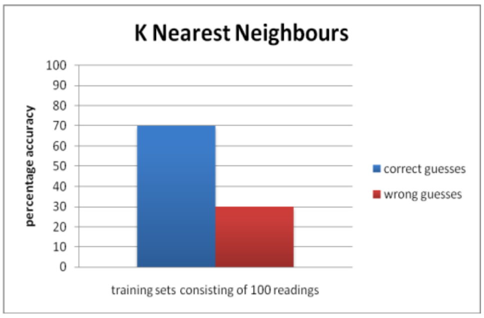

Fig 9. A graph showing percentage accuracy of K-nearest neighbours method with 2 objects.

Testing Decision trees to distinguish between 2 objects by providing a training set of 100 reading and running the test 100 times gives us an efficiency of 82% for accurate classification Fig 10

Fig 10. A graph showing percentage accuracy of Decision trees method with 2 objects.

Testing SVM to distinguish between 3 objects by providing a training set of 100 reading and running the test 100 times gives us an efficiency of 63% for accurate classification Fig 11

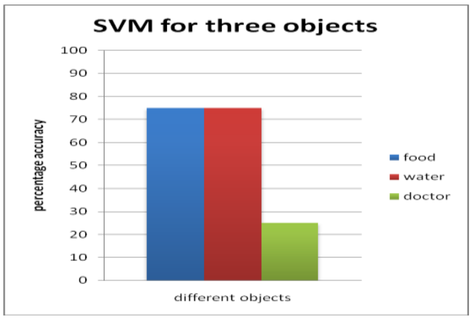

Fig 11. A graph showing percentage accuracy of SVM method with 3 objects.

VI. CONSLUSION AND FUTURE WORK

The main aim of this paper was to implement and compare the three machine learning algorithms for recognition of objects from EEG in real time. The experiment began with the users training the machine to recognize different objects; this was accomplished by showing the user a picture of the object while collecting the EEG signals generated by him/her as a result of seeing the object. This process of recording the signals was done for multiple users and each user recording his /her signals 100 times per object to get a good training set. Once the machine was well trained, it was tested for its accuracy by checking its correctness in classifying a reading for an object that the machine had already learnt. Based on these test results, it can be concluded that decision trees works the best among the three, as it has the most efficiency of 82%., which is 12% more than k-nearest neighbors(70%) and 19% more than support vector machine (63%).

Currently, real-time object recognition is implemented as a standalone application. The next step of the project is to target the medical industry and help paralyzed patients to communicate with their environment and overcome their disabilities to express their thoughts. The future enhancement includes noise reduction using the algorithms like band-pass filters and newer algorithms like fractal dimension, it also includes the usage of a more powerful device that has a stronger and more focused signal readings.

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