k-NN based Object Recognition System using Brain Computer Interface

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ABSTRACT
Brain Computer Interface is a device which provides the communication between the human brain and the computer. This paper provides an idea of object recognition system using Principal Component Analysis (PCA) and Singular Value Decomposition (SVD). This is used to recognize the object by analyzing EEG signals in real time. K-Nearest Neighbors algorithm is implemented to classify the intended object. Multiple training sets and users are taken into account during the experiment and the efficiency of the algorithm is calculated.

Index Terms
Brain Computer Interface, Invasive and Non-Invasive, Electroencephalography (EEG), Emotive epoc, K-Nearest Neighbors, Object recognition

1. INTRODUCTION
BCI started with Hans Berger in 1924. He found out that some electrical activity is generated in human brain. He inserted simple tubes inside the brain and connected that to Lippmann capillary electrodes and observed for the signals. He could found some oscillatory movement from human brain which we call it as alpha wave (8–12 Hz), also known as Berger's wave.

Brain Computer Interface (BCI) is a non invasive Electroencephalogram (EEG) based device, where research has been immensely increased in this area over the past few years. BCI is mainly used for disabled who cannot move their body, basically who are paralyzed. To control BCI device user has to produce different brain patterns which will be identified by the system and then translates into intended commands.

Three main aspects of BCI are data acquisition, noise reduction and classification. In data acquisition, features are extracted from the human brain which is been generated when a person thinks of some objects. The signals are then analyzed and given to noise reduction technique as the obtained signals are not noise free.[4,5] Because of some disturbances EEG signals are distorted which has to be reduced. Proper noise reduction algorithms are run on them to reduce the noise. At last classification algorithms are used to differentiate the signals and map the signals with the intended object whatever the user has thought. Classification is the most difficult task in the brain signals because every user doesn't produce the same signals. It varies from person to person which has to be classified based on the proper and suitable classification algorithms. 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 [1, 2]. The aspect of BCI is shown in fig1.

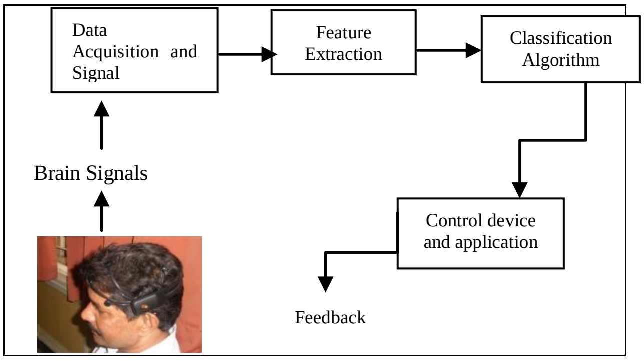

Fig 1. Representation of BCI

This paper presents a system which is mainly designed for object recognition through real time EEG and reduces the noise using some transformation algorithms and later on implements classification algorithm to classify the object and identify the object. The experiment is carried out using emotiv epoc device, and has been carried out by multiple users and each of the users has been tested with different sets of training data and efficiency is calculated [1, 2].

2. EEG BASED BCI
A common method for designing a BCI is to use EEG signals extracted during mental tasks . EEG is the most widely used neuroimaging modality, owing to its high temporal resolution, relative low cost, high portability, and few risks to the users. EEG is the recording of brain's electrical activity along the scalp produced by the firing of neurons within the brain. However, the signals are of low resolution as the signals have to cross the scalp, skull, and many other layers [5]. So the signal strength in the electrodes is weak, in the order of micro volts and very sensitive to noise. Noise is the key factor in EEG signals, as it reduces the signal to noise ratio and therefore the ability to extract meaningful information from the recorded signals . The noise may be either due to additional current fields inside the brain or due to external noise sources.

The EEG recording system consists of electrodes, amplifiers, A/D converter, and a recording device. The electrodes obtain the signal from the scalp, the amplifiers magnify the amplitude of the EEG signals and the A/D converter digitizes these signals. Finally, the recording device stores and displays the data. The EEG signal is measured as the potential difference over time between the active electrode and reference electrode. The multichannel EEG sets contain upto 128 or 256 active electrodes. These electrodes are generally made of silver chloride (AgCl). The EEG gel is an electrolyte which creates a conductive path between the skin and the electrode for the current flow. Electrodes that do not use gels, called 'dry' electrodes, are made with materials such as titanium and stainless-steel.

EEG comprises of a set of frequency bands. These frequency bands are referred to as delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) respectively. Relevant characteristics of these bands are detailed below.

Table 1: Frequency bands in the brain signal

EEG Bands	Frequency (Hz)	Distribution	State of Mind
Delta	upto 4	Central cerebrum and parietal lobes	Deep sleep, non-REM sleep
Theta	4 – 8	Frontal, parietal and temporal lobes	Drowsiness, first stage of sleep
Alpha	8 – 13	Most prominent at occipital and parietal lobe	Relaxed but alert
Mu	10 -12	Central electrodes, over motor and somatosensory cortex	Shows rest-state motor neurons
Beta	13 – 30	Localized	Highly alert and focused
Gamma	> 30	Very localized	higher mental activity, including perception and consciousness

3. METHODOLOGY

The proposed work composed of three separate modules. These modules can be run separately or be run from a main script. The modules are:

1. Data Extraction

This is the first step or module of the proposed work which is used to obtain the electroencephalography (EEG) signals from the neuroheadset in the form of sensor readings and store it in a file. The neuroheadset used in our experiment is emotive epoc [5] which is of 14 electrodes device, high resolution, multi-channel, wireless neuroheadset. Electrodes are placed on 14 different part of the brain scalp of the human brain and connected to SDK of the emotive epoc. Once the device is ready we will get the EEG signals [7, 8] of that user in the form of waveforms. The waveforms obtained are not noise free. Noise has been incurred because of the disturbances created while capturing the EEG signals. Once the waveform is obtained, we extract those signals into numerical and store it in a CSV file. Research Edition SDK includes a proprietary software toolkit that exposes the APIs to extract data in numerical form.Once the interface is done with the device obtained sensor readings can be processed subsequently.

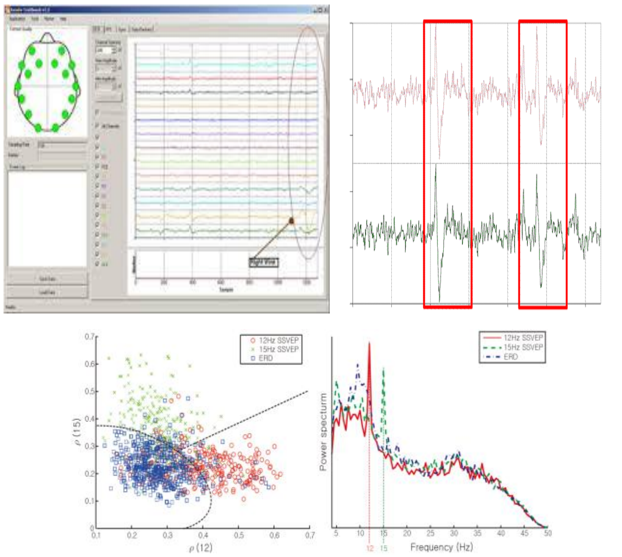

Fig 2: Data extraction from the emotive epoc

2. Noise Reduction

In this step, the idea is to reduce the noise in the EEG signals to some extent. The concepts of Singular Value Decomposition (SVD) and Principal Component Analysis (PCA) have been used to reduce noise in these signals.

PCA is used to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables.

Singular Value Decomposition (SVD) is used to remove noise from the values obtained. The Eigen vectors and Eigen values of the data are obtained by applying SVD. The Eigen values and their corresponding Eigen vectors are sorted in decreasing order of Eigen values. The sum of the Eigen values is found and the Eigen values that contribute 99% of this sum are retained and the ones that contribute to the last 1% are set to zero (0). This removes the effect of the Eigen vectors corresponding to these Eigen values. The rationale is that the small contributions from these Eigen vectors must represent noise.

3. Classification

Finally, the filtered data is classified to one of the categories or classes established in the classification phase. The proposed work employs the use of k-Nearest Neighbour Algorithm to classify the data. The final task is to classify the records into one of the labels defined using training. The model can be built as the training is being performed (early learner approach) or when classification needs to be performed (late learners approach). The proposed work uses k Nearest Neighbors (kNN) algorithm. This is a late learner's technique. This takes longer to classify as it involves a lot of computation at the time classification needs to be performed. [15, 16, 17]

K-Nearest Neighbor

The k-NN classifies the feature vectors based on closest training examples in the feature space.[15] The advantage of the k-NN method over other supervised learning methods is its ability to deal with multiple class problems. The feature vector is classified by a majority vote of its neighbors, and is assigned to the class which has lesser distance amongst its k nearest neighbors, where k is a positive integer, typically small to make boundaries between classes more distinct. Euclidean distance is used as a distance metric for our work and the value of k is chosen as 3 after repeated cross validation. The vector is simply predicted and assigned to the class of its nearest neighbor.

In the training phase of the system, the feature vectors and the corresponding class labels of the training samples are stored. The training samples are vectors in a multidimensional feature space, each with an assigned class label. In the classification phase, the unlabeled feature vector is classified by assigning the label which is most frequent among the k training samples nearest to that query point [17]. From fig 3 the test sample (purple circle) should be classified either to the first class of green squares or to the second class of red stars. If k = 3, it looks for 3 nearest neighbors and it is assigned to the second class because there are 2 stars and only 1 square inside the inner circle. If k = 5, it looks for 5 nearest neighbors, it is assigned to the first class of green squares as there are 3 squares and 2 stars inside the outer circle.

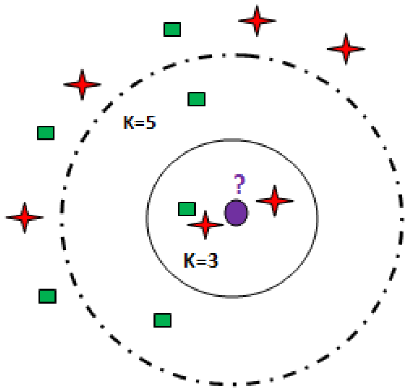

Fig 3. Example of k-NN classification for k=3 and k=5

4. EXPERIMENTAL SETUP

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

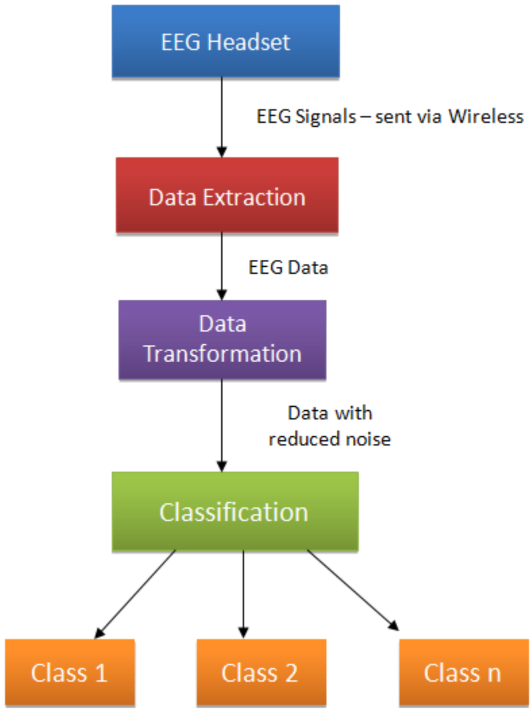

Fig 4. Block Diagram of the system

An experiment was conducted on different individuals consists of boys and girls with ages between 20 and 25 using emotive epoc headset. [16, 17] The proposed work consists of two things.

- Training
    1. {python.exe code/main.py <classLabel>}

The above command classifies the data recorded subsequently as an object whose name is specified by classLabel.

- Testing
    2. {python.exe code/main.py}

The above command tries to classify the obtain EEG signals into one of the class labels recorded during training.

In data extraction, samples were collected for 10 seconds and stores the resultant data in the output file specified as shown below:

3. {code/dataExtraction/dataExtraction.exe <outputFileName>}

Later in noise reduction, it reduces the noise from the data obtained by the neuroheadset. It uses Singular Value Decomposition (SVD) and Principal Component Analysis (PCA) which is as shown below:

4. {code/svd/svd.exe <inputFileName> <outputFileName>}

It performs SVD on the contents of the input file specified and removes some noise from the data. The output is stored in the output file specified.

In Classification, data is classified data into one of the class labels by applying the k-nearest neighbours algorithm as shown below:

5. {code/classification/nearestNeighbour.py<trainingDataSet> <testFile>}

It classifies the contents of test file using the training data set.

5. CONSLUSION AND FUTURE WORK

The main aim of this paper was to implement a system which recognizes the object, analyze the signals by reducing the noise and classify them based on the machine learning algorithm. 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. 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 k-nearest neighbors has an efficiency of 75% in recognizing the objects.

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.

6. REFERENCES

[1] Anupama.H.S, N.K.Cauvery, Lingaraju.G.M, “Brain

computer interface and its types - a study", International Journal of Advances in Engineering & Technology, May 2012.

[2] Anupama.H.S, N.K.Cauvery, Lingaraju.G.M, "Real Time EEG Based Object Recognition system using Barin Computer Interface", Nov 2014, pg no-1046-1051.

[3] G. Lorina Naci, Martin M. Monti, Damian Cruse, Andrea Ku¨ bler, Bettina Sorger, Rainer Goebel, Boris Kotchoubey, and Adrian M. Owen, "Brain–Computer Interfaces for communication with nonresponsive patients", unpublished.

[4] W. Lutzenberger, T. Elbert, N. Birbaumer, W. J. Ray, and H. Schupp, "The scalp distribution of the fractal dimension of the EEG and its variation with mental tasks," Brain Topography, vol. 5, 1992, pp. 27-34.

[5] About Emotive Epoc. http://emotiv.com/epoc/

[6] Nicolas-Alonso, Luis Fernando, and Jaime Gomez-Gil. "Brain computer interfaces, a review." Sensors 12, no. 2 (2012): 1211-1279.

[7] Yisi Liu, Olga Sourina, and Minh Khoa Nguyen, "Real-time EEG-based Human Emotion Recognition and Visualization," unpublished.

[8] Emotiv Software Development Kit, User Manual for Release 1.0.0.3.

[9] Mitchell, T. M., "Machine Learning", McGraw-Hill, New York, NY, 2nd Edition, 1997.

[10] Ravindra Changala, Annapurna Gummadi, G Yedukondalu, UNPG Raju ,"Classification by Decision Tree Induction Algorithm to Learn Decision Trees from the class-Labeled Training Tuples ", *International Journal of Advanced Research in Computer Science and Software Engineering*, Volume 2, Issue 4, April 2012.

[11] Fayyad, U. M., Irani, K. B., "On the handling of continuous-valued attributes in decision tree generation," Machine Learning, 1992.

[12] J. Goleberger, S. Roweis, G. Hinton, and R. Salahhutidnov, "neighbourhood components analysis", *Advances in Neural Information Processing Systems 17*, Cambridge, MA, 2005.

[13] Lal, T.N, Schr¨oder, M.T, Hinterberger, J., Weston, M., Bogdan, N., Birbaumer, B and Sch¨olkopf, "Support Vector Channel Selection in BCI", in the proceedings of IEEE Transactions on Biomedical Engineering, Special Issue on Brain-Computer Interfaces, June 2004.

[14] Mason, Steven G., and Gary E. Birch. "A general framework for brain-computer interface design." Neural Systems and Rehabilitation Engineering, IEEE Transactions on 11, no. 1 (2003): 70-85.

[15] Zhang, Hao, et al. "SVM-KNN: Discriminative nearest neighbor classification for visual category recognition." Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on. Vol. 2. IEEE, 2006.

[16] Python. https://docs.python.org/2.7/library

[17] K-NearestNeighbour. http://saravananthirumuruganathan.wordpress.com/2010/05/17/a-detailed-introduction-to-k-nearest-neighbor-knn-algorithm/