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Task Classification of EEG Signal Using Bayesian Quadratic Classifier

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ABSTRACT

Different techniques for identifying different types of brain activity are offered by brain sensing technologies. In this, we present the use of inexpensive electroencephalograph (EEG) equipment for task classification. In the initial investigation, we are required to complete one of three tasks while seated: mental rotation, mental arithmetic, or rest. In the second trial, participants choose from three different tasks: a relaxation exercise, a PC game without any fighting, or a PC game with fighting. The three tasks' mean classification accuracy is determined.

The use of various machine learning approaches for the classification of mental tasks using Electroencephalograph (EEG) signals is detailed in the task classification section. This is primarily being used to enhance brain computer interface (BCI) devices. Two well-known EEG datasets in the BCI field are used as the basis for the application of Bayesian graphical network, neural network, Bayesian quadratic, Fisher linear, and Hidden Markov Model classifiers. In this work, the Bayesian network classifier is applied for the first instance to classify EEG signals. The accuracy of the Bayesian network is really high..

Keywords: Brain-Computer Interface, human cognition, physical artifacts, task classification, Electroencephalogram (EEG), Bayesian network classifier.

I. INTRODUCTION

With the advancement of technology, people may now converse and interact with machines by thought or build gadgets that can see into a person's head. These concepts have captivated human imagination, leading to advancements in neuroscience and modern science. An EEG is a quantifiable tool used in brain sensing technology to identify brain signals. These technologies are used to track the mental activities that correspond with the physical processes in the brain. The user generates a signal in these systems that can be used to operate computers or other communication equipment.

The brain is a dense network made up of about 100 billion neurons, which are nerve cells.

Every neuron interacts with thousands of other neurons to control the body's functions and generate cognition. Neurons can communicate with one another by exchanging chemicals known as neurotransmitters or by delivering electrical signals through physical connections. Thanks to developments in brain monitoring technologies, we can now see changes in blood flow, chemical reactions, or electrical activity in the brain as it processes information or reacts to different stimuli. We concentrate on the Electroencephalograph (EEG), the most widely used technology in modern times and a tool that is utilized on a daily basis in clinics and hospitals. To do this, job classification is required.

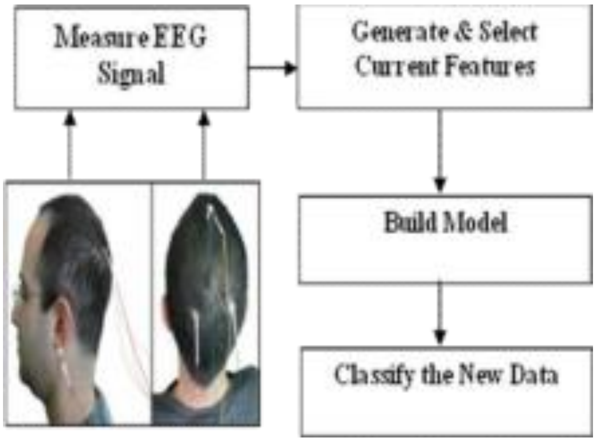

Figure1. Block Diagram of BCI

II. LITERATURE REVIEW

This article focuses on the Electroencephalograph (EEG), a device that is regularly utilized in clinics and hospitals. Electrodes are used to the scalp in EEG to measure the weak electrical potentials (5- 100μV) produced by brain activity. Usually, each electrode is made out of a wire that connects to a gold-plated disk that is bonded to the scalp with conductive gel or paste. Every electrode's voltage is recorded by an EEG in relation to a reference point, which is typically just another electrode on the scalp. Since EEG is a passive measuring tool, prolonged and frequent usage is safe.

The signal provided by an EEG is at best a representation of brain activity due to the nature of the detector. Scalp electrodes are only sensitive to macroscopic and coordinated firing of large groups of neurons near the surface of brain, and then only when they are directed along a perpendicular vector relative to the scalp. Additionally, because of the fluid, bone, and skin that separate the electrodes from the actual electrical activity, the already small signals are scattered and attenuated before reaching the electrodes. Each input channel of an EEG includes a multistage amplifier with a typical gain of 20,000.

EEG systems consist of a number of electrodes, differential amplifiers, filters and needle (pen)- type registers. The EEG signals can be easily plotted on paper. Recent systems use computers for digitization and storing purposes. For digitization sampling, quantization and encoding is done. The effective bandwidth of the EEG signals is about 100 Hz. Thus a minimum of 200samples per second is necessary for sampling. For quantization representation using 16 bits is mostly used. Figure below shows the conventional electrode arrangement recommended by the International Federation of Societies for Electroencephalography and Clinical Neurophysiology for 21 electrodes(called 10-20 electrode position)

III.TYPES OF TASK FOR EEG CLASSIFICATION

Since BCI technology is most helpful as an input control or communication device if the system is able to discriminate between at least two states within the user, we focus on EEG work linked to the task classification problem in this classification. This problem has drawn a lot of interest. By using this capability, a computer can convert changes in one state or the persistence of a state into a format suitable for directing an application. In this classification, we focus on EEG research related to the task classification problem, which has drawn a lot of attention because BCI technology works best as an input control or communication tool when it can distinguish between at least two user states.

Tasks: Based on the results from pilot recordings with our system, we choose three tasks.

I. Rest:

We told the participants in this task to try not to focus on anything specific and to relax. Additionally, we told them to stop working on any tasks that may have been assigned before the rest.

II. Mental Arithmetic

In this exercise, participants mentally multiplied a single digit number such as 7 × 836 by a three-digit number. We designed the questions to be somewhat challenging, yet complex enough that most participants would need more time than the allocated allotment to finish them. If they completed before the time ran out, we told them to check their answers again.

This ensured that they were performing the intended task as well as they could throughout the task period. Since we did not have participants provide us with answers, we confirmed that the problems were keeping them busy for the duration of the task during a debriefing interview.

III. Mental Rotation:

In this task, participants had to see certain objects like a peacock in as much detail as they could as they were spinning in space. The participant was left in charge of the object's specifics.

IV. EEG ELECTRODE PLACEMENT

A worldwide standard for the placement of EEG electrodes on the human scalp is known as the 10-20 System. As seen in Figure 3, the system defines a network of cables in relation to anatomical landmarks on the head, such as the electrode (nasion) between the nose and forehead and the inion (bump) at the occipital. Ten percent or twenty percent increments between these landmarks dictate the positions of the electrodes.

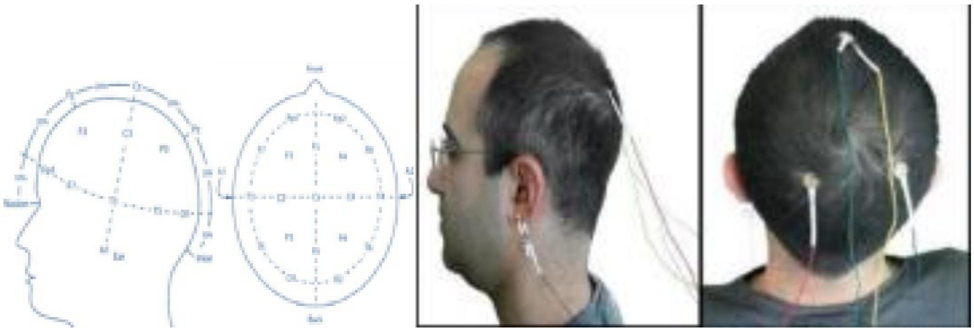

Figure 2.Experimental Set up of Electrode Placement System

In order to identify the parietal (P3 and P4) areas as the sites of interest, we must ascertain the results from the pilot recordings, with both electrode references tied on top of the head located in the center (Cz). Figure 4 illustrates the electrode locations. We were able to compare the readings from each EEG channel in a meaningful way by attaching the references for the two channels together. We connected the ground electrode connector that comes with the Brain master to an ear lobe. Grounding serves as an electrical safety measure to shield the device's delicate inputs from harm.

Their specific locations on the head do not impact the recorded signals. When attach an electrode, we first clean the scalp location small amount of Nuprep solution, an abrasive skin prepping gel used to remove dirt, oil, and dead skin from the area in order to reduce the impedance of the electrical connection with the scalp. Then, we place a small amount of conductive paste on the electrode and attached the electrode to the scalp. The paste improves the electrical connection and provides a temporary bond that holds the electrode on the scalp. The measured impedance of our electrode connections was approximately 2 0 K Ω.The setup procedure requires about 10 minutes. Once the experiment was complete, we removed the electrodes and subjects could wash off any remaining gel and paste with brief water.

V. METHODOLOGY

We converted the time series data into a time independent data set by performing some simple signal processing in order to categorize the signals recorded from our EEG. Then, using mathematical fusion, we generated a set of base features that produced a much bigger set of features. The feature sets were then subjected to a feature selection procedure. We performed the classification by training a Bayesian network with these features. We conclude by talking about how averaging might be applied to improve the categorization accuracy, which gets us to our ultimate conclusions. The following subsections provide descriptions of each of these steps.

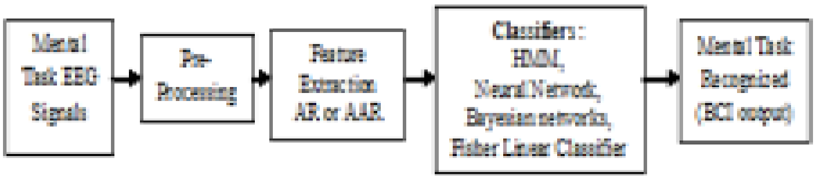

Figure 3.Flow of Methodology

VI. EEG FOR TASK CLASSIFICATION

Bayesian Network is a modeling tool that combines directed acyclic graphs with Bayesian probability. Figure 4 shows the example of Bayesian network which consists of a causal graph combined with an underlying probability distribution. Each node of the network in the figure corresponds to a var iable and edges represent causality between these events. The other elements of a Bayesian network are probability distributions associated with each node. With this information the network can model probabilities of complex causal relationships.

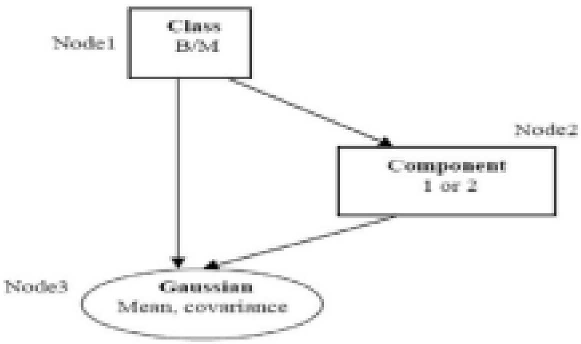

Figure 4.Gaussian mixture model represented as a simple graphical model. B stands for baseline and M for Multiplication tasks

The graphical model corresponding to the Bayesian network used in this work is shown in Figure 6. Note that the square box in the figure corresponds to the input extracted features. The rectangular box corresponds to the Gaussian mixture components. The square and rectangular nodes represent discrete values while the round node in the figure represents continuous values. The graph structure of this model can be represented by the following adjacency matrix: 011, 001, and 000. The Bayesian Network Toolbox (BNT) was used for implementing the classifier. The model was trained using the EM algorithm. EM works by starting with a randomly initialized model (mean and covariance). So, the EM algorithm is composed of two steps. In the first step, each data point undergoes a soft assignment to each mixture component. In the second step, the parameters of the model are adjusted to fit the data based on the soft assignment of the previous step.

VII. RESULTS

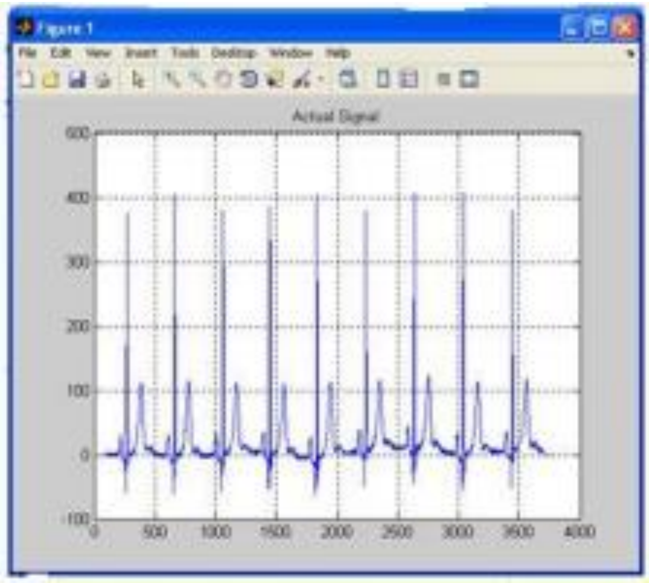

Figure 5. For Normal Case

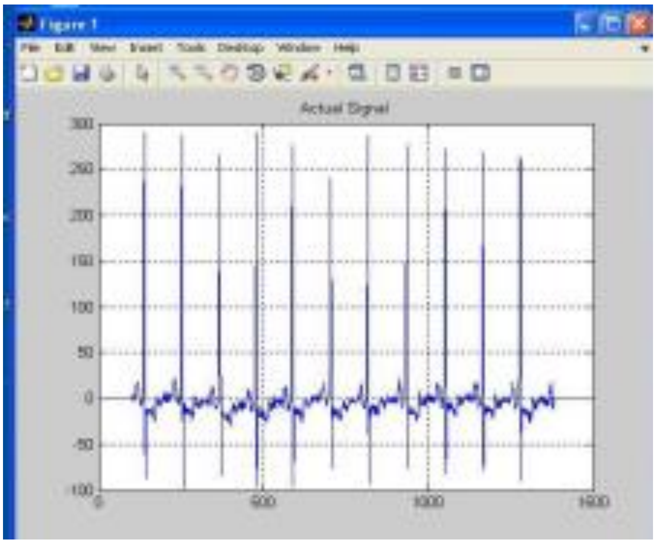

Figure 6.For abnormal Case

Table1.Bayesian Graphical Networks (BNT), Neural Network, Bays Quadratic classifier, Fisher linear and Hidden Markov Model are compared for classification of binary combinations of five mental tasks

Sub.	BNT	Neural Network	Bayes	Fisher Linear	HMM
1	94.07±2.2	92.48±2.9	93.78±2.8	91.15±2.7	70.18±8.8
3	87.43±3.9	85.04±4.3	89.22±3.5	82.77±4.1	64.10±9.1
5	82.48±2.8	82.61±3.0	86.58±3.4	81.79±3.1	62.43±7.8
6	90.31±2.7	89.39±3.1	92.49±3.2	90.38±3.1	64.61±8.3
means	**88.57±3.0**	**87.38±3.4**	**90.51±3.2**	**86.63±3.3**	**65.33±8.5**

Table 2.The summary of the results of different groups on considering the value of MI for Bayesian network, the result of this work ranks second compared to others.

Ranking	Groups	Minimum Error	Maximum SNR	Minimum MI
1	C	10.71	1.34	0.61
2	F	15.71	0.90	0.46
3	B	17.14	0.86	0.45
4	A	13.57	0.85	0.44
5	G	17.14	0.50	0.29
6	I	23.57	0.44	0.26
7	E	17.14	0.34	0.21
8	D	32.14	0.14	0.08
9	H	49.29	0.00	0.00
Bayesian network	-	16.43	1.00	0.50
Neural network	-	15.71	1.04	0.51
Bayes classifier	-	17.14	0.71	0.38

VIII. CONCLUSION

In the field of BCI, two widely recognized EEG datasets serve as the foundation for the implementation of classifiers such as Bayesian graphical network, neural network, Bayesian quadratic, Fisher linear, and Hidden Markov Model. For the first time, the Bayesian network classifier is used in this work to categorize EEG signals. With the Bayesian network, accuracy is quite good.

It is conclude that the task for mental arithmetic vs. Rotation did not do comparing against Rest. In the rotation and arithmetic conditions, the amount of brain activity was similar in accuracy, while the comparisons against the rest task were easily distinguished by the task. With the help of Bayesian network, EEG signal was classified. The Bayesian quadratic classifier is better than other classifier.

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