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A Survey on Thoughts to Text Using Brainwave Patterns

Dipti Pawar[1], Kapil Kamale[2], Ishaan Singh[2], Vishwajeet Kharote[2], Prajwal Goswami[2]

Assistant Professor, Dept. of Computer, Sinhgad College of Engineering, Pune, India[1]

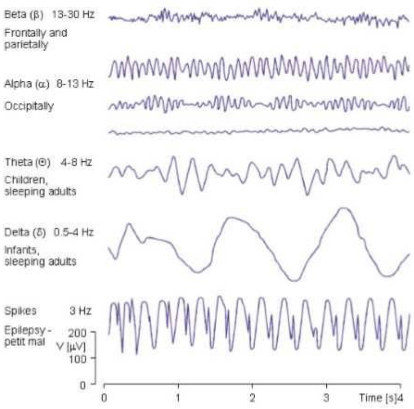
B.E. Students, Dept. of Computer, Sinhgad College of Engineering, Pune, India [2]

ABSTRACT: The art of communication is the language of Development. Sometimes it is hindered due to physical limitations such as lack of speech or limbs. Thus a BCI system is created to detect human mimes through EEG brainwaves as thoughts and predicts the intended word. This system will enable the speechless to communicate, reduces human typing efforts and increases the interaction efficiency of present BCI system. The data required by the system was gathered using RMS-EEG machine in SuperSpecsEEG software. The EEG signal of respecive mimes are broken down into fixed sized array for better understanding of computer. The FFT and Welch power spectrum are applied to the extracted EEG array for feature Extraction. The FFTs are trained for various artifacts used in miming using K-nearest Neighbor (KNN) technique. A probabilistic Model is presented which increases the efficiency of existing KNN system by considering the prediction probability of each EEG channel. Thus the efficiency of the system enhances with increase in datasets. Finally the trained model will be further used to predict and recognize the EEG wave which will aid in thoughts to text conversion.

KEYWORDS: K-Nearest Neighbour; Brain Computer Interface; Brain Machine Interface; Electroencephalography; Automatic Speech Recognition; Feature Extraction; Artificial intelligence

I. INTRODUCTION

Brainwaves :At the root of all our thoughts, emotions and behaviors is the communication between neurons within our brains. When slower brain waves are dominant we can feel tired, slow, sluggish, or dreamy. Similarly the higher frequencies are dominant when we feel wired, or hyper-alert. Different types of brainwaves are discussed in the Figure 1.



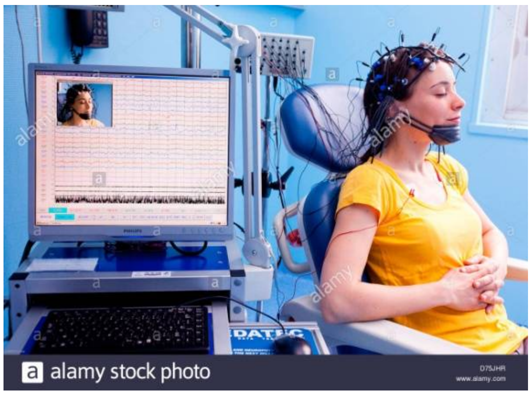


Fig. 2. Setup of RMS-EEG Machine

Fig.1. Types of brainwaves

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In practice things are far more complex, and brainwaves reect different aspects when they occur in different locations in the brain. Brainwave speed is measured in Hertz (cycles per second) and they are divided into bands namely alpha, beta, gamma, theta.

Electroencephalography : Electroencephalography (EEG) is an electro physiological monitoring method to record electrical activity of the brain. It is typically noninvasive, with the electrodes placed along the scalp. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time. The amplitude of the EEG is about 100 μ V when measured on the scalp, and about 1-2 mV when measured on the surface of the brain. The bandwidth of this signal is from under 1 Hz to about 50 Hz. Evoked potentials are those components of the EEG that arise in response to a stimulus which may be electric, auditory, and visual, etc. From the EEG signal it is possible to differentiate alpha (α), beta (β), delta (δ), and theta (θ) waves as well as spikes. No cerebral activity can be detected from a patient with complete cerebral death.

Modern EEG implementation is commonly achieved using RMS-EEG machine. RMS-EEG is a 32 channel machine facilitation simultaneous acquisition of raw data as shown in Figure 2. It also provides Photic simulation to treat patients with seizure. Also, various portable EEG machines like EMOTIV EPOC+ are finding their way into market which enables user to easily gather and process EEG. These machine will aid in providing Brain Computer Interface (BCI) efficiently. Therefore it is necessary to create a system which allows a user to control the computer and type using BCI with minimal efforts.

BCI : A brain computer interface (BCI), also referred to as a brain machine interface (BMI), is a hardware and software communications system that enables humans to interact with their surroundings, without the involvement of peripheral nerves and muscles, by using control signals generated from electroencephalographic activity. BCI creates a new non-muscular channel for relaying a person's intentions to external devices such as computers, speech synthesizers, assistive appliances, and neural prostheses. That is particularly attractive for individuals with severe motor disabilities. Such an interface would improve their quality of life and would, at the same time, reduce the cost of intensive care. A BCI is an artificial intelligence system that can recognize a certain set of patterns in brain signals following ve consecutive stages:

- Signal Acquisition.
- Preprocessing or Signal enhancement.
- Feature extraction.
- Machine Learning Classification.
- The Control interface.

II. RELATED WORK

Today, BCI research is a relatively young multidisciplinary field integrating researchers from neuroscience, physiology, psychology, engineering, computer science, rehabilitation, and other technical and health-care disciplines. In spite of the notable advancement in this field, a common language has yet to emerge, and existing BCI technologies vary, which makes their comparison difficult and, in consequence, slows down the research. Factors contributing to increased difficulty in traditional BCI technology are as follows:

- Limited resolution and reliability of information that was detectable in the brain.
- High variability.
- BCI systems require real-time signal processing which was earlier expensive or inefficient.

Small specialized companies such as Emotive [4] have already developed some initial applications oriented towards the general public. The paper [1] describes the two important phases of speech recognition: features extraction and recognition. The paper uses the wavelet transform to generate the approximation coefficients of the speech signal. The feature extraction step applies the Burg algorithm to these approximation coefficients to estimate the Power Spectrum Density (PSD).

Paper [2] presents a new probabilistic neural network paradigm for dynamic pattern recognition problems. The approach is based on a self-organizing learning approach using information theory principles. The neuron activations

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unsupervised and supervised learning algorithms is used to train the network weights. The neuron probabilities can be further refined by corrective training methods. The neural network can process dynamic patterns of arbitrary length, and can be even used for continuous speech recognition, although it is not a recurrent network. The output activations of the neural network can be evaluated directly or optionally treated as input to Hidden Markov Models in order to construct a hybrid recognition system. The network has been tested for the recognition of dynamic speech patterns and performs better than a discrete HMM system with a codebook size equal to the number of output neurons in the neural net.

Visual Evoked Potential [3] is categorized to control Computer without the use of traditional mouse and keyboard. EEG amplifier with one bipolar channel is designed for the acquisition of raw EEG data from the posterior region of the head over the occipital lobe. The three white LED chessboards with programmable flicker frequencies are used as stimulation to induce different Evoked Potentials. For feature extraction, the Fourier transform of autocorrelation of the EEG signal is used. In MAT LAB, a graphical user interface (GUI) application is implemented, showing the EEG signal in time and frequency domain, both in real time.

Research to control robotic arm using brainwaves is also successful [4]. Emotive commercial hardware was used to extract quality brainwave from the user. MAT LAB was used for classification of signal and two servo motors was moved using the arduino board. The experiments for the servomotors control were carried out without noise, reaching an efficiency of 100% in the identification stage.

Paper [5] proposes a EEG Module consisting a seven sensors demonstrates in a real world setting. The low noise LT6010 operational amplifier is configured for a mid-band gain of 1000. A 100μ F capacitor is used to cut the gain to 1 at frequencies below 1 Hz. This is important since the sensor / scalp interface often generates significant DC offset voltages upto 25 mV. It suggests strategy to improve the convenience and the mobility of EEG recording by eliminating

the need for conductive gel and creating sensors that fit into a scalable array architecture.

Paper [6] proposes gain relaxation in signal enhancement designed for speech recognition with an unaware local noise source. An attention is drawn to a new performance degradation problem in signal enhancement combined with automatic speech recognition (ASR), which is encountered in real products with an unaware noise source. Gain relaxation, as a solution, selectively applies softer enhancement of a target signal to eliminate potential degradation in speech recognition caused by small undesirable distortion in the target signal components. Among basic evaluation of the EEG traces belongs scanning for signal distortions called artefact's [7]. Usually it is a sequence with higher amplitude and different shape in comparison to signal sequences that doesn’t suffer by any large contamination’s. The artifact in the recorded EEG may be either patient-related or technical.

The most common EEG artifact sources can be classified in following way:

- Patient related
  - any minor body movements.
  - EMG
  - ECG(pulse, pace-maker)
  - eye movements
  - sweating

- Technical
  - 50/60 Hz
  - impedance fluctuations
  - cable movements
  - broken wire contacts
  - extensive electrode paste/jelly
  - low power supply

Technical artefact's, can be decreased by decreasing electrode impedance and by shorter electrode wire.

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III. PROPOSED ALGORITHM

This system is typically designed for people with speech and limb disabilities. The System module aims at providing a new utility to the present EEG technology. The system proposes a mechanism to classify the various EEG signals of mimes into the corresponding text. The future implementation of this system will provides a complete BCI using a portable EEG module.

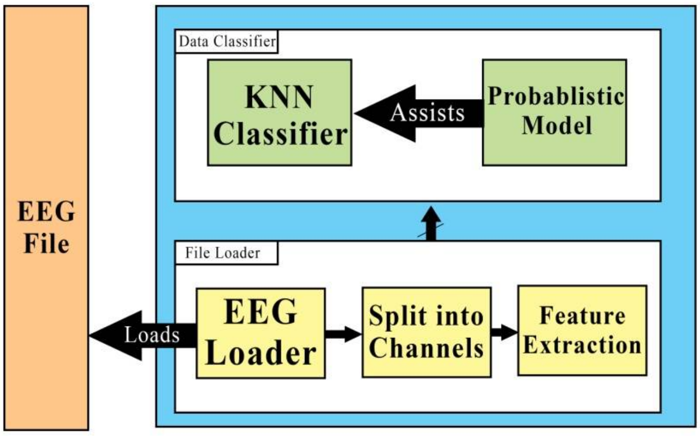

Fig. 4. Overall system flow

The FFTs are trained for various artifacts used in miming using K-nearest Neighbor (KNN) technique.A probablistic Model is presented which increaces the efficiency of existing KNN system by considering the prediction probability of each EEG channel. Thus the efficiency of the system enhances with increase in datasets. Finally the trained model will be further used to predict and recognize the EEG wave which will aid in thoughts to text conversion.

IV. CONCLUSION AND FUTURE WORK

The system proposed will provide a efficient and new mode ofcommunication to people with disabilities. The hindrance caused to many will be greatly reduced and hence independent mobility can be achieved. The expected result is that proper classification is done by machine learning. The issue of portability is also considered so as to make the use easy. The K-nearest Neighbor (KNN) will improve in efficiency over time and its capable of handling input with noise.

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