

Design and Implementation of Human Computer Interaction Using Brain Waves Electric Signals

Saima Ansari¹, Dr. Prof. M. B. Chandak²

¹(C.S.E, W.C.E.M/ RTMNU, India)

²(C.S.E, RKNEC/ India)

Abstract: Human brain mainly works on electric signals transmitting all over the body to send the information in order to operate the body parts. Even while rotating eye ball body increases or decreases the resistance near eye area. This variation in electric signals can be measured using electrodes or the myoelectric sensors. By implementing these signals processor we can interface different devices to control on demand. Hence proposed system is designed to control computer and hardware system using brain waves electric signals. Proposed systems will detection the variations in electric signal strength through voltage level near the eye area and generates a wireless radio frequency signals in order to control the robotic prototype model. By implementing this system we can further extend it to bio enabled human body parts to control through brain waves.

Keywords: Brain-computer interface (BCI), Electroencephalography (EEG), Mind-Machine Interface (MMI), Brain-Machine Interface (BMI)

I. INTRODUCTION

Brain-Computer Interface (BCI) ^[1] technology is a new and fast evolving field that seeks direct interaction between the human neural system and machines, aiming to augment human capabilities by enabling people (especially disabled) to communicate and control devices by mere “thinking” or expressing intent. The increasing success of BCI systems is partially due to a better understanding of the dynamics of brain oscillations that generate EEG signals. In the brain, networks of neurons form feedback loops responsible for the oscillatory activity recorded in the EEG ^[2]. The increasing success of BCI systems is partially due to a better understanding of the dynamics of brain oscillations that generate EEG signals. In the brain, networks of neurons form feedback loops responsible for the oscillatory activity recorded in the EEG. Third, old generation EEG-based BCI had a limited communication capacity and it looked very unlikely to be suitable for control. Based on signal acquisition methods, BCI can be categorized by whether it uses non-invasive (e.g. EEG) or invasive (e.g. intracortical) techniques. Progress on the signal processing and the classification algorithms has increased the communication capacity to a point that real applications are now feasible. A key to the success of any BCI system is the extraction of a set of optimum features that reduce the high dimensionality of a multi-channel EEG signal.

A brain-computer interface (BCI), often called a mind-machine interface (MMI), or sometimes called a direct neural interface or a brain-machine interface (BMI), is a direct communication pathway between the brain and an external device. BCIs are often directed at assisting, augmenting, or repairing human cognitive or sensory-motor functions. A brain-computer interface (BCI) is a device that enables severely disabled people to communicate and interact with their environments using their brain waves. Most research investigating BCI in humans has used scalp-recorded electroencephalography or intracranial Electroencephalography. The use of brain signals obtained directly from stereotactic depth electrodes to control a BCI has not previously been explored.

Electrooculography (EOG/E.O.G.)^[3] is a technique for measuring the cornea-retinal standing potential that exists between the front and the back of the human eye. The resulting signal is called the electrooculogram. Primary applications are in ophthalmological diagnosis and in recording eye movements. Unlike the electroretinogram, the EOG does not measure response to individual visual stimuli. To measure eye movement, pairs of electrodes are typically placed either above and below the eye or to the left and right of the eye. If the eye moves from center position toward one of the two electrodes, this electrode "sees" the positive side of the retina and the opposite electrode "sees" the negative side of the retina. Consequently, a potential difference occurs between the electrodes. Assuming that the resting potential is constant, the recorded potential is a measure of the eye's position whereas Electroencephalography (EEG) is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp. Thus by using Electrooculography^[4] the speed for measuring cornea-retinal standing potential can be easily measured whereas EEG takes a longer time.

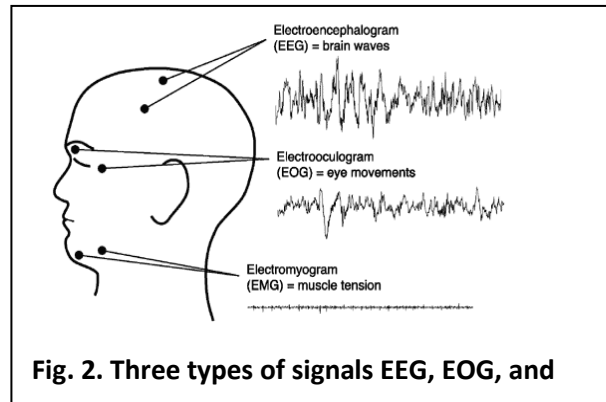


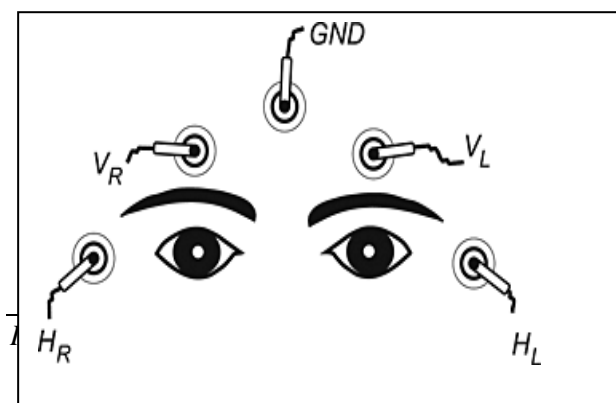
Fig. 2. Three types of signals EEG, EOG, and

II. LITERATURE SURVEY

Phillip Kennedy (who later founded [Neural Signals](#) in 1987)^[5] and colleagues built the first intracortical brain–computer interface by implanting neurotropic-cone [electrodes](#) into monkeys. In 1999, researchers led by Yang Dan at the [University of California, Berkeley](#) decoded neuronal firings to reproduce images seen by cats. The team used an array of electrodes embedded in the [thalamus](#) (which integrates all of the brain's sensory input) of sharp-eyed cats. Researchers targeted 177 brain cells in the thalamus [lateral geniculation nucleus](#) area, which decodes signals from the [retina](#). The cats were shown eight short movies, and their neuron firings were recorded. Using mathematical filters, the researchers decoded the signals to generate movies of what the cats saw and were able to reconstruct recognizable scenes and moving objects. Similar results in humans have since been achieved by researchers in [Japan](#). [Miguel Nicolelis](#), a professor at [Duke University](#), in [Durham, North Carolina](#), has been a prominent proponent of using multiple electrodes spread over a greater area of the brain to obtain neuronal signals to drive a BCI. Such [neural ensembles](#) are said to reduce the variability in output produced by single electrodes, which could make it difficult to operate a BCI.

After conducting initial studies in rats during the 1990s, Nicolelis and his colleagues developed BCIs that decoded brain activity^{[6] [7]} in [owl monkeys](#) and used the devices to reproduce monkey movements in robotic arms. Monkeys have advanced reaching and grasping abilities and good hand manipulation skills, making them ideal test subjects for this kind of work.

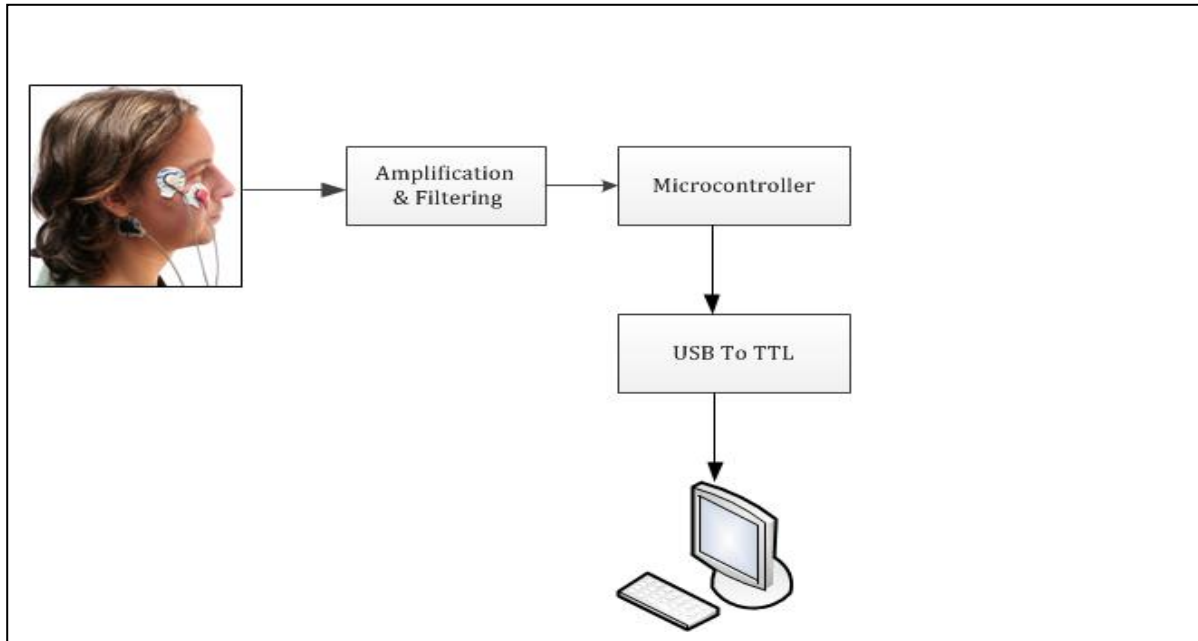
By 2000 the group succeeded in building a BCI that reproduced owl monkey movements while the monkey operated a [joystick](#) or reached for food. The BCI operated in real time and could also control a separate robot remotely over [Internet protocol](#). But the monkeys could not see the arm moving and did not receive any feedback, a so-called [open-loop BCI](#).



Later experiments by Nicolelis using [rhesus monkeys](#) succeeded in loop and reproduced monkey reaching and grasping movements in a robot arm. With their deeply cleft and furrowed brains, rhesus monkeys are considered to be better models for human neurophysiology than owl monkeys. The monkeys were trained to

reach and grasp objects on a computer screen by manipulating a joystick while corresponding movements by a robot arm were hidden. The monkeys were later shown the robot directly and learned to control it by viewing its movements. The BCI used velocity predictions to control reaching movements and simultaneously predicted [hand gripping force](#).

Other laboratories which have developed BCIs and algorithms that decode neuron signals include



those run by John Donoghue at [Brown University](#), Andrew Schwartz at the [University of Pittsburgh](#) and Richard Andersen at [Caltech](#). These researchers have been able to produce working BCIs, even using recorded signals from far fewer neurons than did Nicolelis (15–30 neurons versus 50–200 neurons).

Donoghue's group reported training rhesus monkeys to use a BCI to track visual targets on a computer screen (closed-loop BCI) with or without assistance of a joystick. Schwartz's group created a BCI for three-dimensional tracking in virtual reality and also reproduced BCI control in a robotic arm. The same group also created headlines when they demonstrated that a monkey could feed itself pieces of fruit and marshmallows using a robotic arm controlled by the animal's own brain signals. Andersen's group used recordings of [pre-movement activity](#) from the [posterior parietal cortex](#) in their BCI, including signals created when experimental animals anticipated receiving a reward.

III. PROPOSED SYSTEM

The proposed system consists of designing and building a myoelectric signal or electrodes generated signal detector circuit. It will detect the variations in electric signal strength through voltage level near the eye area and generates a wireless radio frequency signals in order to control the robotic prototype model. By implementing the system can be further extended to bio enabled human body parts to control through brain waves ^[8]. This system aims at developing a signal amplifier circuit which will then amplify the electrode signals to get processed by microcontroller. The next is developing a microcontroller. Next is designing and developing an embedded program to convert these signals into particular action or codes. For generating radio signals on different input gathered from

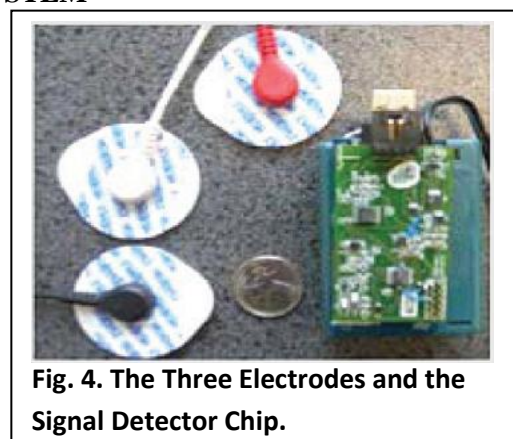


Fig. 4. The Three Electrodes and the Signal Detector Chip.

signal processor, programming of the system is required to be done. Last is to build a wireless robotic vehicle^[9] which will receive the radio signals and act upon it. The use of this kind of system is that the user can control the computer cursor and the applications using electric signals. The below given figure. 1. shows the placement of electrodes. Figure. 2. shows the three different types of signals as EEG, EOG and EMG respectably. Likewise, Fig. 3. and Fig. 4. shows the overview of the system and the three electrodes with the Signal Detector Chip respectably.

IV. METHODOLOGY

Figure. 5. explains the input signals^{[10][11]} received from the eye movement. The signals received are of very low in frequency. Instrumentation Amplifier amplifies the signals multiplying with a (signal*10) factor which increases the range of the received signal. Instrumentation Amplifier^[12] is used to amplify the signal received from eye movement. High pass filter^[13] of 0.1 Hz is used to remove the noise from the signal. After removing noise, if the range of the signal decreases, then the second amplifier is used to amplify the signal to the desired range. Active Low Pass Filter is used to improve the efficiency by checking if there is any kind of noise persisting in the system. Finally, the Analog to Digital converter^[14] is used to convert the analog signal received from Active Low Pass Filter^[15] to digital signal as output. Figure. 6. shows the circuit diagram of signal detection.

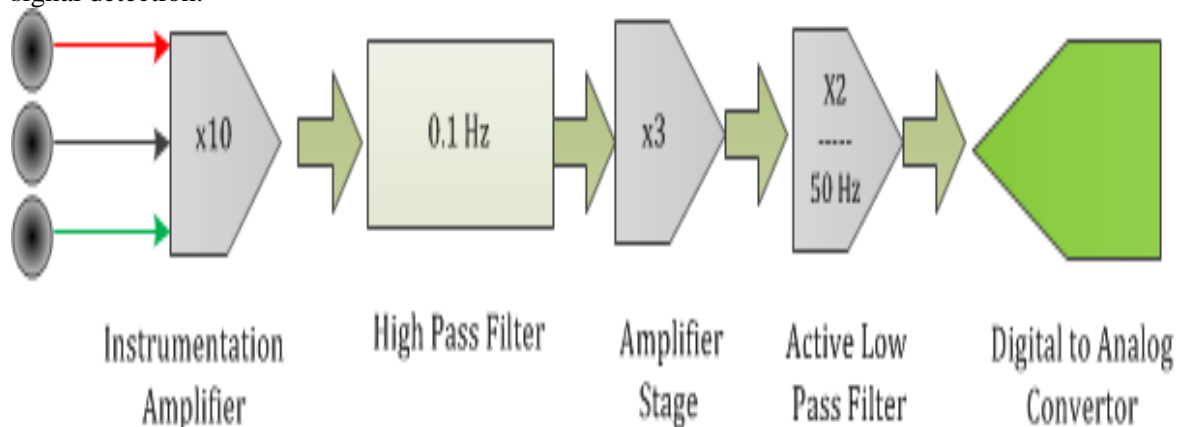


Fig. 5. Flow of Signal

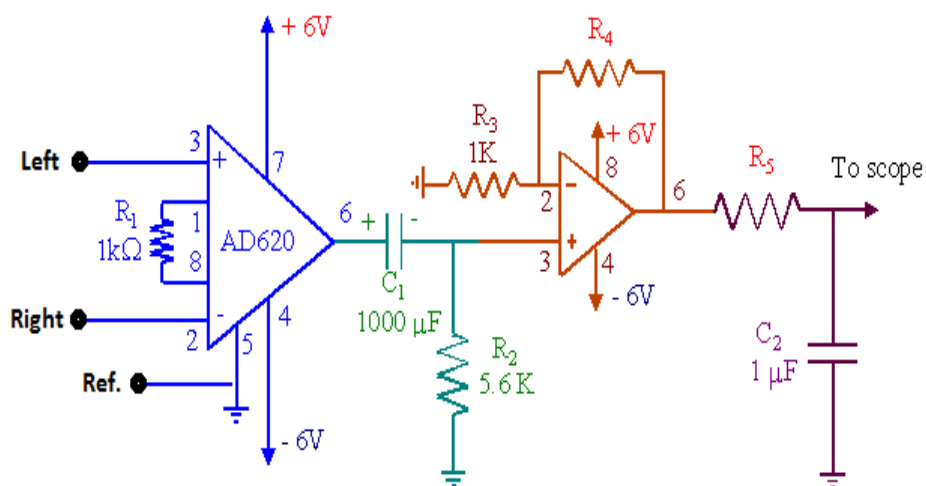


Fig. 6. Circuit diagram of Signal Detection

V. CONCLUSION

Hence, the proposed system is studied successfully which will detect the variations in electric signal strength through voltage level near the eye area and will generate wireless radio frequency signals in

order to control the robotic prototype model. By implementing this system can be further extended to bio enabled human body parts to control it through brain waves. This type of implementation helps the user in controlling the computer cursor and the applications using electric signals.

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