Survey on EEG Based Brainwave Controlled Home Automation

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ABSTRACT: *The project discusses about the brain controlled device based on Brain-computer interfaces (BCI). BCIs are systems that can bypass conventional channels of communication(i.e., muscles and thoughts) to provide direct communication and control between the human brain and physical devices by translating different patterns of brain activity into commands in real time. With these commands the devices can be controlled. Here we analyze the brain wave signals. Human brain consists of millions of interconnected neurons. The pattern of interaction between these neurons are represented as thoughts and emotional states, this pattern will be changing which in turn produce electrical waves. A muscle contraction will also generate a unique electrical signal. All these electrical waves will be sensed by the brain wave sensor and it will convert the data into packets and transmit through Bluetooth medium and the data will be processed using Matlab platform. Then the control commands will be transmitted to the device to process. The intention of the project is to control home devices using brain wave signals.*

KEY WORDS: Brain computer interface, Brain wave signals, EEG signals, Home automation.

INTRODUCTION:

The project analyzes the brain wave signals. According to the human thoughts, this pattern will be changing which in turn produce different electrical waves. All these electrical waves will be sensed by the brain wave sensor and it will convert the data into packets and transmit through Bluetooth medium and the extracted date will be processed using Mat lab platform and the commands will be sent to the device to process

RELATED WORKS:

Feng Duan[1] focuses on how to independently use SSVEP, motor imagery or other signals to recognize human intention and generate several control commands. SSVEP and P300 required external stimulus, while motor imagery does not require it. However the generated commands are limited and cannot control a robot. Taking advantage of both SSVEP and motor imagery, this paper aims to design a hybrid BCI system that can provide multimodal control commands to the robot in this hybrid BCI systems three SSVEP signals are used to control the robot to move forward, turn left and turn right. One motor imagery signal is used to control robot to execute the grasp motion. To enhance the performance of the hybrid BCI system the visual servo module is also developed. The effect of the entire system is verified in a simulation platform and real humanoid robot.

Sumner L. Norman[2] investigated how event-related de-synchronization changed as a function of audio visual stimuli. Notably, ERD was also present when the subjects remained passive and the robot moved their fingers to play the game. This ERD occurred in anticipation of passive finger movement with similar onset timing as for the overt movement conditions. These results demonstrate that ERD can be contigent on expectation of robotic assistant i.e, the brain generates an anticipatory ERD in expectation of a robot imposed but predictable movement.

Rui Zhang[3] proposes an event related potential brain computer interface based environmental control systems that integrates house hold electrical appliances, a nursing bed and intelligent wheel chair to provide daily assistance to paralyzed patients with severe spinal cord injuries. An asynchronous is used to switch the environmental control system on or of to select a device for achieving self-paced control. In this mode, we introduce several pseudo keys and a verification mechanism to effectively reduce the false operation rate. When the users select the function of the device a synchronous mode is used to improve the accuracy and the speed of BCI detection.

Angelo Cenedese[4] aims at providing high accuracy classification for home automation systems which are generally user independent, device independent and device orientation independent. This paper is composed of three main steps event identification, feature extraction and Machine Learning based classification. A pre-processing phase based on principle component analysis to increase the performance in real world scenario condition. This methodology is tested on two data sets of four gesture classes and on a further data set with eight classes in order to describe a real world home automation environment the gesture movements are collected from more than thirty people who freely perform any gestures.

Jin Wang[5] proposes an ant colony optimization based clustering algorithm specifically with mobile sink support for home automation networks. In this work the network is divided into several clusters and clusters heads are selected within each clusters. Then, a mobile sink communicates with each cluster head to collect data directly through short range communication. The ACO algorithms as be utilised in this work in order to find the optimal mobility trajectory for the mobile sink. The extensive simulation show that the proposed algorithm significantly improves home network performance when using mobile sinks in terms of energy consumption and network lifetime.

Alborz Rezazadeh Sereshkeh[6] analyses the communication using brain–computer interfaces can be non-intuitive, often requiring the performance of a conversation-irrelevant task such as hand motor imagery. In this paper, the reliability of electroencephalography signals in discriminating between different covert speech tasks are investigated. The proposed MLP network provided significantly higher accuracies compared to some of the most common classification techniques in BCI. Our findings support further study of covert speech as a BCI activation task, potentially leading to the development of more intuitive BCIs for communication.

Daniela Iacoviello[7] proposes a real-time classification algorithm for the low-amplitude electroencephalography signals, such as those produced by remembering an unpleasant odour, to drive a brain computer interface. The peculiarity of these EEG signals is that they require adhoc signals pre-processing by wavelet decomposition, and the definition of a set of features able to characterize the signals and to discriminate among different conditions. The proposed method is completely parameterized, aiming at a multiclass classification and it might be considered in the framework of machine learning.

Lin Yao[8] hypothesize that a combination of these two signal modalities provides improvements in BCI performance with respect to using the two methods separately, and generate novel types of multi-class BCI systems. Thirty-two subjects were randomly divided into a Control-Group and a Hybrid-Group. In the Control-Group, the subjects performed left and right hand motor imagery .The results indicate that combining two of the tasks in a hybrid manner resulted in a significantly greater classification accuracy than when using two MI tasks combining the induced brain signals from motor and sensory cortex, the proposed stimulus-independent hybrid BCI has shown improved performance with respect to individual modalities, reducing the portion of BCI-illiterate subjects, and provided novel types of multi-class BCIs.

Pietro Aricò[9] aims to highlight recent important aspects to consider and evaluate when passive Brain Computer Interface systems would be developed and used in operational environments, and remarks future directions of their applications.BCI applications in operational environments and new adaptive interface solutions have been presented and described. In addition, a general techniques in the BCI field has been provided. Thus, technologies able to measure in real-time the user's mental states would result very useful in such "high risk" environments to enhance human machine interaction, and so increase the overall safety.

Wei He [10] analyses the performance increase of a BCI and BMI system, we propose some methods and algorithms for electroencephalograph signal analysis. The recorded EEG signal is transmitted to the computer and the upper limb robotic arm interface via a bluetooth. To obtain effective commands from brain, the recorded EEG signal is processed by a front filter, de-noise filter, feature extraction, and classification, while the personal computer software and upper limb arm are driven by EEG-based commands. Through the encoders and gyroscopes on the upper limb arm, we can acquire some feedback signals in real time, such as joint angle, arm accelerated speed, and angular speed. The theory of wavelet denoising method, common spatial pattern algorithm and linear discriminant analysis algorithm are investigated in this paper.

Alex Kreilinger [11] evaluates a new method for detecting errors in continuous brain–computer interface (BCI) applications. Instead of classifying errors on a single-trial basis, the new method was based on multiple events (MEs) analysis to increase the accuracy of error detection. In a BCI-driven car game, based on motor imagery (MI), discrete events were triggered whenever subjects collided with coins or barriers. Coins counted as correct events, whereas barriers were errors. This new method, termed ME method, combined and averaged the classification results of single events (SEs) and determined the correctness of MI trials, which consisted of event sequences instead of SEs.

Marianne Severens [12] extends to investigate its possible use in motor rehabilitation. Most of these investigations have focused on the upper body. However, for stroke patients the rehabilitation of gait is of crucial importance. Therefore, this study investigates if a BCI can be based on walking related de-synchronization features. Two BCI experiments were conducted in which healthy subjects performed a cued walking task, a more complex walking task (backward or adaptive walking), and imagination of the same tasks. EEG data during these tasks was classified into walking and non-walking. The results from both experiments show that despite the automaticity of walking and recording difficulties, brain signals related to walking could be classified rapidly and reliably.

J. A. Mercado [13] presents a novel modular, portable and low-power electroencephalography acquisition system for a Brain-Computer Interface application. The system is based on the versatile microcontroller. The prototype supports both passive and active electrodes; these were also designed and built. Additionally, a graphic visualization interface was developed on the open-source programming language Processing. Common-mode rejection ratio, input-referred noise and magnitude and phase frequency response were measured for each analog EEG channel. Power spectrum of EEG recordings using our prototype and the commercial amplifier USB amp were compared in open/closed eyes conditions (-band reactivity). With this design, it is possible to reduce noise and interferences in EEG signal to decrease the computational workload in digital post-processing, and thus, may increase the likelihood of achieving a completely stand-alone BCI system for clinical applications.

Qasem Obeidat[14] researches into Brain-Computer Interfaces, using brain signals investigated and evaluated in a rolling wheel chair a mobile BCI, which implemented the edges paradigm on small displays with which visual crowding tends to occur. The mobile row-column paradigm has implications for understanding how principles of visual neuro-cognition affect BCI speller use in a mobile context. This investigation revealed that all the overall advantages of the edges paradigm over the row-column paradigm prevailed in this setting. However, the reduction in adjacent errors for the edges paradigm was unprecedentedly limited to horizontal adjacent errors. The interpretation offered is that dimensional constraints of visual interface design on a smart phone thus affected the neuro cognitive processes of crowding.

Jeffrey A. Herro [15] analyzes for many patients, deep brain stimulation of the thalamus is an effective means of treating this condition when medication fails. In current use, however, clinicians set the patient's stimulator to apply stimulation at all times whether it is needed or not. This practice leads to excess power use, and more rapid depletion of batteries that require surgical replacement. In the work described here, for the first time, neural sensing of movement (using chronically-implanted cortical electrodes) is used to enable or disable stimulation for tremor. Therapeutic stimulation is delivered only when the patient is actively using their effected limb, thereby reducing the total stimulation applied, and potentially extending the lifetime of surgically-implanted batteries. This work, which involves both implanted and external subsystems, paves the way for the future fully-implanted closed-loop deep brain stimulators.

CONCLUSION:

This paper has presented the proposed scheme for brain controlled interface using P300.By implementing the BCI technology into this project , the developed system can be applied to control equipments turning on/off with the corresponding comments . Concentration level is the parameter that is being as the trigger for the toggling of power in devices.

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