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BRAIN CONTROLLED HOME AUTOMATION

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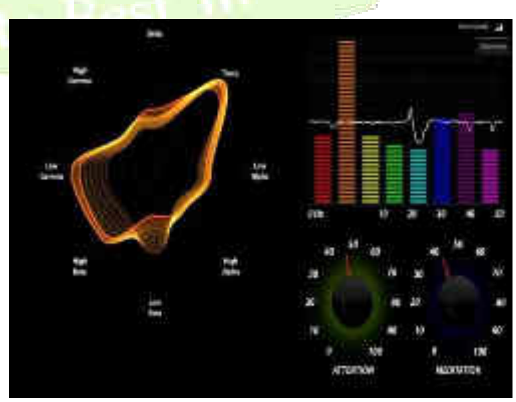
ABSTRACT

The aim of this study is to control home devices using a non-invasive brain computer interface (BCI). The Electroencephalographic signals (EEG) recorded from the brain activity using the **Neurosky mindwave mobile** are interfaced with the help of mouse emulator to a graphical user interface (GUI) on the computer screen. The user will use this GUI to control various devices in a smart home. This application will be very useful especially for people with special needs.

INTRODUCTION

BCI is a system that captures the brain electrical activity in the form of EEG signals; and translates those specific features of the signal that represents the intent of the user into computer readable commands. These commands can control and operate an electronic device. This technology is developing very rapidly, as it has innumerable uses, the most important of which is improving the quality of life of human beings in general and elderly and disabled people in particular. The BCI can be divided into non-invasive and invasive type, where in latter an IC is implanted in the brain by surgery. Hence people prefer non-invasive BCI which involves only wearing of a headset or cap equipped with an active electrode system. In this paper, our main aim is to develop a thought controlled smart home system. We will use a non-invasive BCI device known as Neurosky mindwave mobile to capture EEG signals. The EEG signals are transmitted via Bluetooth to the interface computer.



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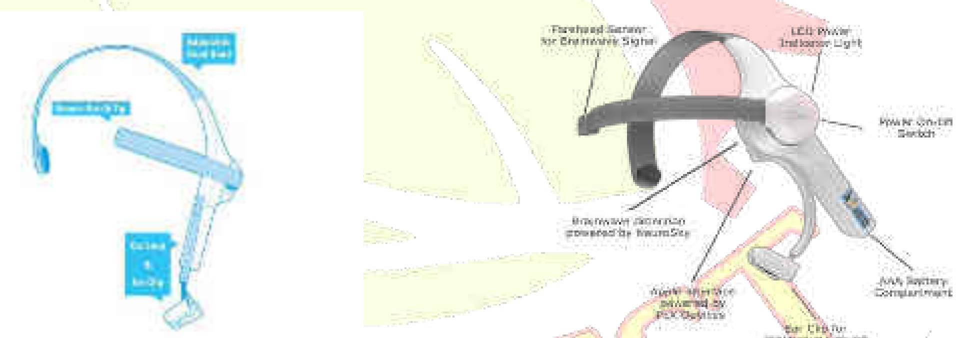
METHODOLOGY

Recent research shows that brain computer interface can be used for motion disabled people, however the mean classification rate achieved is above 80%. This means there is still 10-20% error rate. This error may result in loosing user control. Hence in this study we propose a very simple and effective method for smart home control.

EEG Signal Acquisition and Event Detection

For EEG signal acquisition the Neurosky mindwave mobile is used. It has 14 channels (electrodes) and the sampling frequency is 128 Hz (2048 Hz internal). It has a built in 5th order low pass SINC filter of bandwidth 0.2 to 45 Hz, and is connected wirelessly to the computer through a 2.4 GHz band. The figure shows the Neurosky mindwave mobile and the location of the electrodes. Neurosky mindwave mobile uses three built-in suites to determine the various types of signal inputs: i.e. Expressive Suite for analyzing users facial expressions, the user's emotional state is interpreted by the Affective Suite while the Cognitive Suite analyzes user's intent to control a movement. In addition the gyro can be used as a mouse emulator. The aim of this project is to acquire and identify the EEG signal that is related with the user intention to operate a device in the smart home. Hence for event detection it is necessary to have a unique profile for each user to map the user's brain patterns.



Setup of Virtual Smart Home System

In order to control and operate the home us a virtual home environment has been create environment there is indoor and outdoor act many rooms, each having many devices like temperature control, doors to operate. All these are shown via a graphical user interface computer screen. The user will select his de using a raise of an eyebrow (or a smirk, or actions if needed and to increase the sensitive that will cause a mouse click on the desired c the control will be toggled. For example, the on the light of a room by selecting the blink means light will be turned OFF between the Neurosky mindwave mobile. Figure shows the block diagram of the smart home system. A simple flow chart of the in a brain controlled smart home system is shown. A sample flow chart of event detection is shown.

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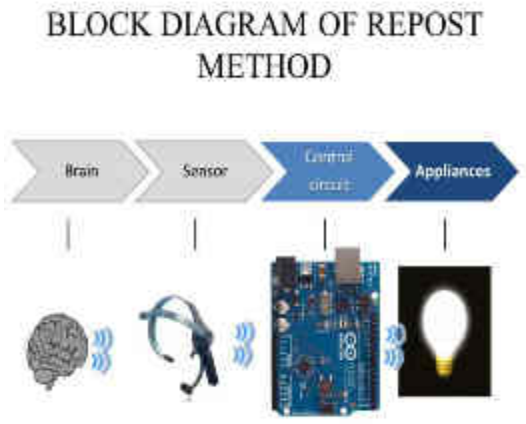

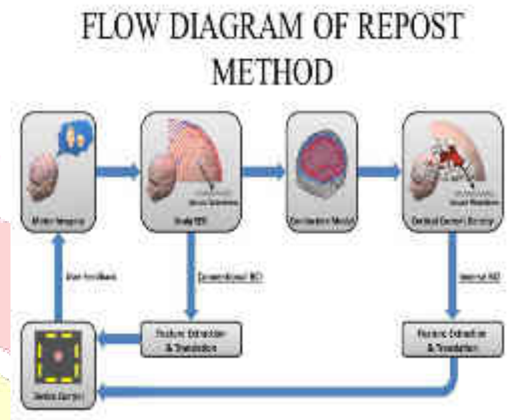

Motor Intention Detection and Closed-Loop BCI Control

The robust detection of motor intention is an essential and critical issue for the development of self-paced close-loop BCI control systems. For BCI control applications, the acceptable delay in control has not been investigated in detail but, in other fields, e.g., multifunction prostheses control by myoelectric signals, a 200-ms delay is considered as acceptable. For the applications of BCI-based neuro-rehabilitation to induce plasticity, it was demonstrated that the necessary delay was in the same range as for control, i.e., in the order of a few hundred millisecond. Therefore, a reliable detection with high accuracy and minimal latency would play an important role in an effective BCI rehabilitation tool. In the current study, the latency was in 200–400 ms, making it ideal for a close-loop BCI control system. In the past decades, SMR has been used to detect motor intention in studies, in which BCIs were used to control visual feedback or trigger external devices. However, it is difficult for native subjects to use an SMR-based BCI system, since a rather long (in the order of weeks) training session is necessary before a reasonably detection accuracy can be attained. In addition, the latency was not investigated in these studies. This may explain why weeks of intervention were required for inducing plasticity, as the association of the Hebbian rule was not established when the afferents arrived at the cortex with too large delay with respect to the movement intentions or attempts. In recent years, slow cortical potentials attracted the attention in the rehabilitation field. Garipelli et al. investigated the effect of different band-pass filter in the detection accuracy of CNV, yielding 0.88 ± 0.05 of area under curve in ROC with the optimal filter in an offline study. Also in an offline study, Ahmadian et al. used constrained blind source extraction and showed that there was a tradeoff between TPR and FP. These studies investigated upper limb movements, which 294 IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 61, NO. 2, FEBRUARY 2014 arguably have more distinctive spatial pattern than dorsiflexion. As such, it is difficult to compare the results of these two recent offline studies with the results from the current online study with lower limb movement. More importantly, the latency was not investigated in these previous studies, although it is a crucial determinant of the efficacy of a rehabilitation training based on this type of BCI switches. In a series of studies by our group, we demonstrated that motor intention could be detected from MRCP using the MF, with satisfactory accuracy and small latency. When such a detection was used to trigger electrical stimulation, plasticity was induced with a short intervention (~30 min), and outlasted the intervention. In the current study, LPP-LDA

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showed higher accuracy and shorter latency than MF, and thus would play an important role in further enhancing the efficacy of this BCI-driven rehabilitation approach that is uniquely designed to induce plasticity specific to the target muscle. Preliminary verification of this hypothesis has been recently reported in abstract form in a study in which we used the LPP-LDA detection approach proposed in this study to trigger an ankle foot orthosis. In that study, plasticity was induced with an even shorter intervention time and more effectively with the algorithm proposed in this study than in previous investigations with MF detector.

Advantages of BCHA (LPP)

A. Robust Performance:

The LPP-LDA yielded a significantly higher accuracy, compared with MF. In addition, passive FP was tested in this study, and LPP-LDA also showed its superior ability in reducing FP when the subjects were in idle condition. This insensitivity to task types demonstrated the robustness of LPP-LDA. There are two reasons why LPP-LDA outperformed MF. One lies in the data organization. For MF, the MRCP template was extracted from the epoch average of all trials of "signal portion" in the training session. This process practically dropped the specific characters of MRCP in different trials, and also discarded the direct information from "noise portion," even though it was implicitly used during the manual adjustment of the threshold. On the contrary, both signal portion (MRCP) and noise portion were used to train the LPP-LDA classifier, which thus made full use of the available information. Another reason is the powerful ability of LPP in preserving the intrinsic structure of the data in its original high dimensional space. That is why it could detect MRCPs when its morphology was changed, and reject false detections induced by signal fluctuation, while MF cannot. Moreover, LPP-LDA showed shorter latency than MF. The DL with LPP-LDA was ~300 ms, which was significantly shorter than that with MF (~500 ms). It should be noted that we used the signal of 0.5 s after the movement onset as part of the templates for both detectors, because the rebound phase (movement monitoring potential) is highly distinctive in many subjects. The DL could be further decreased by choosing a shorter portion of the MRCP as template, at the expense of detection accuracy.

B. Subject Independent Parameters:

The threshold of MF output needs to be optimized. When the threshold is too low, a small variation would result in MRCP detection, leading to high FP. On the contrary, the TPR would be low if the threshold was set too high. That is why there is a tradeoff between the TPR and FP. The optimization step is usually realized by a cross validation of the training data on individual basis. However, two issues should be treated carefully during this process. One is how to define the optimal parameters. There is a balance between the TPR and FP, but it is still not clear which one should have priority. Another issue is that the optimal parameter could be changed as the morphology of MRCP changes during different types of task (i.e., execution or imagery), and likely need to be calibrated from session to session. In the current study, even though the optimal parameter was chosen for the execution tasks, it may not be optimal for imagination tasks. For LPP-LDA, the parameter that needs to be optimized is the dimension of the LPP space. When the dimension was reduced to close to 60%

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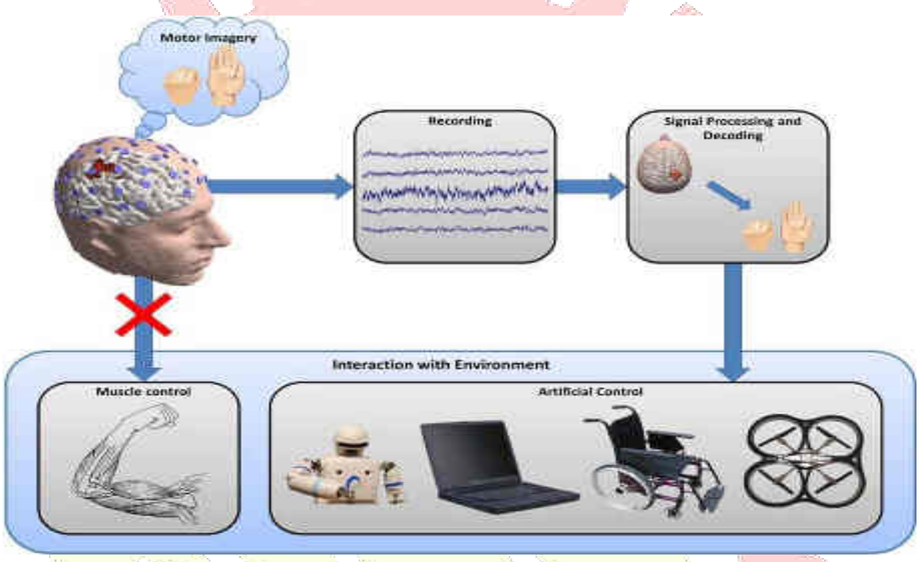
of the total dimension of the training data, the performance of LPP-LDA kept consistent across subjects. It is also possible for BCI applications to set subject specific and session specific parameters. However, the calibration process for optimizing the parameters implies a longer intervention protocol, which could be problematic for users, such as stroke patients. Therefore, the subject-independent property of LPP-LDA is especially desirable for BCI system tailored to neuro-rehabilitation applications.



C. Potential Applications

As demonstrated in this study, LPP led to very good performance for a brain switch with high TPR, low FP, short DL, good robustness with respect to the MRCP morphology, and subject independent parameters. It could be a promising tool in BCI applications. One of these foreseeable applications lies in the BCI driven external device for neuro-rehabilitation. It can play an important role in the development of an effective and versatile BCI system in inducing plasticity.

D. Limitations

In the current study, we collected EEG data of 30 trials of real movement of dorsiflexion as the training data for both the MF and LPP-LDA, and it showed desirable performance. Our preliminary analyses showed that the classifier would not work when the training trials were less than 15. However, the influence of the number of trials on performance for MRCP detection is not systematically investigated. Moreover, for patients who lost complete motor function of the target limb and thus cannot produce detectable EMG, as is many cases in neuro-rehabilitation applications, it would not be possible to use real movements for training. In this case, cue-based (synchronous) imagery training would be necessary and this would increase the number of training trials since MRCPs from XU et al.: ENHANCED LOW-LATENCY DETECTION OF MOTOR INTENTION FROM EEG 295 motor imagery have lower signal to noise ratio than those from real motor tasks. Currently, the corrupted trials were identified and manually removed from the training session. However, this step should be executed automatically in the future. In addition, the target users of the envisioned closed-loop BCI rehabilitation system, i.e., patients with motor disorders, such as stroke,

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were not involved in the current study. Previous studies use MF reported similar results in both healthy subjects and patients with MF, indicating the potential of using MRCP in the patient population. However, the exact performance of the proposed LPP-LDA in patient population needs further investigation.

CONCLUSION

We proposed a Neurosky Mind control classifier for detecting MRCPs in real time, and compared its performance with the standard MF in an online experiment. We demonstrated that LPP-LDA performed significantly better than MF, with higher accuracy and lower latency. In addition, it showed the desirable property of subject-independent parameters. Based on these results, the proposed brain switch is an extremely promising tool for the development of user-intention-driven closed-loop BCI neuro-rehabilitation systems.

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