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MACHINE LEARNING FOR BIOMEDICAL-FOCUS ON BRAIN SIGNALS

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There is a growing interest in machine learning (ML) in this decade. This growing interest is accelerated by cheaper computing power and low-cost memory. Thus, large amount of data can be stored, processed and analyzed efficiently. Machine learning has used in brain machine systems (BMS) system that converts brain impulses into messages or commands. In this paper we propose an EEG-based BMS with the focus on evoked potential. An average classification accuracy of 95% was attained among nine participants. With a rate of 4 flashes per second implemented, selecting one of four possibilities takes 5 s, resulting in an information transfer rate of 24 bits/min. Also, brain computer interfacing using oscillatory activity was measured. The results show that after around 5 h of co-adaptive training over many days, the average 3-class accuracy of the Linear Discriminant Analysis committee classifier reached about 80%, with a false positive rate for motor imagery recognition of around 17%.

Keywords: brain-machine system, EEG, machine learning, classification, accuracy, false alarm rate, human-centered computing

CCS Concepts:

• Computing methodologies∼Machine learning∼Machine learning approaches;

• Human-centered computing∼Human computer interaction∼HCI theory, concepts and models

1. Introduction

During the last decade, the world has witnessed a significant technological breakthrough in Artificial Intelligence (AI). Artificial intelligence (AI) is defined as a branch of science and engineering concerned with the computational understanding of what is commonly referred to as intelligent behavior. Artificial intelligence has been extensively used in recent decades to build applications in fields like deep

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learning, and machine learning AI is becoming a well-known in computer science field as it has improved human life in numerous ways. AI has recently outperformed humans across several domains, and there is big hope that this will happen in healthcare [7]. The field of computer vision has made incredible strides thanks to recent developments in deep learning techniques, which were made possible by improved computing power and the availability of large data sets [1].

Modern assistive technology can help people with severe motor impairments communicate better, manage their home environments, and move around more easily depending on their remaining motor abilities. Systems known as Brain-Machine Systems (Figure 1) are able to translate brain activity into signals that can command external machinery. They may therefore be the only means for people who are severely disabled to maintain or increase their communication and control options [2].

Bypassing the conventional neuro-muscular output routes, BMS use machine learning and digital signal processing to transform brain signals into activity. These systems were initially intended for biomedical applications, such as regaining lost motor function and enabling communication in patients who are completely paralyzed. BMSs have been investigated by more target markets as a novel input device for entertainment and gaming geared for non-disabled persons. It is the responsibility of the BMS to identify and anticipate behaviorally motivated changes in a user's brain signals, also referred to as "cognitive states."

On the other hand, it is well known now that brain signals can be captured non-invasively using electrodes on the scalp (electroencephalogram, EEG). EEG recording techniques and signals have been extensively used to establish techniques to help and impaired people to control a range of devices using BMS.

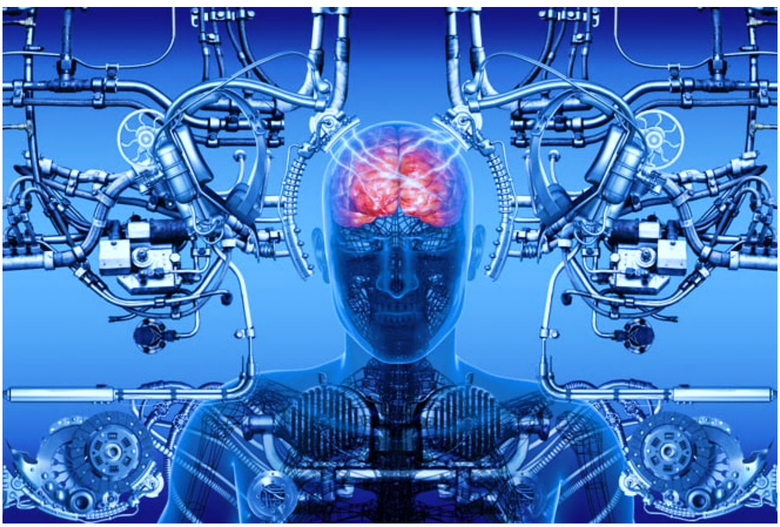

Figure 1. Brain-Computer Interfacing

The user must produce various brain activity patterns that the BMS will recognize and translate into commands in order to operate it. This identification is predicated on a classification technique used in the majority of current BMS. There have been a number of highly interesting BMS reviews published up to this point, but none have been devoted exclusively to a review of the classification algorithms used for BMS, their characteristics, and their assessment [3].

Specifically, chemicals, cells, vasculature, physical morphology, and cognition are all impacted by aging in the human body and brain. As time goes on, biological aging causes dependency and disability. The issue of aging and its effects on daily activities has been addressed in a number of diverse approaches, according to academics. Even for elderly patients and healthy older people, maintaining balance while talking, walking, and paying attention might be difficult. These limitations may make it difficult to carry on family conversations, navigate stairs, retain new knowledge, or operate a vehicle safely. Even if it's just utilizing handrails or canes to climb stairs, most elderly citizens need assistive equipment to help them do daily tasks, despite the fact that everyone's aging process has a varied impact. Unfortunately, they are not given the assistance they require since the expense of caring for them is in the billions of dollars.

BMS technology is increasingly being used to treat many individuals who have cognitive or physical problems. This system has the potential to significantly improve these patients' quality of life by increasing their personal autonomy and mobility. This paper proposes a novel implementation of classification algorithms used in EEG-based BMS applications for the objective of testing these algorithms based on evoked potentials and their accuracy level.

2. Literature review and background

The electroencephalogram (EEG) is a type of brain scan that measures electrical activity in the brain, according to study (Figure 2) [4]. It was written by Avid and published in the article EEG Signal Processing for BMS Applications. By placing electrodes on the scalp and using conductive paste, it is possible to record and analyze the brain's electrical signal, which is measured in microvolts [5]. These evoked potentials are a neurophysiologic study that analyzes the involvement of the auditory sensory system, visual system, and somatosensory pathways through evoked responses to a recognized and standardized stimulus in EEG data. Some of the several kinds of event-related evoked potentials (ERP) and visual evoked potentials (VEP) include auditory evoked potentials (PEA), motor evoked potentials (MRP), and steady state visual evoked potentials (SSVEP).

The goal of a BMS is to recognize and estimate behaviorally induced changes in a user's brain signals, also known as "cognitive states." BMSs built on these recording methods have given both healthy and disabled people the ability to operate a variety of appliances. The BMS system design should be dictated by the characteristics of the EEG feature(s), as this will determine the most efficient system for a specific user. The users are currently tested using the SMR- and P300-based BMS systems, and

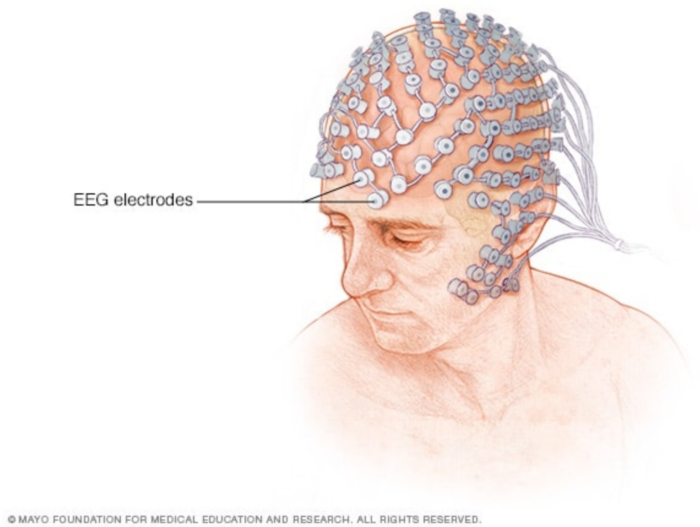

Figure 2. EEG System

the best system is chosen after consideration of speed, accuracy, bit rate, usefulness, and likelihood of use [6]. As we introduce BMS into people's homes, this model may prove to be the most effective.

According to [4], signal processing in the brain occurs in four steps: data acquisition, where brain signals are first acquired using sensors; pre-processing, where information that reduces signal quality is referred to as "noise" and "artifacts"; pre-processing techniques like spatial and temporal filtering can significantly improve signal quality by minimizing noise and artifacts; and feature extraction, where from the pre-processed brain signals, useful signal features are extracted. The majority of brain patterns used in BMS, such as slow cortical potentials (SCP), event-related potentials (ERPs), event-related desynchronization (ERD), and event-related synchronization (ERS), are mirrored by mu and beta rhythms (ERS). ERPs include the P300 and the steady-state visual evoked potential (SSVEP). Finally, the collected features are converted into discrete or continuous control signals that run devices such as a computer, wheelchair, or prosthesis using translation algorithms.

The author of [9] demonstrates how several neurons contribute to the signal measured at a particular electrode, comparing brain signals to the "cocktail party phenomena." The signals from these neurons are integrated and then aggregated at the electrode. Contrary to PCA, which maximizes the variance of the first component in the transformed space, common spatial patterns (CSP) optimize the variance-ratio of two conditions or classes. To put it another way, CSP looks for a transformation that maximizes the variance of samples from one condition while minimizes the variance of samples from the other condition. Temporal filtering, also known as frequency or spectrum filtering, is a crucial component of BMS systems for enhancing signal-to-noise ratio. Temporal filtering, for example, can be used to remove 50 Hz (60 Hz) noise from power sources. Temporal filtering can also be used to isolate motor imagery components from brain signals in a certain frequency band, such as the mu or beta band. One of the neurophysiological signals that can be used with BMSs is SSVEP [10].

The two primary EEG data types employed in BMSs are oscillatory activity patterns and evoked potentials (EPs). When a rare visual input or other external sensory event occurs, EPs, which are phase-locked electrical potential alterations, happen. EEG data are often averaged over time, commencing at the onset of the sensory event and lasting up to one second, in order to study EPs. On the other hand, oscillatory activity patterns can be purposefully created by the user. Most of the time, such imaging results in a power change in particular frequency bands [11].

The user may only need to make a small adjustment because EPs are repetitive brain reactions that are consistent over time. But as a result of feedback from BMS use, a user's oscillatory patterns frequently alter over time, making off-line learning of parameters less effective. In order to observe changes in oscillatory patterns and update the BMS as necessary, brain signals recorded during feedback are examined. The two examples below demonstrate the use of EPs and oscillatory patterns to connect the brain to the computer both physically and virtually [13].

An SVM also uses a discriminant hyperplane to define classes. However, the selected hyperplane in the case of SVM maximizes the margins. Margin maximization is known to enhance generalization skills. Using linear decision boundaries for classification is possible with linear SVM. The usage of this classifier in a sizable variety of synchronous BMS scenarios has been successful. However, with only a slight increase in the classifier's complexity, it is possible to set up nonlinear decision boundaries using the "kernel technique." It includes using a kernel function to indirectly transfer the data to a different space, typically one with much greater dimensions [12].

Furthermore, linear discrimination has been used in BMS as a technique for transforming high-dimensional feature data into a lower-dimensional space. It is then easier to divide the predicted data into two groups. The reparability of data is quantified in Fisher linear discriminant (FLD) by two quantities: the distance between projected class means (which should be large) and the amount of the data variance in this direction (should be small) [14]. The goal of LDA (also known as Fisher's LDA) is to segregate data representing various classes using hyperplanes. LDA presupposes that the data has a normal distribution and an equal covariance matrix for both classes. The separation hyperplane is found by locating the projection that maximizes the distance between the means of the two classes while minimizing the inter-class variation [16].

In fact, not all electrodes placed throughout the entire head are suitable in BM systems. As a result, channel selection is used to choose the most usable channels based on the attributes of a BM system. The EEG signals from the visual cortex are chosen for SSVEP-based BMSs. The channels in the sensorimotor area are chosen for mu/beta based BMSs. The channels with an obvious P300 are chosen for P300-based BMSs. In BMS, temporal filtering is critical for enhancing the signal-to-noise ratio, and it is also useful for extracting band power information.

3. Study design and methodology

A BMS enables a person to communicate with or control a device such as a computer or prosthetic without the use of peripheral nerves or muscles. A BMS in general architecture, which involves six stages of brain signal processing is shown in Figure 3. This procedure is generally separated into six parts, which are as follows: signal capture, preprocessing, feature extraction, classification, translation and feedback. The basic step involves skin preparation and electrode gel administration in the case of an EEG-based BMS. It is required because, large and unequal electrode impedances can degrade signal quality. Good signal quality, on the other hand, is critical for making the already tough task of retrieving information from brain signals easier [16]. Any BMS must be able to convert brain impulses into messages or commands. For signal translation, many signal processing and machine learning approaches have been developed. Most BMS systems require preprocessing because a good preprocessing method enhances the signal-to-noise ratio and spatial resolution, which improves the performance of the BMS. Preprocessing the EEG brain signal is a crucial step in the BMS because it creates an effective signal for the learning stages of detection and classification. From the pre-processed brain signals, useful signal features indicating the user's intent are retrieved. The classification algorithm is tuned after feature extraction, and the best features from numerous EEG channels are chosen and classified. Mainly, preprocessing, feature extraction, and classification are the three main steps. Following the extraction of features that reflect the user's intents, the next step is to transform these discriminative features into commands that run a device. These commands can be discrete in nature, such as letter selection, or continuous in nature, such as pointer movement vertically and horizontally. In BMSs, the best frequency bands are usually subject-specific. A

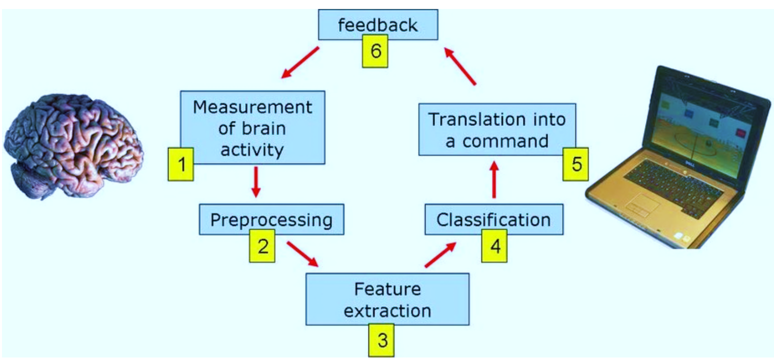

Figure 3. BMS architecture

feature selection method is frequently used to choose frequency bands. A wide frequency band is initially separated into multiple sub-bands that may overlap to carry out frequency band selection in this manner. Finally, feedback is conducted.

The parts of brain signals that reflect the user's objectives are useful, whereas the rest is likely noise. The P300 potential, for example, is a beneficial component in a P300-based BMS speller, whereas noise components include high frequency signals, alpha waves, EMG, EOG, and interference from power supplies and other equipment. The channels with an obvious P300 are chosen for P300-based BMSs.

4. Results and discussion

4.1. Brain machine system based on using evoked potentials

Figure 4 depicts an evaluation and monitoring in which the P300 is used to allow a user to choose from a menu of options. On a computer screen, the options are shown in a grid arrangement. The options in this experiment correspond to segmented images of items from a helper robot's current range of vision. The P300 (Figure 4A, panel 1) is utilized to figure out which object the BMS user wants the robot to pick up and carry to another area (Figure 4A, panels 2–4). The menu changes to image of possible destination locations once the object has been picked up, and P300 is used again to infer the user choice of desired robot's location [15].

The user concentrates his or her attention on the image of choice while the borders of the images are flashed one at a time in random order, to make a selection with the P300. That to say each image is flashed multiple of times in this random

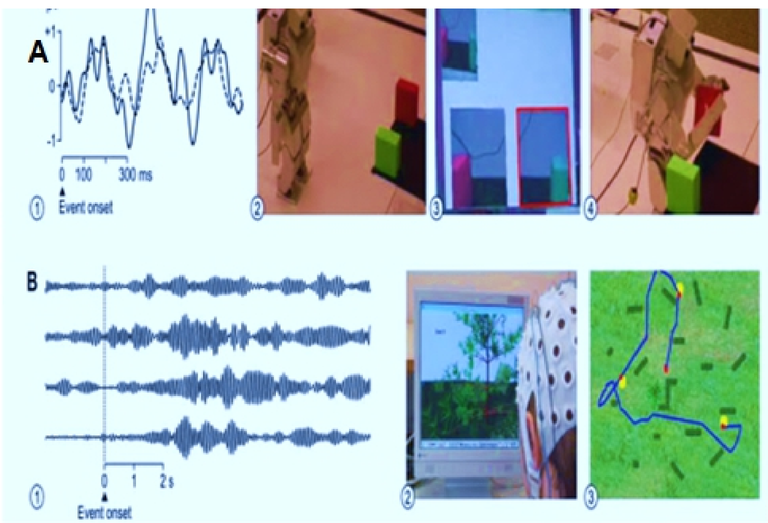

Figure 4. BMS system implementation

order, thus flashed on chosen image create P300 responses while other flashes do not.

A low-dimensional feature vector input was produced by applying a modest set of spatial filters to 32 channels of EEG data acquired from electrodes placed throughout the entire scalp as the SVM's input. These filters are called "spatial" because they are applied to the 32 samples that are spatially scattered throughout the scalp, rather than to samples over time. At each time step, the output of a filter is a linear weighted combination of the 32 EEG channels. To eliminate noise often present at higher frequencies, so each channel was first band pass filtered in the 0.5–30 Hz range. At each time step, 32-channel EEG data is filtered to provide three filtered outputs. The classifier was trained using this low dimensional filtered time series data. During the BMS procedure, the picture with the highest P300 classifications after all flashes were completed was chosen as the user's choice.

For differentiating between four alternatives, utilizing five flashes per choice, an average classification accuracy of 95% was attained among nine participants. The separate accuracy of each participant is shown in Table 1. With a rate of 4 flashes per second implemented, selecting one of four possibilities takes 5 seconds, resulting in an information transfer rate of 24 bits/min.

Table 1. Participant and accuracy

Participant	Accuracy
1	94.8%
2	93.6%
3	98.2%
4	91.6%
5	93.2%
6	90.6%
7	95.3%
8	98.0%
9	97.6%

4.2. Brain computer interfacing using oscillatory activity

Consider traveling in a virtual environment: left hand, right hand, and foot motor images might be used to move left, right, and forward, respectively. The subject's job in the experiment was to traverse and retrieve coins distributed at random across the surroundings (Figure 4B, panels 2–3). A committee of Fisher's linear discriminant analysis (LDA) classifiers was trained to distinguish between the three kinds of motor imagery. Classification features were calculated from 1 s segments by band pass filtering the EEG signal for numerous frequency bands, squaring, and finding the mean over squared values for each band in each segment. To reduce variability, classification characteristics were based on the logarithm of band power estimations. Each subject's most discriminative frequency bands were discovered individually.

Classification was conducted every 40 ms to allow for real-time engagement. Given the emphasis on motor imagery, data was collected from six EEG sensors positioned over relevant sensorimotor regions. To eliminate EEG signal contamination, techniques for on-line muscle artifact identification and eye movement reduction were also applied. After around 5 h of co-adaptive training over many days, the average 3-class accuracy of the LDA committee classifier reached about 80%, with a false positive rate for motor imagery recognition (by the extra LDA classifier) of around 17%. The BMS was effectively used by the subjects to navigate and locate the coins in the surroundings.

5. Conclusion

The brain machine systems (BMS) system, which transforms brain impulses into messages or commands, uses machine learning. We suggest a novel EEG-based BMS in this study with an emphasis on evoked potential. Nine participants achieved a 95% categorization accuracy on average. An information transfer rate of 24 bits/min is achieved by using a rate of 4 flashes per second, which requires 5 s to choose between four options. Additionally, oscillatory activity used for brain-computer interface was measured. The findings reveal that the average 3-class accuracy of the Linear Discriminant Analysis committee classifier achieved around 80% after approximately 5 h of co-adaptive training over several days, with a false positive rate for motor imagery identification of roughly 17%.

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