Research Article

Cognitively Inspired Cyber Physical Systems Design through Brain Signal Analysis and Decoding

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Abstract: Cybernetics, or the study of control and communication, informs the design, modelling, and characterization of cyber-physical systems. In order to construct functional cyber-physical systems in the actual world, the thesis presents a unique method for analysing and decoding brain signals involved in cognitive processes. The goal of this research is to create and evaluate next-generation cyber-physical systems that, when connected to a human brain via a brain-computer (BCI) interface, can read the human brain's neural code and act as smart tools in fields like medicine, gaming, affective computing, and the study of subjective creativity. The non-invasive examination of human memory for the potential early prediction of memory-related disorders like dementia and prosopagnosia is one example of the healthcare application. The use of brain-computer interfaces to simulate the skills of human game trainers for the purpose of robotic game instruction is also discussed. Due to a lack of qualified individuals and the inherent monotony of the work, it is essential that human game trainers be replaced by robots. Using the predicted brain-connectivity (anticipated signalling routes) between active brain lobes/regions, affective computing apps attempt to identify human emotional states. A network study of human emotions has potential for use in psychotherapy. The implementation of a creativity test is crucial for solving issues related to scientific creativity by autonomously detecting subjective creativity from the brain's reaction to memory-generated stimuli.

Keywords: Brain-computer (BCI) interface, Gaming, applications, psycho-therapeutic, Dementia, prosopagnosia

Introduction

Several billion neurons make up the human brain and each play a role in a wide variety of mental operations such as attention, perception, logical reasoning, learning, planning, memory encoding and recall, motor control and coordination, and so on. The cell body of a neuron, also called a nerve cell, is equipped with dendrites that receive electrical impulses from the receptors or nerve terminals/synapses of neighbouring neurons. An action potential is generated by the buildup of electrical impulses in the cell body and then travels down the axon of the neuron to the presynaptic area. The chemical neurotransmitters inside the synapse are activated when the pre-synaptic potential exceeds a certain threshold. When a cell is stimulated, chemicals called neurotransmitters are produced and go to the post-synaptic area, where they are taken up by neurons. Thus, signal transduction in the brain occurs when the electrical impulses created at one neuron are passed on to the next neuron, which in turn passes them on in the same way to the targeted neuron. In biological nervous systems, two kinds of neuro-transmitters are often utilised to either block or stimulate the subsequent neuron in the signal transduction pathway. For instance, acetylcholine is a neurotransmitter that activates the next neuron in the circuit when it is positively triggered. Gamma-aminobutyric acid (GABA) is a neurotransmitter that blocks signals from being sent from one neuron to the next. As can be seen in Fig. 1, there are four major lobes in the human brain. These are the occipital lobe, the parietal lobe, the prefrontal lobe, and the temporal lobe. Despite their superficial similarity, neurons in distinct brain areas have evolved to play unique roles in performing a wide variety of cognitive activities. For instance, the parietal lobe is in charge of strategic planning for movements. The prefrontal lobe contributes to the encoding and retrieval of information in both short-term and working memory, and it also plays a role in decision-making. The occipital lobe is involved in visual processing and recognition. Memory and learning are processes in which the temporal lobe plays a pivotal role. Multiple brain areas are typically active practically simultaneously for sophisticated cognitive tasks, with just little delays between pairings of modules. The reaction of one brain module is sent through the signal transduction channel to activate the next, thereby forming a brain network to accomplish a difficult cognitive problem.

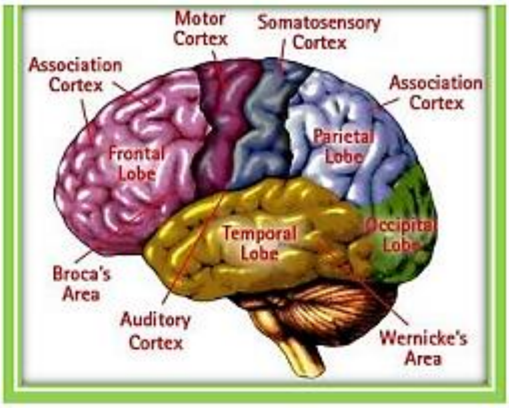

Figure. 1. The brain-lobes

In this study, we discuss numerous computational models of cognitive processes, such as learning and creativity, emotion detection, and gaming, utilising BrainComputer Interfacing (BCI) as the underlying infrastructure. It's fascinating to learn that different cognitive tasks elicit waves of different amplitudes and frequencies from the brain. The N400 signal, for instance, has a unique wave-shape that causes a negative peak 400 ms after the start of the novel learning stimulus. The parietal lobe is responsible for eliciting the P300 signal for attention-related activities. The P300 is unique in that it produces a positive deflection around 300 ms after the commencement of an atypical auditory or visual input. It is often employed in BCI as a measure of the subject's level of awareness and focus on the environment around them. The Parietal lobe is very rich in P300 signal. The motor cortex is also responsible for releasing the BCI signal known as Event Related Desynchronization/Synchronization. The ERD-ERS signal resembles a regular letter V. Therefore, a BCI interface is essential to aid the user in sensing the subject's cognitive state and giving the subject with the relevant feedback via auditory, visual, tactile, and/or other methods. The aforementioned domains of use need concurrent interactions. Therefore, single trace/shot detection of the brain signals is given particular attention throughout the system's design phase. It is a difficult task to decode BCI signals from a single trial. The thesis, thus, gives a comprehensive look into the detection of single-trial BCI signals, particularly the P300 and N400 signals.

Literature Review

D. De Venuto et.al (2016) To determine whether or not a person's movements are voluntary, we suggest a unique technique that combines direct sensing of brain potentials with monitoring of muscle action signals collected by wireless, non-invasive sensors using rapid, real-time algorithms for large-scale data processing and biofeedback response. The system has been field-tested successfully.

Shen Feng et.al (2016) EEGu2 is proposed in this study as a portable embedded BBCI system. EEGu2 is built on a BeagleBone Black (BBB), and its bespoke cape has two printed circuit boards (PCBs): a data acquisition board for 16-channel 24-bit collection up to 1KHz sampling frequency, and a power board for both stationary charging and on-the-go power. With a signal-to-noise ratio of 25dB and an input referred noise of 0.785V peak-to-peak, EEGu2 measurements exhibit a high degree of acquisition accuracy.

Krishna K. Venkatasubramanian (2017) In this research, we introduce Physiology-based System-wide Information Security (PySIS), an extension of PKA that enables end-to-end information security in CHMS from the sensors to the PHR by using the notion of generative models (which produce synthetic physiological signals for a user). The most important change is that we no longer require identical physiological signals on both ends

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for our protocol to function. We also offer a logging method for forensic investigation of the system in the event that PySIS fails and data leaks out.

Cognitive Cyber-Physical Systems

Typically, when people talk about their "cognition," they mean their "mental/psychological processes." Cognition often includes activities like deductive thinking, learning, planning, and making complicated decisions. Complex motor control and coordination in activities like gaming, driving, swimming, and similar pursuits are also included. The design and development of cognitive cyber-physical systems, which address the connection between human and animal cognition and cybernetic systems, rely heavily on the power of the human brain. Researchers have recently shown a strong desire to include human and animal brains into the cyber-physical loop in order to develop more effective real-time systems. In order to make crucial judgements as they arise, it is crucial to keep the human brain in the loop. Autopilot systems that can function without human intervention are good examples of cognitive cyber-physical systems. The past ten years have seen remarkable advancements in the study of brain-computer interfaces (BCI), driven by the two goals listed below. First, BCI works on identifying the optimal stimulus for stimulating the brain to achieve the desired state of control. Second, BCI allows for the evaluation of the learned brain response to the environment to ascertain the present condition of the brain. Brain stimulation may be accomplished by a variety of sensory inputs, including the visual, auditory, olfactory, and tactile. Brain imaging and signal acquisition devices record the brain's reaction to the stimuli. Typically, just one modality is used in BCI implementations. However, multi-modality is also employed to concurrently collect spatial and temporal information of chosen lobes of the brain in order to gain both regions of brain activity and temporal properties of the brain. Using electroencephalography (EEG), we sought to record mental states for this thesis. With a BCI-based CPS, the goal of the system is to improve the interplay between the brain-imaging tool and the creation of control commands for the operation of external equipment. The positional occurrence of the error produced by the arms of the robot comes from the Error Related The potential (ErrP) signal released by the subject upon observing the robot committing the error in BCI based robot position control application [2], where engine imageries are utilised to activate the motion for each link of a robot arm. The robot makes up for the positional inaccuracy by applying a constant offset adjustment. The robot and its surroundings make up the cyber-physical component of the above example CPS, while the BCI interface with the CPS enhances the system's intelligence thanks to the inclusion of a human subject. In automata models of CPS, human-generated commands based on motor imagination and/or ErrP are represented by paths between states representing robotic activity. Such automata must meet stringent criteria for security and lifelikeness. In this case, the safety requirement makes sure the system stays inside its known states, while the liveness requirement makes sure it can wait for an input for a limited amount of time. In the event that no such input is received within the allotted period, the process would restart.

A human's emotional state is a psychological one. Emotions, according to philosophers, start when there are major changes in one's life [1]. Physiological measures such as core body temperature, pulse rate, heart rate variability, and brain signal characteristics are frequently co-occurring with the outward manifestations of emotion such as facial expressions, voice, gestures, and postures. Emotion recognition based on visual and/or physical cues presents an intriguing challenge. The literature reports significant improvement in emotion identification from its appearance.According to a review of the relevant literature [5], the mode of recognition has a significant impact on the accuracy of emotion recognition. Classification accuracies for subjective emotions are often high when using facial expressions and/or speech, but they seem to be lower when using physiological indicators. Although the degree and kind of an emotion may be gauged by how it is manifested, the outcomes of categorization do not always match the feeling that arose. First, the person can't show signs of feeling angry or upset. Second (and more significantly), she doesn't want to show her feelings via her expressions, tone of voice, or physical actions. But for the next generation of HCI systems, the ability to recognise genuine emotion is crucial. This chapter will be helpful in separating genuine feelings from showiness. Previous experiments have shown that it takes many tens of seconds from the commencement of emotion arousal for facial and physical expression to occur. However, when emotional arousal first occurs, brain signals react very instantly. It is understandably challenging to deliberately modulate brain signals in order to hide or fake an emotion while feeling it. This chapter gives a comprehensive evaluation of brain signals for categorising genuine from faked emotional states. Due in large part to the high expense of EEG devices, excellent hospitals were unable to do extensive early research on brain signal processing until recently, limiting the field's progress by around two decades. Fortunately, EEG equipment are now commercially available at affordable prices, making them accessible to the vast majority of brain science research institutions. Therefore, in order to differentiate between genuine emotion and pretence, an EEG study is conducted on patients within a certain age range of 24.4 years. The following are some quick explanations of the fundamental ideas used to categorise an emotion as either "true emotion" or "pretension." According to research into the neurological pathways involved in emotional arousal, feelings first form in the prefrontal cortex before travelling to the motor cortex and on to the pons. Facial expressions alter as a result of electromyogram (EMG) signals generated by contracting muscles in response to inputs from the motor brain.

Here, we use neural net NN1 to mimic the prefrontal cortex (Fig. 2(a) and (b)), and we use neural net NN2 to simulate the motorcortex. In Fig. 3 (c), the NN3 neural network is utilised to investigate potential associations between face characteristics and pre-frontal EEG characteristics. If there is a significant relationship, we may confidently claim that the facial expression is indicative of genuine emotion. If the correlation is low, then the facial expression must be pretence. It is common for feed-forward architecture to be used in NN1, NN2, and NN3 neural networks. A appropriate learning method is used to train these networks using input-output examples from the actual world. Once the neural networks have been trained, they are linked using the shown architecture.

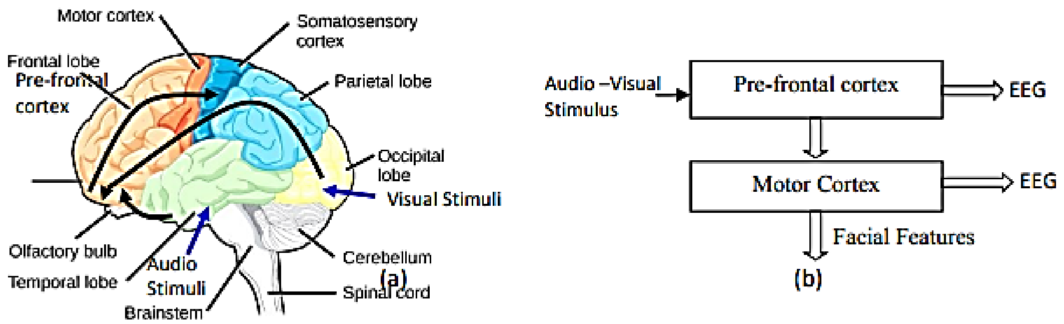

Fig. 2 a) Human brain (viewed from the side) and (b) the neural connections inside the brain when facial expressions of emotion are made.

Experiments and Results

Following an introduction to various brain topologies, this part details the experimental technique that will be used to verify the effectiveness of the proposed model. The process may be broken down into two main phases: training and recognition. After preparing the input and output training examples, the neural networks are trained during the training session. The acquired and preprocessed (input) instances are provided at the input of the pre-trained networks during the recognition phase, which then generates the output. Data gathering, pre-processing (noise reduction), and feature extraction are all necessities for training and recognition sessions. Functional mapping is also necessary for the training session. When submitting a measurement input, the real output is generated via the recognition session. In the identification session, you will work to determine whether a particular feeling is genuine or feigned.

Obtaining an EEG: Ten right-handed people, five men and five women between the ages of 24 and 4, participate in the trials. After stimulating individuals with 10 chosen audio-visual stimuli, EEG data are acquired using a single 14-channel wireless Emotiv headset at a sampling rate of 128 samples per second.

Filtering: The following measures are made to prevent the introduction of unwanted noise into the collected EEG data. First, by averaging the signals in the area surrounding each chosen channel, we can eliminate the impact of eye movement on EEG. The second step in preventing crosstalk from one channel into another is to isolate the required frequency spectrum. Such interference often occurs when the person simultaneously engages in two or more distinct mental operations. To separate the alpha (8-12 Hz) and beta (13-30 Hz) signals from the motor cortex and the prefrontal cortex, we used elliptical band-limited filters of order 6. For this reason, elliptical filters are preferred over other filters with the same amount of filter coefficients because of their quicker transition between the band that passes and the stop band.

Neural Network Training: In order to train the models of neural networks we mentioned before, we need training instances with known inputs and outputs. Back-propagation using the Levenberg-Marquardt learning rule [6] is used to train the FFNN and CFNN, whereas the Orthogonal Least Squares Learning Algorithm [8] is used to train the RBNN and GRNN due to its demonstrably superior performance compared to the standard methods. For FFNN/CFNN, 20 neurons are chosen at random to make up the intermediate (hidden) layer. In order to keep the error at the output layered neurons for RBNN/GRNN below a certain threshold, the number of axons in the hidden layer was fine-tuned. The last layer's mean square error is used to evaluate the effectiveness of neural training techniques. Table 1.below displays the findings of the mean-square error sum for four distinct setups.

Hjorth features For	Mean square error of NN1	Mean square error of NN2	Mean square error of NN3
CFNN	1.227e+7	0.3319	1.1898e+7
FFNN	3.4637e-24	1.202e-16	7.5406e-24
GRNN	3.6210e+4	0.0605	1.5602e-53
RBNN	5.0550e-25	9.0371e-33	4.5652e-34

Table 1: Mean Square Error of Three NN Classifiers

According to Table-1, the RBNN realisation results in the smallest sum of mean squared errors for NN1 and NN2, while the GRNN realisation results in the smallest sum of mean squared errors for NN3.

In this study, we investigate a candidate brain area for learning. Specifically, we have the subject pick one brain area at a time, provide PSD attributes of that region to the classifier, and then verify that the classifier correctly predicts the class that the patient indicated with two consecutive N400 signals. If the N400 negativity goes down, for instance, it's safe to assume that the subject has internalised the instances and the notion they illustrate. If the results of the classification test show that all training examples generated by the targeted brain region were effective, then we identify that area of the brain as critical to the learning process. The ability to correctly apply a notion to an unstated situation is similarly assessed. Again, we choose a brain area at random and feed the PSD properties of the recorded brain signals into a previously learned classifier.

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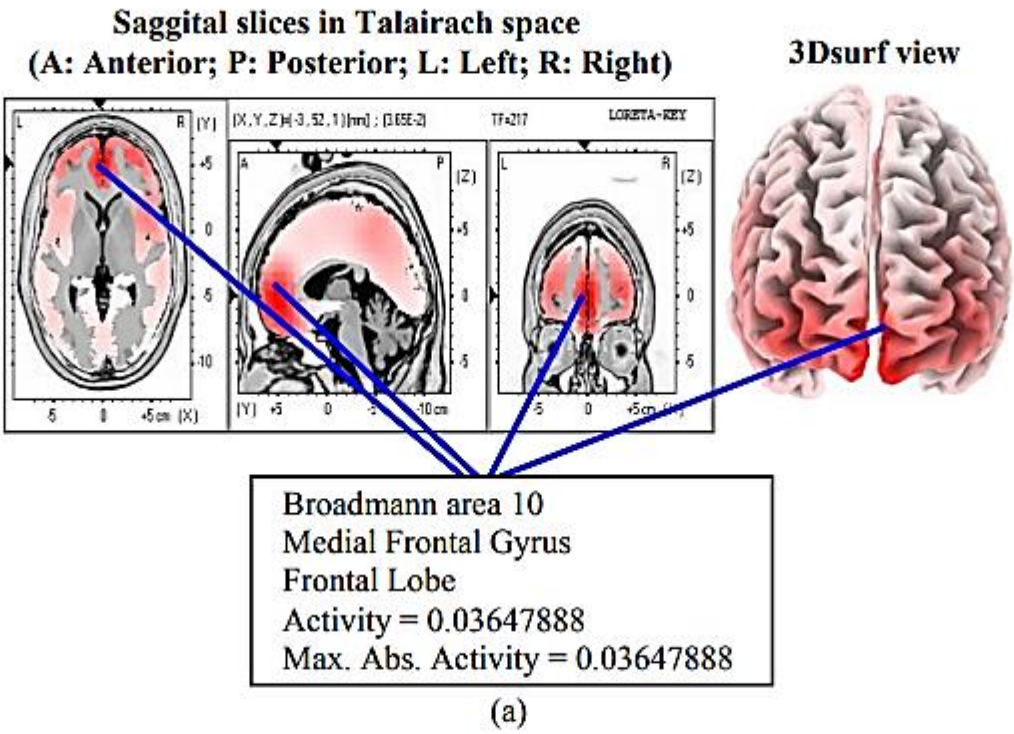

Figure 3.. (a)Theta band PSD (4-8 Hz) and(b) alpha band PSD (8-12 Hz) current density in the brain as measured by e-LORETA during learning and planning, respectively

Conclusion

Another critical problem that is often responsible for system performance is feature extraction and selection. Most current BCI studies choose features arbitrarily, without explaining why those particular characteristics were prioritised. Features are often defined as defining aspects of a signal that, when taken together, adequately characterise the brain signal we want to represent. Moreover, characteristics should be decoupled from one another, such that a small set of features may adequately characterise the signal. Unfortunately, approaches like Principal Component Analysis and Independent Component Analysis have been used to minimise linear inter-dependence of the features in present BCI research. Nonetheless, there is no foolproof mathematical method to extract characteristics independent of non-linear dependencies. In recent years, scientists have used swarm/evolutionary algorithms to find independent traits.

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