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Experimental Analysis and Hypothesis of EEG Signal

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ABSTRACT: In our human brain the information distribution is done through neuronal activity. These neuronal activity gives a detectable electrical waves. These waves are called brain waves. Brain signals has been recently investigated by the scientific community for their use in automatic people recognition systems. A brain computer interface is a new communication channel between the human brain and digital computer. The signal generated by brain is received by a human brain sensor and it will divide into packets and packet data transmitted to wireless medium. Then the wave measuring unit will receive the brain wave raw data and it will convert into a signal using MATLAB -GUI platform.[1-3] Then the instructions will be sending to the home section to operate the modules (bulb,fan,TV). The project operated with human brain assumption and the home appliances on/off condition is based on brain waves.

KEYWORDS: Hypothesis, cognitive functions, frequency bands, sub bands, SWS.

I. PROBLEM SPECIFICATION

EEG frequency bands can be quantified employing spectral analysis techniques. The contribution of the different rhythms to the EEG depends mainly on the level of alertness, on the age and behavioral state of the subject. Moreover an EEG pattern is influenced by neuro-pathological conditions, metabolic disorders, and drug action. The different brain rhythms or some combination of them significantly increase or decrease in relation to other rhythms depending on specific mental states, which can be induced by the performance of a proper acquisition protocol. Specifically, Delta and Theta frequency bands are considered to represent slow oscillating neural synchronization, or slow wave (SW) activity, while Beta and Gamma bands represent fast wave (FW) activity. Brain oscillations in these frequency bands have been linked to various psycho physiological states and cognitive functions, as reported for instance in. A more detailed characterization of the sub bands is given in the following.

• Delta 0.5−4Hz: Delta rhythm is a predominant oscillatory activity in EEGs recorded during the so called deep or slow wave sleep (SWS). In this stage, Delta waves usually have relatively large amplitudes (75 − 200μV) and show strong coherence all over the scalp. In newborns, slow Delta rhythms predominate. An increase in Delta EEG activity during the performance of a mental task has shown to be related to an increase in subjects' attention to internal processing.
• Theta 4 − 8Hz: In human scalp EEG, changes in Theta rhythm are very difficult to detect without the help of computational methods from raw EEG traces. If EEG power in a resting condition is compared with a test condition, an increased activity in the Theta sub band is observed, which is known as Theta-band power synchronization. In particular Theta-band power increases in response to memory demands, selectively reflecting the successful encoding of new information. •
Alpha 8 − 14Hz: The oscillatory Alpha band activity is the most dominant rhythm which emerges in normal subjects, most pronounced in the parieto-occipital region.[4] It is manifested by a peak in frequency spectrum. The Alpha brain oscillations may present amplitudes large enough to be clearly seen in raw EEG traces acquired in specific mental states. Topographic maps (EEGLab toolbox) of rhythms Delta, Theta, Alpha, and Beta (top view of a head). Each map shows in false colors the spatial distribution on the scalp surface of the related EEG rhythm. The mean value of the power spectral density for each frequency band is reported. It is characteristic of a relaxed but wakeful state primarily with closed eyes and attenuates with eyes opening or mental exertion due to event-related Alpha power

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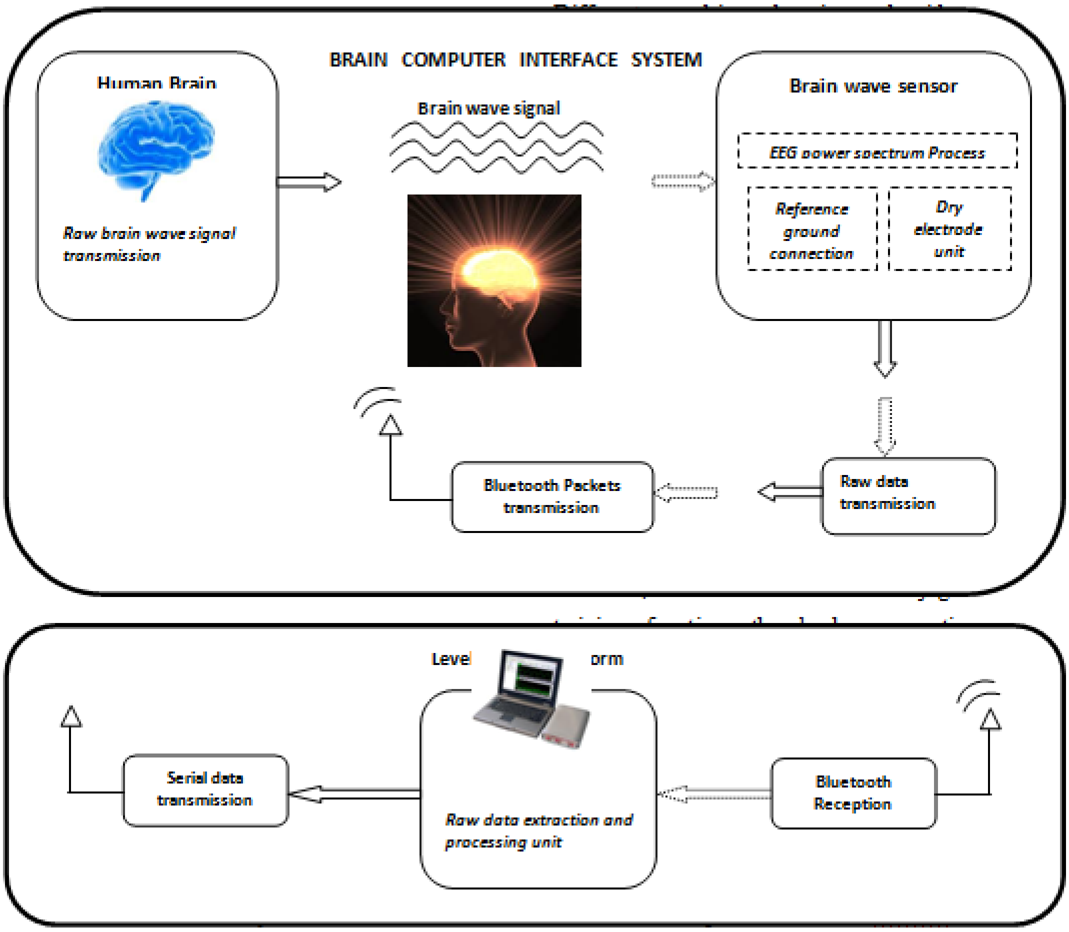
desynchronization. These changes in the Alpha band reflect an increased arousal caused by basic processing of visual information. Moreover there is evidence that attentional and semantic memory demands lead to a selective suppression of Alpha in different sub bands and that the well described effects of visual stimulation represent just a special class of sensory-semantic task demand. This confirms the evidence that Theta and Alpha band power are related to each other, although in an opposite way.[5]

• Beta 14 − 30Hz: Phase synchrony in Beta frequency band is enhanced for consciously perceived stimuli, and detectable mainly from the involved cortical areas, including somatosensory, frontal, parietal and motor regions, depending on the performed task. Specifically, Beta activity is characteristic for the states of increased alertness and focused attention.[6-8]

• Gamma over 30Hz: Neuronal synchronization in the Gamma band is considered important for the transient functional integration of neural activity across brain areas, which represent various functions involving active information processing, e.g., recognition of sensory stimuli, and the onset of voluntary movements. Gamma components are difficult to record by scalp electrodes and their frequency usually does not exceed 45Hz. Components up to 100Hz, or even higher, may be registered in electrocorticogram (ECoG).[9]

II. BLOCK DIAGRAM



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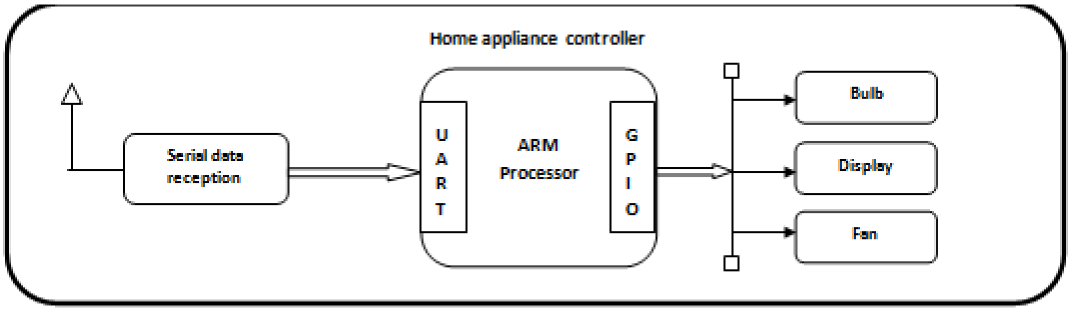

III. CLASSIFICATION ALGORITHMS

The efficiency of the classification algorithms employed for EEG biometrics user recognition depends on the specific distribution of the observed vectors in the feature space. In fact, for a proper solution of the classification problem it is important to use a suitable classifier fitting the scattering distributions generated by the different classes to distinguish among. Different machine learning algorithms present specific capabilities in approximating different boundary surfaces among the actual decision regions in the feature space, representing the classification problem. The most commonly employed algorithms used in literature for EEG biometrics are based on Neural Networks (NNs), suitable in the classification of data not linearly separable in the feature space. Several architectures of NN based classifier have been proposed in the published studies, with different numbers of nodes for each of the considered layers, and different training functions, such as the scaled-conjugate training function, the back propagation algorithm , and the Kohonen's Liner Vector Quantizer.

The training algorithms can be summarized as follows.

Step 1: Define and initialize the parameters of F-ELM.

1) All input attributes are fuzzified to five membership functions. The centers of five membership function are fixed, i.e., **a** = [00.250.50.751]. To explain further, the membership function centered at 0 is defined as very low (or in single label 1), the membership function centered at 0.25 is defined as low (or in single label 2), the membership function centered at 0.5 is defined as medium (or in single label 3), the membership function centered at 0.75 is defined as high (or in single label 4), and the membership function centered at 1 is defined as very high (or in single label 5).

2) Randomly assign training parameter of F-ELM, i.e.,$\sigma \in R+$ (standard deviation of Gaussian fuzzy membership function).[10]

3) Select the number of hidden neurons *(L)*, which is equivalent to number of fuzzy rules.

4) Randomly select the combination of membership functions for attributes of all hidden neuron (fuzzy rules).

This can be done by randomly assign binary values to a 3-D matrix (with *n* attributes × five membership functions × *L* rules), known as rule-combination matrix (hereafter denoted as matrix-**C**). For example, rule-combination matrix *C*(2, 3, 4) = 1 represents the MF 3 of attribute-2 is active, thus it will be used in rule-4.

5) Randomly select the DC bits by assigning binary values to a 2-D matrix (with *n* attributes × *L* rules), known as DC matrix (hereafter, denoted as matrix-**D)**. For example, *D*(2,4) = 1 represents attribute-2 is DC (not used) in rule-4.

Step 2: For all training pair *(***x** *j* , **t** *j),* do the following steps.

Step 2(a): Calculate the fuzzy values of using membership functions for all attributes *x j i*

Conclusion: This article surveys the research of the Evolvable Systems .Bio signal amplifier is design to achieve high input impedance excellent common mode rejection ratio(CMRR) and very low noise level and EEG is obtained by measuring electrical potential between varies points of the scalp using a bio signal amplifier shown in the figure [13]. It is a
means of communication between brain and machine, with the help of brain peripherals interfacing. Information of neural activities of brain can be exchanged with the machine

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