Smart Home for Paralyzed Aid

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Abstract - *The paper proposes a scope of aiding a paralyzed person left alone at home. Primarily focusing on Electroencephalogram data of 25 paralyzed people, the study of changes in brain signals while they feel hungry, thirsty, sleepy, mentally excited or stressed is conducted. On continuously monitoring and systematically analyzing the brain signals for a physically challenged person, multiple modules to meet the basic necessities are developed and tested upon. The Electroencephalogram data is preprocessed and classified based on neuro-fuzzy hybrids. The logical decision making is performed by an Internet of Things based platform. All the control modules are fully automated and hardware is driven by a self-learning fuzzy control machine. Results of performed experimentations proved to be really promising and reached an overall accuracy of 89.73% for automating the aiding units to fulfill basic needs of a paralyzed person and we are looking forward to extend the research to design a smart hospital paradigm.*

Key Words: Electroencephalogram, kNN classifiers, Self-learning Fuzzy, Internet of Things, paralysed, Basic need automation

1. INTRODUCTION

In the last century, engineering advances modified the notion of healthcare. Life expectancies have increased approximately by 34% in the last few decades [1]. The major problem encountered when studies related to Brain-Computer Interfaces (BCI) are emerging is the complexity of nature of Electroencephalogram (EEG) signals. Several predictive models are developing in the last few decades, but mostly they are domain specific or developed for a single objective [2]. For example, most implications of Internet of Things (IOT) are only for communication protocols or Fuzzy logic found a major application in domains of speech recognitions for the last few decades.

For not involving any pain of the test-subject and higher dynamicity for research, non-invasive processes like EEG (with the sole aim of studying electrical activities in brain) is much more preferred than invasive ones. Previous studies described our cerebral cavity divided into four lobes, namely frontal, parietal, temporal and occipital; and spectral sub band frequencies generally includes ((*alpha* (8-13 Hz), *beta* (14-30 Hz), *delta* (0.5-4 Hz) and *theta* (4-8 Hz)) which are measured from the lobes explicitly [3]. *Beta* is generally obtained from deep sleep and often if the patient is suffering fatigue and has not taken any food for last few hours. *Alpha* and *beta* are closely related to change of emotions apart from stress and relaxed mind states. A stronger correlation is observed in case of neural activities, whereas a weaker one when asleep.

Implications of IOT on healthcare was first observed in 2009 where for a P300 based BCI system [4], EEG predictions are justified by IOT realizations in hardware modules. But the activities were solely dependent on flash incidence, accuracy drops down to 54% from 79%, on reducing the number of flashes from 8 to 2. Many recent literatures worked on designing intelligent wheelchairs, some based on visual stimuli [5] or on overall perception through various sensory organs [6]; but an absolute need-based automated module where classified input from EEG signals triggers multimodule IOT paradigm for various everyday functions, was never discussed before.

Furthermore, the disadvantages of fuzzy learning can be ruled off by a sliding approach for the best possible optimized output with a return loop in order to learn from previous state errors. Informally, the model designed is named as Self Learning Fuzzy Sliding Mode Control (SLFSMC) and is used for driving few hardware units for two support modules.

The rest of the paper is organized as follows. Firstly, the experimentations and EEG Signal Processing is described. Next the research methodology uncovers the theories behind driving the support modules for a paralysed person which is followed by the implications of each and every module.

2. EXPERIMENTAIONS AND SIGNAL PROCESSING

The EEG signal is acquired, pre-amplified and the artifacts are removed by filtering. The spectral analysis derives the peak power and thus provides an overall estimate of dominant band of activity. Next kNN based classifiers provide a scaled band activities and label frequency parameters (alpha, beta, delta and so on) for transferring the possible priority for analysis in the IOT platform. Fig. 1 describes the basic principles of EEG Signal Processing.

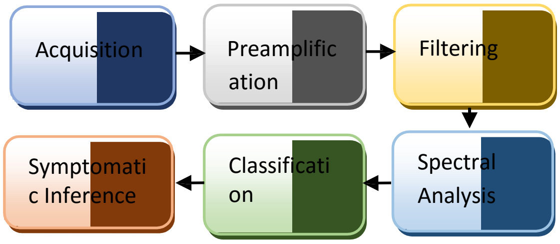

Fig -1: EEG Signal Processing

2.1 Subject Selection Criteria

Twenty-five paralyzed people (14 male and 12 female) of age limit between 55 and 70 years were selected for the study with their formal consent. They were all right-handed individuals and past pathologies assured normal working of their brain. Subjects were included only if they did not have any past neurological histories, had normal eyesight and no hearing ailment and not under any medications for hypertension or diabetes. Standardization of subject is treated as an important criterion for EEG analysis, as past researches revealed remarkable change of perceptions and effects on brain signals based on changing emotional indices (often triggered by age or certain diseases).

2.2 Experimental Basics and Setup

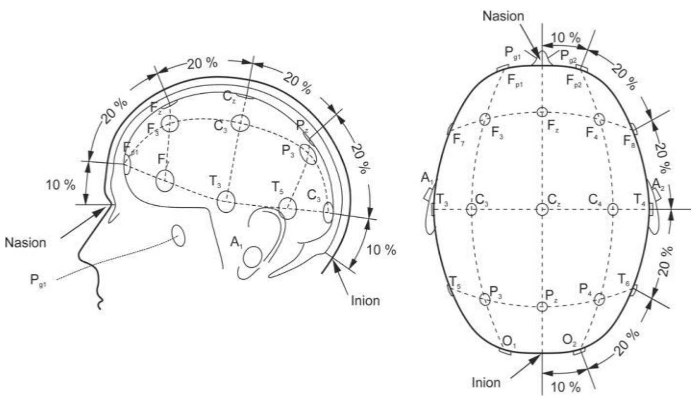

Fig -2: Position of electrode on scalp based on International 10-20 System

For EEG testing, signals are collected mainly in microvolts range, though it may shoot up to a few millivolts scale for shocked or surprised mental states [7] of a paralyzed person. To discuss the scalp placement, as it is well known, the most complex part of a human body is the brain itself. If the cathodes are placed too close to each other, there are chances of least amplitude production due to minimum potential difference [8]; which in turn results a massive drop on spectral analysis and makes the study too convergent to infer. Similarly, if one electrode is placed a lot away from another, the loss of medical data may result in some necessary peak powers and resultant symptoms undiagnosed. Considering all these complexities, electrodes are placed in the scalp obeying 10-20 International System for a 21-electrode setup as shown in Fig.2.

2.3 Signal Preprocessing

One of the basic reasons of the randomness of the neurophysiological signals is the noise content in it. Firstly, when the signals in microvolts are amplified, the artifacts get amplified as well [9]. The reasons of artifacts are many and include, though not limited to: all physical constraints, room temperature, other signal interferences, thought process, calorie content, last night sleep quality, muscular stress, psycho-physiological activity status of subjects etc. [10] The amplified signals are hence to be vividly processed before subjecting to spectral analysis. Next, it is passed through repetitive filtration using band pass Chebyshev filters. If the order of filter is kept low for a simpler calculation, the number of iterations increase. Or if the filter order is increased along with appropriate windowing expected accuracy is obtained in a few cycles (the count stays typically around or below five). Order and rate of filtration solely depends on the nature of the raw signal acquired, and hence treated as a dynamic quantity. Type I Chebyshev filters are used with the sole objective of quicker role-off than Type II [11]. Parametric method for spectral density calculation could be beneficial for such signal due to certain advantages over non-parametric methods like avoiding side-lobe leakages [12]. Based on past researches the *Burg* method and the *Yule-Walker* method are found to be the most efficient for neurophysiological signals' spectra analysis [13]. Both are adapted for the smart home module; one may get switched to another in case of change in specific need for a particular module of aid.

2.4 Filtered Data Classification

The classification can be performed based on any standard neural classifier. Support vector machine or extreme vector machine based classifications, promise a higher accuracy in cost of time [14]. Gradient descent approach is often accompanied with standard back-propagation paradigms [15], which further slows down the rate of computation. Fuzzy system based classification gained popularity in the past few decades; though it is often found to mess up with the border overlap. For example, an EEG left frontal alpha may at some frequency points merge with beta or delta contributions, resulting scarcity of information extraction [16]. An emerging domain of researchers found neuro-fuzzy hybrids quite useful in the context of classifying EEG signals. It helps in a discrete analysis of shorter time lapses. The kNN classifier is found to work good for our classification purpose. In kNN classification, the output is a class member. An object is classified by a majority vote of its neighbours, and weightage of voting increases with decrease in distance between a given neighbour and target. Finally, the object is assigned to the class, most common among k nearest neighbours. k is a positive integer, typically of smaller values. Given the set of classified data, kNN determines the classification of input based on the class labels of k closest neighbour(s) in the classified set. Major two steps of the algorithm include:

i) Find k nearest neighbours of the input x.
ii) Calculate the class membership of x using Eq.1.

$$\mu_{ci}(x) = \frac{\sum_{j=1}^{k} \mu_{ci} x_j d_j}{\sum_{j=1}^{k} d_j} \quad (1)$$

Particularly, the parameter m determines how heavily the distance is weighted while calculating the class membership. As m decreases towards infinity, the term $1/d$ approaches unity regardless of distance. The term mentioned as d_j is defined as:

$$d_j = \frac{1}{\left\| x - x_j \right\|^{\frac{2}{m-1}}} \quad (2)$$

Interestingly, $x_1, x_2, \ldots, x_k$ denotes k nearest neighbors of x. Consequently, the neighbors x_j are more evenly weighted. As m decreases towards 1, however, the closer neighbors are weighted far more heavily than those further away. This also has the effect of reducing the number of neighbors that contribute to the membership value of the input data point. The objective of band priority deduction is often attained solely by kNN classifiers for single priority from user end [17]. For example, on waking up after a 6 hours' sleep the person on study seeks assistance to drink water. But most of the time, in a real scenario there are multiple needs in conscious or subconscious mind, and the objective of the classifier is to determine the prioritized and really necessary needs and generate queries for IOT platform to work on them.

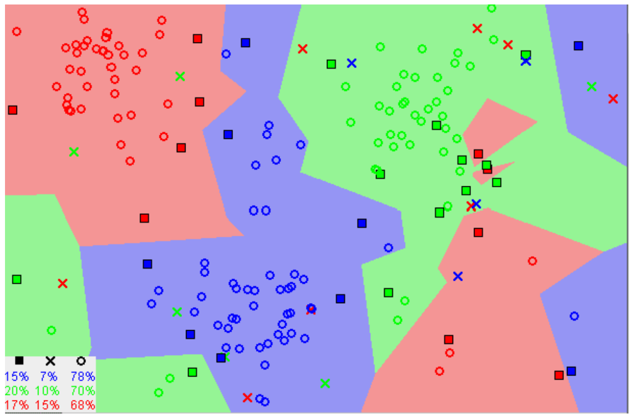

Fig -3: Fuzzy kNN classifier output on analyzing EEG for a 65 years old man eager to take an evening ride

Fig.3. describes the state of a mind for a sixty-five years old man who is eager to take an evening ride in the countryside after spending four hours after his lunch. The boxes denote the alpha contributes, circles the beta attributes and crosses the delta attributes in Fig.2. For simpler visualization three lobes are taken under consideration for the above read: frontal (in red), parietal (in blue) and occipital (in green). The classifier here indicates higher occurrences of beta over alpha and delta in frontal (68%) and parietal lobes (78%) which indicates a wish. The alpha-beta pair in all the three lobes are normally deviated which indicates normal health status and no specific priority task is generated. The task of identifying the expected strands of frontal activities in occipital lobe is on the intelligent module driven by IOT platform, as it is found to be beyond the scope of kNN classifier.

3. RESEARCH METHODOLOGY

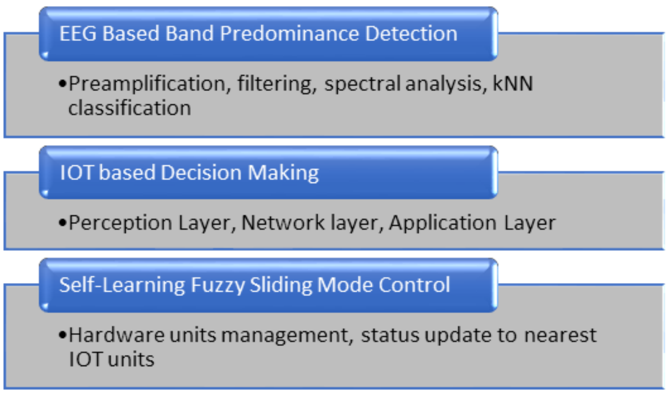

Fig -4: Three staged Task Objective Realization

Three distinct stages are followed for the research as depicted in Fig. 4. At the early stage EEG data is collected, processed and some initial predictions are obtained from kNN classifiers. Next the IOT platform is triggered by the classified data. They have the sole responsibility of maintaining database, communicating each layer and decision making for identifying the best possible necessity of the paralyzed person. The EEG data updates the buffer at an interval of three milliseconds (peak-hours) and fifteen seconds (for sleep mode). The self-learning fuzzy sliding mode control (SLFSMC) unit is designed mainly for end-user device controls associated with temperature control and analysis on emotional indices. The IOT units update the SLFSMC to operate upon and the SLFSMC acknowledges the activity and share device status to the upper layer when asked for routine checks or updating new orders.

3.1 IOT Based Decision Making

The basic principle of IOT is the integration of multiple technologies shared by a common internet. IOT is basically one of the recent emerging technologies which is assumed to be the pioneer in the next generation of internet network [18]. The three effective layers of control on IOT are Perception, Network and Communication layer. The major key technologies of IOT primarily include:

a) Internet technology
b) Sensor Network technology
c) Wireless Communication technology
d) Embedded technology

The model developed can also be classified based on the task to be performed: Information Unit, Control Unit, Decision Unit and Physical Unit. The physical unit consists of the input layer composed of all measuring units and the output layer which operates on the aiding units to the hardware level. The Information unit consists of all the buffers and can sequence clusters of data over time. The Control unit in the processor has a task quite similar to the communication layer but the only difference is, the earlier has the intelligence to choose priority query over another and can also compare data with the buffer to update analyzer. The analyzer activates the decision unit. The sequencing and/or sorting of current input with recent past states is performed in the decision unit in order to identify the major contributive necessity of the paralyzed person left alone at home. Lastly, control unit marks the output from a cluster of possible necessities in a reverse path from the decision unit, once the latter completes operation.

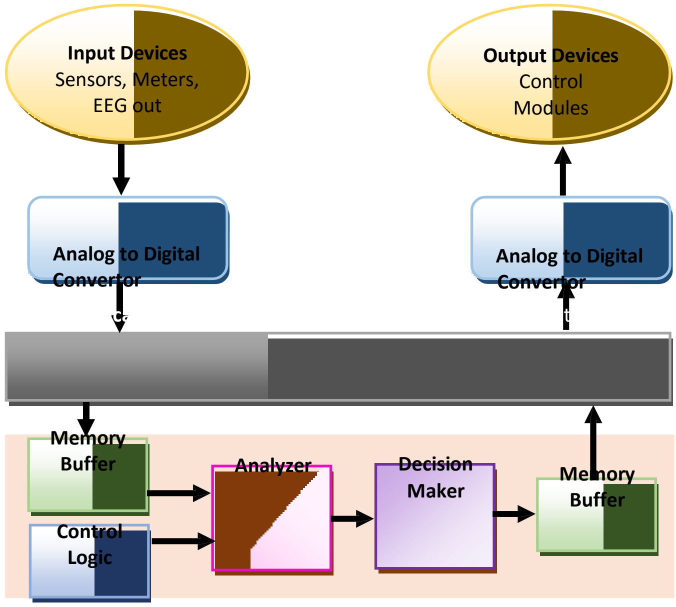

Fig -5: IOT Module for Aiding Paralyzed Person

Based on functionality, the IOT modules can be broadly classified into three layers, *Perception Layer*, *Network Layer* and *Application Layer*. The data acquisition units of Perception Layer play the role of identifying inputs/outputs, acquiring/releasing and updating buffer at a regular interval. Another functionality of Perception Layer is to provide access by transmitting the data from sublayer to global object-conjunction network. Network Layer supports communication by best possible unit; selected based upon priority and privacy of the data passing by. The same also aid partially to information integration: a method of clustering similar data by generating a label for each cluster for easy identification at user end. Finally, the application layer performs some selection, optimization and sorting algorithms to execute the most required action for aiding the paralyzed person.

4. SUPPORT MODULES

Some absolute need-based modules are developed for aiding a paralysed person to feed on time, letting have a nice sleep, offering a soothing room temperature or controlling emotional thrushes. All the support modules are completely automated and associated with a tertiary emergency module updating status of unexpected conditions like rapid health deterioration, natural calamities etc. to selected family members, nearest police station, hospital for ambulance support or fire station (triggered only for temperature control).

4.1 Feeding Module

The hunger and thirst are one of the most basic needs. Not only detecting hunger or thirst psycho-physiologically, but measuring required calorie content and holding a control on protein, carbohydrate and vitamin supplies are some of the basic needs. It also becomes necessary to differentiate between water-requirement or bulk roughage carbohydrate requirement for person under control [19]. Feeding to be performed artificially for critical patients, mainly based on three types:

i) Ryle's tube feeding and saline support
ii) Normal feeding with saline support
iii) Assistive table; no feeding, drinking support

For normal feeding in cases *ii)* and *iii)* a rotational assistive table is designed with preassigned diet but flexible quantities for intake; typically based upon last meal-time and rate of digestion. The patient when mounted to the chair attached to the table, the table rotates to the required bowl, lifts it up to a given height (based on height of paralysed person) and thus aids digestion.

The major advantage obtained for this module is, effect of digestive enzymes reaches much faster to the central nervous system to get detected by EEG for paralyzed people than normal ones. For example, fasting for a paralyzed one, results in wider pulse rate with sudden beta domination and alpha power loss, if three or more hours are exceeded than regular meal time; but this effect gains visual approximately fourteen to sixteen hours gap for a normal person. Observing thirsty nature out of hunger is quite a big challenge, as both returns exactly similar neuronal functions through noninvasive testing like EEG. The method of sorting out the need is depicted in Fig.6; it is a visualization of a forty years old female volunteers' data with non-functional left limbs after a short afternoon nap.

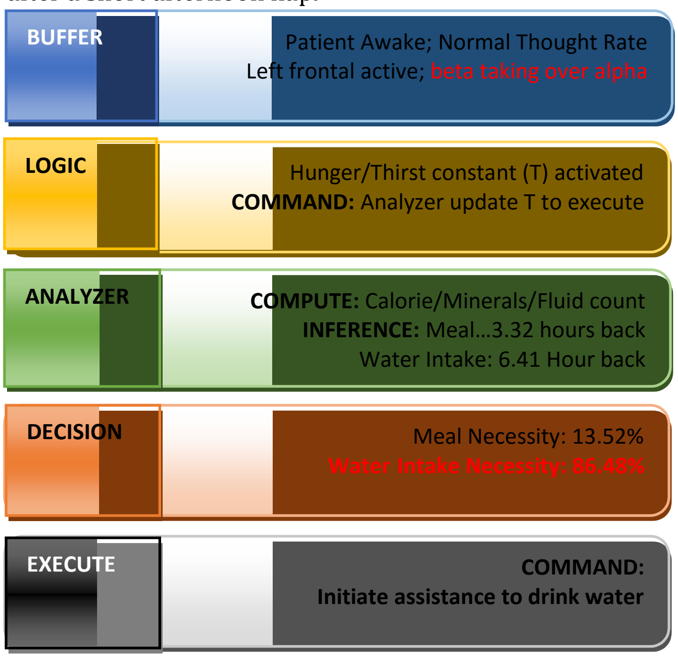

Fig -6: IOT Based Priority Selection of Feeding Module

4.2 Sleep Control Module

Broadly sleeps can be classified of two types, Rapid Eye Movement (REM) and Non-REM sleep [20]. REM sleep generally implies stress, anxiety or more adversely, some latent physical disorders yet to show symptoms [21]. REM can simply occur as well due to over-scheduled last twenty-four hours accompanied with different streams of multiple dreams. For a normal eight hours sleep, in early few hours REM is quite natural though, before diving in deep sleep. Non-REM ones are deep sleeps mainly accompanied by dreams.

Whether sleep is REM or Non-REM can easily be determined by the singularity of alpha in all the electrodes, even if not, by synchronizing left and right parietal lobes alpha. For continuous REM, based on other health status, certain controlled sedatives might get injected in. Whereas, for continuous Non-REM (typically more than twelve hours, without any sedatives or anesthetics in two days' history) on fearing slow approach to coma certain spikes (external activation) might be provided to sharpen pulsed delta concern (external stimulation to facial activity vortex) and wake patient up to rule out other possibilities.

4.3 Temperature Control Module

The realization of feeling heated or cold varies from one person to another based-on immunity and several other factors [22]. A typical temperature sensor is hence accompanied with EEG band analysis. For temperature control, *alpha-beta* pair is compared between actual temperature and temperature realization. Assuming the brain contribute is ∂ and κ is the real temperature, the effective realization can be computed as:

$$\rho = \sum_{i=1}^{k} i\sqrt{\partial^2 - \kappa^2} \; \forall \; i = 1,2,\ldots k \tag{3}$$

A fan, an air-conditioner and a heater are the three targets device to be controlled by the fuzzy module. The discrete time temperature control system is described by:

$$y(k+1) = a(T_S)y(k) + \frac{b(T_S)}{1+e^{0.5y(k)-\kappa}}\rho(k) + [1-a(T_s)]y_0 \tag{4}$$

$$a(T_S) = e^{-\alpha b(T_S)} \text{ where } b(T_S) = \left(\frac{\beta}{\alpha}\right)(1-e^{-\alpha T_S}) \tag{5}$$

where index for discrete time sequencing is k, T_s the sampling period, and y_0 is the initial temperature state. The β and α constraints are adapted from surrounding contributes that impact weather and the system input and output are represented by $\rho(k)$ and y(k) respectively. A self-learning fuzzy algorithm helps in scaling the constraints of Eq. 5. Firstly, $\eta_r(k)$ is defined as the reference threshold temperature whereas $\eta(k)$ is the output temperature from Eq. 3. Assuming the temperature tracking error to be $\in$, the change of error is given by:

$$\Delta \in (k) = \in (k) - \in (k-1) \qquad (6)$$

As an input of the fuzzy inference rules, a sliding surface is chosen as:

$$s(k) = \Delta \in (k) + \sigma \in (k), \sigma > 0 \qquad (7)$$

The self-learning fuzzy sliding-mode control rule base can be defined as:

$$\text{Rule } i : \text{IF } s \Rightarrow F_S^i, \text{THEN } u \Rightarrow r_i, i = 1(1)n \qquad (8)$$

In Eq. (14) F denotes the fuzzy set of s and r_i is a singleton function. The defuzzification is performed by Center of Gravity method.

4.4 Emotion Control Module

Emotion Control is obtained partly by SLFSMC logic and partly by kNN classifier's interpretation from various EEG montages. The nature of EEG parameters, related inference and possible music playing is depicted in below Table 1. A common example is, when one is stressed, switching on a meditative music can offer a sound sleep.

Table -1: Fuzzy Analysis of Emotional Indices for Music

IF				THEN	EXAMPLE
Alpha	Beta	Theta	Delta	Inference (Feeling)	Types of Music on Play
0.49	0.68	0.12	0.02	Pleasant	Happiness yielder
0.33	0.70	0.25	0.01	Unpleasant	Sharp beats; negative emotions yielder
0.31	0.18	0.32	0.04	Soothing; Meditative	Slow, classical; monotonic instrumental
0.84	0.02	0.06	0.05	Energetic; Boost of Happiness	Massive positivity yielder; generally relates past good feels

5. CONCLUSION

Based on a continuous 96 hours study, an accuracy of 89.73% is attained in power saver mode during night-sleep time, which further increase by about 2% if all units are kept operative together. Multiple researches are going on nowadays, from modernizing EEG devices to generating new classifiers. But the concept discussed here for automating the basic needs of a paralyzed person by an IOT platform for decision making and SLFSMC for device controlling, is quite a new one. Fuzzy techniques proposed here has the ability of correcting own previous state-errors for a faster convergence. Further researches can be extended to automate wheelchair controls and finally implementing IOT for controlling HIS to design a Smart Hospital paradigm.

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