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EEG Events Patterns Recognition for Robotics Reasoning and Decision Enhancement

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***Abstract* – Electroencephalography (EEG) based robotics systems, are receiving substantial attentions due to the mass amount of information hidden with human brainwaves. Classification and recognition of electroencephalography of human brainwaves for eye thoughts and movements, is presented within this article. The adopted technique is based on the use of Random Forests (RF) learning paradigm, to classify dissimilar events features, and different human thoughts while looking at images and creating thoughts about the observed images. Features extraction is an essentials stage within this hierarchy, therefore two classes of features extractions were adopted and combined, this include the time domain (TD), and the spectral properties (FD) features. Outcomes of the EEG-related patterns recognition are hence fed into a higher level of decision-making paradigm using fuzzy-based decision system, in such a way to acquire a robotic system diverse robotic tasks and movements. Development of Random Forest classification for the EEG-Robotic system, has shown to be an effective method for modem robotics uses and applications.**

Index Terms* – *Asynchronous direct control, EEG, Random Forests, Patterns Recognition, Classification, Robotics Learning.

I. INTRODUCTION

A. Brain Neural Activities

Electrical activities of the human brain are due to thoughts performed by human while performing tasks. The brain electrical potentials are due to interactions between the neurons and spread of currents over various sub-regions of the brain. All this make the human brain as intricate orgasm.

Despite the complexity and the analysis of electrical activities of the human brain, mining into human brain is still an attractive subject for research and robotics advanced applications. Given this fact, EEG or known as the electroencephalography-based computer (BCI) interface systems, are now in fact receiving substantial attentions due to the massive amount of information hidden with human brainwaves.

Brain Computer Interface technologies (BCI) have shown the applicability of the non-invasive linking techniques, that heavily rely on the neural activities and neural responses recorded from the motor cortex for healthy subject and non-healthy subjects, like paralyzed patients. This is further elaborated in Park et. al.[1], Tajima et. al. [2], Townsend et. al.[3]. On the other hand, building an efficient interfacing system applicable for humans and machines (BMI), has been a subject that has received substantial attraction lately, Chae et. al. [4].

In addition, making use of the potentials of EEG applications are attractive for brain machine interface (BMI) in general context, and for non-robotic applications. This is further reported in Yordanov et. al., [5], Bi et. al. [6], Bensch et. al. [7], Iturrate [8], and Chakraborti et. al. [9]. Electroencephalography robotics interfacing have more and several potentials in military, security, domestic, medical, rehabilitations, and other applications.

One of the potentials, is the control aspects of robotics systems while performing complicated. This includes performance of complex tasks that currently not easy nor cannot be achieved by conventional robotics systems and programming. Other applications of EEG enabled robotics systems, is the learning aspects. Learning aspects of robotics systems does result in much enabled systems with reasoning and cognitive capabilities.

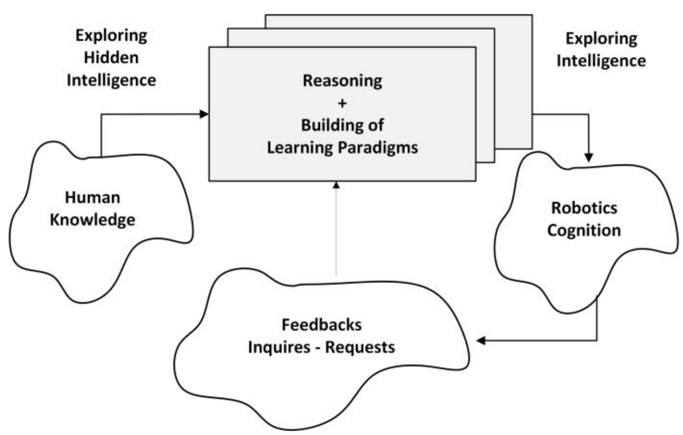

Fig. 1 Overall system hierarchy. A reasoning-based robotics intelligence through EEG, Electroencephalography.

B. EEG Analysis and Understanding

Despite all difficulties associated with achievement of efficient interfacing between human mind reading (EEG), and the machine (robot), the process of interfacing between human and a robotics system is not a straight forward procedure. Brain signals are characterized as noisy, low power, and low frequency interrelated patterns. Hence, according to such properties of brain signals, interfacing EEG with machine-computer interface can be classified as either a reactive or an active BCI-BMI system. Additionally, such classification can also be found in Zander et. al. [10]. For an efficient means for detection and characterization of EEG related events and

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actions, the deterministic chaos of electroencephalography, also plays an important role. For instance, many chaos-producing mechanisms have been created and applied for recognizing the behavior of the dynamics of the system. EEG time-series signals are considered as chaotic in nature, however within which useful information are hidden. Recently studies based on detection of hidden data within EEG have been employed for several biomedical and robotics studies.

C. System Hierarchy

Given above stated facts about BCI, Fig. 1. is illustrating the overall system hierarchy, and data flow from the EEG detection, to the end, i.e. into useful and meaningful robotic system movements. Three major blocks of importance within this hierarchy, the features extraction, how to classify few selected features, and reasoning for robotic decision system.

The main purpose of this research is to apply an asynchronous direct-control system for a robotic system while relying on electroencephalograph (EEG) datasets. In this study, we shall analyze EEG datasets for an experimental setup, hence to construct algorithms designed to make the classification and reasoning of electroencephalography (EEG) signals much accurate and efficient for robotics uses and applications.

D. Paper Organization

To achieve the above stated objectives, this article has been organized into six main sections. In section (*i*), a brief introduction to the subject of EEG-based robotics control is presented. Section (*ii*) is presenting the over system hierarchy and structure for EEG-robotics control. In section (*iii*), we present the adopted dual EEG features extraction, and underlaying details of the adopted technique. Section (*iv*) is related to classification and EEG recognition system. Experimentation and results analysis are given in section (*v*), and finally in section (*vi*) we present few conclusion remarks.

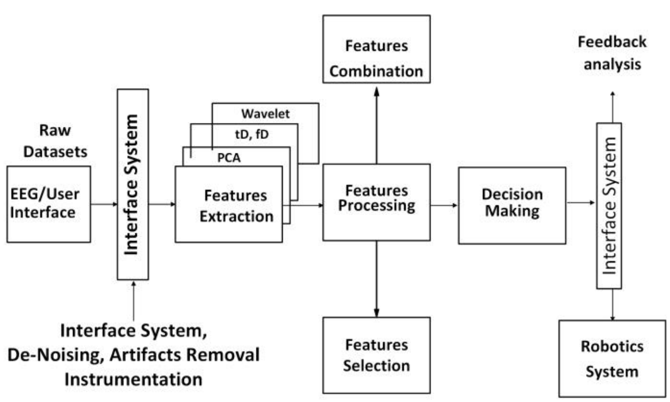


Fig. 2 Detailed inner blocks of system hierarchy.

II. System Hierarchy

A. EEG De-noising and Instrumentation

An initial stage related to EEG is the recording and denoising of the EEG dataset, as shown in Fig. 2. Due to the low potential and strength of the EEG and the low potentials of the resulting neural activities, it is very normal to see that EEG recording is also subjected to other influence introduce noise. This is known as artifact, and removal of such artifact is needed for accurate processing of the EEG datasets. It is very possible that the artifacts do appear from the subject himself-herself due to eye movements, or even from the measurement's instruments. Therefore, prior to processing of EEG datasets, elimination of artifact is primary needed task. It is important to mention that, within this paper the field of brain which was contact with the motor direction and sight was chosen, Pfurtscheller et. al. [11], and Chartg-Hwan et. al. [12]. The electrode sites $O_1, O_2, O_z, C_3, C_2, and\ C_4$ have been chosen.

B. Features Extraction

A fundamental step towards building an EEG-robotic cognition system, is the EEG features extraction. This is further depicted in Fig. 2. The processing of features also involves selecting the most important features (known as features selection). There are several approaches to perform features extraction, as will be elaborated at a later stage.

C. Off-line Features Classification

The third stage of building an EEG-robotics cognition system is the classification of the neural activities features. There are various procedures and routines related to classification of EEG features. To attain clear, understandable, and accurate extraction of features, few off-line and processing is done. This includes noise removal, artifact removals, filtering, features detection, and classification.

D. Decision Making and Robotics Interface

The final stage of building the hierarchy is the use decision making, and the robotics interface. Given the nature of the classified events and features and how is related to the experimentation setups, we have adopted a fuzzy based decision-making methodology. This is also related to building few fuzzy based rules and memberships adjustment based on learning routines.

III. Features Detection and Analysis

A. Features Selection

Features extraction and selection methods are important for EEG mining. Features extraction is refering to detection of most related characterization and relevant information of the EEG over lower dimensionally. In addition, not all features are relevant, few of which are not important. Therefore, we shall select the most effective features that make relevance to the EEG understanding of event. There have been a number and various time-frequency methods used for detection of features, and features extraction. Given this fact, t^d time-domain methods analyze the time-varying characterization of the EEG, whereas the frequency-domain f^d do detect the spectral characterization of the non-stationary EEG signals.

B. f^d Discrete Wavelet Transform Features

At this stage, we shall perform few operations for further processing of the EEG. This is achieved by using the Discrete Wavelet Transform (DWT) and use the features identifier (the coefficients) of EEG. Given this fact, DWT does decompose a set of EEG patterns into coefficients of multi-resolution subsets. These coefficients are of a detailed coefficient subset cD_i, in addition to an approximation coefficient subset cA_i at a designated level (i).

Furthermore, time-frequency localization is great benefit of using the *wt*, "wavelet transforms". Wavelet transform has the advantages of multi-rate filtering, and scale-space analysis. Wavelet is also a tool being used in the field of pattern recognition, and is based on identification of wavelet coefficients as expressed by Eq. (1) and Eq. (2):

$$\varphi(t) = \sqrt{2}\sum_k h_{0k}\varphi(2t-k) \qquad (1)$$
$$\emptyset(t) = \sqrt{2}\sum_k h_{0k}\emptyset(2t-k) \qquad (2)$$

here (h_{0k}) is the low pass coefficient, whereas (h_{1k}) is the high-pass coefficient of the wavelets as expressed by:

$$h_{0k} = \frac{1}{\sqrt{2}}\int \varphi(t)\varphi(2t-k)dt \qquad (3)$$
$$h_{1k} = \frac{1}{\sqrt{2}}\int \varphi(t)\varphi(2t-k)dt \qquad (4)$$

Finally, the recomposed wavelet form is computed as a sum of wavelet coefficients, as in Eq. 5:

$$f(t) = \sum_k S_{j,k}\varphi_{j,k}(t) + \sum_k d_{j,k}\vartheta_{j,k}(t) + \cdots + \sum_k d_{1,k}\vartheta_{1,k}(t)_k \qquad (5)$$

In Eq. 5, here J is the level, k represents the coefficient number of levels, whereas $S_{j,k}$, $d_{j,k}$, ….. and $d_{1,k}$ are the wavelet coefficient of the transform. Further details of such formulation can be farther found in Mallat [13].

C. Geometric Based Features Detection

The t^d features detection includes EEG root mean square (rms_i): $rms_i = \sqrt{\frac{1}{N}\sum_{n=1}^{N} D_i^2(n)}$, mean absolute value ($mav_i$): $mav_i = \frac{1}{N}\sum_{n=1}^{N} D_i(n)$, the integrated EEG ($ieeg_i$) $ieeg_i = \sum_{n=1}^{N} D_i(n)$, simple square integral (SSI), $ssi_i = \sum_{n=1}^{N}|D_i(n)|^2$, variance of EEG (var_i): $var_i = \frac{1}{N-1}\sum_{n=1}^{N} D_i^2(n)$, average amplitude change (aac_i): $aac_i = \frac{1}{N}\sum_{n=1}^{N} D_i(n+1) - D_i(n)$, the co-variance features $cov = \frac{X^tX}{n-1}$. Finally, another characterization to measure pathology of the combination among amplitudes and frequencies characteristics of the EEG signal is found by $L = \frac{1}{N-1}\sum_{i=1}^{n-1}|x_{i+1} - x_i|$, as was defined by Esteller et al. [14] in which x is a signal, i are indices from signal sample, and n represents number of channels, of the captured EEG.

D. PCA Features Detection

Principle Components Analysis (PAC), is another powerful analysis of multi-dimensional datasets. PCA is characterized as a powerful transformation computational technique, as was reported by de Cheveigne´ and Simon [15].

Principle Components Analysis (PAC), has proven to achieve excellent analysis, and an effective mathematical and statistical based approach to detect the foremost statistical characterization of interrelated large datasets. Further background related to this theory, was introduced by Jollife [16]. PCA has been applied to EEG brainwaves for dimensionally reduction, and for detection of main features for an invoked response potential (ERP). PCA operates while reducing dimensionally of EEG dataset, while operating on several interrelated variables, while current variation in the dataset is kept maintained to an extreme as possible.

$$X = UDV^t \qquad (6)$$

U and V in Eq. 6 are defining the left and right singular vectors matrices. The product of $UU^t = I_n \in \mathcal{R}^{(n\times n)}$, $V^tV = I_p \in \mathcal{R}^{(p\times p)}$. In addition, we need also to compute for D, which represents a designated diagonal matrix with singular values λ_i in such a "declining" order as defined in Eq. 7:

$$\lambda_1 \geq \lambda_1 \geq \lambda_1 \ldots.. \geq \lambda_p \geq 0 \qquad (7)$$
$$i = 1,2,3, \ldots., p$$

Performing few mathematical operations by squaring the diagonal matrix D and dividing the result by $(n-1)$, one can obtain:

$$cor(X) = V\sum V^t \qquad (8)$$

as stated in Eq. 8, $cor(X)$ is the sampled data correlation matrix, if X has been standardized variables.

IV. Robotic Cognition

A. Cognition Building

Within this section we shall elaborate on building the robotic cognition system, and how to build the knowledge base system. Cognition has been built based on using fuzzy rule-based system. This is further illustrated in Fig. 3.

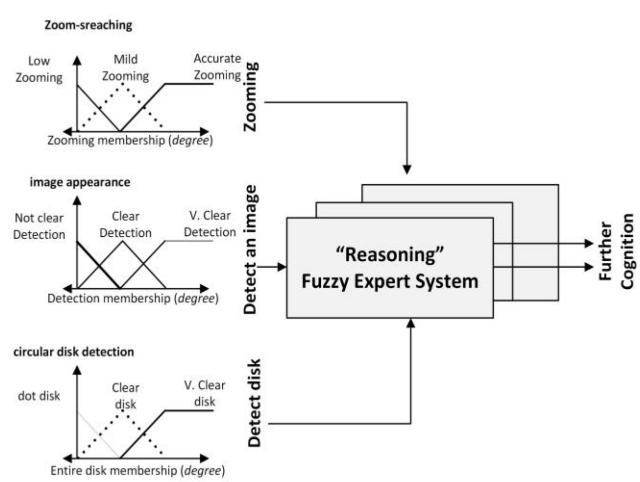


Fig. 3 Fuzzy expert system. Inputs to fuzzy-rule based system are the classified events (*event_1: Appear of gray image, event_2: Search for a disk, event_3: Detection of disk on screen*). Fuzzy rule base can generates further new rules for building a robotic system cognition.

In reference to Fig. 3, there are three inputs associated with the shown fuzzy system. Inputs are related to the recognition of the three brainwaves status (events), that occurred during the experimentation. Inputs to the fuzzy-rule based system are the three recognized and classified events (*event*_1: appear of gray image, event_2: search for a disk, *event*_3: detection of disk on screen). Fuzzy rule base can also generate further reasoned rules for building the robotic cognition.

B. Random Forest Classification

Additional important and an essential block for connecting thinking related EEG to a learning robotics system is the high degree of classification routines. Building a classification process is not a straight forward step. This involves an adequate known about the dataset for classification. The classifier is to decide on various states the subject thinking, and changes occurring into subject thought, while looking and searching within a gray scale image. Given this fact, the main classification algorithm employed within this research, is the Random Forest classifier, which is one of classification algorithms based on trees. The method depends on the availability of classification and regression trees (CART), which are the independent classification trees. Classification predication is computed by finding majority of voting for formed classification tree. Random forests are in fact an extension of the classical search algorithm known as the "Decision Tree", where each tree depending on a group of random variables. Mathematically, for a n-dimensional randomly defined variable $x = (x_1, \ \dots \ ,x_n)^t$ of y:

$$e_{xy}(L(y, f(x))) \tag{9}$$

here $(L(y, f(x))$ represent how close of $f(x)$ to y. The random forest, depends on the minimization of $e_{xy}(L(y, f(x))$, for zero-one loss, i.e.:

$$f(x) = argmax \ \text{for} \ y_{\in \zeta} \ P(Y = y|X = x) \tag{10}$$

the classification $f(x)$, is found as the most frequently predicated type or class (voted for) as:

$$f(x) = \frac{1}{J}\sum_{j=1} h_j\,(x) \tag{11}$$

in which, the classification function $f(x)$, is the repeated predicted classes known as the voting variable and defined by:

$$f(x) = argmax_{Y \in \Upsilon} \sum_{j=1} |(y = h_j(x)) \tag{12}$$

In specific, for the above algorithm in Eq. 12, the j^{th} learner base, is $h_j(X, \phi_j)$ in which ϕ_j is a set of random variables, whereas ϕ_j' s, are in fact the independent for $j = 1, \dots J$. Definitely, there are a number of advantages of using the random forest for the EEG classification. One of the most important characterization of this classification paradigm, is the unessential need for features normalization. Features normalization is usually a time consuming and might cause delays. Other potentials of the random forest are related to the individual decision trees, and how can be trained in parallel fashion, in addition to the reduction in over fitting, as further depicted by Abilash [17] in Fig. 4.

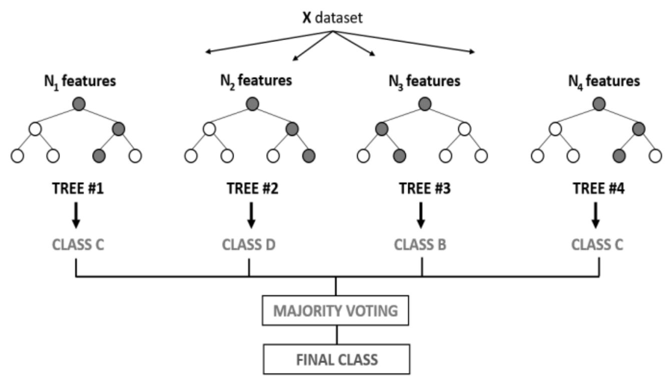


Fig. 4 Random Forest classification involves definition of the EEG thoughts events. Topographical representation of RF trees classification, Abilash [17].

V. EXPERIMENT RESULTS AND DISCUSSION

A. Electroencephalography Dataset Origin

The EEG dataset origin have been selected from a well-documented and approved EEG experiments. We acquired EEG data from a German university that made the data available on a website for research purposes only. The experiment setup ensures recorded datasets are up to standards, to ensure the effectiveness when used in researches. Therefore, we used the publicly available data described in Damien et. al., [18]. Given this fact, in order to create a relation between real physical experiment and the resulting EEG brainwaves, an Eye-thought related experiment has been run. All the related details of the experiment can be found in reference to Eye-EEG toolbox" and "Eye-EEG extension" project, which has been reported and already used by many researchers. Refer to Damien et. al. [18] for more experimental and research motivation. Further information about the real-clinical setup-based experiment is found in Eye-EEG toolbox. Additionally, in order to make sure that the EEG data is useable for further basis of studies, especially when it comes to robotics, the brainwaves were recorded by Electroencephalogram (EEG) setup. To record the electrical activities that were happening inside the human brain, up to (25) electrodes (also known as channels) were placed on the scalp. This headcap basically measures the variations in voltage resulting from within the neurons of the brain. This is due to the need to find the corresponding EEG data to the brain activity once it happens. This makes the analysis of dataset easier and uncomplicated. Refer to Table 1. for further details about the subjects and experimental settings. As indicated to earlier, it is important to mention that, within this paper the field of brain which was in contact with motor direction and sight. Further specification about this choice is given by Pfurtscheller et. al. [11], and Chartg [12]. The electrode sites were O_1, O_2, O_Z, C_3, C_2, and C_4.

B. Experimentation Setup

In reference to Damien et. al., [18], the adopted experimentation setup has included a 25 channels (electrodes) head cap. Electrodes are then connected to an amplifier (for signals instrumentation). Human EEG signal is approximated to be $(10 - 100)\mu V$ in amplitude and they are to be amplified in order to analyze these brain waves thoroughly. Hence it must be of the best quality in recording.

The dataset has been collected according to standard clinical standards. The experiment was run for 150 seconds. A participant is to search for a small target stimulus inside grey scale image of random natural scenes. The experiment mainly involves searching for an increasing in size disk, as it appears over a gray-scale image in front of a subject. Initially, the computer screen will display blank screen (no image), the subject must indicate that (he-she) is in a waiting state, and ready to start the watching of a blank screen by pressing a bell. After that, once a gray scale image appears, the subject must press a bell, as a sign that a gray scale image has appeared. Secondly, after the gray image is showing over the computer screen, the subject must search or (keep searching) for an increasing in size dot on the gray scale image. Therefore, once the subject finds the dot, he-she is to press a bell also. In total, there are three bells, as associated with three events. The meanings of the time-stamped labels have been defined by three events or sessions. Sessions (events) were recorded as in reference to well defined time tags and indexes. There are four-time indexes related to this visual experiment: (S_{103}, S_{12}, S_1, S_{99}, and S_{20}). This is further summarized by:

S_{103} : synchronization related to event start.
S_{12} : picture on the screen event.
S_1 : (grey-disc), onset of search target within picture.
S_{99} : target is seen, and button pressing.
S_{20}: end-event for synchronization.

This experiment was repeated for five 5 times (i.e. 5 trials of recordings), This is because of the varying time needed to find the target, given the fact that all trials have different duration. Each of these trials are divided into three different events that are onset of the picture on the screen, and onset of the search target. Furthermore, Table I also indicates the different datasets, and how they are related to the subjects, electrodes positioning, and the subject status.

TABLE I
CLINICAL DATA AND EXPERIMENTATION SUMMARY

Type of measurement	CLINICAL DATA AND EXPERIMENTATION		
	DATA SET 1	DATA SET 2	DATA SET 3
Subjects	healthy M/F subjects	healthy M/F subjects	healthy M/F subjects
Electrode type	Surface	Intracranial	Intracranial
Electrode placement	International 10-20 system	Within motoring zone	International 10-20 system
Subject's state	Awake and eyes open (Normal)	Awake and eyes open (Normal)	Awake and eyes open (Normal)
Number of events/trails	3events /5 trails	3events /5 trails	3events /5 trails
Epoch duration (s)	36 seconds	40 seconds	32 seconds

EEG data sets were collected from an experiment that have been run for five trails, as indicated to in Fig. 5. This means each subject is to repeat the experiment for five times in a sequence. Each trail includes three events, as related to the thoughts in reference to the eye movements. The participant gets the relaxation time, before the start of the second trial. The same analysis was done for the rest of the four trials. It was noted that each trial had a varying time to find the target.

C. *Time-Frequency Features Results*

A significant phase after collecting the EEG dataset is to observe the EEG brainwaves for the experiment, over both the time domain and spectral or frequency domain. Fig. 6 and Fig. 7 indicate to (f^d) characterization. This is further used at a later stage for features extraction.

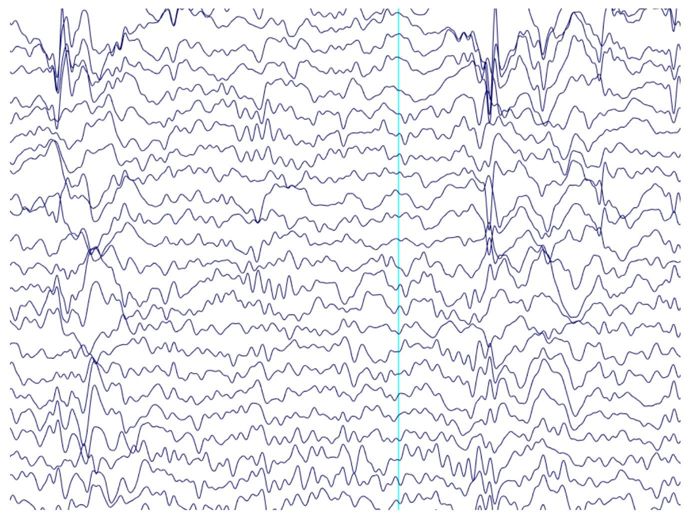


Fig. 5 Typical time domain, (t^d) using EEG-Lab analysis of the eye-movements brainwaves. Time domain features extraction includes finding the mean, STD, the max, the min and others statistical parameters for the all (25 channels) EEG dataset.

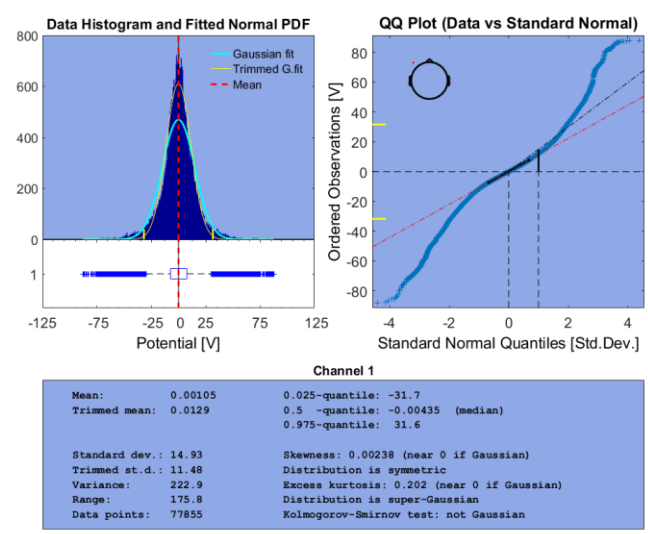


Fig. 6 Frequency domain, (f^d), is involving the computation of statistical patterns from the power spectral properties, for all channels. EEGLab spectral analysis of eye-movements thoughts.

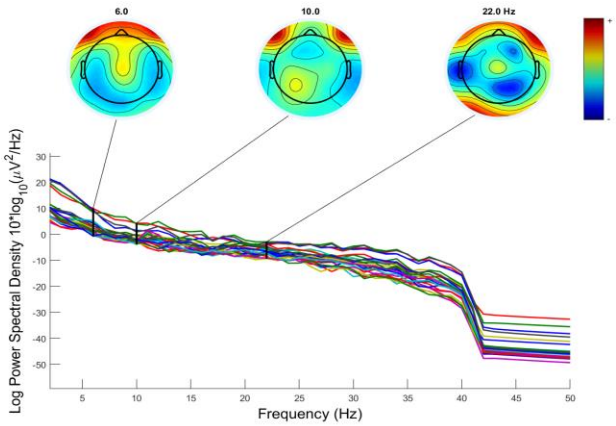
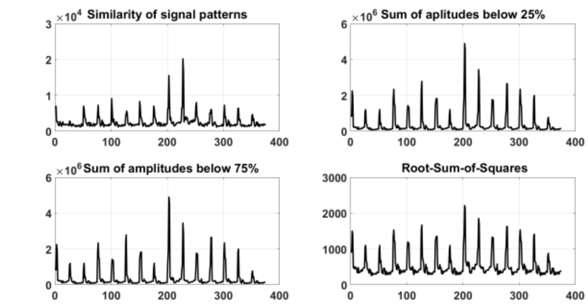


Fig. 7 EEG skull spectral characterization.
Spectral densities as detected by experimentation electrodes.



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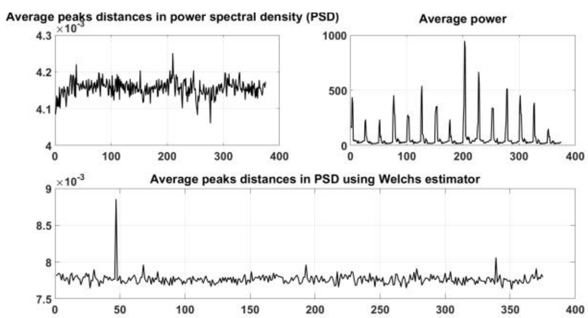

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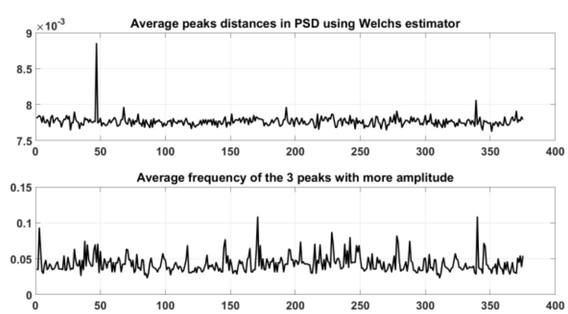


(*iii*)

Fig. 8 For figures (*i-iii*), details about the three events features extraction both in time-domain, (t^d), and frequency-domains, (f^d). (*Seven*) main features have been identified for (t^d) and (*five*) main features have been identified as the spectral densities features.

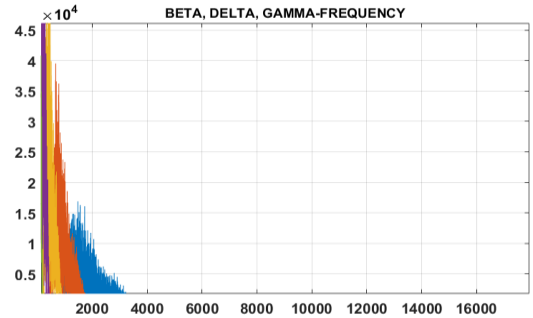
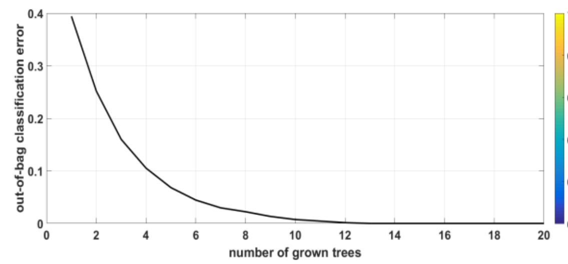


Fig. 9 Wavelet coefficients (*wt_coff*), for the three events feature detection.

At this stage, we have gathered large number features, that can be combined to enhance the recognition process. This is further shown in Fig. 8, and Fig.9. More analysis about detection of features for both the time (t^d), and frequency (f^d) and spectral analysis during eye-movements have been undertaken. This involves the selection of the best features. In addition, three main features of eye-movement events have been identified. This characterization and distinction are shown in both Fig. 8. and Fig. 9.



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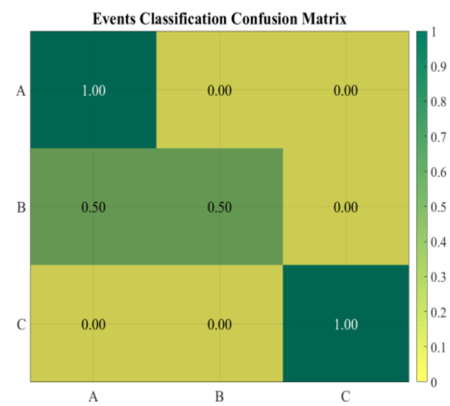

(*ii*)

Fig. 10 EEG-Eye, recogintion accuracy. (*i*) the classifier "Random Forest" learning curve, indicating number of grown trees. (*ii*) Forest Tree (*tree-bagger*) recognition accuracy using events confusion matrix. Classifcation results has scored up to 86% accuarcy, which as a high degree of accuacy.

Finally, Fig. 10 is showing the EEG-Eye, recogintion accuracy. In part (*i*) we show the classifier "Random Forest" learning curve, indicating number of grown trees. The figure indicates the performance of the random forest algorithm (out of bag prediction error). The leaf sizes are varied from 5 to 60 and up to 20 trees are grown. In part (*ii*), we show the random Forest

Tree (tree-bagger) recognition accuracy. Classifcation results has scored up to (86%) accuarcy, which is a high degree of accuacy. As mentioned earlier, the subject will be running three events by pressing bells. The associated labels are: Initially, for label (1), this is for seeking a gray image on the computer screen). Label (2), has been used while the subject has seen the gray image. Finally, label (3), this is used to label the event once the subject has seen the gray image with an increasing dot on the computer screen. The final stage of this research is building of a fuzzy expert system three sets. The first set is related to first event. The second is related to the image appearance. Finally, the third is how zooming by human into an area within a scene is achieved. Using the three fuzzified inputs, even much higher hierarchy of decision making is constructed.

VI. CONCLUSION

This article has presented a focused research related to building robotic system intelligence, while relying on thoughts expressed by an electroencephalography. The motivation for this study was to achieve an EEG robotics interface. Study motivation was also to create learning robotic system to operate in self decision-making basis for complex tasks. The presented research concept was mainly related to detect the main EEG signaling features, hence to use the identified features for classification paradigm. Two diverse classes of features have been detected by three main methodologies. The first was time-domain related features (t^d). The second was frequency-domain related features, or the spectral properties of features (f^d). Finally, features resulting from a much-reduced data sizes, through (PAC). Combining the three features paradigms was not a straight forward task, due to distinct nature of the features. The three classes of features have been then used to build a classification routine. Classification was based on using a random forest classification, this is due to the nature of the features being classified. Three main EEG thoughts related events have been identified. Events characterization are then used to build a fuzzy reasoning system, for a robotic system. While using EEG to control a robotic system, this in fact involves several stages, moreover, this process gets much complicated once to use the EEG brainwaves to create a learning paradigm for the robotic system. Results have indicated that, building a reasoning system with a fuzzy rule-based system was an effective way to create a cogitation system to train a robotic system, and to achieve complex tasks. The presented methodology was novel in sense to create a learning through (pool of rules) for robotic control, which is usually achieved using classical way of teaching robotics systems.

ACKNOWLEDGMENT

This work would not have been achieved without the supply of the EEG dataset, related experiments details, and events recording. Gratitude and appreciations are expressed to the developers of '*Eye-EEG toolbox*' and '*Eye-EEG extension*'. Thanks, and appreciations also for supplying the Eye_EEG dataset, and the availability of the experimentation details, as reported by Dimigen et. al., [18].

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