Electroencephalography for Enhancing Robotics Learning: CNN Convolutional Neural Network Approach

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***Abstract* - In context of EEG based robotics systems, this is an active area of research. This paper is presenting developing a learning system for robotics hand grasping and manipulation of objects while relying on human Electroencephalography – EEG cognition. Nowadays, EEG is playing major roles in current robotics applications. EEG brainwaves are also being employed to learn how human is performing daily complex tasks, while emulating human acts to robotics devices. There are tremendous efforts to employ EEG brainwaves signals and patterns for robotic applications. However, due to complexity of EEG patterns, making use of these patterns for robotics is not a trivial task. Therefore, the paper is focusing on introducing EEG decoding and using learned patterns to achieve defined tasks. The paper will present how Convolutional Neural Network Techniques (CNN) classification algorithms have been used to classify human behaviors and how to assemble these behaviors for building much expert and fuzzy based learned robotics systems.**

Keywords – Electroencephalography, CNN, Fuzzy Systems, Feature Extraction, Classification, Multi-fingers Robotics Hand control, Hand Manipulation.

I. INTRODUCTION

A. EEG and Brain Anatomy

The brain is the most important part of any intelligent life. It controls all parts in the body. For such control, there must be some sort of biological communication. During hundreds of years in medical research, it was found that; brain communicates with origins using electrical signals that are periodically sent. There are billions of neurons in the brain and spine. These neurons are connected to nerves using synapses. This is the fundamental structure of the nervous system that oversees communications between the brain and the rest of the body. Brain signals are basically electrical currents. These signals are generated chemically from ions (mainly Na+, K+, Ca++, and Cl-). These ions create electrical potentials which generates the currents, as in Atwood and MacKay [1]. Electroencephalogram (EEG) is a test to detect electrical activity in brain using electrodes attached to the scalp. Because of electrical currents in brain, there must be electrical fields generated as well. This is the fundamental concept behind the EEG. Electroencephalography captures the electrical activity in the cerebral cortex of brain using multiple metal electrodes located in on a head cap, Niedermeyer et. al.

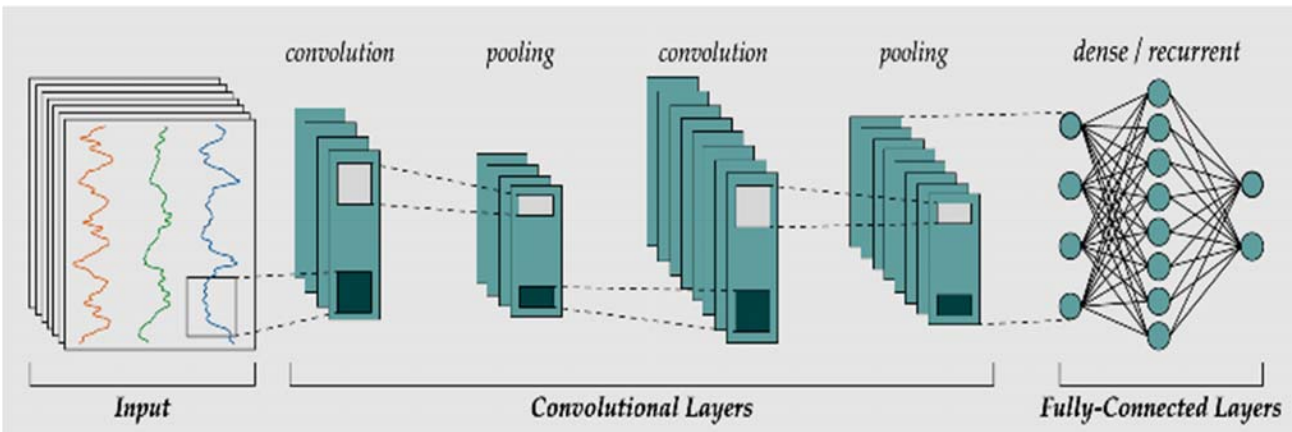

Figure 1. A typical COVnet topology with different convolutional layers. Picture source, Baldominos et. al. [1].

EEG is an electrical technique for recording the pattern of the electrical activity of waves within the human brain. Small metal discs (electrodes) are attached to the scalp with thin wires. The electrodes reveal the analysis of electrical charges and impulses resulting from cell activity in the brain, where charges are amplified and sent as a graph to a computer and the results are recorded. In this regard, growth in medical signal processing technologies has led to EEG in diagnosing brain diseases and in the field of the BCI computer interface that uses EEG signals as an input to control devices such as the computers robotic hand. The EEG plays an important role in diagnosing brain disorders and diagnostic tests to discover potential problems. Exploring brain electrical activities using electroencephalogram (EEG) signals has also increased recently. Electroencephalography: The recoding of electricity activities of brain. Each electrode is placed at one brain area activity. [2].

Electroencephalogram (EEG) is a test used to find problems related to electrical activity of the brain. An EEG tracks and records brain wave patterns. Small metal discs with thin wires (electrodes) are placed on the scalp, and then send signals to a computer to record the results. Dataset: Each raw records one time step. EEG datasets are huge and interrelated Brain-Computer Interface (BCI), classification of hand movements stages, person authentication etc..., are just some applications of EEG signal analyzing.

Hand movements provide large artifacts of the EEGs, making data analysis difficult and possibly impossible. Hand movements play a major role in electroencephalographic (EEG) recordings, as the combination of Hand-EEG is suitable for training machine learning for various tasks, including sentiment analysis. Given this background, we would like to build a learning system based on deep learning topology (COVnet), in such a way to learn and classify the various human actions from the EEG dataset. Once a classification is done, fuzzy decision-based system is then added to give more cognition to the robotics system though some fuzzy (if then rules). Refer to Fig. 1. for a typical COVnet topology with different convolutional layers.

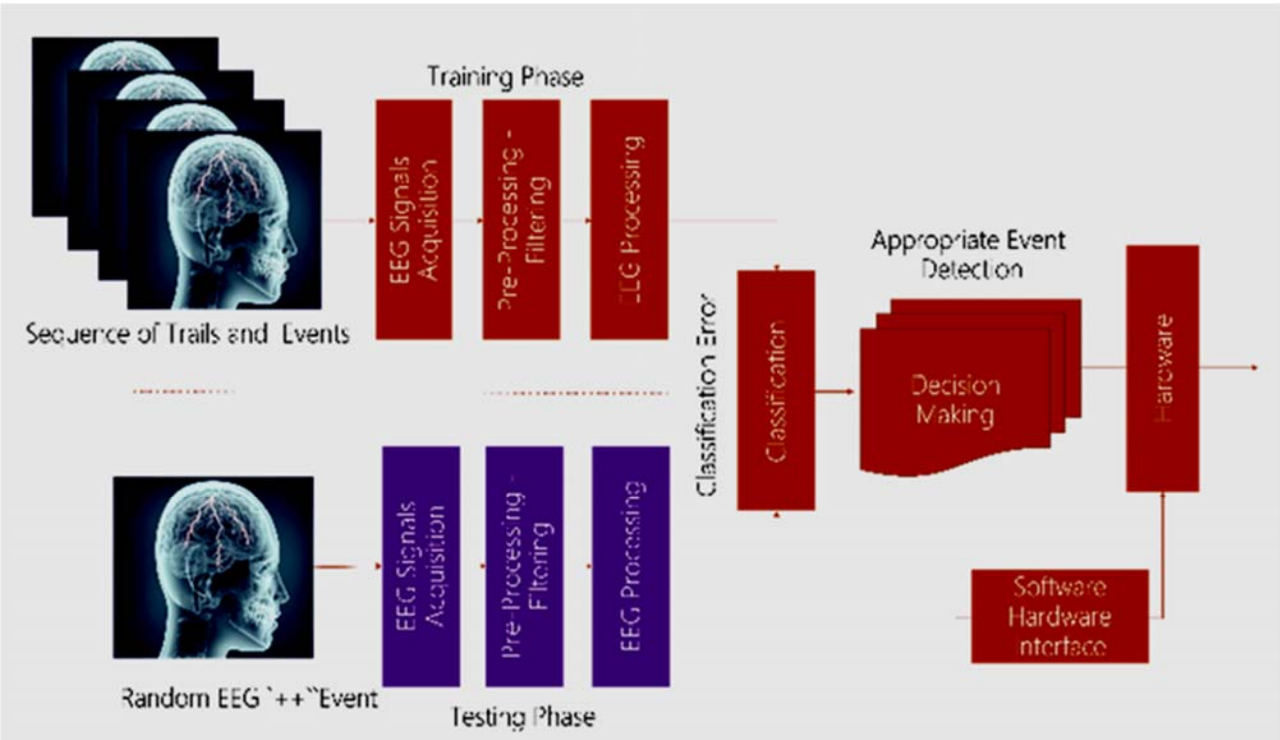

Figure 2. System layout for developing of an EEG robotic learning mechanism.

Moreover, this development has many benefits, such as measuring sciatic reaction times and displaying stimuli by accidental staring. EEG has also been used for building a robotic learning mechanism. In this regards, Fig 2. indicates a typical layout for building an electroencephalography based robotic learning mechanism. This involves building a robotic intelligence using convolutional networks and information inherent in the EEG patterns and related brainwave to control the joints movements for the robotics hand, as in Fig. 3.

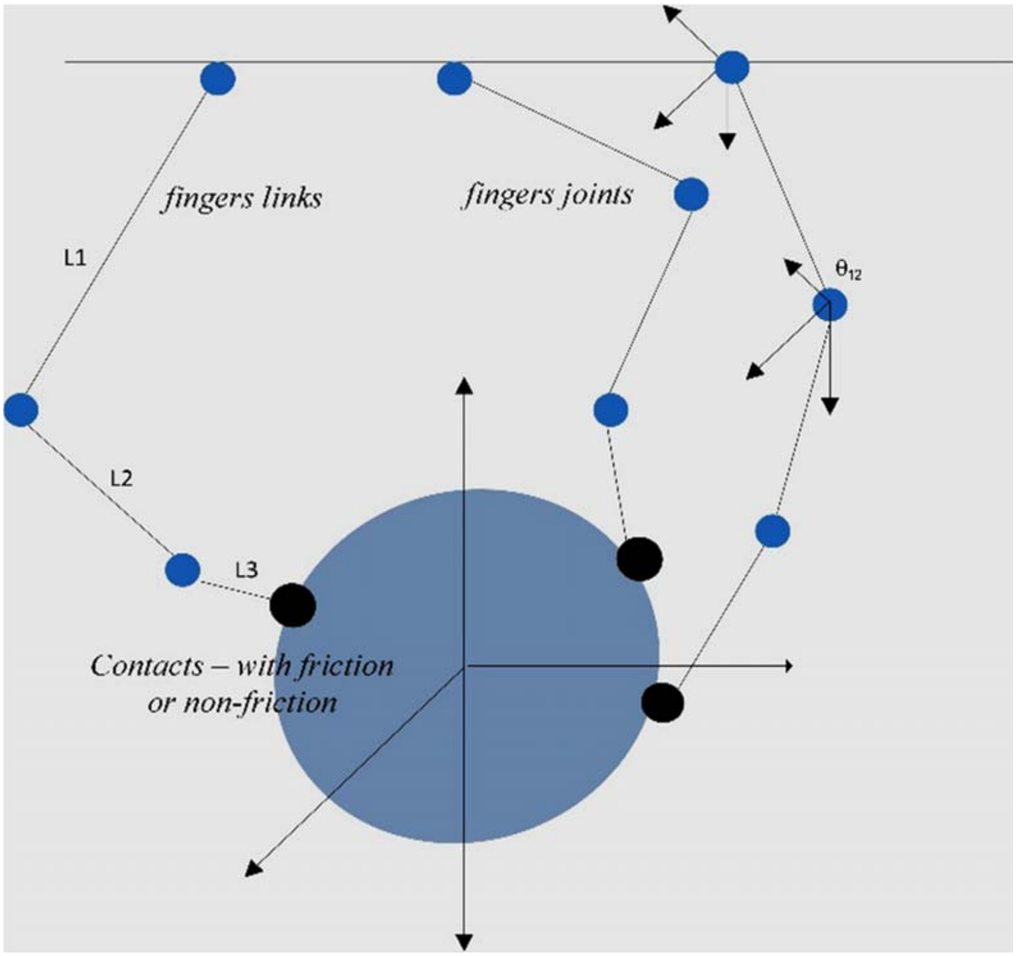

Figure 3. A multi-finger robotics hand dynamics and kinematics relations.
Figure 1.

B. Paper Outline

This research outline is presenting a continuous research process towards investigation study related object grasping. The main sections within this article are the introduction to the research, prosthetics/robotics, electroencephalography interpretation, Problem Statement, Machine Learning Tools – CNN, the experiment, and the conclusion remarks. The paper has been divided into five main sections. Section (*i*) is presenting a general frame works related to electroencephalography and robotics also presenting the overall system hierarchy. Section (*ii*) is related to features extraction as a complicated process once dealing with random and stochastic EEG, therefore aspects of EEG features extraction techniques are presented in this section. Section (*iii*) is further expanding on concepts of features classification and how to build machine learning and CNN topology. Section (*iv*) presents an implementation aspect of EEG Robotic system. The section is also presenting an analysis of EEG data and EEGLAB results. Finally, section (*v*) is presenting few conclusions remarks and future works. EEG- Power Spectral Density.

II. EEG HIDDEN FEATURES

In terms of EEG features, there are several efficient features extraction algorithms that have been developed for extracting features for this purpose. For instance, Zhao and Zhang [5] have developed temporal and spatial features extraction as an algorithm. This includes the common spatial patterns (CSPs) algorithm which has been proven as a very useful to produce subject-specific and discriminative spatial filters. Principal component analysis (PCA) has also been used for EEG features extraction. For the PCA, the following sub-section summarizes efforts to use the PCA a means for EEG features detection.

A. PCA and ICA Algorithms for EEG

PCA is a technique for reducing the dimensionality of such datasets, increasing interpretability but at the same time minimizing information loss. This is to find patterns which corresponds to features by identifying the similarities and differences. PCA is also able to reduce the data dimensionality without any loss of important information. This is very helpful when dealing with huge data such as EEG. The theory behind applying PCA on EEG signals was inspired by Rahmana et. al. [6] with some modifications. In addition, there are a number of newly related research outcomes related to using machine learning classification algorithms, as have been documented in [6],[7],[8],[9],[10], and [11]. There are a number of research outcomes related to analysis of hand EEG using advanced computer algorithms for patterns recognition related applications. This is further found in [12],[13],[14], and [15]. Creation an application of these advanced algorithms for robotics use has been also an area of a focus. Therefore, this research aims to applying artificial intelligence methods for analysis of a visual related electroencephalography (related to a repetitive visual stimulus thinking process). Analysis includes identifying thinking and hand movements for a stimulus. The main EEG information and features are then used for robotics applications such as BMI and BCI. The specific functions should also relate to using of ICA analysis to learn features of thinking related to thoughts of hand movement. These features are then exploited to build a classification algorithm using Bootstrapping ML classification. For automated system applications, controlling a robotic hand is an example. In term of constraints, there are several constraints to be considered. This includes: (*i*) Time spent in measuring EEG waves, as the maximum wave in EEG is 150s and according to the (Shannon sampling theorem), which states: "ideally, samples of a frequency signal are converted and reconstructed so that sampling of the waveform should be performed at a frequency greater than twice the speed of the higher frequency component" : (fs=$2f_{max}$) , i.e. ($f_{sampling}$>$2f_{max}$). (*ii*) Experimental environment, which requires a special place to prevent the leakage of electromagnetic waves and reduce noises, (noises that are results of EEG artifacts). (*iii*) Digitization standards, as it should follow standards specified by IEEE for conversion from analog to digital. (*iv*) Design, where the hardware has a specified number of currents and voltages. For the hardware, there are several connections can be used as (input/output). One of its constraints is that the current works with the voltage in reverse, as when the device takes a very large current, this leads to a significant decrease in voltage in the supply of the Arduino. With presence of a microcontrollers, it is easy to achieve this restriction under an appropriate size, weight, and price. In terms of standards, this includes using (IEEE standards) to record the EEG brainwaves, by erecting electrodes on the scalp. Locations and names of electrodes are determined through the global (10-20) standards for most clinical and research applications, i.e. (10-20 distances between adjacent electrodes).

B. Power Spectral Density Features

As indicated earlier, there are different approaches by which features of EEG signals could be extracted and analyzed. These methods generally could be categorized in two basic categories, one of which is called "non-Parametric models" and the other one is the "parametric models". Nonparametric methods are the most common method used for analyzing EEG signals, as further indicated by Lotte et. al. [17]. In general, this includes spectral analysis, as a one of the standard methods used for quantification of the EEG. The power spectral density (PSD) spectrum reflects the frequency content of the EEG or the distribution of signal power over frequency band. Another approach for features extraction is the temporal resolution. Spatial and temporal features are two important features for characterization of EEG patterns. Other effective approaches also do include the combination of the three components, i.e., to combine the spectral – temporal – spatial features.

C. System LAYOUT and ML Tools

Example of Machine learning problems that are used today are Decoding: Using neuronal recordings from the spinal cord, and spike times distinguish between itch and pin signals. State Identification: Using EEG recordings of patients with seizure, can power spectrum distinguish between blocks of EEG taken. Immediately before a seizure from EEG taken interracially. Problems for machine learning Identifying what distinguishes two populations. Optimizing a therapy to maximize outcome. Quantifying classification and directly comparing different measures. Machine Learning Classes: Supervised What features identifies the class subject belongs Linear discriminant analysis. Support vector Machine: Support Vector Machine: Much Flexible than the LDA. Powerful. kernels allow complicated relationships between classes. Not as affected by curse of dimensionality. The nice thing about the SVM, that kernel trick allows for more complex interactions. Properties: Over fitting, Cross validation, Double Cross-validation.

III. THE CNN TOPOLOGY

For enhancing the learning abilities of a robotics system, here we adopt an CNN approach. The CNN methodology has several advantages. One of the great advantages is the limitation of the features extraction stage. Instead of doing this process (features extraction) as a separate process, this is included in the CNN (conversational Neural Network - COVNET) topology (i.e. a deep leaning approach).

CNNs have been used mainly for image classification applications. Now a day, they have also been adopted and used for time series and multi signal analysis. The ability of CNNs to detect complicated patterns have made them very useful for complicated multi-dimension signals analysis. The CNNs are different than the standard MLP and others ANN structures,

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this is due to the inclusion of the convolution layers in the MLPs topological structures. The convolution layers are having the ability to detect patterns related (or within) to the inputs. The convolutional layers are more dedicated to a filter operation (the filters do detect the patterns). The filters do detect specific patterns, that are within the input patterns, more complicated patterns, means more advanced filters operation.

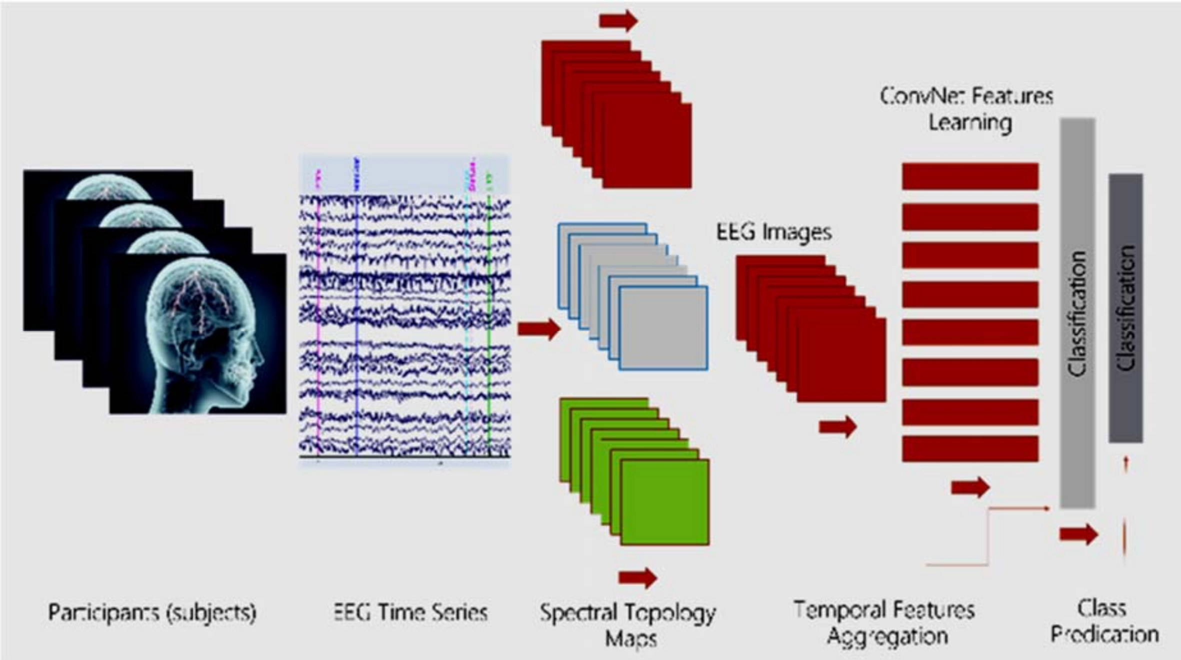

Figure 4. The CNN toplogy – CNN architecture, the features learning via the CovNet.

The deeper layers, the more advanced detection of hidden patterns in the input. The moment we add the convolutional layers, then we specify the number of filters to be adopted to detect certain patterns. This is done in terms of defining matrix elements. The number of filters at the convolutional layer, are hence decided by the complexity of the user. These filters are in fact patterns detectors. The more filters are being used … the more ability to detect complicated patterns. When we build a CNN classifier for the EEG, this means we detect a label for the input EEG pattern. The experiment: The EEG data were adopted from a well-known experiment conducted by (Luciw et. al. [18]). The experiment involved a number of human - the subject interaction with the experiment. The experiment is described as below: The main objective of the experiment is to build a classifier to classify the subject intension from the EEG. There are six classes related to this experiment.

A. EEG PSD features

As indicated earlier, there are different approaches by which features of EEG signals could be extracted and analyzed. These methods generally could be categorized in two basic categories, one of which is called "Non-Parametric models" and the other one is the "Parametric models". Nonparametric methods are the most common method used for analyzing EEG signals, as further indicated by Lotte [16]. Further elaboration for the feature extraction methods is depicted in Fig (4). In general, this includes spectral analysis, as a one of the standard methods used for quantification of the EEG. The Power Spectral Density (PSD) spectrum reflects the frequency content of the EEG or the distribution of signal power over frequency band. Another approach for features extraction is the temporal resolution. Spatial and temporal features are two important features for characterization of EEG patterns. Other effective approaches also do include the combination of the three components, i.e., to combine the spectral – temporal – spatial features. Spectral method: Frequency domain analysis and estimation of spectral power are two important features of EEG brainwaves. This includes the use of the FFT, out of the Fourier transform, i.e.:

$$f(w) = \int_{-\infty}^{\infty} f(t) e^{i\omega t}\, dt \tag{1}$$

Once it comes to EEG hand, the discrete Fourier transform (DFT) is much appropriate approach, as in Eq. 2.

$$x_k = \sum_{n=0}^{N-1} x_n\, e^{-i\pi 2kn/N} \tag{2}$$

A fast Fourier transform (FFT) is an algorithm that computes the discrete Fourier transform (DFT) of a sequence, or its inverse (IDFT). The algorithm can be used for signal processing and signals feature extraction. The method creates accurate incomes or tools or equations for analyzing EEG information. The method utilizes to change signals from time-domain to frequency-domain and vice versa. Features of the obtained EEG signal are calculated by power spectral density (PSD) estimation. This includes selection of characterization of the EEG model's signal. Four frequency bands cover the main characteristic waveforms of EEG spectrum. We have ended up with the summation of two terms. The advantage of this approach lies in the fact that, even and odd indexed sub-sequences can be computed concurrently. This is further mathematically defined by a set of inter-related set of equations:

$$x[k] = \sum_{n=0}^{N-1} x[n] e^{-\frac{i2\pi kn}{N}} \tag{3}$$

$$x[k] = \sum_{n=0}^{\frac{N}{2}-1} x[2r] e^{-\frac{i2\pi k(2r)}{N}} + x[k] = \sum_{n=0}^{\frac{N}{2}-1} x[2r+1] e^{-\frac{i2\pi k(2r+1)}{N}} \tag{4}$$

$$x[k] = \sum_{n=0}^{\frac{N}{2}-1} x[2r] e^{-\frac{i2\pi k(2r)}{N}} + x[k] = e^{-\frac{i2\pi k}{N}} \sum_{n=0}^{\frac{N}{2}-1} x[2r+1] e^{-\frac{i2\pi k(2r)}{N}} \tag{5}$$

$$x[k] = \sum_{n=0}^{\frac{N}{2}-1} x[2r] e^{-\frac{i2\pi k(2r)}{N/2}} + x[k] = e^{-\frac{i2\pi k}{N}} \sum_{n=0}^{\frac{N}{2}-1} x[2r+1] e^{-\frac{i2\pi k(r)}{N/2}} \tag{6}$$

$$x[k] = xeven[k] + e^{-\frac{i2\pi k}{N}} xodd[k] \tag{7}$$

EEG Power spectral density (PSD): The power spectral density (PSD) is one of the most used features in the extraction of characteristics of Brain Computer Interface methods. This is represented by the distribution of power on the axis of frequencies. The characteristics are defined as the square modulus of the Fourier transform, divided by the integration time (t) or the calculation of the Fourier Transform the auto correlation function, as in Lotte [16]. For the Time-frequency domain analysis, this is related to localization of power time and frequency the (wavelets). We need a tool that has high resolution in the frequency domain in addition to time domain, that allows us to know at which frequencies the signal oscillates, and at which time these oscillations occur, Lotte [16]. For a continuous signal $x(t)$ from one dimension, its transformed wavelet into a 2D space is defined as:

$$S(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \emptyset \left(\frac{t-b}{a}\right) dt \tag{8}$$

Autoregressive Features: Autoregressive (AR) methods estimate the power spectrum density (PSD) of the EEG using a parametric approach. For the (Yule-Walker) method, in this approach autoregressive parameters or coefficients are estimated by exploiting the resulting biased approximate of the autocorrelation data function. This is done by subsequently finding a minimization of the least squares of the forward prediction error as given below:

$$\begin{bmatrix} r(0)_{xx} & r(-1)_{xx} & \cdots & r(-p+1)_{xx} \\ r(1)_{xx} & r(0)_{xx} & \dots & r(-p+2)_{xx} \\ \vdots & \vdots & \ddots & \vdots \\ r(p-1)_{xx} & r(p-2)_{xx} & \dots & r(0)_{xx} \end{bmatrix} \begin{bmatrix} a(1) \\ a(1) \\ \vdots \\ a(p) \end{bmatrix} \tag{9}$$

where (r_{xx}) can be defined by:

$$r_{xx}(m) = \frac{1}{N} \sum_{N=0}^{N-m-1} x^* (n) x(n+m), \quad m \geq 0 \tag{10}$$

While calculating the above set of $(p+1)$ linear equations, autoregressive coefficients can therefore be obtained as in eq. (11):

$$P_{xx}^{BU}(f) = \frac{\sigma_{wP}^2}{|1+\sum_{K=1}^{P} \hat{a}_P(k) e^{-i2\pi fk}|\text{^}2} \tag{11}$$

In Eq. (11), the $\hat{\sigma}_{wP}$ term gives approximated lowest mean square error of the path order predictor as further expressed by Eq. (12):

$$\sigma_{wP}^2 = E_P^f = r_{xx}(0) \prod_{k=1}^{P} [1 - |a_k(k)|^2] \tag{12}$$

Burg's Method: It is an autoregressive spectral estimation based on reducing the forward and backward prediction errors to satisfy Levinson-Durbin recursion. Burg's method estimates the reflection coefficient directly without the need to calculate the autocorrelation function. This method has the following strength: Burg's method can estimate PSD's data records to look exactly like the original data value. It can yield intimately packed sinusoids in signals once it contains minimal level of noise. The difference between method of Yule-Walker and Burg's method is in the way of calculating the PSD. For Burg's method, the PSD is estimated as follows:

$$P_{xx}^{BU}(f) = \frac{\hat{E}_P}{|1+\sum_{K=1}^{P} \hat{a}_P(k) e^{-i2\pi fk}|\text{^}2} \tag{13}$$

Parametric methods, i.e. autoregressive models, do reduce the spectral leakage issues and yield better frequency resolution. However, selecting a proper model order is a very serious problem. Once the order is too high, results of computation will rather induce false peaks in the spectra.

IV. EXPERIMENT AND RESULTS

Models: Convolutional neural network Experiment: Grasping is Complicated. Precision Grasp-And-Lift (GAL) Paradigm. Dataset was collected from (12 subjects) with each having (328 trials) which resulted in a total of 3,936 grasp and lift trials. 4 males and 8 females all aged between 19 and 35. Each trial started by relaxing the shoulders and making sure that both arms are close to the body. The wrist was below the elbow level. Then, an LED light turns on which signals the subject to start the movement sequence. For the Experiment: Grasping is Complicated. Precision Grasp-And-Lift (GAL) Paradigm. The input EEG signals have various ranges (in terms of magnitude), therefore features of such waves were standardized by removing the mean and scaling to unit variance. This has made it easy to deal with such variant in the signal's patterns.

–Figure 5. The experimnet details. Dataset was collected from (12 subjects) with each having 328 trials which resulted in a total of 3,936 grasp and lift trials. Picture source: Luciw et. al. [18].

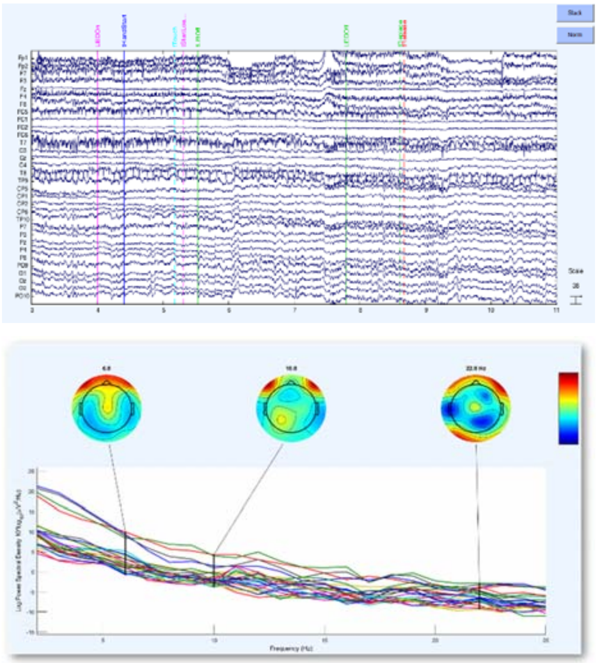

Figure 6. EEGLAB dataset analysis for a total of (3,936 grasp) and lift trials. The EEG recodring was of (32) channels.

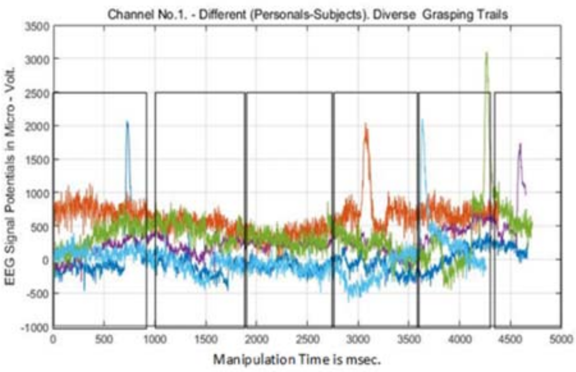

Figure 7. A total of 3,936 grasp and lift trials, for six grasping events. The EEG recodring was of (32) channels. Refere to [17] for analysis details.

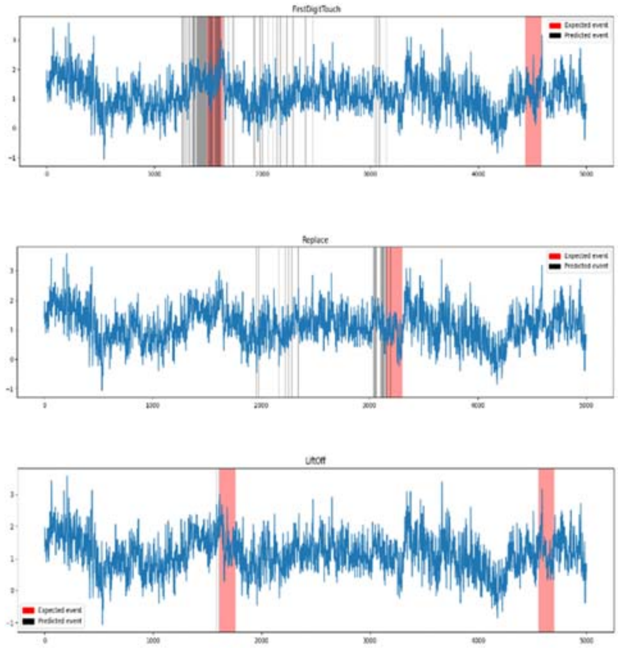

Figure 8. Typical classification results that are used by the fuzzy classifier. Classification of hand events are then used for building a fuzzy expert system and building an intelligent grasping and manipulation system. Identical classes have already been developed and obtained by the (Grasp and Lift Hand Movements) experiments for EEG classification.

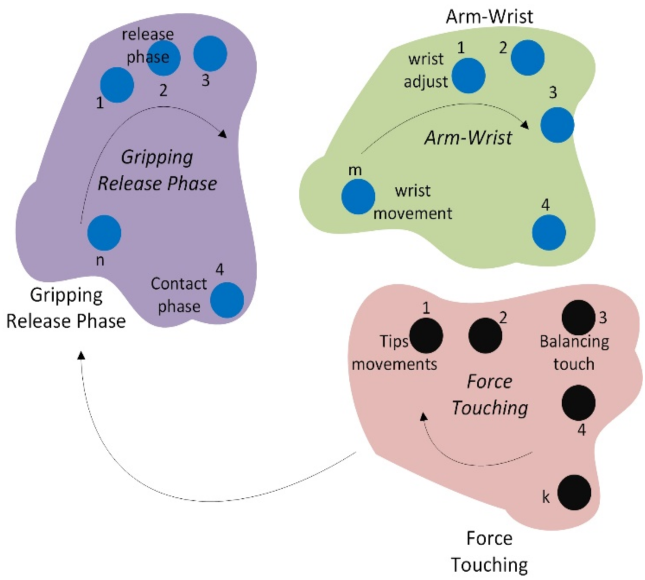

Figure 9. Building a fuzzy rule based expert system over the CNN classifier. A number of (if then rules) around the different classifications of hand movements events.

V. CONCLUSION

In this research we have presented a methodology for using electroencephalography for building a robotic decision-based system. The research was a four stages process. The first was related to an analysis of EEG patterns using the EEGLAB. The second was feature extraction using an autoregressive method. This involves estimating the EEG power spectrum density by fitting a parametric approach. The third stage was the classification using machine learning based training model algorithms and CNN.

We have seen success in analyzing the electroencephalogram (EEG) dataset to do a recognition related to visual thinking tasks. A broader understanding of this technology is by analyzing how thinking relates to EEG, and how to apply artificial intelligence tools to demonstrate features of EEG-related events. Other related thoughts are related to adding new technologies and events through the results we've had in the past, like manipulation of more devices by fingertips. This is further shown in Figure 9. Figure 9 is a typical classification result. Classification results are used for building a fuzzy expert system and building an intelligent grasping and manipulation system.

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