Machine Learning for Electroencephalography Decoding and Robotics Dextrous Hands Movement

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***Abstract*— This work focuses on using machine learning (data analysis) for interpretation and understanding of brainwaves resulting from electroencephalography during a grasping task. Electroencephalography – EEG - was used for acquisition of brain neural signals thought activity, hence to layout a control strategy for robotic hand and fingers movements. This is done via decoding, in real-time, the neural activity associated with fingers motions. Results are used for training robotics dexterous hands, and might allow people with spinal cord injury, brainstem stroke, and ALS (amyotrophic lateral sclerosis) to control a robotic-prosthetic by thinking about movements. The project is novel in a sense, it relies on detecting grasping features for a human grasping using Principle Component Analysis (PAC), hence to learn these features for recognitions applications.**

Keywords*— *EEG, Prosthetic, NF Learning, PAC.

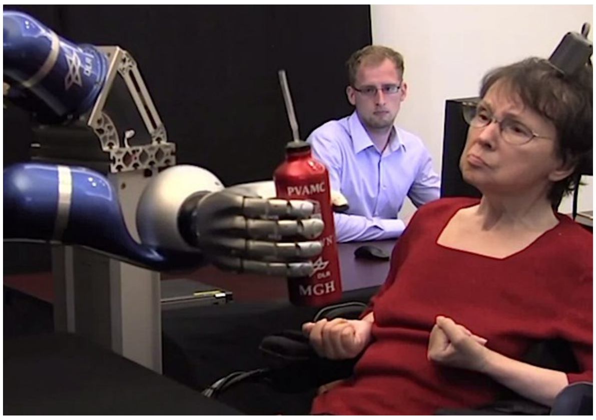

Fig. 1. Electroencephalogram (EEG) brain waves have been used extensively for people with disabilities, [1].

I. Introduction

A. Related Work: BMI

It has been reported clinically that, diseases like stroke and traumatic brain injury do cause long-term, unilateral loss of motor control. Neurological disabilities and related diseases are causing the permanent loss of motoring of limbs, in addition to sensory malfunction. In particular, even in specific and related cases, limbs disability is very severe that it is not likely to feed oneself or even communicate. With the advances on technology, and in specific - BMI - Brain Machine Interface, there is a new research direction that aims to support disabled patients by translating neural signals from the brain into useful control signals for guiding prosthetic limbs. The prime objective in developing a neural prosthesis is to substitute neural circuitry in the brain, that no longer functions correctly or efficiently, Fig.1. While achieving such goal, this requires artificial reconstruction of neuron-to neuron connections in a way that can be recognized by the remaining normal circuitry, and that promotes appropriate interaction. It is estimated that approximately (9 million) people worldwide suffer from stroke every year and that almost (30%) of stroke survivors suffering from irreversible motor impairments, Teo et al. [2]. According to Andrew et al. [3], brain-controlled interfaces are devices that capture brain transmissions involved in a subject's intention to act. Neural activated prosthetic devices is becoming an important domain, and progressively relevant to a number of clinical and various neurological related diseases treatments.

In particular, we refer to Fayad and Elmiyeh, [4], where it was mentioned about such input devices for stimulating zones within the nervous system, in particular, have been especially successful in achieving therapeutic effects. Charles et al. [5] also reviewed the challenges to clinical translation and discusses potential solutions. They made a focuses on hardware reliability, state-of-the-art decoding algorithms, and surgical considerations during implantation.

Donoghue, et al. [6], presented the issue related to paralysis. They mentioned that "Paralysis is a widespread problem, common to many disorders such as spinal cord injury, muscular dystrophy, stroke, cerebral palsy, and amyotrophic lateral sclerosis (ALS)", Donoghue, et al. [6]. There have been several recent developments towards the use of neural motor prosthetic control signals [7][8][9][10][11]. Latest research work has indicated to an increased speed and reduced variability of communication between neural-cortical signals and the prosthetic limbs, as in [12][13][14].

Offline, information from other degrees of freedom, such as fingers and wrist, has been extracted as well, as indicated by Vargas et al. [15]. State-of-the art prosthetic limbs currently have more degrees of freedom than one can easily control with conventional approaches, Kuiken et al. [16]. In addition, Wandera et al. [17] have reported an investigation for the role of distributed cortical networks in BCI skill acquisition. They have recorded population-scale neural activity simultaneously

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from various locations across the cortex using electrocorticography while subjects performed a BCI task. In [18], Fok et al. presented a novel BCI, the IpsiHand. In [19], Berger et al. have presented a study, where an application of a specially designed neural prosthesis using a multi-input/multi-output (MIMO) nonlinear model is demonstrated by using trains of electrical stimulation pulses to substitute for MIMO model derived ensemble firing patterns. Berger et al. [19], have mentioned that, ensembles of CA3 and CA1 hippocampal neurons, recorded from rats performing a delayed-nonmatch-to-sample (DNMS) memory task, exhibited successful encoding of trialspecific sample lever information in the form of different spatiotemporal firing patterns. In [20], Rajesh et al. have presented a research work for a direct Brain-to-Brain interface in humans. In Townsenda et al. [21], a general P300 brain–computer interface presentation paradigm based on performance guided constraints was presented. There are a number of efforts that are documented for controlling a robotic hand with neural signals bypassing, [22]. In [23], it was reported that, a direct interface with motor cortical neurons could provide an optimal signal for restoring movement.

B. *Research Outcomes, and Paper Organization*

The main objective of this research is to learn features associated with EEG waves during grasping and manipulation task. Learning of these features will help in building a control strategy for robotics dexterous grasping, in addition to prosthetics hand control. The presented work will also related to other outcomes: electroencephalography, brainwaves analysis, modeling, and decoding of clinically (*non-invasive*), as are needed for typical robotics hand control. In this respect, the paper has been divided into FIVE sections. In section (*i*) we presented an overall review of some related and recent typical research outcomes. In section (*ii*), we present concept of machine learning for EEG waves understanding. Section (*iii*) is about behavior and knowledge building. In section (*iv*), we present details of multi-channel EEG grasp recording, and a link to the Umeå University [24] is established. Results are further presented in Section (*iv*). Finally, section (*v*) draws few conclusions and remarks.

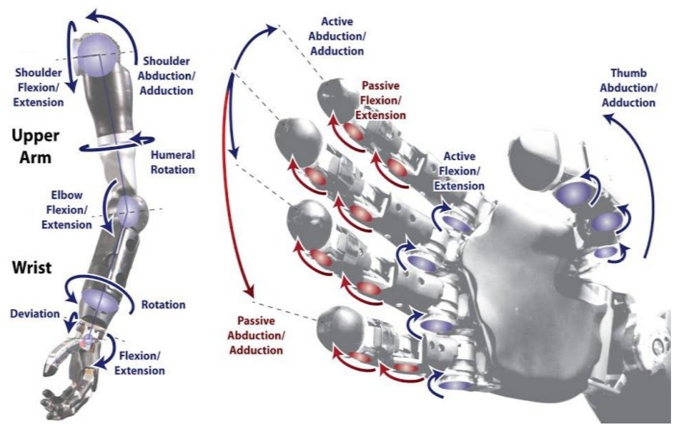

Fig. 2. Towards human like fingers and hand control. EEG brainwaves gives lots of perception about a typical structure of robotics/limbs control, http://cronelab.github.io/motorbmi.html.

II. Machine Learning Tools and System IntelligEnce

A. *EEG features Extractions*

In reference to Fig. 2, dexterous robotics grasping relates joints and fingers movements together in a synchronized way. The proposed system in thought includes brainwaves electrodes, acquisition, neural signals filtering, and decoding. The reason that the system is to be assembled, this is due to the need to shape a system BCI structure, even for future development and research. In addition, we shall acquire the updated technologies in this field. Therefore, an objective of this research will be achieved by assembling the FUNDAMENTALS FRAGMENTS of such planned project. It involves use of the right technologies. This involves: (*i*) Setting up of brain computer interface. (*ii*) Brain waves signals detection. (*iii*) Acquisition electronics, signals conditioning and processing. (*iv*) Massive brain waves signals analysis, features extractions, neural decoding, and nonlinear multivariable signals modeling. (*v*) Connecting a multi-fingered prosthetic hand motoring mechanism with brainwaves sensory. (*vi*) System testing and validation. Both Fig. 3, and Fig. 4 (with PCA in details) show the typical machine learning tools used to detect the brainwaves main features.

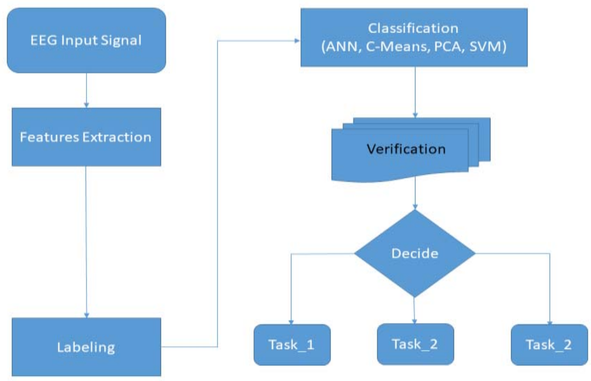

Fig. 3. EEG features extractions, and machine learning outline.

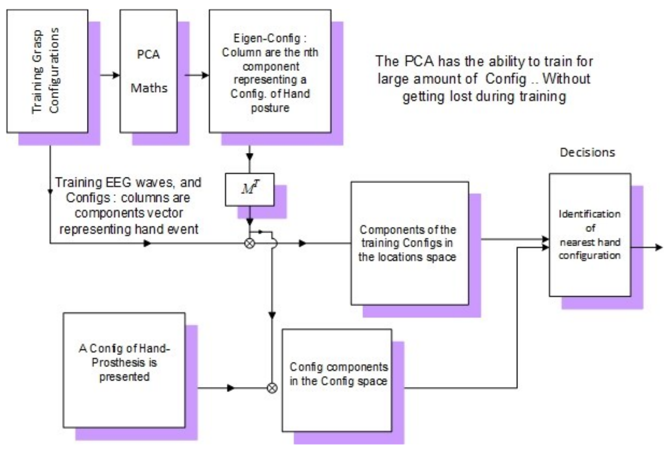

Fig. 4. In details PCA process, to detect main features of EEG waves during grasping tasks, while reducing the size of EEG brainwaves.

B. Neuro-Fuzzy System, EEG Features Learning.

For using EEG brainwaves in hand control, two learning stages were adopted. The *first* is related to detecting features using PCA. PAC also was used, as due to massive EEG waves sizes. The *second* is using a *Neuro-Fuzzy* system to learn these features. Due to interrelated nature of EEG, modeling of such massive multivariable signals will be involving intelligent approaches, Fig. 5. The Neuro-fuzzy system is observed as a broad-spectrum parametric knowledge systems, that learns to represent specific input-output relationship. For the robotic hand, the relation which will be used to train the Neuro-fuzzy is defined in terms of specific training patterns neural waves features, hence to map this to hand movement. Configurations and associated parameters and defined in cartesian configurations u_a^c, changes in configurations Δu_a^c, and whatever appropriate within a space $\Delta\Theta_{k-1}$ into decisions.

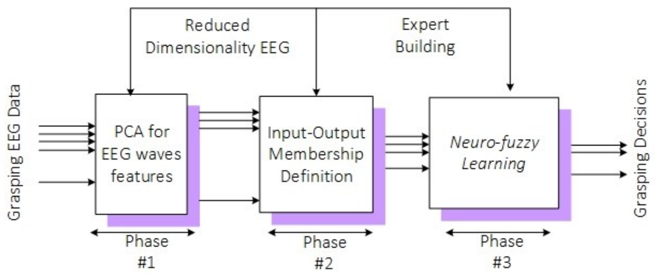

Fig. 5. Neuro-fuzzy learning to learn grasping PCA features.

This is given by Eq.1, such a relation is defined:

$$\aleph = f_{neural}\left(NN, \Delta u_a^c, u_a^c, \Delta\Theta_{k-1}\right) \qquad (1)$$

$$\aleph = f_{neural}\left(\varphi_{1f}, \varphi_{2f}, \varphi_{3f}, \varphi_{4f}, w_{1ij}, w_{2ij}, w_{3ij}, w_{4ij}, \ldots, \Delta u_a^c, u_a^c, \Delta\Theta_{k-1}\right) \qquad (2)$$

In Eq.1, undertaken robotic hand grasping decisions and configuration grasp space are made function of *Neuro-fuzzy* parameters $\left(\varphi_{1f}, \varphi_{2f}, \varphi_{3f}, \varphi_{4f}, w_{1ij}, w_{2ij}, w_{3ij}, w_{4ij}, \ldots\right)$, in addition to hand motion parameters. A key purpose of this *Neuro-fuzzy* system is to establish an appropriate decision among a number of suitable actions. Examples of actions includes (*No Grasping, Soft Grasp, Power Grasp*), which are totally dependent on optimal forces distribution. Input and output training patterns from the EEG features, to be prepared and collected for training. However, in its initial context, desired cartesian hand positions u_a^c, changes in positions Δu_a^c, a step variation in position of joints. Outputs are desired decisions to be taken by hand control. Desired object posture values are obtained in advance by moving the hand to the required position. Subsequently, the adopted Neuro-fuzzy learns relations among input and output hand-prosthesis patterns sufficiently.

C. PCA Analysis, EEG Waves Dimensionality Reductions

PCA is used as a means of recognising prosthesis hand while in a grasping or moving configurations. This PCA forms the core of the configurations recognition process. PCA was coded using Matlab computational environment. Figure 5. illustrates the multi-stage adopted PCA paradigm. PCA coding will be further described in details at a later stage. In the introduction, it was mentioned that; what was known as "*task configuration recognition*" is a broad term. It may be further specified as one of the following tasks: (*identification)*, here labels of individual hand configurations are to be obtained, (*recognition*) of the configurations, where it should be decided upon if the hand configuration has already been trained, and *categorisation*, where the task configuration or figures shaping must be assigned to a certain category.

D. PCA and Eigen Configuration Recognition

As has been said, PCA computes the basis of a space which is represented by its training vectors. The basis vectors computed by PCA are in the direction of the largest variance of the training vectors. The direction of the largest variation (from the average) of the training vectors is described by the second eigen_representation of configurations. The direction of the second largest variation (from the average) of the training vectors is described by the third eigen_representation of configurations, and so on. Each eigen_representation of configurations can be viewed as a feature. When a particular configuration is projected onto the configuration space, its vector (made up of its weight values with respect to each eigen_representation of configuration) into the configuration space describes the importance of each of those features in the configuration. The configuration is described in the configuration space by its eigen_representation of configuration coefficients. For convenience, the weight vector is normalised. Since the laboratory configuration developed in the configuration data-set is the real configuration, weight of the first eigen_representation of configuration is very high, almost equal to unity. In fact, PCA finds the direction of largest variations of various hand configurations. The first eigen_representation of configuration accounts for the maximal variation, the second one accounts for the second maximal variation. Letting (E) be the matrix of first eigen_representation of configurations, where the first column is the first eigen_representation of the configuration, … and so forth, (f_I) be a configuration in data space, and (f_F) be same configuration in data space.

$$f_F = \left(f_I E^T\right) \qquad (3)$$

This is a many-to-one transformation, since dimensionality of configuration data-set space is far larger than the dimensionality of configuration data-set. The transformation introduces an error, that can be seen by looking at a reconstructed configuration. The reconstruction is performed by computing the inverse transformation of Eq. 3:

$$f_I = \left(f_F E^{-1}\right) \qquad (4)$$

For instant, we can show a grasp configuration along with its PCA reconstruction. The magnitude of the difference between the original configurations and its reconstruction, is known as the reconstruction error, is easily calculable. Let

f_l^T as reconstructed configuration of a configuration f_l, and λ, the reconstruction error:

$$f_l^T \; f_l\,,\; f_l^{'} = E^T E f_l \text{ and } e = \left| f_l - f_l^{'} \right| \qquad (5)$$

Since $e = \left| f_l - f_l^{'} \right|$ vectors are normalised, evaluating the cosine distance is used instead of the Euclidean distance:

$$e = cos\left(f_l^{'}, f_l^T\right) \qquad e = \left(1 - f_l^{'} f_l^T\right) \qquad (6)$$

$\left(f_l^{'}\right)$ and $\left(f_l^T\right)$ are normalised. Once an inner products of configurations have been computed, grasping configuration space has to be populated with the known configurations. Grasping configurations are captured from the training set. This is done by allowing the robot hand to move and hence capture joint space postures (hand configuration) using the information from each joint in each finger. Each known hand configuration is transformed into the configuration space and its components stored in memory. At this stage, the hand recognition procedure can also begin. An unknown hand configuration is presented to the *e*_Grasp simulator. Configuration is identified as being the same individual as the configuration which is nearest to it in configuration data-space. For instant, if the rule-base contains two fuzzy *if-then* rules of (*T-S*) type. A typical rule can be expressed as:

$$if \;\; x_{(k-1)} \; A_1 \,\&\; x_{(k-2)} \; B_1 \rightarrow f_1 = \left(p_1 x_{(k-1)} + q_1 y_{(k-1)} + \alpha\right)_1$$
$$if \;\; x_{(k-1)} \,\&\; x_{(k-2)} \; B_2 \rightarrow f_2 = \left(p_2 x_{(k-1)} + q_2 y_{(k-1)} + \alpha\right)_2$$

Within the this layer, every node in this layer is a square node with a node function:

$$O_i^1 = \mu A_x x(k-1) \qquad (5)$$

$x(k-1)$ is the input to i^{th} node, and A_x is the linguistic label (*small , medium large*, …) associated with this node function. O_i^1 is a membership function of A_x, that specifies degree to which the input (x) satisfies quantifier A_x, and $\mu A_x x(k-1)$ is chosen as a bell-shaped with maximum $\rightarrow \{1\}$, minimum $\rightarrow \{0\}$:

$$\mu A_i x(k-1) = exp\left(-\left(\frac{x(k-1) - c_i}{a_i}\right)^2\right) \qquad (6)$$

(a_i, b_i, c_i) is the parameter set. For the second layer, every node in this layer is a circle node. It multiplies incoming signals and sends the product out. For instance:

$$y_i \mu A_i x(k-1) \times \mu B_i y(k-2)\,,\; (i = 1 \rightarrow 2) \qquad (7)$$

Using this *NF* architecture we have learned and reuse human signals for simple grasping, where human grasping reasoning was used for that purpose. Still we need to map these learned signals into fingertips displacements. In Fig. 5, we shown the three stages related to EEG learning of waves main features.

E. Prosthetic Hand Decision Making Process

There two sets of patterns. Training and testing. Set of pattern are of four input and four input variables. Typical inputs to the *Neuro-fuzzy* Decision Based system are further summarized in Table (1), as follows:

TABLE 1. DEFINITION OF FUZZY INFERENCE SYSTEM.

FUZZY INPUT VARIABLES		FUZZY OUTPUT	
Input #1	*Hand Config- Open, Close, …*	*Output #1*	*No Grasp*
Input #2	*Finger Config -Extended, Curl*	*Output #2*	*Soft Grasp*
Input #3	*Wrenches - Strong, Weak …*	*Output #3*	*Fair Grasp*
Input #4	*Behaviour - Motion class, …*	*Output #4*	*Hard Grasp*

First Stimuli (*Hand Configurations*):

This stimuli is representing few knowledge about the hand configuration, i.e. the current shape. This is defined in terms of shapes. Within this study, space of configuration of grasp, where the robot hand is to move was divided into five main configurations. This is defined in terms of the following input sets:

{*Config_#1, Config_#2, Config_#3, Config_#4 ,.. Config_#k*}

Second Stimuli (*Fingers Configurations*):

This stimuli is dedicated towards the definition *fingers configurations* of grasp. Of a particular interest within a grasp space is the fingers shape of hand grasp. This tells how the robot hand fingers are shaped at a particular moment of time. An shape of fingers grasp is also defined within a particular hand configuration. There are a number of fingers shapes of grasps. This could be a hard or soft grasp or even for any hand configuration within a defined situation, as defined below by the following input sets:

{ *fingers_Configurations#1*: *Curled_Config,*
fingers_Configurations#2: *Non_Curled_Config,*
fingers_Configurations#3: *Circular_Config,*
....
fingers_Configurations#n : ..... }

Third Stimuli (*Fingertips External Wrenches*):

Within a particular hand configuration or fingers configuration, it is needed to let the robot hand acting with particular actions. This depends on the acting wrenches Examples are:

{ *Fingertips_Wrenches_#_1*: *Vertical Wrench,*
Fingertips_Wrenches_#_2: ....,
Fingertips_Wrenches_#_3: *Vertical Wrench* ... .
…… *Fingertips_Wrenches_#_n*: .... }

Fourth Stimuli (*Behaviour*):

This stimuli is an important input. It defines situations when the robot hand is detecting any *unusual behaviour*. It takes the appropriate actions, in reference to the define situation. This stimuli do represent particular behaviours of the robot hand, at particular hand configuration, within a configuration of a grasp. Example of which, when the robot hand within {*Config#1*, *Fingers_Configurations#1*, *Fingertips_Wrenches_#_1* }, then it is expected to have a particular *grasping actions* within this configuration of interests, or it should hardly grasp the object and servo it … and so forth ….. depending on how we define various behaviours for each *hand configuration* and *fingers configuration* for a grasp.

{*Behaviour#1: fine_motion_Around, Behaviour#2: slow_motion_Around, Behaviour#3: Behaviour#n: Fast_motion_Around ...* }

All the above defined situations, and defined appropriate actions are further enlisted next.

IV. Behavior Knowledge Building

A. *EEG Acquisition: The Universal Experiement*

We refer to data source from Umeå University [24]. The data set do include large number of real experimentations, for achieving human grasping. This included up to (3,936 grasp and lift trials) with varying weight and friction, Luciw et. al. [25], Fig. 6. Experimentations were addressing the issue making use of brain waves, neural signals, to motor the artificial limbs. Motoring will be based only on human thoughts, hence the focus was on setting up experimental setup.

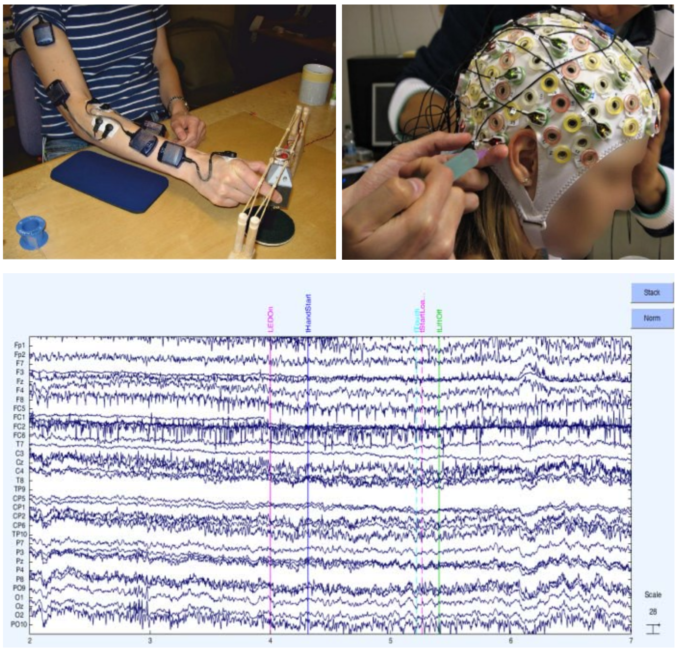

Fig. 6. EEG recording and Experimentations, [24], Luciw et al. [25].

B. *Neuro-fuzzy Learning Paradigm*

Neuro-fuzzy inputs are the EEG waves main features. Different hand configurations, have resulted in large number of features. As the hand is in motion, or even at a static posture, features are used to train the *Neuro-fuzzy*. Due to the massive possible configurations, PCA learning network was used to reduce the dimensionally. Building the robot-prosthesis hand grasping intelligence, is the succeeding phase. Such a phase requires blinding all previous inputs (*stimuli*), for attaining the most appropriate grasping behaviors. The designated learning and decision making architecture is a *Neuro-fuzzy*. The system inputs, and system outputs were listed earlier and they do represent various circumstances the robot-prosthesis hand can be in. Details of *Neuro-fuzzy* system inputs are listed here as:

Neuro-fuzzy (INPUTS):
Input_#1*= Stimuli related to Hand Configurations.*
{*Hand configurations. Configurations data from joint-space values*}.
Input_#2*= Stimuli related to Fingers Configurations. of grasp* {*Fingers configurations*}.
Input_#3*=Stimuli related to Finger Acting Wrenches during a grasp task* {*Fingertips wrenches*}.
Input_#4*= Stimuli related to BEHAVIOURS during a grasp task* {*Unusual behaviour, ...* }.
Neuro-fuzzy (OUTPUTS): ***Output_#1*** *= No Grasp.* ***Output_#2*** *= Soft Grasp.* ***Output_#3*** *= Fair Grasp.* ***Output_#3*** *= Power Grasp.*

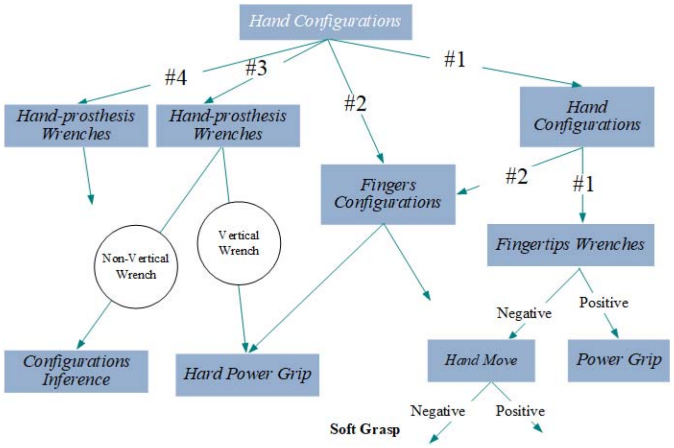

Fig. 7. EEG decoding has helped in understanding EEG features. A typical robotic hand grasp decision TREE.

For such defined sets of inputs and outputs, an adequate hand intelligence was created for generating appreciate finger joints motion and forces to deal with a defined situation. Thus, will helps in generating appropriate signals to move the hand-prosthesis, once brain-wave was generated. That was further elaborated and shown in Fig. 7.

C. *EEG Features Learning, and the Fuzzy Rules*

Building a decision system with four inputs and four outputs is not an obvious procedure. As mentioned earlier, the four system inputs do represent various situations the robot hand can be within any movement of grasp time. In addition, the four system outputs do represent the system outputs the hand should undertake at a particular situation. Using fuzzy system, we are able to build an *if- then* statement, as stated below:

If (*Input_#1 is ..... and Input_#2 is ....*) *then* (*Output_#1 is .... and Output_2 is ....*)
CASE #1: *If* (*Hand in Config_#1..... and Fingers in Fingers_Configurations#1....*) *then* (*Soft Grasp*)
CASE #2: *If* (*Hand in Config_#3..... and Fingers in Fingers_Configurations#3....*) *then* (*Power Grasp*)
CASE #3: *If* (*Hand in Config_#1..... and Fingers in Fingers_Configurations#3....*) *then* (*No Grasp*)
CASE #N: *If* (*Hand in Config_#2..... and Fingers in Fingers_Configurations#1....*) *then* (*Soft Grasp*)

For a number of inputs and outputs, and while using abilities of *Neuro-Fuzzy* decisions, we able to build a sophisticated hand behavior for a number of particular situations.

V. Conclusions

This article has elaborated on a concept of building an intelligent grasping behavior for a robotic hand-prosthesis. That was based on using Electroencephalography. Due to enormous sensory and hand-prosthesis data to be analyzed, the article has presented a reduced dimensionally and size of the hand sensory data using PCA. The dimensionality reduction of hand information and features, are hence used as stimuli to a *Neuro-fuzzy* architecture. Stimuli of the decision-based learning architecture, are (*hand, fingers configurations*), wrenching, and behaviors related to particular grasp. Learned behaviors are (*no-grasp, start to grasp, fair, soft, power grasps*) with multi-levels of hand-prosthesis intelligence. The article has presented the details of the designed intelligent based robot hand-prosthesis that learn human intended behavior through the use of the EEG brainwaves.

Acknowledgment

Brain EEG signals patterns, are the ownership of *Umeå University* [25]. Thanks to *Matthew D. et. al.* [26], for the availability of the data and grasping experiments details.

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