



PCA Based EEG Event Features Extraction for Robotics Dexterous Grasping

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Abstract: The presented work is dedicated towards deep understanding of resulting Electroencephalography (EEG) brainwaves during a typical grasp and lift human grasping task. During grasping, forces are applied by fingertips dexterously, as observed through resulting EEG waves. For mirroring this to a dexterous robotic hand, methods have to be developed to find features for optimal forces, movements, and right finger joints displacements. Resulting EEG brainwaves during grasp and lift task are very useful, however these EEG waves are related, correlated, complicated, and raw. With the potential and analysis of Principal Components Analysis (PCA) of EEG, it indicated an overlap of valuable neural behaviors from various locations over the human skull, indicating interrelated and coupled events for robotic grasping. PCA has been used to unlock few main features of EEG waves during a grasp and lift task. The foremost grasping features are hence used in creating events for a robotic dexterous grasping.

Keywords: Electroencephalography (EEG), Robotics Learning, Grasping, PCA.

1. INTRODUCTION

A. EEG Based Robotics Control Paradigm

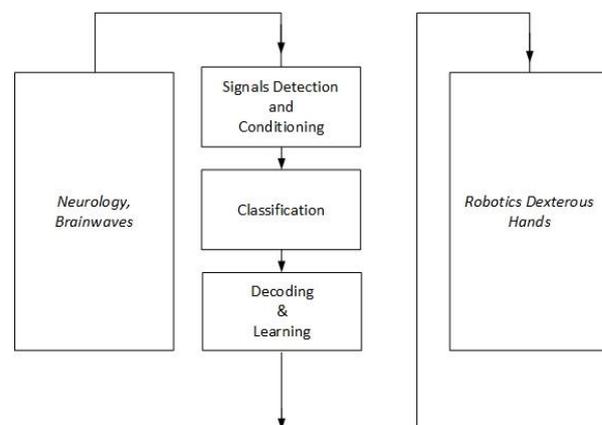
Modern robotics systems are getting much complicated, this is due to the sudden advancement of robotics technologies, and developments of further much sophisticated computing algorithms.

Control of articulated and much closer to human behavior robotics systems, are needed today for a wide spectrum of applications, this is due to integration of robotics systems for much human-type use. In this sense, this work is focused towards bio-inspired robotics control mechanisms. In particular, grasping and manipulation, i.e. moving an object with robot hand and fingers, is not an easy and straight forward task. This is due to the involvement of a number of relations, in addition to compilation of closed system chain dynamics. The problem even gets much complicated once forces of a grasp are needed to be computed.

Use of Electroencephalogram (EEG) brainwaves for robotics, is also gaining a good ground recently, due to advancement of robotics applications. EEG waves are such raw data, and the signaling behavior are very complicated, correlated, related, and they are of such

multi-rate waves, hence is not an easy task to detect, decode, and understand. In reference to Fig.1, here we show two important different paradigms of developments related to robotics dexterous grasping.

The top diagram relates the main blocks of EEG based manipulation, whereas the bottom image shows a typical complicated robotics hand and fingers, where computing the fingers forces still remain a fundamental issue.



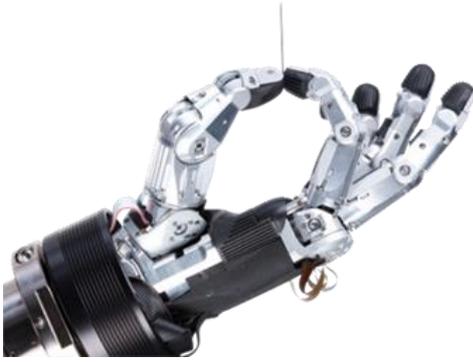


Figure 1. (Top): Typical EEG/Robotic hand/prosthetic main flow graph components. (Bottom): Robotic hand dexterous behavior (Source: Servo-electric 5-Fingers Gripping Hand SVH). Over the past, analytical approaches have been used to compute grasping forces to perform tasks.

B. Decoding and Orthosis Control

Robots/prosthetic hand control using EEG signals became very popular with increasing number of advanced robots. There have been a number of efforts to use EEG data for robotics grasping applications. In this respect, Bell et al. [1] investigated the use of EEG signals to control a humanoid robot with better functionality than an art. Xiao and Ding [2] also investigated using EEG signals to identify features related to individual finger movement. It's harder to find features for individual fingers than for bigger body parts like hand or arm. Three EEG features in same channels were decoded using support vector machine (SVM) technique that analyses data and finds patterns associated with different fingers. For Agashe and Contreras [3], this is a vital part for having a prosthetic hand that replaces a human hand. They tried to implement similar techniques but using EEG. Since earlier studies found that low-pass filtered ECoG (local motor potential LMP) shows precise features, Liao et al. [4] tried to decode individual finger movement, hence they used findings from previous ECoG and implemented them using EEG, hence compared the results with ECoG findings. More complex techniques try to estimate the movement and approach of the hands. In this respect, Bradberry et al. [5], tried to decode EEG data to reconstruct 3D hand movement velocity. They tried to find scalp areas responsible of controlling hand reaching. Another interesting work for decoding was performed by Ashari [6], as he tried to incorporate classifications techniques used on video sequences in P300-based BCI. The issues with classifications can be reduced using principal angles between subspaces. Another way is to use machine learning methods as presented in Dantanarayana [7], the main purpose of the study was to generate mapping for high dimensional data, and hence features of these data, hence to be represented in one or two variables.

C. Problem Statement

While investigating fingers related motion, for this particular work, it is vital to deal with massive nature of grasping EEG, this is due to the complexity, and interrelations of the EEG resulting patterns while performing grasps. In this research, it is needed to detect the foremost events features that are resulting from set of *Grasp and Lift* tasks human grasping. This is investigated further here, while employing PCA for reduced dataset dimensionally. As a technique, PCA was used to unlock main events features from the EEG patterns. PCA has been firstly employed for all the (11 persons, with 9 trails) participating data, hence to correlate the few main features of events related to the basic defined tasks Grasp and Lift trails.

2. EEG GRASPING DATA DIMENSIONALTY REDUCTION: PAC THEORY

At this stage, it is needed to deal with reduced EEG dataset sizes, instead of dealing with the entire datasets.

A. EEG PAC Analysis

Principal Components Analysis (PCA) is a statistical method that is used on data such as EEG signals to find patterns which will correspond to features in EEG data by identifying the similarities and differences. It is able to reduce large data without any loss of important information. This is very helpful when dealing with huge data such as EEG. Theory behind applying PCA to EEG signals was inspired by Wang et. al. [8] with some modifications. For a matrix (X) made of EEG signals (x_k), where $k=1, 2, 3, \dots, n$, assuming (n) rows where each of the signals contains (m) samples as given by Eq (1).

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,N} \\ \vdots & \ddots & \vdots \\ x_{M,1} & \cdots & x_{M,N} \end{bmatrix} \quad (1)$$

Computing mean of all (n) columns separately:

$$\bar{x}_n = \frac{1}{M} \sum_{m=1}^m x_{mn}, n = 1, 2, \dots, N$$

\bar{x}_n is the mean of each (n) column ($n = 1, 2, \dots, n$).

$$Xc = \begin{bmatrix} (x_{1,1}-\bar{x}_1) & \cdots & (x_{1,N}-\bar{x}_N) \\ \vdots & \ddots & \vdots \\ (x_{M,1}-\bar{x}_1) & \cdots & (x_{M,N}-\bar{x}_N) \end{bmatrix} \quad (2)$$

In its context, PCA requires the matrix to be centered by subtracting the mean from each column. This will cause the mean of each column to be zero. Δ_n is the column of the (X) matrix after subtracting the mean from the original column. This will cause the data to be



moved close to the center (origin) of the principal components.

$$\Delta_n = x_n - \bar{x}_n \tag{3}$$

B. Covariance Matrix, Measure of Similarity

The variance is how much the data varies from its mean and the covariance is used to find some kind of a relationship between only two dimensions. For example, relationship between velocity, and car crashes. So, the covariance matrix is just all the combinations of the covariance between each dimension and another. The value of the covariance determines the relationship between the two dimensions. If it is positive, then if one dimension increases the other will increase as well. If it is negative, then the relationship is inversely proportional and when one increase the other decreases. Finally, if it is zero, then the two dimensions are independent of each other or have a nonlinear relationship. The magnitude of the covariance will determine the amount of increase that will occur in the other dimension with maximum relationship of unity to unity. As defined by Wang et. al. [8], the covariance matrix C is:

$$C = \frac{1}{N} \sum_{n=1}^N \Delta_n * \Delta_n^T \tag{4}$$

Δ_n^T is the transpose column of Δ_n . A covariance matrix is given in Eq. (5), Smith [9]:

$$C = \begin{bmatrix} x_{1,1}-\bar{x}_1 & \dots & x_{1,N}-\bar{x}_N \\ \vdots & \ddots & \vdots \\ x_{M,1}-\bar{x}_1 & \dots & x_{M,N}-\bar{x}_N \end{bmatrix} \begin{bmatrix} x_{1,1}-\bar{x}_1 & \dots & x_{M,1}-\bar{x}_1 \\ \vdots & \ddots & \vdots \\ x_{1,N}-\bar{x}_N & \dots & x_{M,N}-\bar{x}_N \end{bmatrix}$$

$$C = \begin{bmatrix} cov(x_1, x_1) & \dots & cov(x_1, x_N) \\ \vdots & \ddots & \vdots \\ cov(x_N, x_1) & \dots & cov(x_N, x_N) \end{bmatrix} \tag{5}$$

$$AX = \lambda X \tag{6}$$

$cov(x_1, x_1) = \sigma_{ij}$. In addition, there is a relation between covariance coefficient and correlation coefficients, as computed by:

$$r_{ij} = \frac{\sigma_{ij}}{\sqrt{\sigma_{ii} \times \sigma_{jj}}}$$

where r_{ij} is the correlation coefficient is a normalised covariance coefficient. There are (n) eigenvalues for an $(n \times n)$ transformation matrix, since every eigenvector is scaled by an eigenvalue, we will have n eigenvectors as well. Eigenvalues can be found by solving Eq. (7):

$$(A - \lambda I)X = 0 \tag{7}$$

(I) is an identity/unity matrix, It doesn't alter value of the matrix it is multiplied with. Getting determinant of $(A - \lambda I)$, hence solving it will give eigenvalues.

$$det(A - \lambda I) = 0 \tag{8}$$

Substituting each of (λ) in Eq. (8) and solving for X , gives eigenvector X for that λ . The eigenvectors calculated are orthogonal (perpendicular) to each other. The eigenvectors are adjusted to have length of unity. The eigenvectors calculated are the principal components. To find the principal components in terms of the most to the least important based on the explaining the data in terms of variance, we must look at the eigenvalues corresponding to the eigenvectors. Higher the eigenvalue, the more important eigenvector.

Finally, getting the principal components PC_1, PC_2, \dots, PC_n with PC_1 being the most important. The first PC , i.e. (PC_1) explains the most variance in the data, the second PC (PC_2) is orthogonal to PC_1 and explains most of the remaining variance in the data (residuals). This is the same for the remaining PCs, Smith [9]. This square matrix is said symmetric around the main diagonal because it was the result of multiplication of a matrix and its transpose. The main diagonal is just the covariance between the dimension and it self. Once looking to find the relationship between the dimensions, we will look at the non-diagonal elements and judge based on their value, Smith [9]. To be able to understand the patterns of the normalized data, we need to compute the covariance of the EEG data. In finding eigenvectors for the covariance matrix C , because of its square nature, is a requirement for eigenvector calculations, Smith [9]. For an $(n \times n)$ matrix A if we find a row vector (X) $(n \times 1)$ that could be multiplied by A and get the same vector (X) multiplied by a value λ called an eigenvalue and the vector is the eigenvector. Since matrix A transforms vector (X) to a scaled positions by an amount equal to (λ) , it is called a transformation matrix. To project data on the PCs, we will take all eigenvectors in order of importance, and place them in column vector which will result in an $(n \times n)$ matrix. This vector is called a feature vector as demonstrated in Smith [9]:

$$C Ev = \lambda Ev \quad (C - \lambda I) Ev = 0 \tag{9}$$

$$FeatureVector = [Ev1 Ev2 Ev3 \dots EvN]$$

To find the eigenvalue λ , we need to find the determinant (X) are the eigenvector. Transferring EEG $(n \times n)$ data signals onto the eigenvectors by multiplying the transpose of the original centered data with the transpose of the feature vector. These are called principal component scores since they are found for each principal component, as in Smith [9]. $PC \text{ scores} = FeatureVector^T \times CenteredDataMatrix^T$.

$$Scores = FeatureVector^T * Xc^T \tag{10}$$

Finally, computing the loadings from the Ev and λ ,

$$Loadings = EvN * \sqrt{\lambda N}$$

Data reduction can be done by leaving out the least important eigenvectors in the feature vector. This way

we are saying that there is no need for some of the data because they do not add significant information. The least significant eigenvector are correlated to noise and leaving them out removes some of the noise in the EEG signals. Thus projecting the original data onto a new axis that best describes the patterns. The same data will be there if we used all the principal components (eigenvectors). Otherwise, just most important data, Smith [9]. Number of principal components varies a lot depending on the data used and the type of analysis needed. First two or three PCs are used. To choose, we need to define a threshold on how much variance is sufficient to understand the data. This is completed by first getting the PCs percentages, hence adding them and comparing them to a threshold that was pre-assigned.

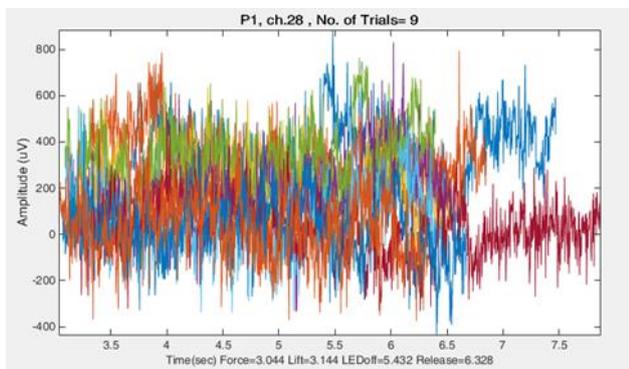
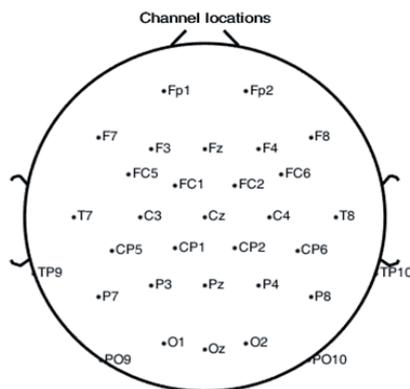


Figure 2. (Top): Typical EEG channel reading location, Luciw et al. [10]. (Bottom): Typical EEG dataset recoding. First participant's, and (9) trials of channel (28) reading.

3. GRASPING ELECTROENCEPHALOGRAPHY: MASSIVE WAVES ANALYSIS

After defining the mechanism for reducing the size of the large EEG dataset, we shall look into the mechanism for EEG dataset relation and collection, as in respect to the defined task. This an essential observation.

A. Grasping Data Acquisition

We acquired the Grasp and Lift EEG data from Luciw et al. [10]. To make sure that the EEG data is usable as

the basis for studies on robotics and prosthesis grasping, it was recorded while adhering to the precision grasp-and-lift (GAL) paradigm. This meant that there was multiple sensors recording the motions of the hands and the object that was being lifted while the EEG data was recorded. The sensors used included a head cap with (32) channels for EEG recordings, EMG sensors to record hand, forearm, and shoulder muscles (5 channels), some sensors to identify the 3D position of the moving parts of the experiment including the object, both the index and the thumb fingers, and the arm. The amount of force from both fingers on object when gripping it was recorded using sensors with (3 force) channels and (3 torque) channels.

Dataset was collected from 12 subjects with each having 328 trials which resulted in a total of 3,936 grasp and lift trials. These subjects included 4 males and 8 females all aged between 19 and 35. Each electrode is named based on its position on parts of the brain. They were named from front to back *F* (frontal), *C* (central), *T* (temporal), *P* (posterior), and *O* (occipital). Odd numbers were for left side and even numbers for right side (ex. T_3 for left and T_2 for right). Middle were giving small letter *z* (zero) instead of a number (ex. T_z). C_z is mainly used as reference electrode because of its position in middle or on one or both ears is used as reference. Ground electrodes are mainly either F_{pz} (front to polar) or the ears. This is presented in Fig. 2. First data were loaded for first person (P1), and then plotted all the channels in the time domain, as seen in Fig. 2. The signals here are time stamped with labels of what they correspond to in action that happened in the experiment and was recorded by all of the sensors. These are just the main events and they include the LED turning on and off, when the hand starts moving, when each figure touches the plates, the object lift off the table and replacing it back to original position, if the new trial includes expected or unexpected high or low weights, and finally the release of the fingers from the plates. It is visible in Fig. 2 that after the LED was turned on there was a minor increase in the voltage due to the intent to move in response to the event (ERP).

In addition, once the hand started moving, there was a minor increase in some channels and decrease in the reference channels due to hand movement. After, the finger touched the object and force was applied only minor change happened until the lift off, which caused a high-low voltage for lift and then relax in destination after (0.5 sec) from lift off. Finally, after releasing the object there was a drop in when relaxing the fingers and returning into original position.

B. Time Domain, and Data Analysis

EEGLab Toolbox, Delorme and Makeig [11], was also used, as it enables plotting raw EEG signals in time and frequency domain, and shows power spectrum. It shows

the channels where activities happen if loaded with the correct channels of EEG data. This is shown in Fig. 3.

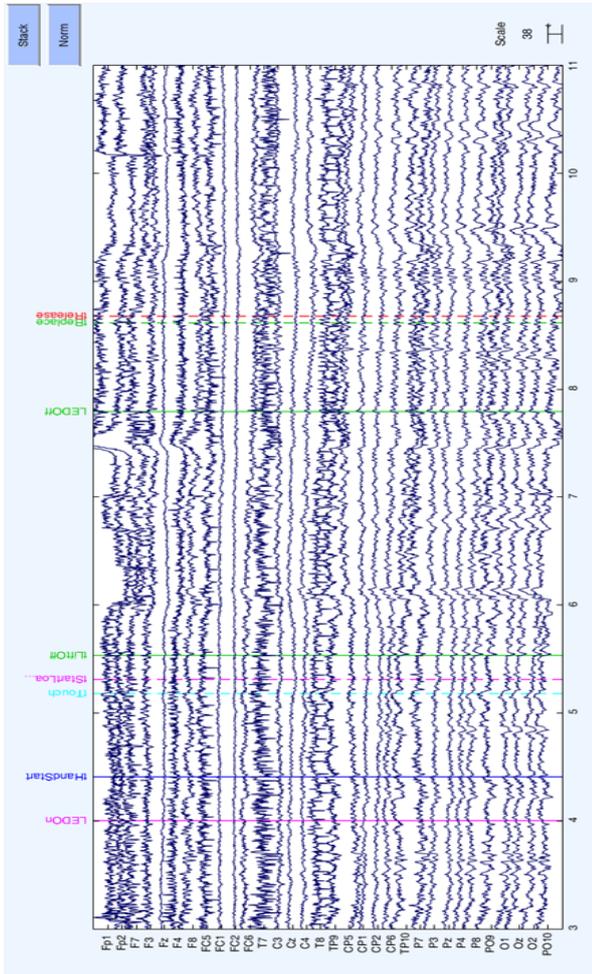


Figure 3. Analysis of the resulting EEG waves via EEGLab. EEGLab time plot for (P4) for all (32 channels), (Voltage (μV) vs. Time (Sec.)).

It shows the interlaced patterns generated during (11 seconds) time elapse of grasping.

C. Frequency Analysis: Power Spectrum

We will now examine the spectral power changes and the corresponding area of the brain, that all the electrodes cover. This is further analyzed in Fig. 4. In addition, this will indicate any part of hand movement and its origin.

1st PARTICIPANT:

In reference to Delorme and Makeig [11], we can deduce that power changes accrued at (5.9Hz) in theta band and corresponded to the frontal part of the brain which indicates relaxation. There were only minor changes at (9.8Hz) in alpha band. Finally, there were big power changes in F8, FC6, and T8 and minor to the

counterpart at (22Hz) in beta band side this could indicate the blinking artifact we saw earlier.

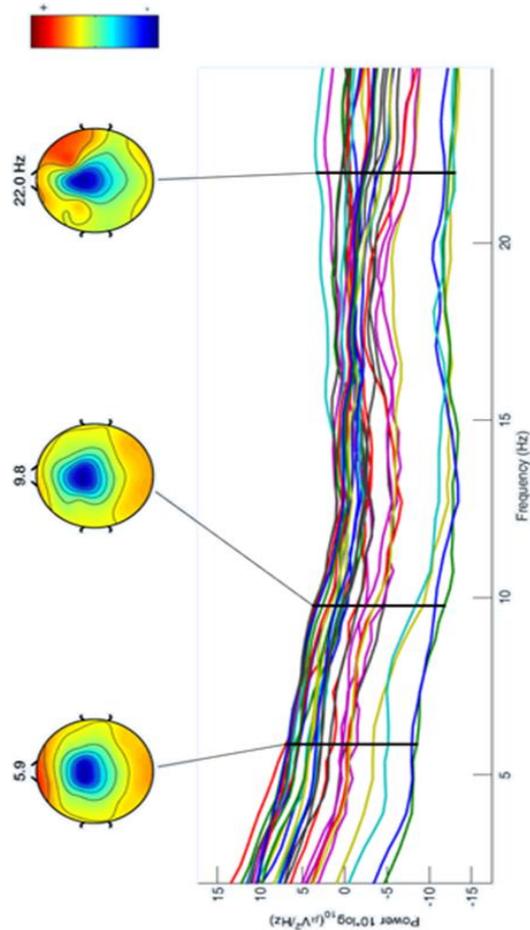


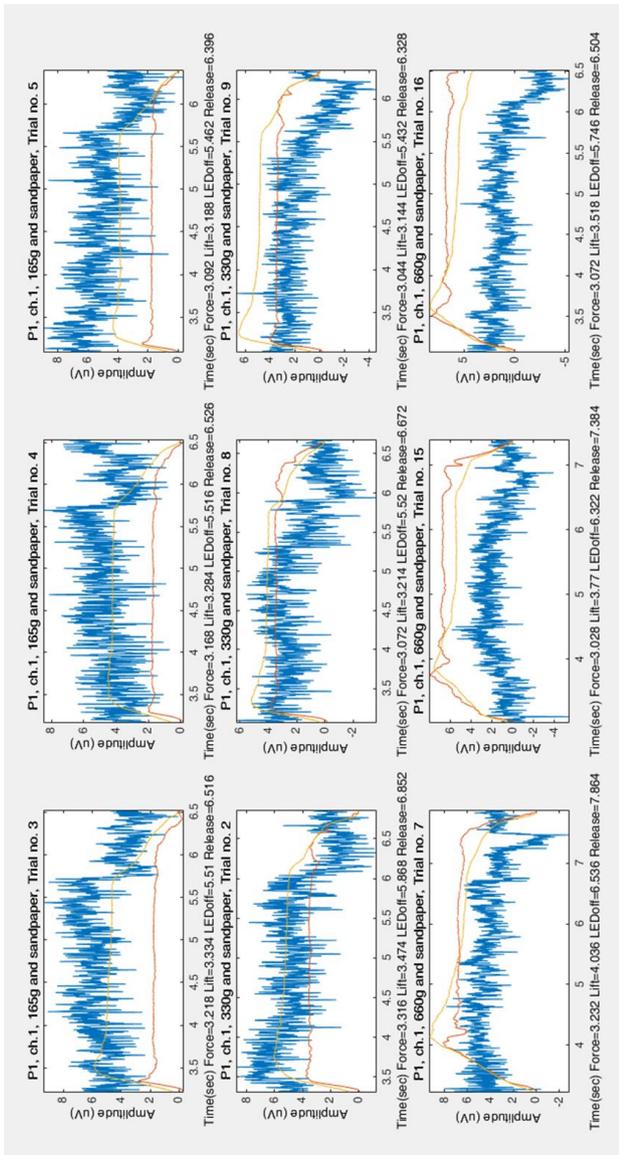
Figure 4. Frequency power spectrum analysis during the grasping task for (P1) for all (32 channels). Power spectrums indicates the fashion in which the ways are propagating through the various brain neurons.

2nd PARTICIPANT:

We can see similar patterns for the second person especially for blinking artifact in (22Hz) in beta band. There is significant difference in at (9.8Hz) which could be due to the finger or hand movement. This will be further investigated next using PCA.

D. PCA Analysis of Individual Channels, Different Trials

Now we shall look at PCA analysis of individual channels for different trials, from applying force until release only. Since there were a lot of artifacts before and after the period we are concerned about, we will look at only the signals from the beginning of applying the force on the object until the release (grasping period). Here, we would like to identify the channels that show consistency and clear features.



We have examined all the channels for first 9 trials from the time of applying force until release and found out that there was some consistency in the 15th, 17th, 25th, and 28th channels corresponding to (C4, TP9, Pz, and PO9) and shown below, respectively. Since different trials change in weight, we are not expecting the same response for all of the trials in the same channel. *FIRST*, of all the first trial has some unnatural spike at 5.3 seconds ($800\mu V$) which affected all the channels in the same way, this only affects the middle of the signal so it can be ignored only here and it will not be used in the PCA analysis. *SECOND*, almost all of the channels have a low-to-high activity when starting to lift the object and then starts going down after reaching the object's max height. Most noticeable activity is just after the LED turning off which indicated that this increase corresponds

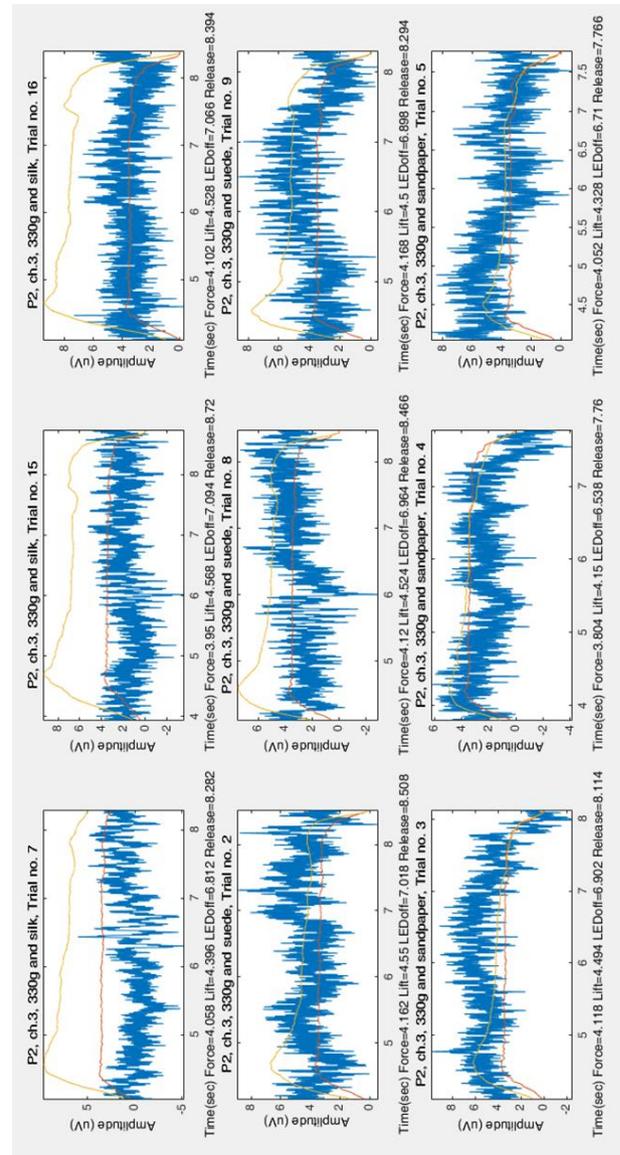


Figure 5. Typical participant's EEG plot, in terms of channels/personals. Event was from force grasp, till release for 9 trials, Plot of channel 11 for 9 trials. (Left): Participate X, trial 3. (Right): Participate Y, trial 7.

directly to lowering the object, and then decrease once object was released. This is valid for all channels. This is further illustrated in Fig. 5. Almost all resulting EEG experiments look similar, however they follow an identical time domain patterns.

TABLE 1. Grasping Experimentation and Patterns Events Mapping using PCA.

Exper.	Participate X	Participate Y	EEG Classified Patterns & Association
EXPE-1	Motion	Grasping	Clusters 1,3
EXPE-2	Touch and Force	Touch and Force	Clusters 2,3
EXPE-3	Finger Move	Apply Force	Clusters 3,2

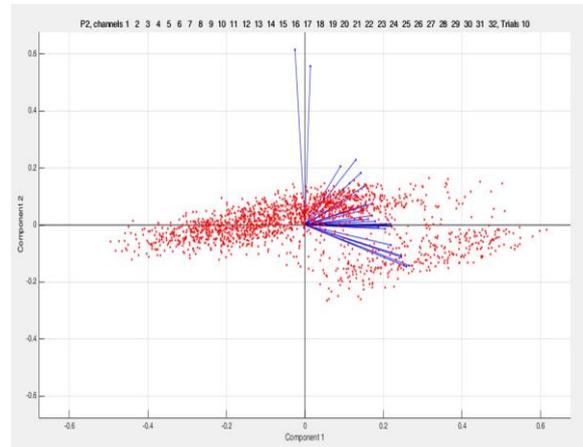
E. PCA Analysis of Individual Channels for Different Trials

Have performed a number of trails by different and same identical participates, now we shall create a relation between the PCA results, and the corresponding events. Thus, we shall detect the main features, they defined events during the grasp and lift trails. Such events features are important as they will help to define how grasping was performed by fingers.

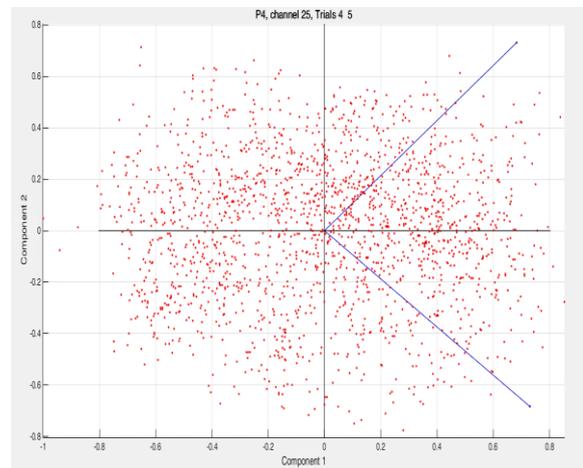
Now we shall do PCA analysis for same channel different trial, i.e. for all the signals patterns shown in Fig. 5. For example, look at PCA for P1. In reference to Fig. 6, it is also vital to indicate the requirement to establish the right mapping between capture waves features, and related actions.

This is indicated in terms of correlating the force and position sensors. Forces components corresponding to force/torque sensing, with axis directions corresponding to lift force and to gripping force. The neural waves recordings were also synchronized at the moment when fingertips had made contact with the object. This is further indicated and classified in Table 1.

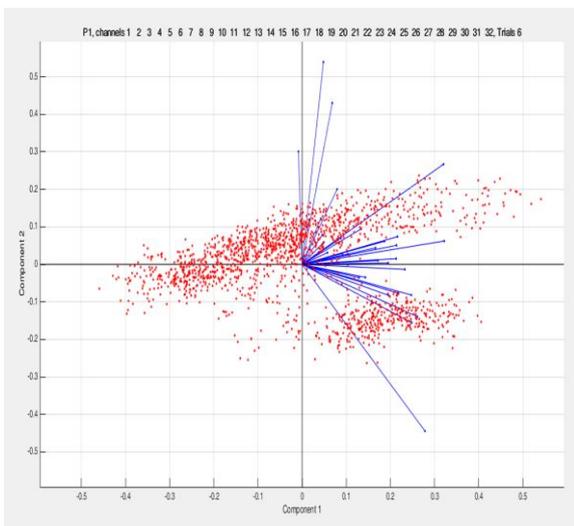
For each real grasping experiment, it was found the identical and similar EEG patterns that was detected by the locations of the clustered and gathered data of the recoding. In this context, the gathered PCA behavior do indicate the inherent knowledge about how the grasping was conducted. This knowledge is further decoded for generating the most suitable patterns of motorizing finger motion to be used for the robotic hand, or human type prosthesis. Fig. 6 shows the different PCA analysis for different trails/different participates. Definitely, it shows how the principle competent are related to other, even if the trails are different, or the individuals are diverse.



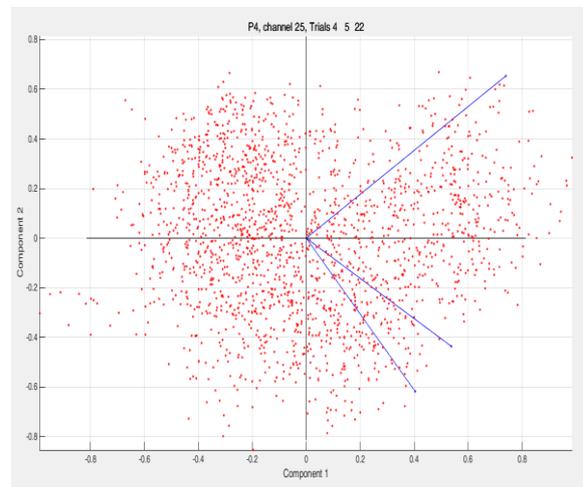
(ii)



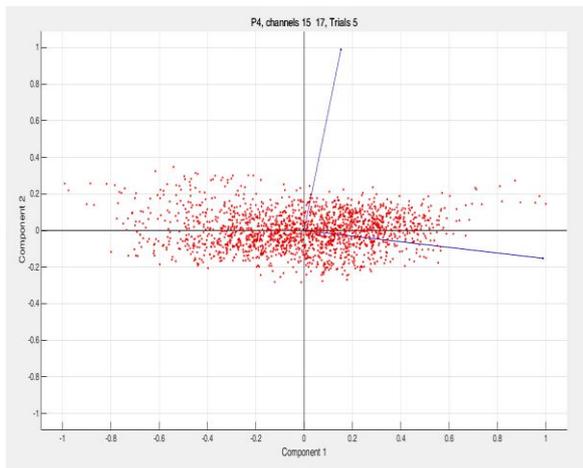
(iii)



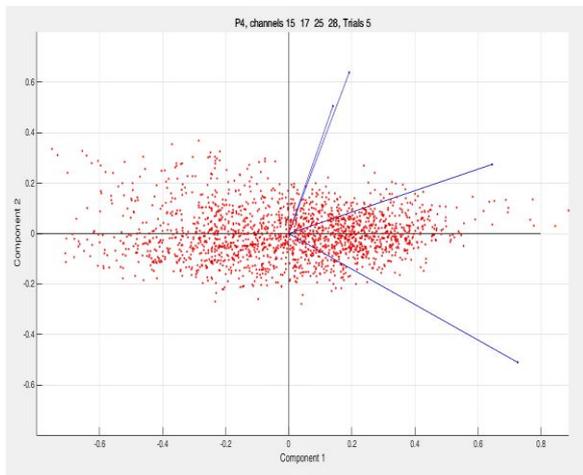
(i)



(iv)



(v)



(vi)

Figure 6. A number PCA analysis for a different trails, different channels, different participates. Results indicate how the PCA components are related to each other, even for different trails, for different participates.

(i,ii): PCA for the two repeated tasks by participants 1,2, and the PCA detected clusters during the grasp and lift task. For this particular cases, eigenvalues have plotted amount the directions of the eigenvectors. Although two districts cases of trails, but in terms of eigenvalues they are almost similar.

(iii, iv, v, vi), PCA detected clusters during the grasp and lift task for same trail, no. (9), for (different channels), trials 8 & 9 (same participant). Computing for the major eigenvalues, helps in finding the similar events, thought for different trails. The study has relieved that, despite the large number of experiments and nature of grasping by both gender, the features almost remain similar. This will help in designing a realistic grasping tasks for robotic hands.

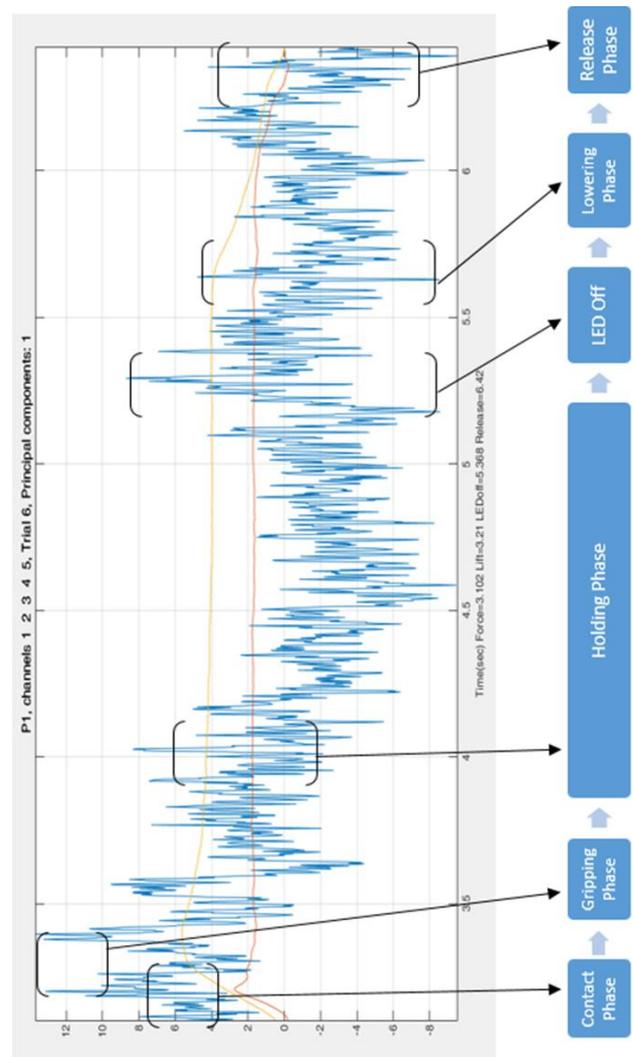


Figure 7. Projection of all the eigenvalues, and direction of eigenvector, as related to the time of events. Finding grasping features: Grasping events features extraction, looking at only first 5 channels.

In reference to Fig. 6, the two figures (i,ii) they show how the PCA for the two repeated tasks by participants 1,2, and the PCA detected clusters during the grasp and lift task. For this particular cases, eigenvalues have plotted amount the directions of the eigenvectors. Although two districts cases of trails, but in terms of eigenvalues they are almost similar. For the cases of figures (iii, iv, v), the PCA detected clusters during the grasp and lift task for same trail, no. (9), for (different channels), trials 8 & 9 (same participant). Computing for the major eigenvalues, helps in finding the similar events, thought for different trails.

Finally, while observing the main PCA components of all the related grasping experiments, we came to a conclusion that there are clear events related features for the grasping experiment. There were six main event feature, as seen from the PCA and eigenvalues related



values. These are presented in Fig. 7. In reference to Fig. 7, it is similarly vital to indicate the requirement to establish the right mapping between capturing waves features, and related actions. This is indicated in terms of correlating the force and position sensors.

Forces components corresponding to force/torque sensing, with axis directions corresponding to lift force and to gripping force. The neural waves recordings were also synchronized at the moment when fingertips had made contact with the object. This is further indicated and classified in Table 1. For each real grasping experiment, it was found the identical and similar EEG patterns that was detected by the locations of the clustered and gathered data of the recording. In this context, the gathered PCA behavior do indicate the inherent knowledge about how the grasping was conducted. This knowledge is further decoded for generating most suitable patterns of motorizing finger motion robotic hand or prosthesis. Knowing such main features for grasp and lift are to be transmitted from the human brain to the hand mechanics.

4. CONCLUSION

This study has introduced a computational approach for understanding the inherent and deep behavior of a set of raw brain waves during a task of human grasping, which is a grasp and lift experiment. The approach was based on using such resulting features that can be also used for robotic grasping applications. The study has used Principle Components Analysis (PCA) as a powerful tool to analyze and detect similar behaviors of the massive patterns of EEG brain-waves while grasping and lifting objects. PCA has also been used as dimensionally reduction tool for the resulting multidimensional EEG waves. Behaviors of EEG waves due to thinking, have been analyzed in a search for main event features, during grasping and lifting. The study has relieved that, despite the large number of experiments and nature of grasping by both gender, the features almost remain similar. This will help in designing a realistic grasping tasks for robotic hands. Eigenvalues for such similar data patterns, has detected six main features of events that have appeared, thus confirming the grasping and lifting event nature. Analysis of the resulting eigenvalues and direction of the vectors, PCA has been used to computationally identify a number of major events during and for large number of similar grasping tasks, achieved by similar participant, and different participates. In its current phase, the study has found that force and motion issues of such prosthesis and robotic hands, still remain the crucial problem that is to be looked into in depth. The next phase of this work will be also directed for the analysis of the resulting hidden waves due the fingers, and thus to compute the resulting grasping and directions of the forces and torques exerted by the different participates.

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