EEG Based Motor Imagery Study of Time Domain Features for Classification of Power and Precision Hand Grasps

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Abstract— **Grasping objects is one of the most important hand utilisation in everyday life. Due to neuromuscular ailments or injury, some people are unable to move their hands. Though myoelectrically controlled prostheses are widely available in the market, they require some muscle based control points which are hardly available for many. Motor Imagination (MI) controlled prostheses will surpass this shortcomings for them. However, restoring human grasping from MI is a challenging task. In this study, we have decoded two major types (Power and Precision) of grasping along with their three subtypes each from motor imagery. A comparative study of various time domain analysis combined with different classifiers is presented here to find an optimum choice of feature and corresponding classifier. It has been concluded that Hjorth parameters classified with kNN classifier have yielded the highest accuracy of 97.9% while separating different types of grasping from motor imagination.**

I. Introduction

In our daily life, when we grasp any object, we do not think regarding reaching the object or pre-shaping our hand. Finger posture is mainly depending on the geometric properties (e.g., shape, size, position) of the objects and task requirement. This overall process of grasping is controlled by our nervous system. But people with disabilities due to injury or ailments, are unable to make natural grasp. They have to depend on others for their activities of daily life (ADL). Restoring their grasping activity using EEG can provide them a self-sufficient normal life.

Based on requirements of task, grasp type is divided into two broad categories: Precision and power grasp [1]. In power grasping (holding a can), the object is grasped between fingers and palm, whereas, in precision grasping (holding a pen), tips of thumb and opposing fingers are used. In case of strength and stability of the grasped object, power grips are used but precision grasped is required for manipulability of the object.

People having very low or no muscle based control points or very high level of amputation are not capable of utilizing myo-electrically operated prosthetic hands [2]. Brain-computer interface (BCI) based control surpasses these difficulties by utilizing brain signals as the source of control signal. Movement Imaginations (MI) are decoded through BCI and neuro-prosthesis is used to generate the movement. Hand and fingers control in different stages of grasping has been studied for underlying kinematics and neural activities through exhibited neural spike modulations. Grasp aperture and finger movements while grasping, have shown promising possibilities to be decoded from intracortical exploration in monkeys. Furthermore, through electrocorticography (ECoG), individual finger kinematics are also decoded in humans with a classification accuracy of 88% for power and precision grasping [3].

In this study, we investigated the use of EEG signals for movement imagination of different hand configurations used to grasp house hold objects. Six different grasp types were performed and imagined by the subjects on a familiar object: Spherical (Ball), Cylindrical (Can), Tool Power (Screw Driver), Lateral Precision (Credit card), Tripod Precision (Pen) and Pinch (Coin). We studied whether the recorded EEG signals during this grasping task shown some significant changes for controlling prosthesis grasping. Signal components which provide information regarding grasping movements were also investigated. Various spatiotemporal and nonlinear features were evaluated for different sub-bands and compared the classification accuracies with KNN and SVM. The flowchart of this study is given in Fig. 1.

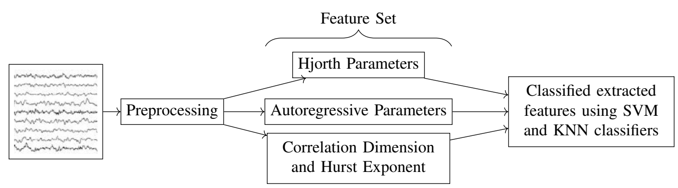

Fig. 1. Flowchart of the overall process.

II. Methodology

A. Subjects

Ten non-impaired right-handed subjects, aged between 20 and 27 years old were chosen. The subjects had no history of neuromuscular ailments. They were asked to perform as well as imagine grasping tasks with their dominating arm. None of the subjects were informed about the experimental procedure in prior to minimise biasness.

B. Task

The subjects were seated on an armchair in front of a table with their palms flattened on the table. Six objects were

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placed on the table in a semicircular manner near the right hand of the subject. The objects were chosen based on daily life grasping activities: obj1: ball (Spherical Grasp), obj2: can (Cylindrical Grasp), obj3: screw driver (Tool Power Grasp), obj4: card (Lateral Precision), obj5: coin (Pinch Grasp) and obj6: pen (Tripod Precision). Fig. 2 shows different grasp types for various shaped objects.

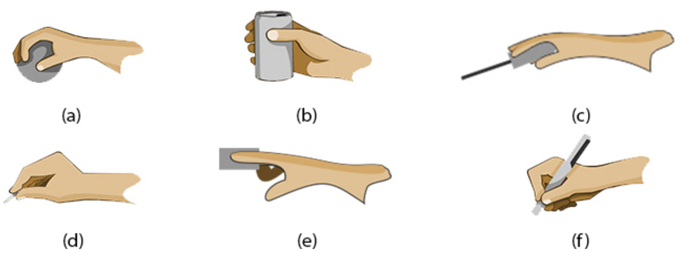

Fig. 2. Different types of hand preshaping for grasping. a) Spherical Grasp, b) Cylindrical Grasp, c) Power Tool Grasp, d) Lateral Precision, e) Pinch Grasp, f) Tripod Precision.

C. Experimental Paradigm

There were two different sessions in the experiment, one was for actual grasping of each object and the other was to imagine corresponding grasping actions. Each session contained four actions: 1. Relax the mind, arms and hands. 2. Perform grasp task. 3. Hold the grasped object and 4. Release. Through auditory cues, the subjects were given instructions. The experiment was performed in a sound proof room. Each subject performed 30 trials (5 trials per object) in a pseudorandom sequence generated by uniform sampling from the set of objects stated in Section B. After initial rest period of 10s, the subjects were presented with an audio cue to close the hand to grip the objects securely and holding them for 3s and releasing subsequently. Same procedure was repeated for imagination also. After each trial, the subjects were asked to rest while seated to avoid fatigue. Fig. 3 shows the timing of the stimulus.

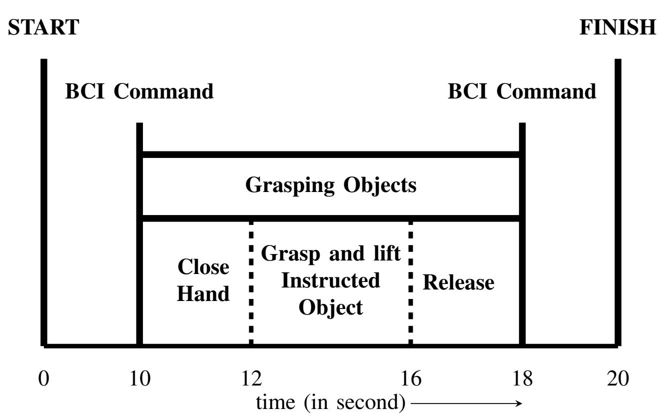

Fig. 3. Timing details for the visual stimulus.

D. EEG Acquisition

As previous studies suggest that frontal and sensorimotor regions are most likely to reflect motor planning and execution [4], EEG data of a normal subject were recorded at a sampling rate of 512Hz from positions FP1, FP2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, TP9, CP5, CP1, CP2, CP6, TP10, P7, P3, Pz, P4, P8, O1 and O2 by scalp electrodes placed according to the International 10-20 system. The reference electrode was placed to the right earlobe and the ground electrode (GND) was placed on the forehead (AFz) to form a feedback loop. The EEG recording was carried out using g.Hiamp (g.tec, Graz, Austria) hardware with 29 monopolar channels. 8th Order butterworth bandpass filter with 0.01 - 60Hz range and 50Hz Notch filter were added at the recording time to remove linear trends and electrical noise.

E. EEG Preprocessing

After referencing, both actual and imagined grasping signals were detrended and further processed for EOG and EMG artefact removal. As suitable EEG reference has great influence over sensitivity to artefacts and classification accuracy, Surface Laplacian [4] was applied for spatially filtering the EEG data with the mean of four next-nearest neighbouring electrodes for each electrode. Alpha, upper beta and gamma subbands were extracted from the preprocessed EEG data as they are already documented in literature to exhibit motor imagery [5], [6], [7]. FIR filters were used to these sub bands.

F. Feature Extraction

Various time domain features were extracted from the each sub-band(Alpha, Lower Beta, Gamma) of the pre-processed EEG as following:

1) Autoregressive Parameter: Autoregressive (AR) methods estimate the power spectrum density (PSD) of the EEG using a parametric approach. Therefore, AR methods provide better frequency resolution than nonparametric estimation. Estimation of the coefficients were calculated by Burg's Method [8].

However, selecting the proper model order is a critical to determine as high order will induce false peaks in the spectra and low order will produce smooth spectra. So, optimum model order (p) was chosen from the Akaike information criterion (AIC) figure of merit [9]:

$$AIC(p) = N.ln(\hat{\lambda^2}) + 2p \tag{1}$$

where N is the number of data samples and λ^2 is the estimated white noise variance. In this study, the order of AR parameters was calculated to be 12.

2) Hjorth Parameter: One of the most documented statistical property of EEG in the context of motor imagery is Hjorth parameters. Activity, Mobility and Complexity are the three kinds of parameters of it [10]. Surface of power spectrum is indicated by Activity parameter in frequency domain. Mobility parameter is a proportion of standard deviation of power spectrum. Complexity parameter shows the similarity of shape with a pure sine wave.

$$activity(x(t)) = var(x(t)) \tag{2}$$

$$mobility(x(t)) = \sqrt{\frac{activity(x'(t))}{activity(x(t))}} \tag{3}$$

$$complexity(x(t)) = \frac{mobility(x'(t))}{mobility(x(t))} \tag{4}$$

3) Correlation Dimension: EEG is a nonlinear dynamic system. Evolution in time of a nonlinear dynamic system could remain in the close neighbourhood of attractors. Complexity is the geometric property of attractors, whereas chaoticity measures the convergence or divergence of trajectories in phase space. Correlation Dimension (D_2) provides the attractor complexity to characterize the attractor. Here correlation dimension is utilised to study the difference in chaotic behavior of grasping imaginations for different shaped objects. To calculate correlation dimension, optimum lag for each EEG subbands were determined first from the first local minima of auto mutual information coefficient versus lag time plot. Afterwards, minimum embedding dimension was calculated by Cao's method [11]. Finally correlation dimension was computed by Taken's estimator considering radius (ϵ) as 10% of the size of lagged phase space [12].

$$\nu = -\left[\frac{2}{N_C(N_C-1)}\sum_{i=1}^{N_C}\sum_{j=1}^{N_C} log\frac{|Y_i(d_M)-Y_j(d_M)|}{\epsilon}\right]^{-1} \tag{5}$$

where $N_C(= N - m_0 d_M)$ is no. of points of the finite signal Y with optimum lag m_0 and embedding dimension d_M, $Y_i(d_M)$ and $Y_j(d_M)$ are i^{th} and j^{th} locations of lagged phase space and radius ϵ.

4) Hurst's Exponent: To explore the correlation of the data, we have calculated Hurst exponent (H)[13], estimated using Rescaled range analysis (R/S). This method was proposed by Hurst and well established by Mandelbrot, and Wallis. For a given set of data series, R/S is defined as:

$$\frac{R(n)}{S(n)} = \frac{max(0, W_1, ..., W_n) - min(0, W_1, ..., W_n)}{\sqrt{S^2(n)}} \tag{6}$$

where $W_k = x_1 + ... + xk - k\bar{x(n)}, \bar{x(n)}$ is the mean, $S^2(n)$ is the variance and n is the time span of the signal. Then we can get

$$\frac{R(n)}{S(n)} = Cn^H, as\ n \to \infty, C\ is\ a\ constant \tag{7}$$

The power H is defined as Hurst's exponent.

G. Classification

Decoded features from each subband were separately fed into multiclass K-nearest neighbours (KNN) and Support vector Machine (SVM) classifiers [14]. A 10-fold cross-validation were performed for both the classifiers.

III. Results and Discussions

Fig. 4 shows the EEG channel contribution towards the imagined grasp types during power and precision grasp types. It can be clearly seen that different level of activations in terms of power have been there for different grasping patterns. In case of precision grasping scalp position C3 and P3 show high activation. On the other hand, in power grasping, left hemisphere is whole together activated.

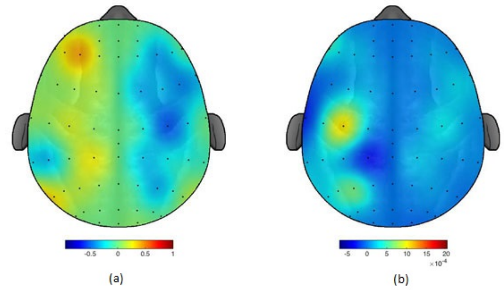

Fig. 4. EEG channel contribution for a)Power grasping, and b)Precision grasping

We have studied the EEG data for both actual and imagined grasping activity for a particular object. Power Spectral Density curves of actual and imagined grasping are compared in Figure 5. We can observe there exists correlations between actual grasping and the corresponding imagined one for a specific type of grasping.

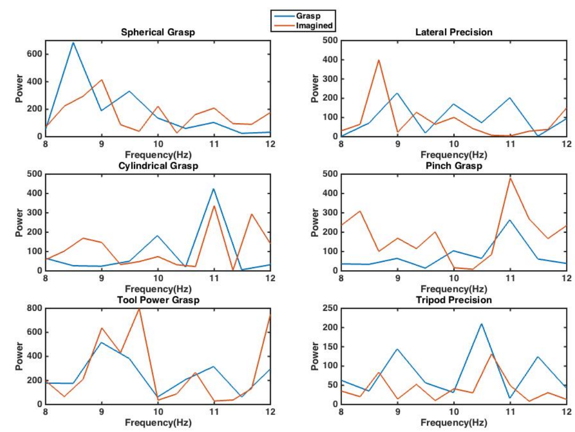

Fig. 5. Comparison between alpha (8-12Hz) PSD of actual and imagined grasping for different preshaping.

Fig. 6 shows the PSD from autoregressive parameters which exhibits promising contrast between different grasping patterns, namely, Precision Grasping and Power grasping. Power grasping has higher power distribution over Precision grasping. Furthermore, Pinch Grasp and Tripod Precision have very close trends which is very obvious due to similarity in the hand preshapings. For calculating correlation dimension, optimum phase lag was found to be 6 from auto mutual information coefficient plot and the corresponding minimum embedding dimension was found to be 4 from Cao's method as shown in Fig. 7. The Hurst's exponent was evaluated from the slope of the best fit curve from rescaled range analysis. Fig. 8 shows a sample of that curve for C3 electrode. Here the scatter points are the actual data points and the line is the best fit plot. The slope of this best fit plot is the Hurst's exponent.

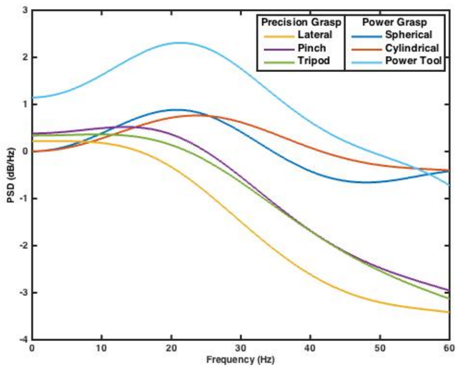

Fig. 6. Comparison of PSDs of AR parameter of C3 electrode for a particular subject

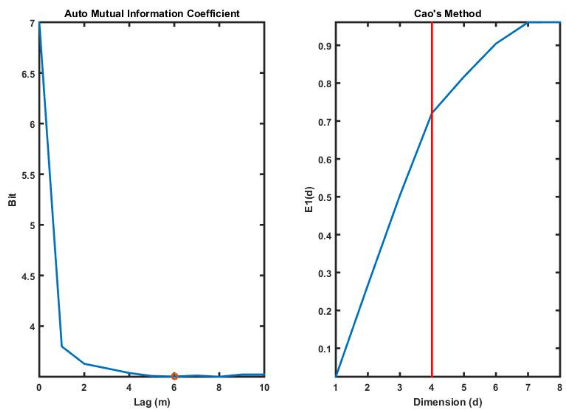

Fig. 7. Optimum Lag and Minimum Embedding Dimension of C3 electrode for a particular subject.

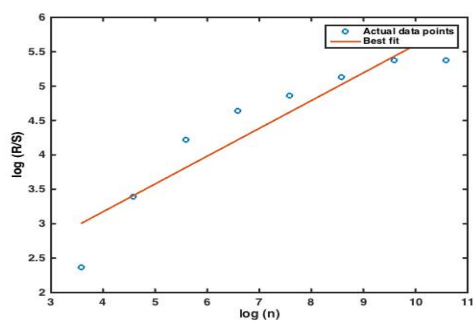

Fig. 8. Rescale Range Analysis of imagined spherical grasping for C3 electrode of a particular subject

All the features, were fed into classifiers separately. The accuracies for both the classifiers for each cases are shown in the Table I. We can see that SVM provides better accuracy in Hjorth parameters whereas kNN produces better accuracies in AR feature sets. Moreover, in case of AR features, Upper Beta (18-30Hz) exhibit promising distinction and Gamma (30-60Hz) also exhibit better distinction while considering Hjorth parameters. However, accuracy rates in case of nonlinear approach do not vary significantly for different classifiers. It can be concluded that imagination of preshaping of hand can be identifiable in higher frequency subbands of EEG.

TABLE I

CLASSIFICATION ACCURACIES FOR DIFFERENT SUBBANDS.

Features	Subbands	kNN	SVM
Hjorth Parameters	Alpha (8-12Hz)	69.0%	94.0%
	Upper Beta (18-30Hz)	80.0%	**97.9%**
	Gamma (30-60Hz)	88.0%	**97.9%**
Correlation Dimension & Hurst's Exponent	Alpha (8-12Hz)	61.2%	79.2%
	Upper Beta (18-30Hz)	89.7%	87.5%
	Gamma (30-60Hz)	90.0%	93.8%
AR Parameters	Alpha (8-12Hz)	96.0%	93.7%
	Upper Beta (18-30Hz)	91.3%	**97.9%**
	Gamma (30-60Hz)	**96.0%**	91.7%

IV. CONCLUSION

We have shown that decoding grasp types from EEG based motor imagination is possible with high accuracy. As grasping is a most important part of everyday human living, these results will benefit BCI to allow the paralyzed people to control grasping movements through imagination. High accuracy rates, achieved from the correct choice of feature set as well as classifier may lead to classification of other grasp types.

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