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Electroencephalography Based Dexterous Robotics Hand Grasping and Manipulation: A Short Review

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Abbreviations : PCA: Principle Components Analysis; ICA: Independent Components Analysis;

LDA: Linear Discriminant Analysis; ANN RBF: Radial Basis Function - Neural Net; FL C-Means: Fuzzy C-Means Knowledge Based Classification; SVM: Support Vector Machine

Introduction

In general context, robotics hands do play an important milestone towards achieving a much advanced and complicated robotic grasping. In parallel to this, robotic hand grasping and dexterous manipulation have been under focus for a while. This is also considered an essential step onward for performing advanced operations and tasks that are needed for current robotics use. Definitely, not always analytical approaches for finding the right set or optimal set of forces and wrenches for robotics hands will work, examples are found in Han et al. [1]. This issue also is much complicated while considering robotics hands with five digits (curling fingers applications). Use of electroencephalography (EEG) brainwaves for robotics applications, is also gaining a good ground recently. This is due to advancement of robotics applications. EEG data recording and analysis is much easier than before due to the advancement in technology related to neurology. In contrary to positive and advantageous use of EEG for robotic learning, EEG waves are such raw data, and the signalling behaviour are very complicated, correlated, related, and they are of such multi-rate waves. It is not a straight forward task to detect, decode, and understand these waves. There are key steps for using Electroencephalography for robotics grasping. Definably, there is electroencephalography Classification, Decoding and understanding. However, due to the massive, raw, coupled nature, and highly nonlinear nature of EEG data, there are a number of issues related to interpretation of these waves. While stating that, electroencephalography is also related to define tasks as human is achieving. Therefore, it is important to relate electroencephalography (EEG) with defined tasks.

Given the above mentioned EEG related issues, there are a number of analysis to be performed before using EEG for robotics applications, or for BCI in general. This involves EEG signal classification using a number of well defined techniques. PCA (*Principle Components Analysis*), ICA (*Independent Components Analysis*) ICA, LDA (*Linear Discriminant Analysis*), ANN RBF (*Radial Basis Function - Neural Net*), FL C-Means (*Fuzzy C-Means Knowledge Based Classification*), and SVM (*Support Vector Machine*). These techniques have shown interesting results in terms of the ability of were investigated by a number of classifying various features of EEG waves.

In this respect, Xiao & Ding [2] has achieved an evaluation of EEG features in decoding individual finger movements for a single hand. They tested three possible techniques to find the features that could be used in the future for finger control. First, they investigated the Spectral Principal Component (SPC) projections. Then, event related synchronization and desynchronization (ERS and ERD), and finally for temporal data. Testing was done on six individuals in a relatively isolated room and was done in timely manner to get the specific data needed. All the necessary EEG signal processing was done on the data to increase the SNR using temporal and spatial filters. The three EEG features in the same channels were decoded using support vector machine (SVM) technique that analyzes the data and finds patterns associated with the different fingers. The accuracy of the decoding was measured between all the EEG features used and the guess level. The results showed that the PC projections using first three spectral PCs showed the highest average accuracy at (45.2%).

In Cerný & Štastný [3], they have achieved an application of common spatial Patterns on classification of the right hand finger movements from EEG Signal. In this context, the paper used common spatial patterns (CSP) for the classification of the thumb and little finger. This procedure processes the multivariate signal and converts it to additive subcomponents. It was accomplished that using a combination of different spatial filters for different band yields the best results. The spatial filter used mu or beta bands for training. Comparing the CSP with the Laplacian filter yielded marginally better results in terms of classification score (63.8% ± 5.2% vs. 61.9% ± 6.9%). Most subjects scored better with CSP and some subject scored better with Laplacian. However, when considering speed of BCI the CSP was faster during EEG classification. This was due to the fact that Hidden Markov Models (HMM) training only needs to be done two times with CSP as opposed to Laplacian which needs training for all of the electrodes used. In contrary to previous research and earlier studied, Agashe in [4] has achieved the decoding the evolving grasping gesture from electroencephalographic (EEG) activity. In contrary to the earlier projected papers, this work focuses on the type of grasping the user intends to do when manipulating different daily objects. This is a vital part for having a prosthetic hand that replaces a human hand.

Previous studies mainly focused on invasive techniques such as ECoG to extract the intended grasping method. This paper tried to implement similar techniques but using EEG. Since earlier studies found that low-pass filtered ECoG (local motor potential LMP) shows precise features, they low pass filtered EEG signals. This was used as the basis for decoding continuous hand kinematics when grasping. The paper focused on five different types of grasping when trying to grasp objects. To collect the data, the participants were asked to reach and grasp some objects within their proximity and then return them to initial position. The study was able get near optimal method using EEG-predicated PC1 and PC2 trajectories on recursive Bayesian method with EEG-predicated PC1 and PC2. This technique was computationally efficient and demonstrated the feasibility of real time application by getting information before movement on set as well as decoding data in less time than the data duration. However, the algorithm needed a relatively long time to complete (10-15min). Also, some misclassification happened with similar grasps.

Agashe et al. in [5], they proposed a global cortical activity predicts shape of hand during grasping. In this context again, this paper is similar to previous one in terms of decoding hand grasp by recording EEG signals of people trying to grasp everyday items and returning them. However, this paper actually implemented their technique on an amputee using hand neuroprosthesis. This paper uses EEG signals, hand joints angular velocities, and synergistic trajectories recorded during reach to grasp movement to predict hand grasping. Based on the recorded data, the joint angle velocity and synergy spaces of the hand trajectories was reconstructed. Linear regression model was used for decoding. The grasping showed to affect mainly the power of the 0.1-1Hz band. This inherently meant that the EEG data had to be low-pass filtered at 1Hz. Decoding accuracy between the predicted and actual movement for all 15 hand joints was r =0.49±0.02 where r is the correlation coefficient. All of the information was used in a closed loop system that was used by an amputee. After proper training the amputee was able to get 80% success rate for over 100 trials. The amputee imaged reaching and grasping the objects and the neuroprosthesis was used to implement the grasping. The research was able to use simple linear models to decode the hand grasping just like the previous study since these models have shown to have high accuracy. This study was able to prove in real time application the accuracy of the system.

Liao et al. in [6], they studied the decoding individual finger movements from one hand using human EEG signals. This paper tried to decode individual finger movement. They used the findings from previous ECoG and implemented them using EEG and compared the results with the ECoG results. In six seconds they had to do specific things. For the first two seconds they had to get ready for to be still while the screen is black. Next, resting data was recorded while the subjects were looking at a fixation on the screen for two seconds. For the final two seconds a random word describing the finger to be moved twice appeared on the screen. The EEG data was subjected to power spectrum analysis to be able to extract the features. Mainly principal component analysis (PCA) and power spectrum decoupling. To demonstrate the decoding accuracy, they decoded all pairs of fingers movement in one hand. They achieved an average accuracy of 77.17%. They implemented similar techniques on ECoG signals and achieved 91.8% accuracy. The results achieved here are better than many other studies especially to the one with single bands (alpha, beta, and gamma). These are promising results since they decoded pairs of fingers which is a harder task.

Hazrati & Erfanian [7], have shown results for an online EEG-based brain–computer interface for controlling hand grasp using an adaptive probabilistic neural network. The subjects were naïve and had no experience. The subjects had to relax to keep a virtual hand open and the imagination of grasping will make the hand grasp. At first the hand was open, then a ball started falling and the subjects tried to grasp the ball. When the ball gets held it will change color and then the hand was finally opened. The subjects received feedback from the first parts of the experiments to be able to train an online classifier without offline data. Adaptive and static classifiers were also employed. The adaptive is the one that uses the online training while the static uses the already trained classifier. For the classification, an adaptive probabilistic neural network (APNN) was used to handle the variabilities in everyday

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brain signals. In this respect, the classification accuracy was (75.4%) for first session and (81.4%) for the second session. Such result were obtained while using online training. For the third and eighth session, the accuracy was (79%) and (84%) respectively, these were done using the already train classifier. This definitely indicates that the ERS/ERD patterns are better after the consecutive sessions of training. The classifier is shown to be robust in time-varying and non-stationary environments. Static classification gave consistent results. The adaptive classifier improved the results and the resulting classifier gave the same results when used in the static scheme.

Previous analysis does show a new trend towards the use of EEG for teaching robots cognitive movements, and not to rely solely on the classical ways of programming robotics systems. Using Electroencephalography to teach robots the right movements is a new challenge; however, there are still a number of not solved problems in this context. A major issue is entirely related to not to rely on online learning, however, the challenge is to move towards off-line of EEG based learning. This means that to synthesis movements of robotic fingers and hand dexterous grasping, even in an absence of human online simultaneous learning.

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