Vol. 7(26), Oct. 2017, PP. 3595-3609

Contents list available at IJMEC

International Journal of Mechatronics, Electrical and Computer Technology (IJMEC)

Journal Homepage: www.aeuso.org

PISSN: 2411-6173 - EISSN: 2305-0543

# Telemanipulation of a Robotic Arm using EEG Artifacts

Kamal Sharma[1], Dr. Neeraj Jain[2], Dr. Prabir K. Pal[3]

[1&3] *Division of Remote Handling & Robotics, Bhabha Atomic Research Centre, Mumbai, India*

[2] *National Brain Research Centre, Manesar, India*

***Corresponding Author's E-mail:** kamalf45@gmail.com*

## *Abstract*

There has been extensive research in the field of Brain-Computer Interfaces (BCIs) and the field is continuously evolving in order to provide an easy to use interface for people with motor or other disabilities. The implementation of non-invasive BCIs using Electroencephalography (EEG) signals requires considerable signal processing to decode the brain signals as well as extensive training of the user. The Electromyography (EMG) signals produced from eye blinks, teeth clenching, etc are regarded as artifacts in EEG signals and are easy to generate and decode. This paper presents use of teeth clenching and eye blink 'artifacts' for an intuitive and easy to use control of a robotic arm in three dimensions to perform a pick and place task. Efficiency of the proposed technique is compared with a standard telemanipulation technique using a haptic device. Decision trees were used to adapt the technique for different operators.

***Keywords:*** *Electromyography (EMG), Electroencephalography (EEG), Brain Computer Interface (BCI), Blink, Teeth Clench, Decision Tree.*

## 1. Introduction

A Brain-Computer interface provides a direct pathway between brain and an external device. This is of great help for people with motor disabilities and allows them to control devices such as a prosthetic limb, a wheelchair or some other external device just by using their thoughts. The electrical activity of the brain can be conveniently captured non-invasively using an Electroencephalography (EEG) cap. The EEG cap has a number of electrodes placed over the scalp, over different brain regions. There have been various BCIs that use EEG signals as in [15], [11], [14], [12]. The EEG signals have poor spatial resolution, and each electrode captures a mix of neuronal activities from different brain regions. The BCIs using EEG signals thus need extensive signal processing so as to separate meaningful EEG signals from the mixture signals. Then the best features need to be extracted that correspond to different thoughts in the brain. Finally some classifier is trained using those features so as to predict in real-time the thought in the brain. None of the classifiers that have been used is able to accurately decode the brain signal with 100 percent accuracy, which is partly due to low SNR of EEG signals. The user needs to spend a good amount of time over training so that proper EEG signals could be generated in real-time for control of an external device.



***Article History:***

**Received Date: May. 19, 2017**
**Accepted Date: Aug. 03, 2017**
**Available Online: Oct. 01, 2017**

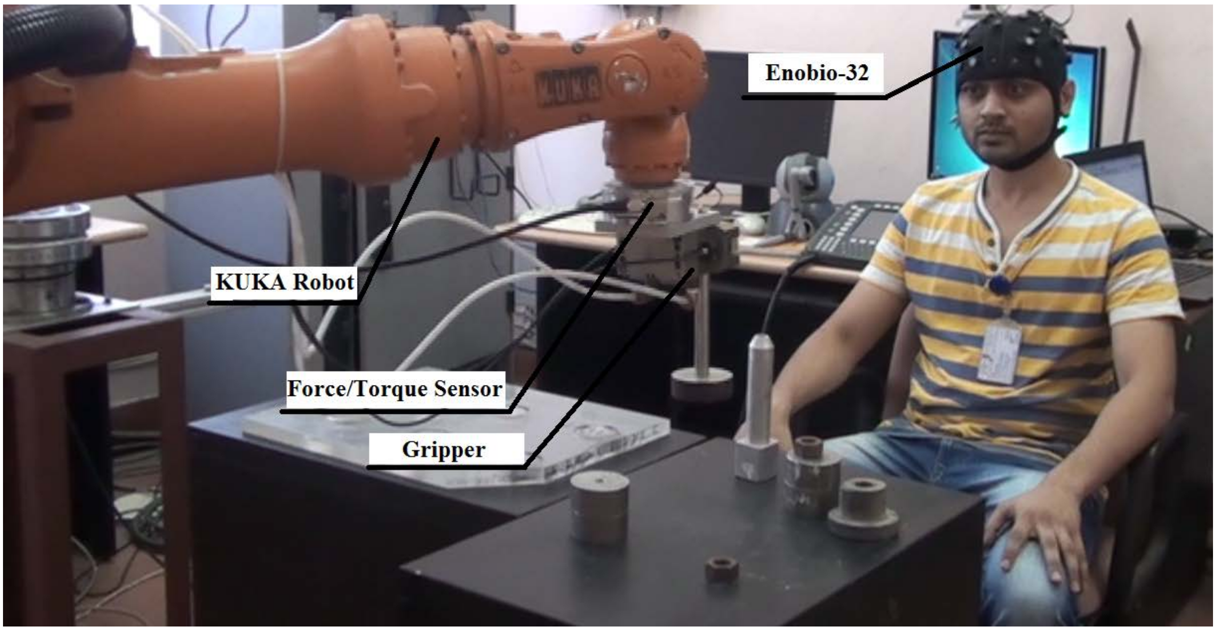



**Figure 1:** Experimental setup

The electromyography (EMG) signals in the head are generated from various activities like teeth clenching, eye blinks, etc. These signals have higher SNR as compared to EEG signals and are captured by the EEG electrodes as EEG artifacts. These artifacts are easy to detect and require almost no training for their generation. These signals have been variously used for aiding a BCI or for some full-fledged control. The eye-blinks have been used for home automation [5] and a wheelchair control [1] and [9]. Teeth clenching has been used for indicating termination of a task in BCI-assistive drinking [10], for cursor control and mouse clicks [2], and for bi-directional robotic arm control [3]. Generally, the EEG artifacts have been used either as a switch or as a motion command with pre-fixed step sizes in a particular direction. This discrete nature of such mappings makes the control less-intuitive to use.

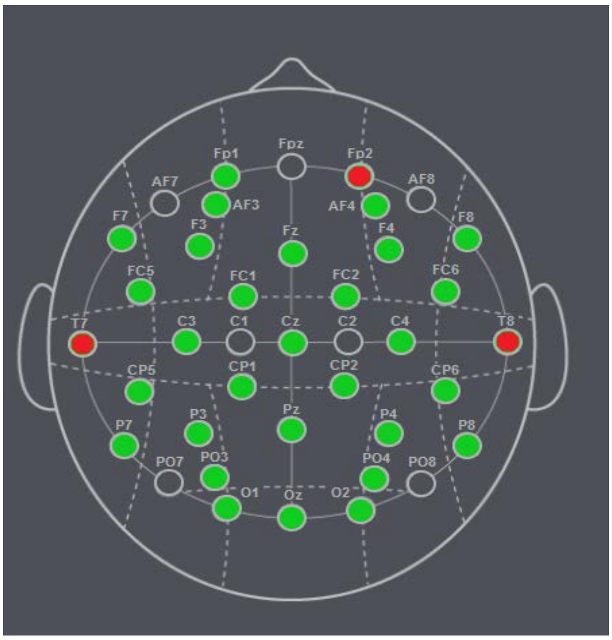



**Figure 2:** Electrode Montage for Enobio-32
(Electrodes used in this work are shown in Red)

This paper suggests an intuitive way of using EEG artifacts for a robotic arm control in three dimensions to perform a pick and place task. Here, we map the teeth clenching intensity to the speed of the robot giving a sensation of continuous control of the robotic arm. Only three electrodes (other than ground and reference) were used for the detection of EEG artifacts. A decision-tree based training and classification method was used to adapt various parameters specific to an operator. As a safety add-on, a force-control feature was added to avoid any collisions of the robot with the environment during motion. Section 2 of this paper describes the experimental setup used. Section 3 discusses the techniques used for mapping EEG artifacts for teleoperation of the robotic arm. Section 4 presents the experimental results obtained. The paper is finally concluded in Section 5.

## 2. Experimental Setup

The overall setup is shown in Figure 1. We have used Enobio-32 system from Neuroelectrics for the acquisition of EEG signals. It is a 32-electrode system with both dry as well as gel-based EEG Electrodes. Here, we have used the dry electrodes for teeth clenching and gel-based electrode for eye-blink signals (since eye-blink signals were captured at the forehead, where gel-based electrode was found to be more comfortable as compared to the dry one). The system has a sampling rate of 500 Hz. It can transfer the signals to a computer via Bluetooth. We have used three electrodes T7, T8 and Fp2 (shown in Red, Figure 2) to acquire the EEG data. Also the Driven Right Leg (DRL) and the Common Mode Sense (CMS) electrodes are put on the right earlobe for reference purpose.

For telemanipulation, a KUKA KR-6 ARC robotic arm is used which is a 6-degrees of freedom industrial robot capable of performing pick and place operations in a 3-D world. The robot is fitted with a Schunk pneumatic two-finger gripper. An ATI 6-axis force/torque sensor is mounted on the robot wrist to measure the forces generated when the robot interacts with the environment.

Four healthy male subjects (age between 25-35 years) were involved in the final experiments.

## 3. Robot Telemanipulation with EEG Artifacts

The Enobio-32 system records the EEG activity from the scalp. The EEG signals get mixed with the artifacts generated from various muscle activities like Eye-Blinking, Teeth-Clenching, etc. These artifacts are easy to generate deliberately with little training. These artifacts are generated due to the activity of Frontalis and Temporalis muscles as explained in [6]. The Eye-Blinks can be captured easily by one of the frontal electrodes. We chose Fp2 electrode for capturing the eye-blinks. The teeth clenching can be done either

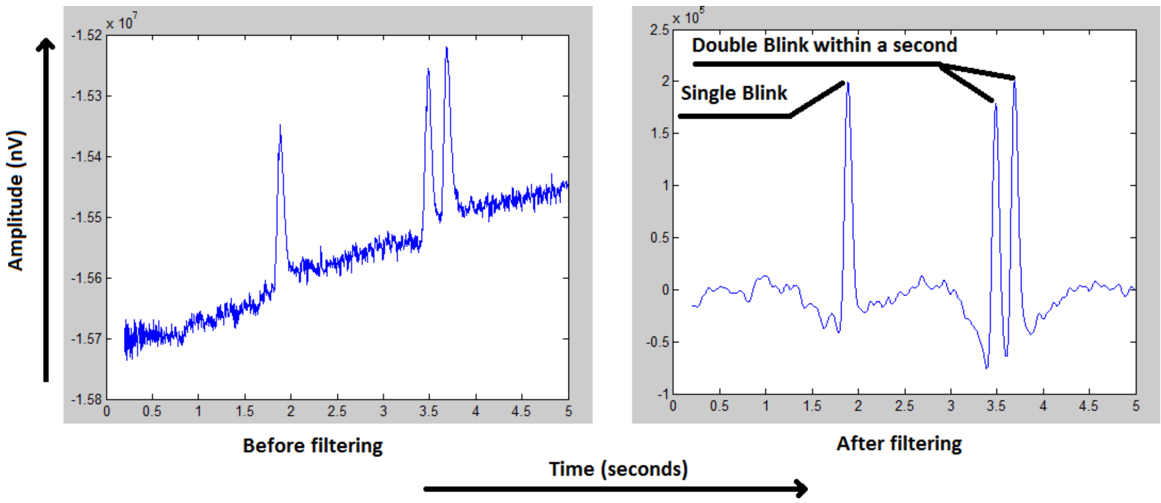



**Figure 3:** Filtered eye-blinking signal before and after filtering (Electrode Fp2)

**Table 1:** Thresholds for blink detection

| Subject | Threshold for Experiment 1 (nV) | Threshold for Experiment 2 (nV) |
|---|---|---|
| K | 0.7*10^5 | 0.7*10^5 |
| A | 0.7*10^5 | 0.7*10^5 |
| R | 0.7*10^5 | 0.7*10^5 |
| D | 0.6*10^5 | 0.7*10^5 |

with left half or the right half of the jaw. The signals for left teeth clenching are captured using the electrode T7 and the signals for right teeth clenching are recorded using the electrode T8. The premolar and molar teeth were mainly used to generate the clenching signals. Following subsections discuss the processing of eye-blink and teeth clenching signals.

### 3.1. Eye-Blink Signals

In our setup, the eye-blink signals are recorded using electrode Fp2. The data is acquired every 1 second. The signal is first filtered through a Butterworth band-pass filter with lower cut-off at 0.75 Hz and upper cut-off at 10 Hz. The output before and after filtering is shown in Figure 3 which shows a single blink as well as two consecutive blinks within a second. In the filtered data, first the peaks are detected. The peaks are defined as locations where sign of the slope changes from positive to negative. Thereafter, a peak is classified as a blink if the difference between its amplitude and the average signal amplitude is greater than a threshold. The threshold, which is subject specific was set for a particular user after analyzing training data recorded for him. The threshold values for the experiments carried out in this paper are reported in Table 1.

We have used the double-blink as a switch for selection of an axis of motion for the robot. Using double-blink, the user can alternate between x, y and z axis of the robot motion as shown in Figure 4, e.g. if the user is moving the robot in x-axis, the user can select y-axis by performing a double-blink. The next double-blink will choose the z-axis for robot motion and so on cycling among the axis.

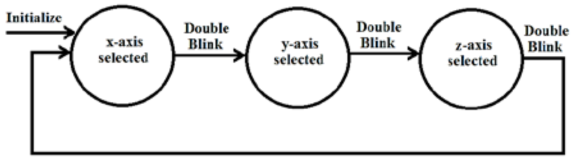



**Figure 4:** Robot axis selection using Double-Blink

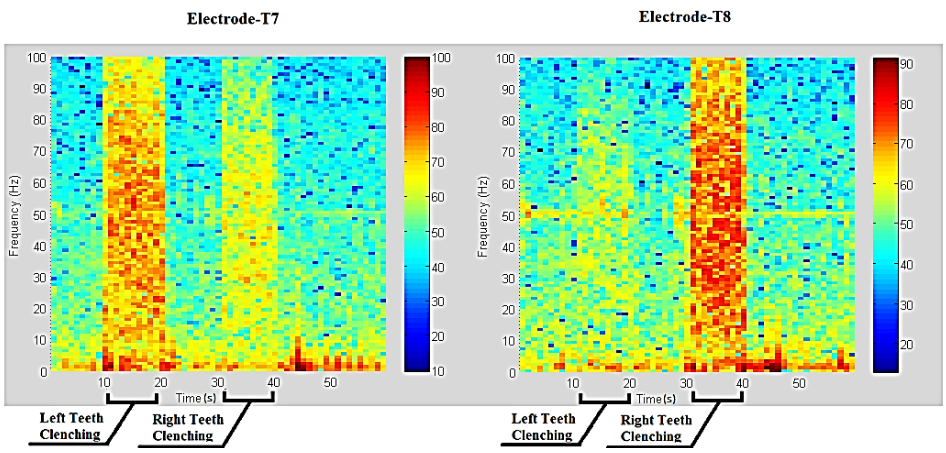



**Figure 5:** Spectrograms for teeth clenching signals



International Journal of Mechatronics, Electrical and Computer Technology (IJMEC)
Universal Scientific Organization, www.aeuso.org
PISSN: 2411-6173, EISSN: 2305-0543

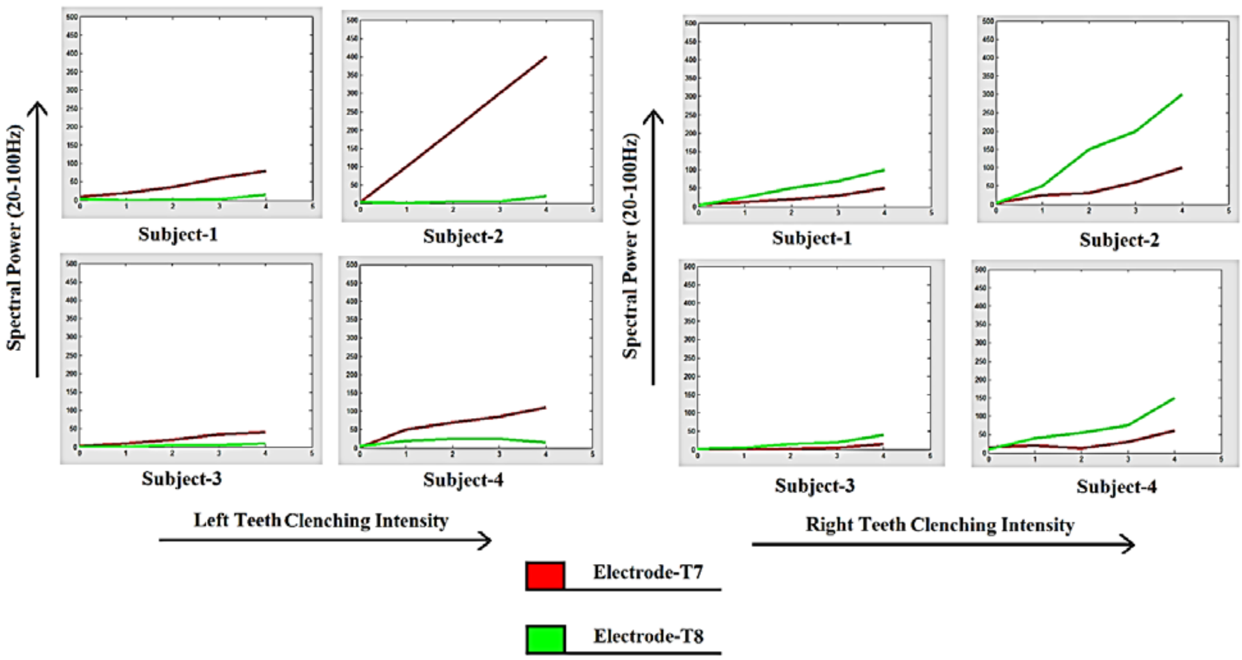



**Figure 6:** Variation of Spectral Power with Intensity of Clenching

### 3.2. Teeth Clenching Signals

In our setup, the teeth clenching signals are recorded using electrodes T7 and T8. The left-side teeth clenching generates dominant signals in T7 whereas the right-side teeth clenching generates dominant signals in T8 as can be seen from the spectrogram of the recorded signals in Figure 5. From the observations, we chose the frequency range of 20-100Hz and found that the intensity of teeth clenching affects this frequency range proportionally i.e. the power of frequency components in the range of 20-100 Hz increased proportionally with the intensity of teeth clenching (observed qualitatively) which is also mentioned in [6] and can be seen in Figure 6 where we asked the subjects to perform left and right clenches of 4 varying intensities (the clench level 0 indicates rest or no clench, level 1 indicates a light clench and so on up to level 4 for the hardest or full clench, for a particular subject). The quantitative analysis of clenching force and the EMG signals is made in [4], which also suggests a linear relationship between the two.

From this observation, we tried to map the intensity of clenching to the speed of the robot in a chosen axis as explained under.

The signals were recorded from T7 and T8 for 1 second and the discrete fourier transform (DFT) of the signals was taken. The absolute values of DFT components in the range 20-48 Hz and 52-100 Hz were summed up (the range of 48-52 Hz is left out to avoid the line noise at 50 Hz) to get the intensity of clenching ($I$). The range of values of $I$ is linearly mapped onto the robot speed. The clenching intensity for T7 ($I_{T7}$) is used to control the robot's speed in the negative direction of the axis selected and the clenching intensity for T8 ($I_{T8}$) is used to control the robot's speed in the positive direction of the selected axis. Thus, if the x-axis of the robot is selected (using double-blink as explained in the previous section), where the robot can be moved left or right, the user can clench left half of the teeth to move the robot in left and right half of the teeth to move the robot in right direction. Moreover, the intensity of clenching will decide the robot's speed. This kind of speed mapping helps to efficiently perform the pick and place operations since the robot needs to be moved longer distances when reaching an object from a far-off position but it needs to be moved slowly and accurately when grasping the object and placing it. This is quite possible with a speed mapping as done here.



International Journal of Mechatronics, Electrical and Computer Technology (IJMEC)
Universal Scientific Organization, www.aeuso.org
PISSN: 2411-6173, EISSN: 2305-0543

The gripper is actuated when both $I_{T7}$ and $I_{T8}$ cross a threshold value i.e. when left as well as right teeth are clenched (full jaw teeth clenching). Such a clenching toggles the current state of the gripper i.e. if the gripper is open, full teeth clenching will close it and if the gripper is closed, full teeth clenching will open it. This

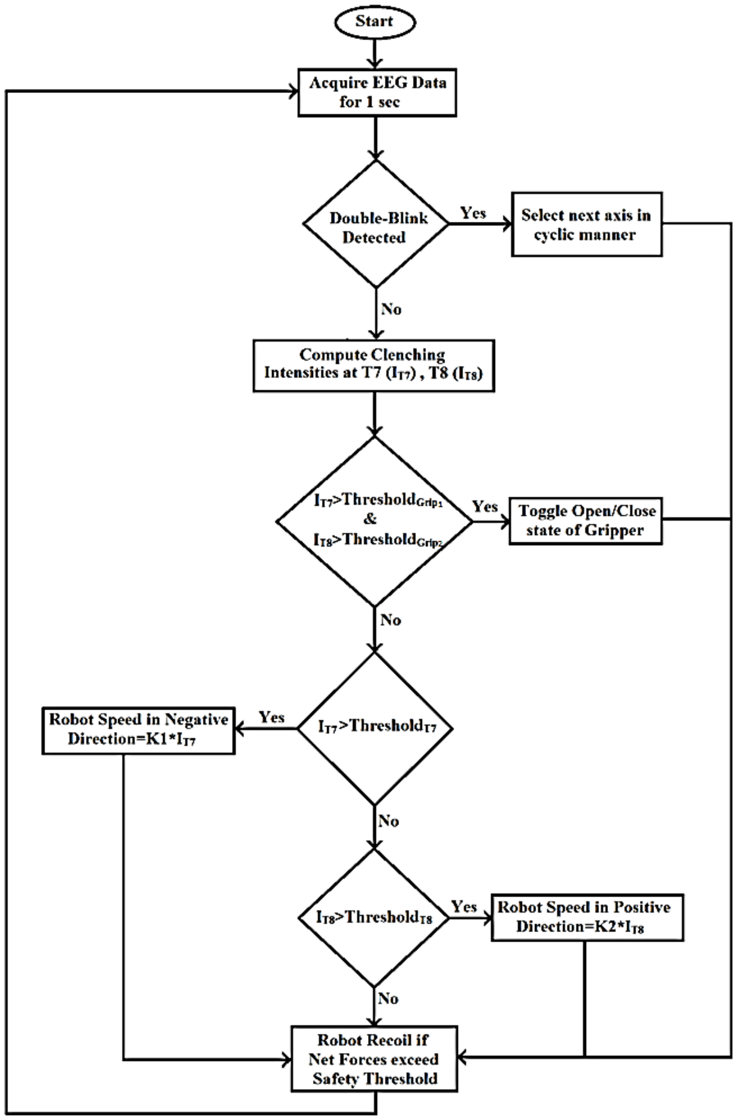



**Figure 7:** Flowchart for Telemanipulation using EEG Artifacts

methodology can be implemented as presented in Figure 7. From Figure 7, we can see that the actuation of the robot and the gripper depends upon various thresholds. We can also see from Figure 6 that the intensities of clenching vary among different subjects and hence the thresholds would be different for different subjects. To compute these thresholds and automatically incorporate them in the robot control program, we used a decision tree based training and classification technique which is explained in the next subsection.

### 3.3. Training and Classification

A decision tree was used to learn the different clenching thresholds and classify the clenching signals into rest (no-clench), left clench, right clench or a full clench. For training, a subject was shown a screen where a command appeared as either rest or teeth clench (left, right, full or no-clench (rest)). The subjects were asked

**Table 2:** Classification accuracies for different subjects

| Subject | Classification Accuracy (%) |
|---|---|
| K | 100 |
| A | 92.5 |
| R | 82.5 |
| D | 100 |

to perform the clenching with varying intensities. The rest command appeared for 1 second and after that the clench command appeared. The recording of clench signals starts after 0.5 second of clench command and lasted for 1 second. Hence, one recording was complete in 2.5 seconds. In this manner, total 20 recordings were taken for each type of clench command thereby making total 80 recordings. Hence, one training session lasted for 200 seconds or 3.3 minutes.

From these recordings, the clenching intensities $I_{T7}$ and $I_{T8}$ were computed as discussed in 3.2. It was found that the ratio of these intensities was helpful to classify full-clench. Hence the ratio was also used for the training purpose. The training data looked like ( $I_{T7}, I_{T8}, \frac{I_{T7}}{I_{T8}}$, label), where the label was 1 (left clench), 2 (right clench), 3 (rest or no-clench) or 4 (full clench). This set of data for a particular subject was used to train a decision tree using Gini index for the splitting criterion [7]. This training was done for 7 subjects and a set of test data was used to measure the classification accuracy. For a training set of 80 recordings, another set of 40 recordings was recorded as the test data. The 4 subjects with classification accuracy>80% were involved in the final experiments. The classification accuracies for the 4 final subjects are shown in Table 2. The confusion matrices for the 4 subjects are shown in Figure 8.

Predicted (columns), Actual (rows)

| n=40 | Left Clench | Right Clench | Full Clench | Rest |
|---|---|---|---|---|
| Left Clench | 10 | 0 | 0 | 0 |
| Right Clench | 0 | 10 | 0 | 0 |
| Full Clench | 0 | 0 | 10 | 0 |
| Rest | 0 | 0 | 0 | 10 |

Subject K

Predicted (columns), Actual (rows)

| n=40 | Left Clench | Right Clench | Full Clench | Rest |
|---|---|---|---|---|
| Left Clench | 10 | 0 | 0 | 0 |
| Right Clench | 0 | 7 | 3 | 0 |
| Full Clench | 0 | 0 | 10 | 0 |
| Rest | 0 | 0 | 0 | 10 |

Subject A

Predicted (columns), Actual (rows)

| n=40 | Left Clench | Right Clench | Full Clench | Rest |
|---|---|---|---|---|
| Left Clench | 7 | 0 | 1 | 2 |
| Right Clench | 0 | 6 | 3 | 1 |
| Full Clench | 0 | 0 | 10 | 0 |
| Rest | 0 | 0 | 0 | 10 |

Subject R

Predicted (columns), Actual (rows)

| n=40 | Left Clench | Right Clench | Full Clench | Rest |
|---|---|---|---|---|
| Left Clench | 10 | 0 | 0 | 0 |
| Right Clench | 0 | 10 | 0 | 0 |
| Full Clench | 0 | 0 | 10 | 0 |
| Rest | 0 | 0 | 0 | 10 |

Subject D

**Figure 8:** Confusion matrices for different subjects

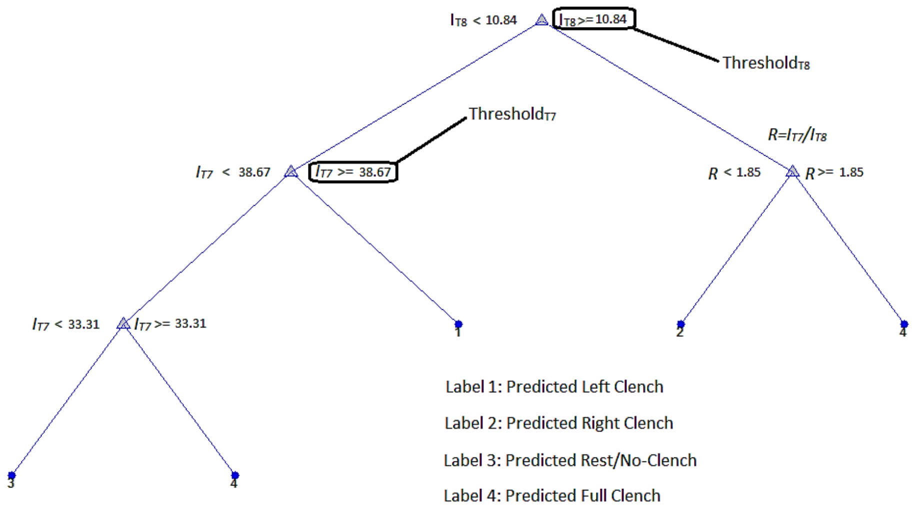



**Figure 9:** Decision tree for one of the subjects

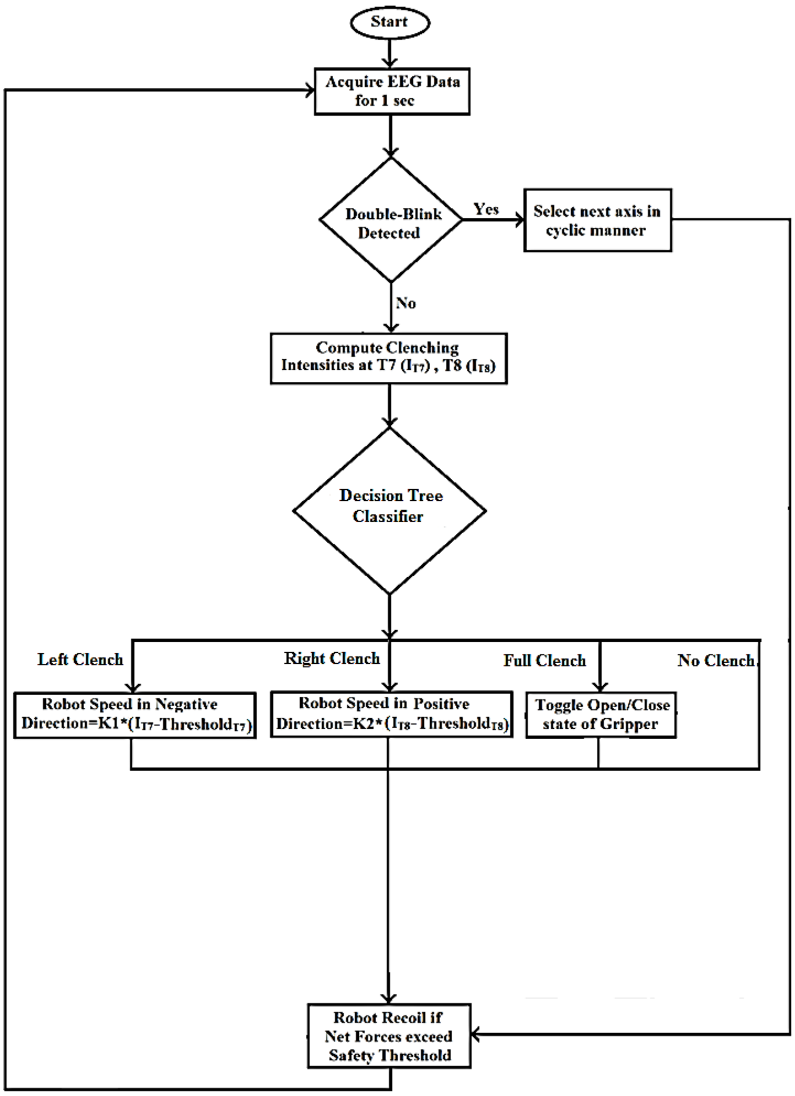



**Figure 10:** Final methodology for telemanipulation using EEG artifacts

The wrong classification of a rest into a clench is dangerous as it would lead to motion of the robot without the operator's intention. We can see from Figure 8 that there are no such wrong classifications of rest into a clench. Also, the wrong classification of some input into a full clench can lead to opening or closing of the gripper while carrying some object. This may lead to falling of the object. To minimize this, we added logic such that any classification into full clench would lead to opening/closing of the gripper only if the two earlier classification states were rest (no-clench). This means that the robot is in rest since last two time instances. Hence this avoids opening/closing of the gripper during motion.

A decision tree for one of the 4 subjects is shown in Figure 9. We can see that the tree learns various thresholds for a particular subject and classifies the signals into left, right, full or no clench. For the speed-control of the robot, we need access to the thresholds. These thresholds were extracted from a decision tree as shown in Figure 9. The minimum value of $I_{T7}$ that qualified as left clench (label-1 in Figure 9) was taken as $\text{Threshold}_{T7}$ (Figure 7). Similarly, $\text{Threshold}_{T8}$ was extracted from the decision tree. The final methodology for control of the robotic arm using the decision tree is shown in Figure 10.

A force control feature was added as a safety add-on to the robot as in [13] so that any accidental collision of the robot is avoided with objects in the environment. With the help of force/torque sensor mounted on the robot's wrist, the force values were monitored continuously. If the force exceeds a threshold, the robot temporarily overrides the user's program and recoils in the direction of the net force. This is quite useful for pick and place operations.

## 4. Experiments

Two different experiments for the robotic arm control were carried out with the 4 subjects as discussed in the next subsections.

### 4.1 Graphical User Interface

A GUI (Figure 11) was provided to the operator for controlling the robotic arm. The GUI shows the currently selected axis, gripper status, net force observed at the robot's end-effector and the clenching intensities for left and right teeth. The intensities are converted into motion command by multiplying them with a proportionality constant (after subtracting the thresholds as shown in Figure 10). These constant multipliers for left teeth and right teeth clenching can be adjusted using the GUI.

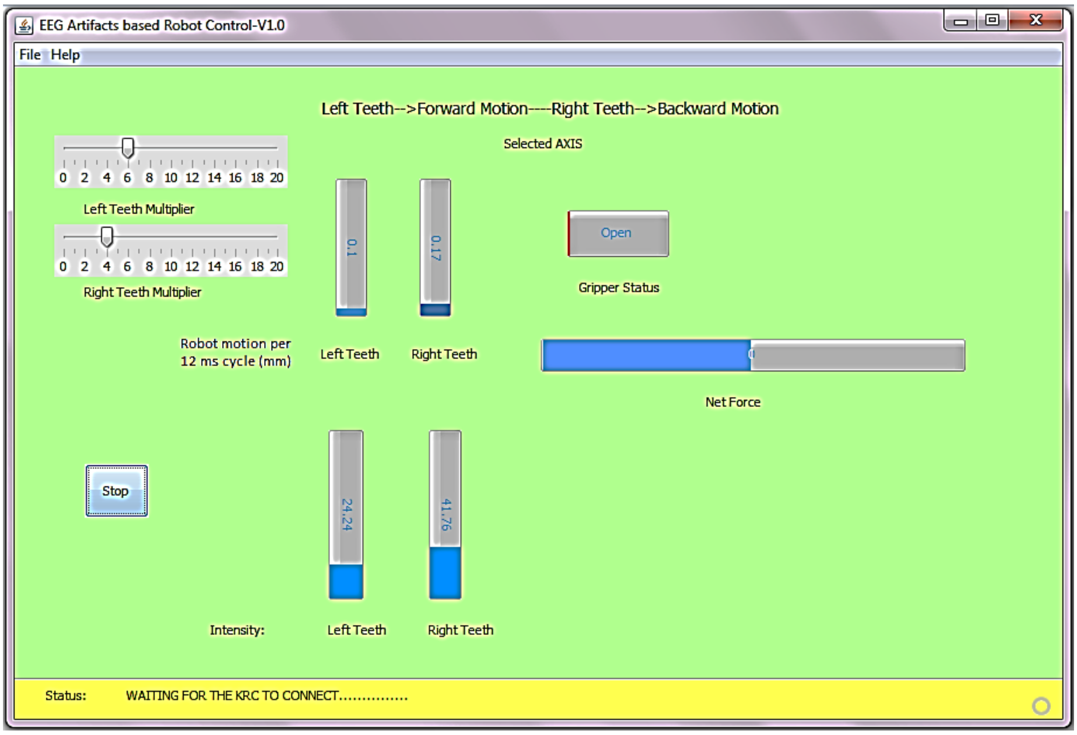



**Figure 11:** GUI for telemanipulation of the robotic arm

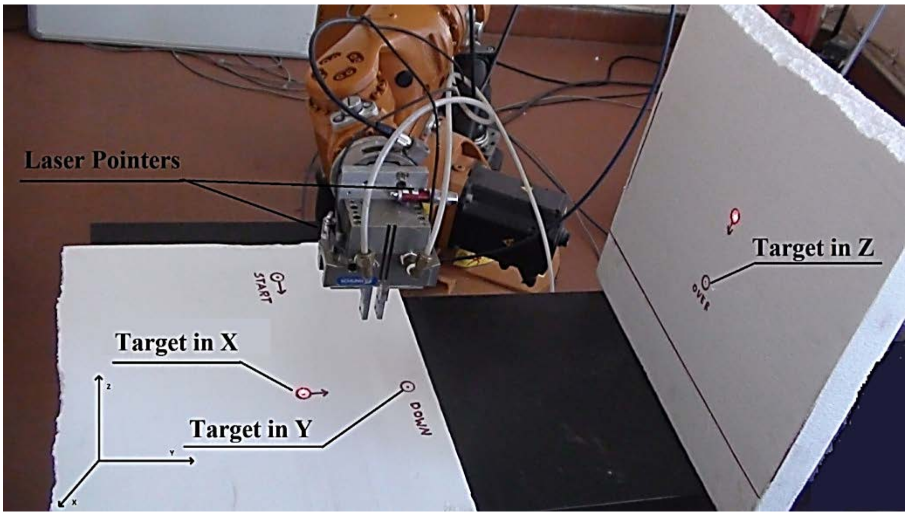



Figure 12: Setup for Experiment 1

For the experiments in this paper, we adjusted these constants such that the maximum speed of the robot remains around 40 mm/sec for both left as well as right teeth clenching. Since the robot takes a motion command every 12 ms cycle, 40 mm/sec speed corresponds to 0.5 mm per cycle.

### 4.2 Experiment 1: Target reaching in respective axes

In the first experiment, the subjects were asked to move the robotic arm to the target positions in x, y and z-axis respectively. The target positions in each of the axis were marked by a dot surrounded by a circle of radius 10 mm. The robot's end-effector was mounted with laser pointers. Hence, the aim was to move the robotic arm so as to position the laser pointer as near to the target dot as possible. The setup is shown in Figure 12.

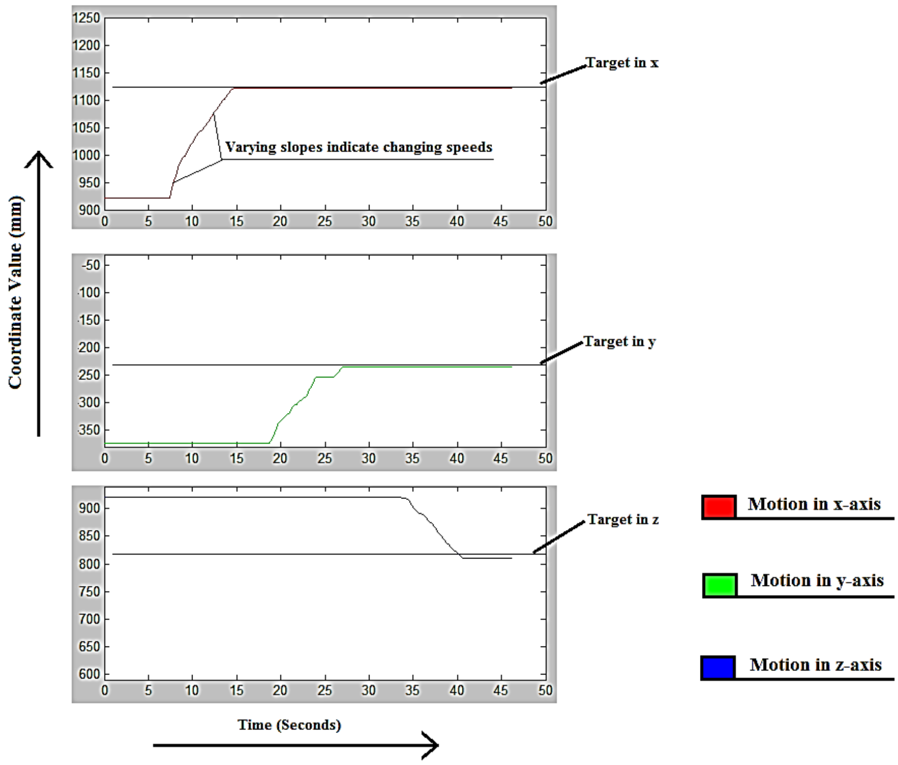



**Figure 13:** Path traversed by the robotic arm during a trial of Experiment 1

**Table 3:** Root Mean Squared error and average time taken for target reaching experiment (over 10 trials for each subject)

| Subject | R.M.S. Error in X (mm) | R.M.S. Error in Y (mm) | R.M.S. Error in Z (mm) | Time taken (seconds) |
|---|---|---|---|---|
| K | 3.4 | 4.3 | 10.0 | 53 |
| A | 4.0 | 5.6 | 13.4 | 105 |
| R | 4.4 | 3.1 | 15.1 | 60 |
| D | 5.4 | 7.4 | 30.2 | 50 |

This experiment was done to assess how accurately the robot can be moved in each of the axis so as to reach a particular target. This experiment also provided the operator training for the telemanipulation experiment described in the next subsection. The path traversed by the robotic arm during one of the trials of this experiment by one of the subjects is shown in Figure 13. We can see from Figure 13, how the operator uses speed control to reach a particular target.

This experiment was repeated 10 times by each of the subjects. The root mean squared errors (1) over the 10 trials for the respective axis and the average time taken by each of the subjects are shown in Table 3. We can see that the errors are near 10 mm (radius of the circle surrounding the target dot) except in z-axis for the subject D.

$$R.M.S\ Error = \sqrt[2]{\left(\sum_{i=1}^{n}(T_i - P_i)^2\right)/n} \tag{1}$$

$$Where, n = Total\ number\ of\ trials, T_i = Target\ in\ a\ particular\ axis$$

$$and\ P_i = Position\ reached\ by\ the\ robot$$

### 4.3 Experiment 2: Pick and place experiment

In the second experiment, the subjects were asked to operate the robotic arm so as to pick an object from one fixed location to a fixed target location. Hence, this operation included the gripper control also. The object to be picked was having a circular disc shaped base (with radius 65 mm) with a shaft at its center. The setup can be seen in Figure 14.

A circle of radius 80 mm was drawn at the target location. Hence, the aim was to place the object inside the target circle. This experiment was done to assess the performance of the techniques described in this paper for a pick and place task. We can see the path traversed by the robotic arm during one of the trials for this

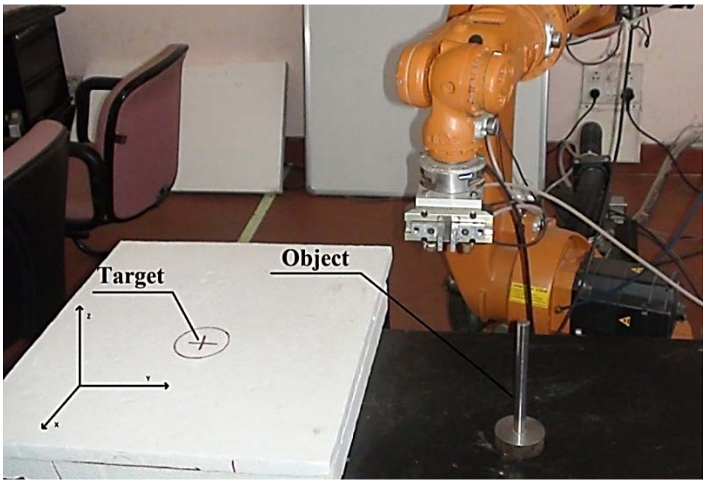
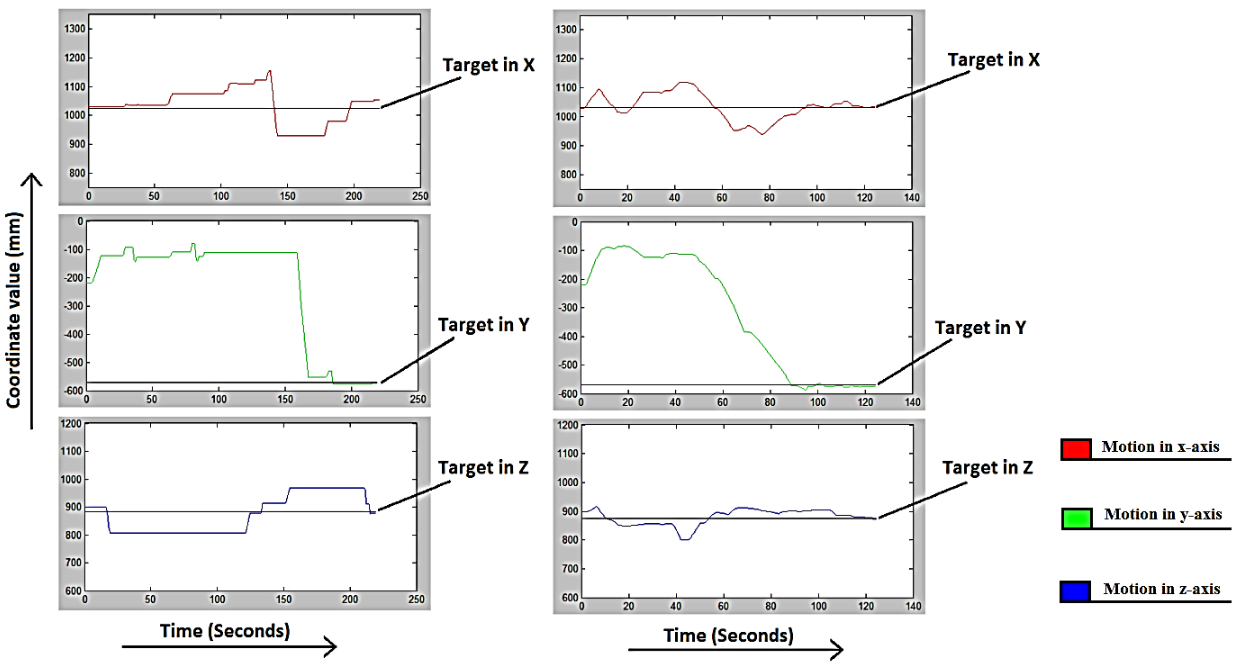



**Figure 14:** Setup for Experiment 2




(a) Trial using EEG Artifacts

(b) Trial using Haptic Device

**Figure 15:** Path traversed by the robotic arm during a trial of Experiment 2

**Table 4:** Root Mean Squared error, average time taken and number of falls for pick and place experiment (over 5 successful trials for each subject)

| Subject | R.M.S. Error (mm) (Using EEG Artifacts) | Time Taken (seconds) (Using EEG Artifacts) | Falls/Total no. of Trials (Using EEG Artifacts) | R.M.S. Error (mm) (Using Haptic Device) | Time Taken (seconds) (Using Haptic Device) | Accuracy Index | Speed Index |
|---|---|---|---|---|---|---|---|
| K | 15.4 | 128 | 0/5 | 4.3 | 92 | 0.3 | 0.7 |
| A | 16.9 | 201 | 1/6 | 5.3 | 106 | 0.3 | 0.5 |
| R | 18.4 | 159 | 2/7 | 4.9 | 117 | 0.3 | 0.7 |
| D | 16.2 | 156 | 1/6 | 5.5 | 79 | 0.3 | 0.5 |

experiment in Figure 15 (a) where the robot can move only in a single axis at a time. This experiment was repeated 5 times by each of the subjects. Table 4 shows the root mean squared errors (for the target position in all the three axes together) over the 5 successful trials and the average time taken by each of the subjects. There were falls of the object during some of the trials as discussed in section 3.3. The experiments were repeated by a subject till total 5 trials without any fall were obtained. The numbers of total trials to get 5 successful trials without any fall, for the 4 subjects, are also reported in Table 4.

The same experiments were repeated using a haptic device and a motion mapping called joystick control as discussed in [8]. In the motion mapping described in this paper, the robot's speed is proportional to the clenching intensity and the robot keeps moving till the teeth are clenched, similarly in the joystick control, the robot's speed is proportional to the current position of haptic device from a pre-specified origin and the robot keeps moving till the haptic device's button is kept pressed. We can see the path traversed by the robotic arm during one of the trials for this experiment in Figure 15 (b) where the robot can move in all the axes simultaneously. To have a fair comparison, we kept the 40 mm/sec or 0.5 mm per cycle bound on the speed for the experiments with the haptic device also as discussed in section 4.1. The root mean squared errors over the 5 trials and the average time taken by each of the subjects for the experiments with the haptic device are reported in Table 4. There were no falls of the object (as a separate button was provided on the haptic device, for opening and closing of the gripper); hence the falls are not reported for these experiments.

We can see from Table 4 that the error is lesser with the haptic device, but the error with EEG artifacts is near 15 mm (radius of the circle in which the object was to be placed). The error in both experiment 1 and 2 is near radius of the reference circle because the subjects were instructed to reach within the circle and not exactly at its center.

Also, the time taken for the experiments using haptic device is lesser than the time taken for the experiments using EEG artifacts. This is obvious as the robot can be moved in all the axes simultaneously using the haptic device, whereas, using the EEG artifacts, the robot can be moved only in a single axis at a time. To quantitatively compare our technique with the haptic device's performance, we define two metrics viz. $Accuracy\ Index$ & $Speed\ Index$ (2, 3):

$$Accuracy\ Index = \frac{R.M.S.Error\ using\ Haptic\ Device}{R.M.S.Error\ using\ EEG\ Artifacts} \tag{2}$$

$$Speed\ Index = \frac{Time\ taken\ using\ Haptic\ Device}{Time\ taken\ using\ EEG\ Artifacts} \tag{3}$$

The indices defined above compare the performance of telemanipulation using EEG artifacts with respect to the telemanipulation using a haptic device in terms of accuracy achieved and the time spent. We can see from Table 4 that the $Accuracy\ Index$ for all the four subjects is 0.3 and the $Speed\ Index$ is 0.5-0.7. Thus the telemanipulation technique described here reaches around 30% accuracy with 50-70% speed as compared to the haptic device.

## Conclusion

This paper presented the utilization of EEG artifacts such as blinks and teeth clenching for telemanipulation of a robotic arm. The generation of these artifacts requires a small training time. The mapping of clenching intensity to the robot's speed provides an intuitive and easy to use interface for pick and place tasks.

Since clenching intensities were different for different subjects, a decision tree based learning technique was used to classify different types of clenching and to compute the user-dependent clenching thresholds. The subjects were able to perform telemanipulation after a small training time of 3.3 minutes. A retraining was required once the cap was removed and worn again. The efficacy of proposed technique was compared to the telemanipulation using a haptic device in terms of the $Accuracy\ Index$ and the $Speed\ Index$. Any telemanipulation technique should aim at increasing these two indices.

## Acknowledgement

We would like to thank all the 7 participants who were involved in the training part (Mr. Abhishek, Mr. Reddy, Mr. Dave, Mr. Kamal, Mr. Rahul, Mr. Saurabh and Mr. Jagadish) out of whom the first four finally participated in all the experiments.

## References

[1] Ahmed, K. S. "Wheelchair movement control VIA human eye blinks." American Journal of Biomedical Engineering 1.1 (2011): 55-58.

[2] Barreto, Armando B., Scott D. Scargle, and Malek Adjouadi. "A practical EMG-based human-computer interface for users with motor disabilities." Journal of rehabilitation research and development 37.1 (2000): 53.

[3] Costa, Álvaro, et al. "A Supplementary System for a Brain-Machine Interface Based on Jaw Artifacts for the Bidimensional Control of a Robotic Arm." PloS one 9.11 (2014): e112352.

[4] Ferrario, Virgilio F., et al. "Maximal bite forces in healthy young adults as predicted by surface electromyography." Journal of dentistry 32.6 (2004): 451-457.

[5] Goel, Kratarth, et al. "Home automation using SSVEP & eye-blink detection based brain-computer interface." 2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, 2014.

[6] Goncharova, Irina I., et al. "EMG contamination of EEG: spectral and topographical characteristics." Clinical neurophysiology 114.9 (2003): 1580-1593.

[7] http://www.academia.edu/7032069/An_example_of_calculating_gini_gain_in_CART

[8] Jaju, A., Das, A.P. and Pal, P.K., 2013. "Evaluation of Motion Mappings from a Haptic device to an Industrial Robot for effective Master-Slave manipulation." International Journal of Robotics and Automation, 28(1).

[9] Lin, Jzau-Sheng, and Win-Ching Yang. "Wireless brain-computer interface for electric wheelchairs with EEG and eye-blinking signals." Int. J. Innov. Comput. Inf. Control 8 (2012): 6011-6024.

[10] Looned, Ritik, et al. "Assisting drinking with an affordable BCI-controlled wearable robot and electrical stimulation: a preliminary investigation." Journal of neuroengineering and rehabilitation 11.1 (2014): 1.

[11] Naeem, M., et al. "Seperability of four-class motor imagery data using independent components analysis." Journal of neural engineering 3.3 (2006): 208.

[12] Pfurtscheller, Gert, et al. "Mu rhythm (de) synchronization and EEG single-trial classification of different motor imagery tasks." Neuroimage 31.1 (2006): 153-159.

[13] Shirwalkar, S., Singh, A., Sharma, K. and Singh, N., 2013, December. “Telemanipulation of an industrial robotic arm using gesture recognition with Kinect.” In Control, Automation, Robotics and Embedded Systems (CARE), 2013 International Conference on (pp. 1-6). IEEE.

[14] Wang, Yijun, Shangkai Gao, and Xiaornog Gao. "Common spatial pattern method for channel selelction in motor imagery based brain-computer interface." 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference. IEEE, 2005.

[15] Wolpaw, Jonathan R., et al. "Brain–computer interfaces for communication and control." Clinical neurophysiology 113.6 (2002): 767-791.