Robotic Control by EOG-EEG-RFID based Multimodal Interface and Shared Control Technology

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Abstract. This study describes a robotic control application that uses Radio Frequency Identification (RFID) technology as shared control architecture and Electrooculography (EOG) and Electroencephalography (EEG) biosignals for multimodal Man-Machine Interface. The proposed application had to steer a robot along a given route aimed at helping people with mobility disabilities in performing daily tasks independently. With proper threshold selection, EOG signals were classified. Whereas, EEG interface used Minimum Energy (ME) combination for feature extraction and Linear Discriminant Analysis (LDA) based classifier. Both EOG and EEG signals had been synchronously used for robotic movement control and both complements each other. Further, RFID was used to identify the object and perform the pick/place operation. The proposed model provides longer range of applications with less fatigue. The effectiveness of the proposed model had been verified by controlling a mobile robot successfully.

Keywords: SSVEP, EOG, multimodal, robot control, EEG, RFID, shared control, MMI

1 Introduction

The recent advances in biomedical instrumentation lead to increase in its applications in Man Machine Interface (MMI) systems as assistive devices for disabled persons. It is used for aiding people having motor disorders due to some stroke or spinal cord injury and they are not able to connect with the outer world. This technique can be helpful not only for the disabled but also for healthy persons in some situations, where other communication means are currently not available or occupied. The MMI systems based on biological signals such as Electroencephalography (EEG), Electrooculography (EOG), and Electromyography (EMG) facilitates a new control approach for disabled persons as well as for healthy people.

Researchers have given several algorithms for monitoring characteristics of different EEG-based brain activity, for instance, P300, SSVEP, motor imagery, and achieved satisfactory results in terms of classification accuracy and other performance parameters such as response speed, specificity, sensitivity, usability with these algorithms[1]. Among these, SSVEP-based Brain-Computer Interface (BCI) is more practical as it supports larger number of output commands, and need short or no training[2]. However, all of these algorithms are

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having some drawbacks. Although EEG-based MMI systems are a reality, these drawbacks prevent wider real-world applications of these techniques[3].

EOG is one of the frequently used, easy, simple, and intrusive techniques in various MMI systems for different applications. EOG can be helpful for those people having control of their voluntary muscles such as eye movement to communicate with their surroundings and to control devices. The visual angle for vertical EOG is between ±30◦ and for horizontal EOG is between ±50◦. The response speed of EOG-based system can be significantly high. Due to its modesty and fast response time, it seems appropriate for real-time control applications[4]. Although, EOG would be unacceptable for some applications, such as driving a car because it can restrict the field of vision by putting the electrodes around the eyes on the user's face[5]. EOG interface is usually restricted to a few eyelid movements only and can not provide a large number of reliable control commands. Linear behaviour of EOG corresponds to lesser voltage for vertical EOG as compared to horizontal EOG. Therefore, larger visual angle is required for vertical EOG detection, which leads to eye fatigue, and the user feels exhausting[6]. Furthermore, unlike BCI, the EOG is a type of muscle dependant signal, which means that it certainly causes fatigue if used continuously for a longer time.

Usually, any single modality whether it is EEG, EOG, or EMG, is capable to manage some specific kind of task only. Using a single modality, it is harder to have a globally vigorous system applicable to the divergent environment. To overcome the drawbacks of using single modality, everyday new approaches are being explored such as multimodal interface, hybrid BCI, shared control[7]. A multimodal interface can be a combination of two or more mono-modal systems working independently or can be dependent on each other. The modalities to be combined can be either all BCI or non-BCI (EOG, EMG, etc.). The multimodal systems allow us to choose separate subsystems for distinct tasks, providing more flexibility and functionalities, more independent and higher degree of freedom (DOFs). In multimodal interface system, users need not to continuously concentrate on the same operations, which implicitly make less tedious for them mentally and physically both, while keeping the system complexity low and acceptability high. There can be an immense opportunity for expansion by combining more than one modality in a single system and make a multimodal system, for instance, multimodal interface-based and hybrid BCI based robot control[8]. Although, the increase of control commands even in Multimodal systems can cause fatigue in humans, resulting in the incapability of continuous control over a device.

The use of bio-signal interface alone whether it is single-modal or multimodal has some limitations to optimally guide and control external devices when the environment demands a more precise and complex manipulation of control commands. To further enhance the control results and usability of the system without putting more burden on the user, shared control architecture can be implemented. When total control task for a particular problem is divided into parts and different approaches are used to control different parts, it is called shared control approach. Shared control is used as a support to the bio-signal interface. To get rid of some dangerous situations and for telemanipulation tasks, RFID technology can be used as shared control technique along with multimodal interface[9]. RFID has two components: a reader and tags. The reader read the object information stored in the tag[10]. Each tag has its own memory where it stores information of objects which are to be identified. RFID technology does not need a line of sight which made it more flexible and useful for tracking applications as well.

In this study, EOG-EEG-RFID based multimodal interface and shared control approach has been proposed. The application results have been applied to control a robot. The model has three modes: (a) EOG mode, (b) EEG mode, (c) RFID mode. EOG is responsible for two horizontal movements (right, left) and EEG is being used for two movements (forward, backward) and emergency alarm. RFID mode is used to identify the object and to perform pick/place operation.

2 Materials and Methods

This section describes the experimental procedure, as well as hardware and software that have been used in this experiment. The procedure includes the processing methods for EEG and EOG signals and their classification. Furthermore, the algorithm used to synchronise the commands from EEG and EOG signals to establish a multimodal interface has been explained. Finally, the strategy of using RFID technology as a shared control technique for the ease of accessing objects has also been detailed.

2.1 Participants and Data Acquisition

EEG and EOG signals were acquired using g.USBamp (a bio-signal amplifier) and g.GAMMA box (g.tec medical engineering, Austria) with active Ag/AgCl wet electrodes. The acquired signals were send to the computer via USB for further processing and analysis. The sampling rate was 256Hz. The in-built bandpass filter (BPF) with cut-off frequencies 0.1–100Hz was applied to remove the baseline drift effect and to eliminate high-frequency noise. The signals were acquired from nine healthy subjects aged between 21 and 30 years having normal as well as impaired vision. The users had been informed about the requirements of the procedure before taking their data. The volunteers agreed and gave their consent to take part in the test. Reference and ground positions were the same as conventions. All the electrodes were used in unipolar mode. The abrasive gel was applied to get better contact with the scalp and to achieve impedances on the electrodes below 5kΩ. All data had been acquired in our lab at National Institute of Technical Teacher’s Training and Research, Chandigarh, India after getting proper consent of volunteers.

EOG Data Acquisition - EOG is a well-known technique for eye movement detection. It is measured as the potential difference between retina and cornea, which is usually negative and shows changes in its potential difference with every movement of eyeballs. This potential difference is linearly proportional to the angle of eye movements.

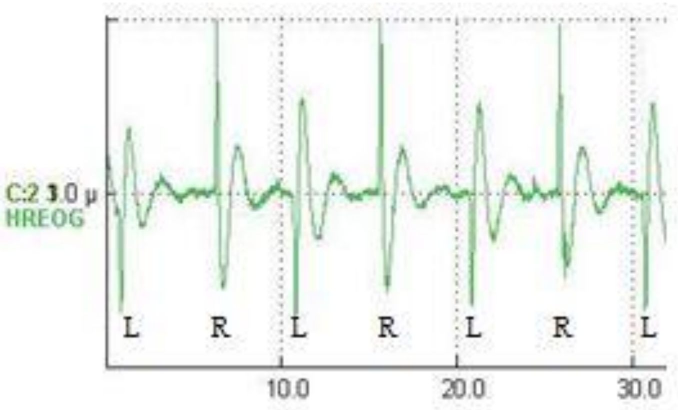

Fig. 1. Acquired Horizontal EOG waveforms

In this work, only horizontal eye movements are included. EOG signals were acquired using one active Ag/AgCl wet electrode placed on any one side of the eye. This is a commonly used electrode position to measure the horizontal eye movements. Additionally, one electrode was placed on the forehead for ground and reference electrode at the right earlobe. Fig.1 shows the acquired horizontal EOG signal waveforms and Fig.2 shows the electrode position for data recording.

EEG Data Acquisition - An electromotive force, obtained from the scalp influenced by a visual stimulus modulated at some fixed frequencies is called “visual evoked potential (VEP)”. If the stimulation frequency is greater than 3.5Hz, the EEG signals are called “steady-state visual evoked potential (SSVEP)” as the distinct responses overlap each other and consequently, result in an increase in EEG activity as partly sinusoidal oscillation at the same stimulus frequency[11][12]. The goal is to detect the presence of these frequencies reliably and to detect the absence of these frequencies, henceforth detect the instances when the subject does not focus on the flashing LED (stimulus).

Fig. 2. Electrode placements for EOG and EEG signal recording

In this work, only three channel combinations ‘O1 (in the left cerebral hemisphere)’, ‘O2 (in the right cerebral hemisphere)’, and ‘Oz’ (on the central line) as suggested by many pieces of literature were chosen to acquire SSVEP signal[13] using three active Ag/AgCl electrodes. Electrodes were placed as per the international 10-20 system with reference and ground electrodes at the right earlobe and on the forehead at 'Fpz' position respectively. The electrode placement positions for both EEG and EOG signal recording are shown in Fig.2.

2.2 EOG Interface

EOG Threshold calculation - In this study, two very common horizontal eye movements (left, right) have been detected. To detect the different directions of eye movement from the EOG signal, it is mandatory to process the raw EOG signal with an appropriate and suitable processing algorithm. We can get the EOG signals for eye movements in various angles as the angles are proportional to the amplitude of the measured EOG signal. However, for simplicity of the control algorithm, in this paper, the user has to perform a fast movement of his/her eyes only in the left and right directions without blinking.

From Fig.1, it can be observed that waveforms of both the eye movements have a typical characteristic and pattern. One of them has a positive peak followed by a negative peak and another one has a negative peak followed by a positive peak. This characteristic can be utilized as a feature to detect and distinguish the eye movements. Apart from this pattern feature, another most common algorithm to detect eye movements is to compare the amplitude of the obtained signal with a predefined threshold value which can be chosen subject-wise or common to all[14]. Therefore, selection of the appropriate threshold is an important and deciding factor for accurate detection of EOG signals. With the careful observation of the signal, the maximum amplitudes for both directions of eye movement were calculated and shown in Table 1.

Table 1. Maximum amplitude of Horizontal Eye movements for different users

User	Max. Amplitude for Left (uV)	Max. Amplitude for Right (uV)
S1	150	-130
S2	150	-150
S3	150	-140
S4	150	-150
S5	90	-90
S6	90	-90
S7	90	-90
S8	135	-155
S9	200	-200

Calibration and thresholds are the key features for getting accurate results in eye movement detection and getting better performance from the proposed algorithm. The vertical movements are not included in this work as vertical movements are complex to distinguish and demand more precise threshold selection to negate the influence of blinks and to get an accurate distinction for the classification.

Eye movement detection algorithm - As we know, eye movements have identifiable waveform patterns that can be easily classified using the thresholding technique. Sharp positive peak followed by a negative peak is observed for the *right movement* and a sharp negative peak followed by a positive peak is observed for *left movement*.

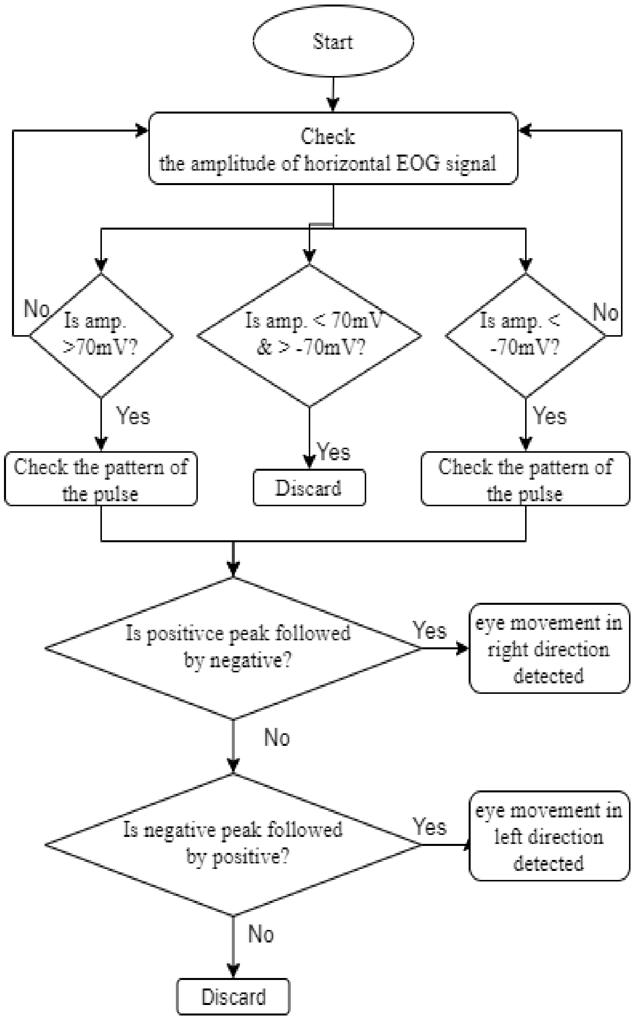

Fig. 3. Flow chart for Horizontal EOG Detection

To that end, a very effective and simple multi-threshold algorithm applicable to both the eye movements has been designed. A small training session has been included to determine the correct threshold values common to all users for both the movements. Based on these thresholds, the eye movement detection algorithm was developed and shown as a flow chart in Fig.3. If the signal amplitude and pattern of pulse, both conditions are satisfied for any of the two movements, the corresponding control signal is generated, which remains high for the next 2 seconds even if the signal value changes, to minimize the error due to small fluctuations.

2.3 EEG Interface

Experiment Stimuli and Paradigm - While acquiring the EEG signal, subjects were asked to sit comfortably on a non-revolving armed chair around 100cm distances in front of a flat computer screen. All are instructed not to move and to keep the body relaxed and to fixate on the SSVEP box (a 12x12cm box equipped with four white LEDs, the light intensity of each LED was 1500mcd and diameter was 8mm). Another four small green LEDs assist the user on which white LED he/she has to concentrate during the training phase. For visual stimulation, flickering frequencies of LEDs are controlled using g.STIMbox which is a digital I/O box (driver box) for precise time stimulation and USB 2.0 was used to connect to the computer and MATLAB/Simulink has been used to access it. The output channels of the STIMbox are configured for the desired frequencies through the corresponding block in the Simulink. Four LEDs were set to flicker at frequencies 10Hz, 11Hz, 12Hz, and 13Hz for 15s each sequentially. The driver box provides 5V with maximum overall output current 200mA while connected.

The paradigm Simulink block controls the stimulation. Here we define different modes of the experiment to be chosen for training or testing, trial period, active time, and initial offset time. The length of a trial was set as 10.5s out of which 70% was the active time during which the user had to concentrate on a LED in every trial. Initial offset is time before starting the trial which was set as 10s. After this offset time, LED starts flashing to give enough time to the user to be prepared for the trial.

Offline Training Phase: EEG - In the training phase, the mode of paradigm block is set as training. After the initial offset time (10s), all white LEDs start flashing. The small green LEDs assist on which white LED the user has to focus. After one trial, green LEDs keep glowing all together for a few seconds to give enough time to the user to switch his/her focus from one LED to the next in the clockwise direction.

The acquired EEG data from users were sent to the MATLAB/Simulink. All pre-processing, feature extraction, and classification were performed with the g.tec BCI system in MATLAB environment. A BPF with lower and upper cut-off frequencies was chosen as 0.5Hz and 30Hz respectively to eliminate high-frequency noise and a notch filter was applied to suppress the 50Hz frequency power line interference.

EEG interface uses Minimum Energy (ME) combination for feature extraction and Linear Discriminant Analysis (LDA) for classification. ME approach has been considered for feature extraction as it requires no training and itself finds the best combination of channels [15]. The SSVEP based EEG signal was acquired by the projection of oscillations with frequencies same as stimulation frequencies and its 1st harmonic towards the perpendicular complement of the EEG-signals artificially. As per the theoretical evidence, after this operation, the signals comprise the undesired noise only. Now, minimal energy had been achieved by combining the channels in a specific way through weight vector. Then, a statistical test is performed to calculate the ratio of the signal incorporated with the estimated SSVEP responses and the signal without the visual stimulus. In other words, the ME approach is used to compute the Signal/Noise Ratio of stimulus frequencies (10Hz, 11Hz, 12Hz, and 13Hz) which are contained in the input data concerning the base EEG signal. The process is repeated for all channels and all stimulation frequencies. Seventh order autoregressive model has been used to estimate noise content in each signal. The index number of the frequency with the highest SNR is the output of the ME approach[2]. Furthermore, a moving median filter was applied for smoothing the output signal of minimum energy by calculating medium onto the last 10 samples of the data.

For classification, at first, we had calculated LDA classifier with the help of g.BSanalyze (an interactive environment for offline analysis and processing of biosignals) based on feature matrix obtained from ME combination. LDA classifier had been trained using this feature matrix. Classifier configuration gets updated at each time-point and gives classification accuracy as a result corresponding to that configuration. Then the classifier configuration with the best accuracy had been picked for online classification to predict the class of new data.

2.4 EEG-EOG based Multimodal Interface

In day-to-day practice, most of the control scenarios are multitasking. In a mono-modal system, performing similar action repeatedly can easily build-up fatigue hysically and mentally both. The EEG (SSVEP) interface does not impose any type of physical burden on the user. However, constantly looking at the flashing LEDs can result in restlessness and exhaustion, which consequently may affect the system performance. Combining EOG and EEG interface can have full benifits of both and individual disadvantages can be compensated. For instance, EOG interface system can achieve very high ITR, which compensates the largest weakness of SSVEP-based EEG interfaces. With the multimodal interface, the user does not need to continuously concentrate on the same operations, which implicitly make less tedious for user mentally and physically both.

An EEG-EOG multimodal interface system had been implemented in MATLAB/ Simulink environment. It has two modes. One is the EOG interface to detect horizontal eye movements in the left and right directions. Another one is the EEG interface to detect SSVEP signal. In EEG mode, the EOG interface is inactive. Therefore, EOG control signals will not be considered. Similarly, in EOG mode, EEG control signals will not be considered. However, the system continuously detects EEG signals because a predefined EEG signal value is used to switch between the two modes and an another EEG signal has to ring an alarm for any emergency call by patient. For other values of the EEG signal, the system is made non-responsive in EOG mode. An EEG-driven switch is used as a priority decider to decide the priority of commands from EOG interface and that of EEG interface and facilitates smooth switching between two modes.

The algorithm for the proposed multimodal interface system has been described as:

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If SSVEP signal frequency x (i) = 10Hz;
            {Control signal = 1}; # not used
  Else if SSVEP signal frequency x (i) = 11Hz;
             {Control signal = 2}; # robot will move forward.
  Else if SSVEP signal frequency x (i) = 12Hz;
            {Control signal = 3}; # robot will move backward.
  Else if SSVEP signal frequency x (i) = 13Hz;
            {Control signal = 4}; # emergency alarm will ring.
           [% Since EEG control signal is ≥2, EOG signal is
  ignored in above three conditions.]
  Else if SSVEP signal frequency x (i) = 0 or 1;
  [% model will switch to EOG mode]
           If Eye movement y(i) = Left;
              {Control signal =5}; # robot will move left.
          Else if Eye movement y(i) = Right;
              {Control signal) =6}; # robot will move right.
          Else if Eye movement y(i) = None;
              {Control signal =0}; # robot will remain idle or
  stop.
```

2.5 Proposed Model: EOG-EEG-RFID Based Robot Control Architecture

A multimodal BCI configuration based on EOG-EEG along with RFID technology as shared control architecture has been implemented to find a suitable setup for movement control of a robot.

In this configuration, EEG-EOG based multimodal system controls the robot movement in forward, backward, left, and right directions. EEG signal has also been used to ring a buzzer to indicate an emergency call from the patient. If the classification gives no confident result, the robot remains in idle state, which is named as pseudo zero class. Otherwise, classification results are sent to the robot via Simulink. RFID shares control over object interaction.

A low-cost high frequency (HF) RFID Reader MFRC522 Module which is a chip-based board is used here for shared control architecture. Its wireless operating frequency is 13.56MHz. Maximum 10Mbit data can be transferred per second and the reads range is approx. 30cm from the tag. MFRC522 is considered as the best choice in the development of portable hand-held devices due to its low power consumption, compact size (40mm × 60mm), and low cost. Two tags RFID 1K Key Fob and Plain white printable PVC RFID card were used in this work for object identification. It uses a 3.3V power supply and can communicate directly with any CPU via SPI protocol, or can easily communicate with Arduino through appropriate pin connection.

Control protocol - The robot operation explained in the previous section is controlled by the developed multimodal interface and shared control architecture following a specific control protocol. There are two control protocols: one is MMI control which is executed through MATLAB and the second one is RFID control which is executed in a remote environment.
Following three conditions must be fulfilled to identify an object and to perform pick and place action:

- Proximity condition: If the tag is in the read range of the RFID reader (< 3cm).
- Possibility condition: The robot can perform the pick action only if the gripper is open and the tag on the object is identified. Similarly, it can perform the place action only if the gripper is carrying an object.
- Blocking condition: When the robot is at a position to perform the pick/place operation, the movement of the robot will be blocked and will allow it to perform the operation.

The control protocol has been explained step by step as follows:

1. Switch on the robot to connect and place it at the start position.
2. A test session starts by detecting the output of the EEG-EOG based multimodal interface and moving direction of the robot is updated according to EEG/EOG control signal.
3. The robot moves around 7cm in a direction once it receives the corresponding movement control signal. Then stop and wait for the next command.
4. After completing the predefined path, the RFID reader looks for the object with a particular tag ID. To execute pick/place operation, it was checked if the first two conditions (Proximity and Possibility condition) were fulfilled. An LED glows to indicate that object has been identified and the third condition (blocking condition) was activated. The robot automatically picked the object and placed it in a predefined zone and all conditions were reset.
5. If the first two conditions were not fulfilled, the protocol returned to step 2.

3 Application Results and Discussion

To evaluate the performance of the proposed model, two parameters classification accuracy (%) and speed have been calculated as suggested in the literature[9]. The classification accuracy is the ratio of truly classified trials and the total number of trials. Speed is the time taken to complete the pick/place action starting from the initial position.

(a) Performance of EOG Interface

The EOG detection algorithm performed excellently and gave 100% classification accuracy. The generated control signals have been calibrated as numeric values 3 and 4 that correspond to the movement of the robot in the left and right directions respectively.

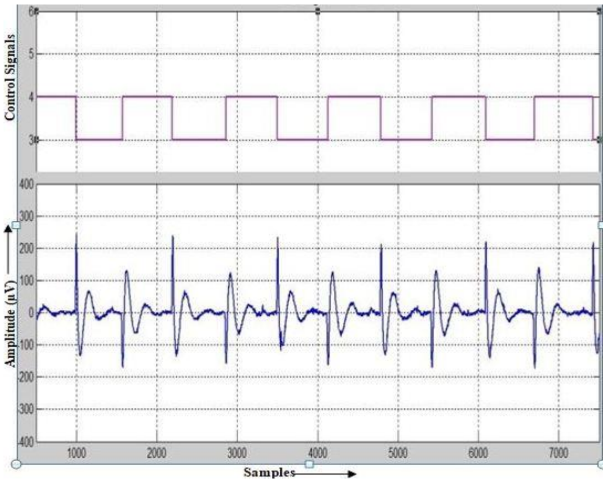

Fig. 4. Horizontal EOG signal and corresponding control signal

EOG signal and its conversion in corresponding control signals are shown in Fig.4. The figure itself says that the performance of the developed EOG interface model is undoubtedly excellent and acceptable for any type of 2-class application.

(b) Performance of EEG Interface

The EEG processing algorithm has been evaluated with an LDA classifier. The classifier trained itself with the provided training data set.

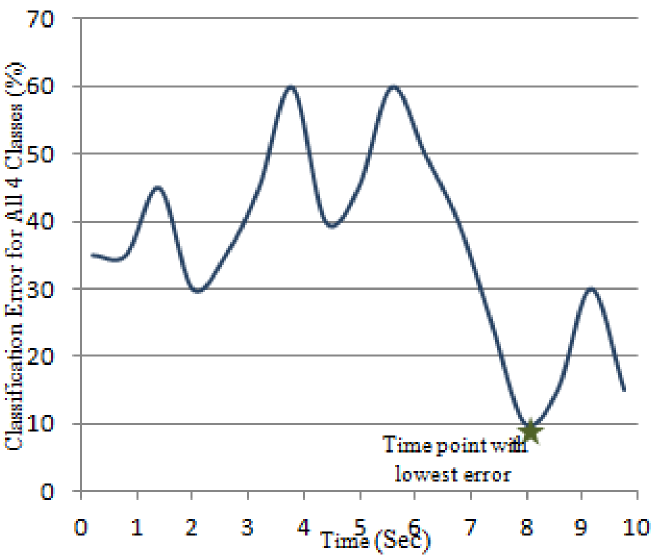

Fig. 5. SSVEP classification output with 100-100 validation method for LDA classifier

Table 2. SSVEP classification output with 100-100 validation method for LDA classifier

Classification Method: Linear Discriminant Analysis (LDA)					
Training- and testdata option: 100:100					
class 1: 10HZ					
class 2: 11HZ					
class 3: 12HZ					
class 4: 13HZ					
Time (sec)	**Total error**	**Error class 1**	**Error class 2**	**Error class 3**	**Error class 4**
0.199	35.0	5.0	15.0	10.0	5.0
0.797	35.0	5.0	15.0	10.0	5.0
1.395	45.0	5.0	15.0	10.0	15.0
1.992	30.0	0.0	15.0	5.0	10.0
2.590	35.0	5.0	15.0	5.0	10.0
3.188	45.0	10.0	20.0	5.0	10.0
3.785	60.0	15.0	20.0	10.0	15.0
4.383	40.0	10.0	5.0	5.0	20.0
4.980	45.0	15.0	10.0	10.0	10.0
5.578	60.0	15.0	20.0	15.0	10.0
6.176	50.0	5.0	15.0	20.0	10.0
6.773	40.0	5.0	10.0	15.0	10.0
7.371	25.0	5.0	10.0	5.0	5.0
7.969	10.0	5.0	0.0	5.0	0.0
8.566	15.0	5.0	0.0	0.0	10.0
9.164	30.0	20.0	0.0	0.0	10.0
9.762	15.0	10.0	0.0	0.0	5.0

The algorithm keeps on changing the classifier parameters and built different classifiers at every time-point during training. Table.2 shows the classification error of different classifiers built at different time-points for SSVEP signals while training using Train 100% - Test 100% (100-100) validation method and total classification error for all 4 classes has been shown in Fig.5. it can be observed that the classifier built at time-point 7.969s shows minimum classification error 10% if considering all four classes (shown in green color), 5% error if considered three classes and even 0% error (100% accuracy) at many different time points if considering only two classes. It can be concluded that the performance of EEG interface model is satisfactory for many 4-class or 3-class applications and perfect for 2-class applications.

(c) Performance of EOG-EEG-RFID based Robot Control Architecture

It has been already discussed in the previous section that the EEG interface shows the lowest classification error 5% at time-point 7.969s if three classes (class-2, class-3, and class-4) are considered which is acceptable for many applications. To that end, to increase the number of commands, the classifier model built at time point 7.969s having the lowest error has been picked-up and combined with the EOG interface to develop the multimodal interface system in MATLAB/Simulink environment and used to control the robot movement in forward/backward, left/right directions and to ring an emergency alarm. An EEG-driven switch was used as a priority decider for smooth switching between two modes. The algorithm for multimodal interface had been already explained in Section 2.4 It has been observed that the proposed model smoothly switches between two modes as per the algorithm and perfectly combines the output of both the interfaces without any delay.

Apart from offline and online verification of multimodal interface discussed in the previous section, final verification was done for EOG-EEG-RFID based shared control system by controlling a mobile robot to perform an assistive application as explained below.

3.1 Application Description

In this experiment, an assistive robot environment has been developed and a realistic application has been designed in which disabled users can reach an object placed at a distance and bring it closer to them only by using their EEG and EOG signal with the help of proposed model.

With this goal, an empty glass is taken as the desired object which is placed in zone 2. Zone 1 which was close to the user, has empty space to place the object.

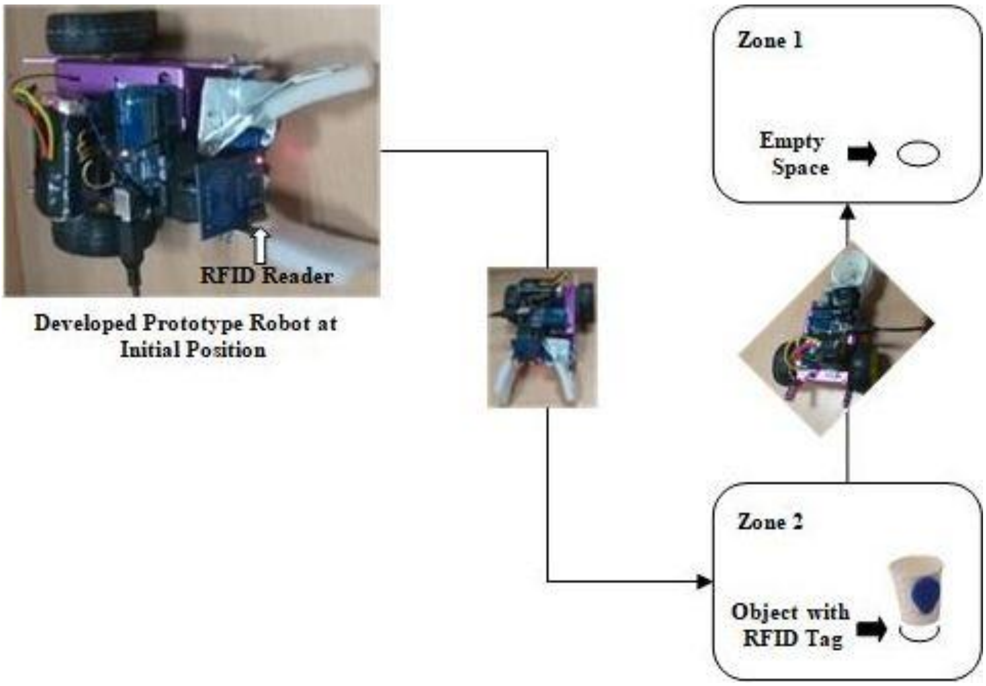

Fig. 6. Final Application Process

Final application process is shown in Fig.6 and the sequences of the application are the following:

1. The assistive robot will move according to EEG and EOG signals of the user, and reach in the proximity of the object.

2. The RFID reader will identify the object,
3. Pick the object from zone 2,
4. Place the object in zone 1.

The average time taken to complete the pick and place action has been measured and shown in Table 3 for each user.

Table 3. Application results

User	No. of Sessions	Average Time (s)	EOG accuracy	EEG accuracy
S1	2	29	4/4	5/6
S2	2	29	4/4	5/6
S3	3	30	6/6	7/9
S4	2	29	4/4	5/6
S5	2	27	4/4	6/6
S6	2	27	4/4	6/6
S7	2	27	4/4	6/6
S8	4	28	8/8	11/12
S9	3	28	6/6	7/9

The minimum time taken to perform a perfect test by using the minimum number of commands was 27s. This minimum time is used to calculate an index of speed (in terms of percentage) to get comparative analysis.

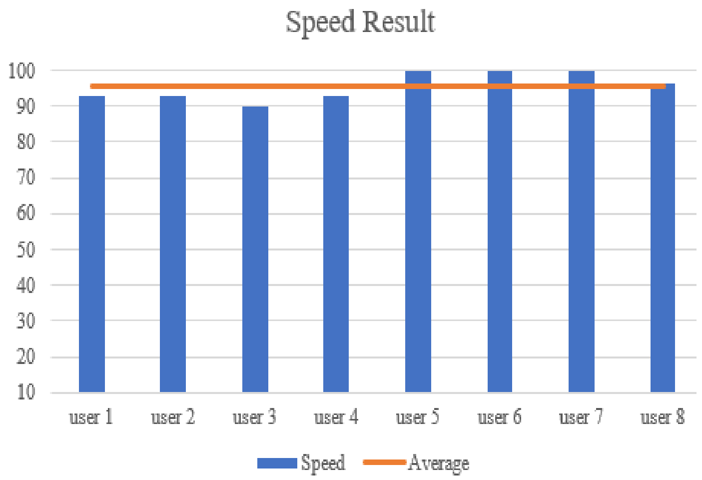

Fig. 7. Average Speed Results of users

The index of the speed of the task for all subjects is shown in Fig.7 and the average of indices of all tests is represented by a level line in red color. All subjects were able to perform the application task. The average time of the complete task was about 28s. The speed results shown in Fig.7 support this conclusion. All the users achieve average speed above (90%).

Conclusion

The work in this paper was affirmed to control a robot by combining EOG-EEG based multimodal interface with RFID based shared control and evaluate its usefulness. Combining a multimodal interface and shared control architecture for a pick/place application can be a good mobility assistive technique for disabled as well as healthy people. The proposed algorithm and use of RFID ensures reaching to the right object through the shortest path while taking lesser time.

Wearable and portable devices based on multimodal and shared control system can be implemented with a little modification in the proposed model or by adding more modalities. However, some practical emphasis needs to be given to switch between different algorithms while using a shared control technique. Normalization and calibration function can be applied to solve the inter-subject variation problem for thresholding. An auto-adaptive system can be implemented for online adjustment of the EOG thresholds to solve the threshold-change problem due to fatigue. It is needed to involve people having motor disabilities in further studies to test the proposed assistive system with real potential users.

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