HMM based automated wheelchair navigation using EOG traces in EEG

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HMM based automated wheelchair navigation using EOG traces in EEG

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Abstract
This paper presents a wheelchair navigation system based on a hidden Markov model (HMM), which we developed to assist those with restricted mobility. The semi-autonomous system is equipped with obstacle/collision avoidance sensors and it takes the electrooculography (EOG) signal traces from the user as commands to maneuver the wheelchair. The EOG traces originate from eyeball and eyelid movements and they are embedded in EEG signals collected from the scalp of the user at three different locations. Features extracted from the EOG traces are used to determine whether the eyes are open or closed, and whether the eyes are gazing to the right, center, or left. These features are utilized as inputs to a few support vector machine (SVM) classifiers, whose outputs are regarded as observations to an HMM. The HMM determines the state of the system and generates commands for navigating the wheelchair accordingly. The use of simple features and the implementation of a sliding window that captures important signatures in the EOG traces result in a fast execution time and high classification rates. The wheelchair is equipped with a proximity sensor and it can move forward and backward in three directions. The asynchronous system achieved an average classification rate of 98% when tested with online data while its average execution time was less than 1 s. It was also tested in a navigation experiment where all of the participants managed to complete the tasks successfully without collisions.

Keywords: human–machine interface, electroencephalography, autonomous wheelchair, rehabilitation, eye gaze tracking, hidden Markov model, support vector machine

1. Introduction

Over the years, various forms of human–machine interface (HMI) systems have been developed for different purposes. Recent advancements in signal processing have enabled HMI users to issue commands in the forms of voice, motion of body parts, electromyography (EMG) [1, 2], electrooculography (EOG) [3–5], electroencephalography (EEG) [6, 7] or a combination of input signals [8, 9]. HMIs using voice and visual cues, such as hand gestures, have been successfully used by people with Parkinson disease, quadriplegia, amputated or missing limbs, and motor skill disorders [5]. However, these HMIs are not so useful for patients suffering from amyotrophic lateral sclerosis (ALS), motor neuron diseases, or Guillain–Barre syndrome. Since they cannot perform voluntary muscle movements with ease, EEG and EOG signals are the only convenient means for them to interact with HMI systems [10].

In this study, EOG traces embedded in EEG signals of alpha and delta rhythm are used to navigate a motorized wheelchair. Features extracted from these signals are used as inputs to a few support vector machine (SVM) classifiers to determine the eyelid position and gaze direction of the eyes, which are regarded as observations to an HMM. Based on the observations and transition probabilities, the HMM dictates the direction that the wheelchair should go. The wheelchair can move forward and backward, in a total of six directions. The asynchronous system was tested by a number of participants to execute real time instructions. It was also used to navigate along two routes where all of the participants managed to complete the tasks successfully without collisions.

2. Background study

Neuromuscular disorders affect the nerves that control the voluntary muscles [11, 12]. When the neurons are affected,
communication between the nervous system and the muscles deteriorates, thereby weakening the muscles progressively [13, 14]. People with severe motor disabilities can still maintain an acceptable quality of life with the use of HMIs that do not take signals that require muscle control as inputs. A semi-autonomous wheelchair is an example of a HMI where the user interacts with the system to navigate, both indoors and outdoors. Examples of semi-autonomous wheelchairs with different levels of manual assistance are listed in table 1.

EEG is an electrical brain signal that is recorded from the surface of the scalp using electrodes. EEG signals have been utilized by researchers from diverse fields to study epilepsy, apnea, coma, and various brain or neural functions and disorders. EEG signals have also been used to help those with disabilities translate their intentions into computer commands via a HMI. Several useful derivatives of EEG signals, such as P300 wave [15–17], mu and beta rhythms and steady-state visual evoked potentials (SSVEP), have been investigated [18–20]. EOG is an electrical signal or potential difference between retina (negative pole) and cornea (positive pole) of the eye. The induced voltage can be measured in a vertical or horizontal direction using two sets of electrodes placed at the outer canthi. The EOG signal can vary from 50 to 3500 μV, with a frequency below 100 Hz. The positive pulse is generated when the cornea moves towards positive electrodes, and vice versa. Besides noise, EOG signals may also contain artifacts from EEG, EMG, electrocardiography (ECG), head movement, and luminance. Likewise, EEG signals may also contain noise and traces of other signals, like EOG. The advantage of using the EOG trace in the EEG signals over tapping the EOG signal at outer canthi directly is that the user can have an unobstructed view since there are no electrodes placed around the eyes.

Blinking and horizontal eye movement signals can be traced from dipolar artifacts in EEG signals [31]. The spectral amplitude of the trace in the alpha response is higher when the eyes are closed than when they are open [32]. Therefore, the eyelid position can be inferred from the trace obtained during closed eye than open eye, as shown in figure 1. We find that the CTM ratio of the alpha trace is smaller during closed eye than open eye, as shown in figure 3. In our experiment, the radius of the circle (r) was fixed at 2. Both variance and CTM are used together to determine whether the eyes are closed or open.

3. Methodology

The O2, F9 and F10 signals are sampled at 256 samples per second (Hz). The EOG trace in the O2 signal is obtained by bandpass filtering the signal with a Butterworth filter, with a passband of 8–15 Hz. The F9 and F10 signals are filtered with a Chebyshev lowpass filter, with a cutoff frequency of 4 Hz. Then, for each filtered signal, a window of 128 samples is analyzed every 0.5 s.

3.1. Open or closed eye classification

The alpha trace of channel O2 exhibits a higher amplitude of signal fluctuation when the eyes are closed than when they are open, as shown in figure 2. The common amplitude of the signal is around 5–10 μV when the eyes are open and 20–40 μV when they are shut.

From the alpha trace, two simple features can be calculated to distinguish closed from open eyes, which are: variance and central tendency measurement (CTM). The variance ($\sigma^2$) of the 128 samples in the 0.5 s window is given by

$$\delta^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2$$

where $N$ is 128 and $\mu$ is the mean of the samples.

CTM is simply a 2D plot of sample difference. It is a plot of $[x(n+2) - x(n+1)]$ against $[x(n+1) - x(n)]$, which displays the rate of variability in a time series. From this plot, the ratio of the samples that fall inside a circle of radius $r$ over the total number of samples is calculated. Let $N$ be the total number of points in a window frame. Excluding the end points, there are N-2 points in the CTM plot. The CTM ratio is defined as

$$\delta(i) = \begin{cases} 1 & \text{if } \left[ (x(i+2) - x(i+1))^2 + (x(i+1) - x(i))^2 \right]^{0.5} < r \\ 0 & \text{otherwise} \end{cases}$$

$$\text{CTM ratio} = \frac{1}{n-2} \sum_{i=1}^{n-2} \delta(i)$$

We find that the CTM ratio of the alpha trace is smaller during closed eye than open eye, as shown in figure 3. In our experiment, the radius of the circle ($r$) was fixed at 2. Both variance and CTM are used together to determine whether the eyes are closed or open.

3.2. Gaze direction classification

In our system, only three gaze directions are used, they are: left, center and right. As the eyeballs move from one direction to another, voltage levels of the F9 and F10 traces changes in the opposite directions. For example, when the eye gaze shifts from center to left, the F9 trace decreases but the F10 trace increases by the same amount. The same phenomenon is observed when the gaze moves from right to center. But when the eye gaze moves from center to right, or from left to center, the F9 trace increases while the F10 trace decreases.

The eye gaze can also shift directly from left to right, or the reverse. When this happens, a higher jump in voltage levels in F9 and F10 traces is observed, as shown in figure 4. This is probably due to a full distance shift by the eyeballs going from corner to corner as compared to a half distance
Table 1. Examples of semi-autonomous wheelchairs.

<table>
<thead>
<tr>
<th>HMI system</th>
<th>Navigation type</th>
<th>Control method</th>
<th>Safety sensors</th>
<th>Specialty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nav-Chair [21, 22]</td>
<td>Semi-autonomous</td>
<td>Joystick</td>
<td>Ultrasonic sensor</td>
<td>Avoid obstacles</td>
</tr>
<tr>
<td>Berman autonomous [23]</td>
<td>Semi-autonomous</td>
<td>Joystick</td>
<td>Sonar sensor</td>
<td>Avoid hazards</td>
</tr>
<tr>
<td>SENARIO [24]</td>
<td>Semi and full autonomous</td>
<td>Voice and goal to goal</td>
<td>Multiple types of sensor</td>
<td>Control without hand</td>
</tr>
<tr>
<td>OMNI [25]</td>
<td>Semi/full autonomous</td>
<td>Joystick and goal to goal</td>
<td>Multiple types of sensor</td>
<td>Can be run in high or low level autonomous navigation</td>
</tr>
<tr>
<td>MAid [26]</td>
<td>Semi-autonomous</td>
<td>Joystick</td>
<td>Motion sensor</td>
<td>Crowd avoidance</td>
</tr>
<tr>
<td>Wheesly [27]</td>
<td>Semi-autonomous</td>
<td>EOG</td>
<td>Proximity and sonar sensor</td>
<td>Command system can change by the need of the user</td>
</tr>
<tr>
<td>VAHM [28]</td>
<td>Semi/full autonomous</td>
<td>Joystick and goal to goal</td>
<td>Ultrasound sensor</td>
<td>Combination of high and low level autonomous navigation</td>
</tr>
<tr>
<td>Smart wheelchair [29, 30]</td>
<td>Semi-autonomous</td>
<td>EEG, P-300 wave</td>
<td>No sensors</td>
<td>Run by mental task</td>
</tr>
</tbody>
</table>
Figure 1. The positions of the electrodes and samples of their trace signals.

Figure 2. Alpha signal during closed and open eye.

Figure 3. (a) CTM plot of closed eye alpha with CTM ratio = 0.24. (b) CTM plot of open eye alpha with CTM ratio = 0.89.
shift from center to corner (or corner to center). To accentuate the effect of the opposite voltage level movements in F9 and F10 traces caused by gaze shift, we subtract F10 from F9 and extract two features from the difference signal, which are: the voltage level rise and average first derivative. The derivative of the \( i \)th sample is defined as

\[
d_i = \begin{cases} 
|x_{i+a} - x_i| & \text{if } i < a \\
\frac{(x_{i+a} + x_i)}{2} & \text{if } a < i < n - a \\
|x_i - x_{i-a}| & \text{if } i > n - a 
\end{cases}
\] (4)

where \( n = 128 \) and \( a = 5 \) in our experiment. Then the average of the first derivatives \( f \) is calculated as

\[
f = \frac{1}{n} \sum_{i=1}^{n} d_i.
\] (5)

The two features are fed to a series of SVM classifiers that classify a gaze shift into five classes, which are: unchanged, half right, half left, full right and full left. Full right is the corner to corner gaze shift from left to right, while full left is the corner to corner gaze shift from right to left. Half right and half left are semi gaze shift to the right and left, respectively. Half right represents either a center to right or left to center gaze shift since they both produce the same voltage level change. Similarly, half left represents either a center to left or right to center gaze shift. Knowing the eye gaze direction prior to half left or half right gaze shift allows the system to determine the final gaze direction.

3.3 Double blink detection classification

When the user blinks his eyes, intentionally or otherwise, a short positive pulse or spike is temporarily detectable in both the F9 and F10 signals. Therefore, adding F9 and F10 signals should accentuate the blink signal and attenuate the effect of horizontal eye movement, as shown in figure 5. Since natural and intentional blinks generate an identical pulse in the added signal, they are indistinguishable. Thus, a double blink is instead used as one of the instructions in the system. Since a
double blink consists of two close blinks, two spikes or pulses should be observed within two consecutive window frames. Variance and average first derivative can be extracted from the sum signal (F9 + F10) to detect the presence of a double blink.

3.4. Sliding window

While monitoring the alpha trace, a conventional window frame might capture an interval when the eyes are just about to open or shut. During this short period, the signal is in transition from low amplitude to high, or vice versa. In this case, the samples in the window are a mixture of those with low and high amplitudes, as shown in figure 6. Consequently, the variance obtained neither represents open nor closed eye condition. Therefore, a sliding window is used to adjust the position of the frame, so that it will either contain samples of closed or open eye exclusively.

First, the absolute values of the samples in the window are divided into eight adjoining subintervals where each subinterval contains 16 samples. Then, the average of samples in each subinterval is calculated and the averages of the first and last subinterval are compared. If the absolute difference of the two averages is more than a specified threshold, the window is shifted to the right by 16 samples. The process is repeated until their difference is less than the specified threshold. Once this condition is met, the variance and CTM of the samples in the whole window can be calculated.

For the sum and difference signals of the F9 and F10 traces, the position of the window is also adjusted so that an important cue will be at the center of the window, as illustrated in figure 7. This step is necessary to obtain a high classification accuracy. First, the samples in the window are divided into eight adjoining subintervals, where each subinterval contains 16 samples. Then, the average first derivative of samples in each subinterval is calculated and the averages from the first and last subinterval are compared. If their absolute difference is more than a specified threshold, the window is shifted to the right by 16 samples. The process is repeated until the difference is less than the threshold. Once this condition is met, the variance, VLD and AFD of the samples are calculated.

3.5. SVM classifier

An SVM is a binary classifier that is useful for segregating the input features into two classes. For closed or open eye classification, using the alpha trace features only a single SVM is sufficient. This is also true for the double blink detection using features from the sum signal. However, to classify the gaze shifts using features from the difference signal, four SVMs are needed. The first SVM determines whether the gaze is shifted or not. If the gaze is shifted, then the second SVM decides whether the shift is to the left or right. If the gaze is shifted to the right, then the third SVM will further classify it into full or half shift. Similarly, if the gaze is shifted to the left, then the fourth SVM will determine whether the left shift is half or full. The classification process is depicted in figure 8. Using the outcome of this classification and the initial gaze direction (prior state), the HMM will decide the current gaze direction (current state) of the system and the appropriate command for the wheelchair.

3.6. Hidden Markov model (HMM)

The system is designed to allow the wheelchair to move forward and backward in three different directions. It should be able to stop as well. However, there are only a limited number of distinct horizontal eyeball movements and they are insufficient to move the wheelchair in six different directions. Another problem is that, left to center and center to right gaze shifts produce the same voltage change in the difference trace signal. This is also true for right to center and center to left gaze shifts. Thus, we resort to using an HMM to tackle this challenge.

An HMM is a statistical model where the state is not directly visible. In our case, the state is left, middle, or right. The transition from one state to another is governed by the features extracted from the alpha and delta traces. The probability of the current state of the model P(S_t|Model), is obtained by multiplying the transition probability of the previous state to current state P(S_t|S_{t-1}) and the probability of detecting the current observation given the current state P(O_t|S_t). The gaze direction that maximizes the product of the probabilities is chosen as the current state, as stated in the
following equations.

\[
P(S_t|Model) = P(S_t|S_{t-1}) \cdot P(O_t|S_t)
\]

\[
S_t = \arg \max \left( P(O_t|S_t) \right).
\]

It is assumed that the previous state is known. At the beginning \((t=0)\), when the previous state does not exist yet, the initial probability \(P(\pi)\) is used to replace the transition probability \(P(S_t|S_{t-1})\). Details on the fundamental and implementation of HMM are available in [34]. The hidden Markov model is shown in figure 9.

3.7. The overall system

The system is designed to have two modes of operation, namely: the ready and run mode. Both modes contain three states, which are right, middle and left, as depicted in figure 10. In both modes, the state of the system follows the gaze direction of the eyes. The O2, F9 and F10 traces are analyzed every 0.5 s. The features extracted from these signals are used to inspect the condition of the eyes, whether they are closed or open, the occurrence of double blink, and gaze shift.

The ready mode allows the system to be executed at software level only so that the user can train and check the system functionality while the wheelchair is stationary. This mode also allows the user to select either forward or backward as the direction the wheelchair will go when it enters run mode. For run mode, both the software and hardware of the system are fully functional. In this mode, the wheelchair will move according the gaze direction. It can move straight, turn left or turn right, in a forwards or backwards direction. It stops if the user closes his eyes or double blinks.

When the system is turned on, it is assigned to the middle state of the ready mode by default. The state should follow the gaze direction of the eyes at all time. If the state of the system fails to follow the gaze shift correctly, then an error occurs. The system is designed to correct minor errors automatically but inform the user when a major error is detected. A minor error occurs when the state is correct but the command signal is wrong. For instance, the current state is middle but the command asks the system to move the state from left to right. In this case, the system will just move the state from center to right. A major error occurs when the state is wrong and a command cannot be executed at all. For example, the state is right and the command is to move the state from left to right. In this case, the system cannot execute the command because the state is already right. Thus, the system will alert the user to move his gaze to the center and reset its state to the middle.

For whatever reason, the user can also reset the system manually by closing their eyes for at least 3 s. This is a backup measure to correct a major error if the system fails to
correct it automatically. The wheelchair is also equipped with a proximity sensor to detect nearby objects and avoid collisions.

Once the user is familiar with the system, they may want to command the wheelchair to move. The first step is to choose the direction that the wheelchair will go in when entering the run mode, either forward or backward. The move direction is chosen by shifting the state to the right or left, for forward or backward direction, respectively. Then, the user should maintain their gaze in that direction for at least 3 s or 6 consecutive frames to lock the chosen direction. The user can change the move direction by gazing in the opposite direction and maintaining their gaze for at least 3 s. But if the user wants to unlock the move direction, they simply have to shut their eyes for at least 3 s. This action unlocks the move direction and returns the system to the middle state of ready mode. The user is expected to set their gaze to the center when opening their eyes so that their gaze will match with the default state. Once a move direction is selected, and the user is ready to move the wheelchair, they should blink twice to send the system into run mode immediately.

Upon entering the run mode, the user is given 3 s to direct his gaze to where he wants to go before it is taken as the

Figure 8. Flow of classification process.

Figure 9. Hidden Markov model.
first instruction to move the wheelchair. Each instruction will be executed for at least 2 s to maintain the stability of the moving wheelchair and avoid command overcrowding. Another restriction is that the wheelchair will stop before turning or changing direction. And finally, only a gradual change of direction is allowed. An abrupt change of direction from left to right, or vice versa, will be executed with an intermediate step of going straight for 2 s. For instance, if a user wishes to change the direction of the wheelchair from right to left, then the wheelchair will change direction gradually from left to straight first before turning left. This is to prevent the wheelchair from toppling over. At all times, the wheelchair moves at 5 km h\(^{-1}\). If a user wishes to stop the wheelchair, all they have to do is to close their eyes for at least 0.5 s, so that the system will terminate whatever command it is executing and stop. This action makes the system restart the system or rest.

It should be noted that in run mode a double blink cue is not used because detecting a double blink is more time consuming since it occupies two consecutive windows. The last point to note is that in a span of 2 s, only one command is kept for the next move while the wheelchair is executing the current instruction. If the user produces multiple instructions within that interval, only the latest is kept as the next command to be executed.

4. Experiments

The EEG signals are recorded using the g-USBAMP toolkit from Guger Technology at a sampling rate of 256 Hz. Silver electrodes are placed at five different locations on the scalp according to the standard International 10–20 system. The locations are F9, F10, O2, with the earlobe as reference and FPz as ground. These locations are selected since they contain the strongest EOG trace in a filtered signal with minimum noise. The horizontal gaze movement and blink are interpreted from the F9 and F10 channels. Closed and opened eye conditions are inferred from the O2 channel. The recorded signals are analyzed using the LabView software from National Instrument. The window size is 0.5 s since it is the smallest possible for capturing a blink pulse.

The experiments are conducted in three sessions, namely: offline, online, and navigation sessions. In the offline session, the user is exposed to the system functionality and data are collected to train the SVMs and HMM, as well as to determine the values of thresholds needed for sliding window adjustment. This is followed by an online session where the user is asked to move the wheelchair according to randomly chosen instructions. Lastly, a real time navigation session wherein the user is asked to navigate the wheelchair along two routes is performed. Details of the experiments in each session are described in the following section.

4.1. Offline session

The objectives of the training session are to check the system condition and record the alpha and delta signals for calculating thresholds and training the SVMs and HMM. This session is conducted in ready mode and thus the wheelchair is stationary. A series of instructions are issued to the user and the time allocated for each instruction is 5 s. Then, a 5 s break is given before the next instruction is issued. Turn left, turn right, go straight, double blink and close eye are the five possible instructions that are randomly assigned. The participant is expected to respond within 2 s after the instruction is announced. The change in states and modes are shown by the LED display on the user interface. If any of the instructions are wrongly or not executed, then the instruction is repeated. Altogether, 100 instructions must be executed by each participant and the output signals recorded.

4.2. Online session

The online session is conducted in run mode and thus the wheelchair will move according to the user’s commands. First, each participant is instructed to lock the move direction to forward and enter the run mode. In run mode, there are only four possible instructions, which are: turn left, turn right, go straight and close eye. In total, 20 instructions are assigned to each participant, five from each command. The instructions are randomly assigned every 5 s without break. Upon hearing a command, the participant is expected to perform it accordingly. A command is considered successfully executed if the user is able to move the wheelchair correctly in less than 2 s.

Next, the participant is instructed to change the move direction to backwards. Then, 20 instructions are assigned to each participant randomly, five from each command as before. Throughout this session the changes in the state are
also displayed on the user interface panel by LED lights. After this, the participant is given 30 min to tinker with the system freely to gain more familiarity before the navigation session commences.

4.3. Navigation session

Two routes are designed to allow the user to navigate in an indoor environment, as shown in figure 11. The passage width is in the range of 4.5 m to 1.5 m. The first route is shorter and its total optimal length is 13.5 m with four checkpoints of A1, B1, C1 and D1. The second route has a total optimal length of 54.4 m with seven checkpoints from A2 to G2. The participants are responsible for maneuvering the wheelchair to pass through these check points, starting from the first point to the last point, and then return to the first point. However, when the participants reach the dead end points of D1 (in figure 11(a)) and G2 (in figure 11(b)) they are expected to reverse the wheelchair backwards to exit the tight end and only make a u-turn at point C1 and F2 respectively. Each participant is given three attempts to repeat the task and at the end of the session they are asked to answer a set of questionnaires regarding their experience.

4.4. Hardware implementation

From the result of the classifier, a command to the wheelchair is identified and issued. The system checks whether it is the same command that is currently being executed. If it is the same, then the execution of the current command is prolonged. If it is different, then a new instruction in the form of a digital command is sent to a digital to analog module that converts the digital signal to an analog voltage level. The module used in our experiment is a NI9264 from National Instrument. The analog output is then sent to a motor controller that controls the right and left motors of the wheelchair, as shown in figure 12(a). The controller will switch on the right, left, or both motors if the command is turn left, turn right, or move forward, respectively. If a shut eye is detected, both motors will stop and the system will exit run mode and enter ready mode at a middle state. The mode, move direction and current state are all displayed in front of the user by led lights, as shown in figure 12(c).

5. Results and discussion

5.1. Offline and online session results

A total of 20 healthy subjects participated in the offline and online sessions. They were mainly undergraduate and postgraduate students who had no neurological impairments or nystagmus. Other data on the subjects are given in table 2. In the offline session, the participants were required to perform double blink, eye closed, and horizontal saccades to the left and right. Altogether, 2000 signals were recorded from the participants. Features extracted from the EOG traces were used to train the SVMs and calculate the thresholds necessary for the sliding window operation.

This is followed by the online session where participants were instructed to execute the four commands in forward and backward directions. Throughout the session, each of the four commands was performed 100 times in the forward and then backward direction. A summary of the online tests is presented in the confusion matrix of table 3. From the total of 800 commands issued, 786 are correctly executed, so that the total execution rate is 98.25%. It can be observed that the go straight and close eye commands are perfectly classified and executed. Six turn right and eight turn left commands were wrongly executed. Out of these errors, eight commands were
not executed within 2 s and the remaining six errors are corner to corner gaze shifts that were wrongly interpreted as corner to center shift. This is mainly due to the user failing to shift his/her gaze from corner to corner rapidly. This generates weaker pulses in F9 and F10, which are similar to the ones generated by corner to center gaze shift. Factors that may cause this error are fatigue, inattention, and distraction. Another possible cause is that the wheelchair movement might lead to head or body movement, which could result in unwanted EEG or EOG artifacts. The artifacts might in turn affect the accuracy of command estimation.

A comparison with similar wheelchair navigation studies is given in table 4. Although the classification rate achieved by Rebsamen et al [16] is slightly higher, the execution time of their system is considerably higher than 1 s. On top of this, our system features backward movement, which is not available in these other systems. Furthermore, they employed a P300 synchronous system, which requires the user to follow the system pace.

5.2. Navigation session results

Five participants with the highest score in the online session were selected to perform the navigation tests. In this session, the participants were free to use as many commands as necessary to control the position and direction of the wheelchair along the paths. Then, the performances of the wheelchair system and the participant were evaluated according to the following criteria:

(1) Task success: completion of the navigation through the end of path.
(2) Path length: distance in meters traveled to accomplish the task.
(3) Time: time in seconds taken to accomplish the task.
(4) Path optimality ratio: ratio of the path length to the optimal path (the optimal path was 13.5 m for route 1 and 54.4 m for route 2, see figure 5).
(5) Time optimality ratio: ratio of the time taken to the optimal time to complete the task (the optimal time was approximately 9.7 s for route 1 and 39 s for route 2 based on maximum and rotational velocities of 1.39 m s$^{-1}$ and 0.4 rad s$^{-1}$).
(6) Collisions: total number of collisions during the tasks. A collision is not considered to be a failure as long as the system is able to continue with a new command, or requires a brief intervention from the supervisor.
(7) Mean velocity: mean velocity in meter per seconds during motion.
Table 3. Confusion matrix for system errors in direction estimation.

<table>
<thead>
<tr>
<th>Commands</th>
<th>Actions</th>
<th>Right-middle</th>
<th>Left-middle</th>
<th>Middle-right</th>
<th>Left-right</th>
<th>Middle-left</th>
<th>Right-left</th>
<th>Close eye</th>
<th>Not executed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Go straight</td>
<td>Right-middle</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Left-middle</td>
<td>0</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Turn right</td>
<td>Middle-right</td>
<td>0</td>
<td>0</td>
<td>98</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Left-right</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>96</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Turn left</td>
<td>Middle-left</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>97</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Right-left</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>95</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Stop</td>
<td>Close eye</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>HMI system</td>
<td>Classifier</td>
<td>Classification accuracy (%)</td>
<td>Time (s)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>----------------------------</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Huang et al (2012) [35]</td>
<td>Imagery</td>
<td>Synchronous</td>
<td>84.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kus et al (2012) [36]</td>
<td>Imagery</td>
<td>Asynchronous</td>
<td>74.84</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Choi et al (2013) [37]</td>
<td>Imagery + SSVEP + P300</td>
<td>Asynchronous</td>
<td>84.4 – 91</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Long et al (2012) [38]</td>
<td>Imagery + P300</td>
<td>Asynchronous</td>
<td>83.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Diez et al (2011) [40]</td>
<td>SSVEP</td>
<td>Asynchronous</td>
<td>81.68</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed study</td>
<td>EEG + EOG</td>
<td>Asynchronous</td>
<td>98</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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</tbody>
</table>
All of the subjects succeeded in navigating the wheelchair along the routes without collision. The results of the corresponding metrics are summarized in Table 5. The average distances travelled by the participants were 15.76 meters and 75.42 meters for route 1 and route 2, respectively. The path optimality ratios were low (1.17 for route 1 and 1.35 for route 2), which suggests that the participants were able to travel close to the designated paths. The average times to traverse the routes were 15.04 and 85.67 s for route 1 and route 2, respectively. On average, the ratios of the optimal times were 1.55 for route 1 and 2.05 for route 2. The participants took a longer time to complete the second route because it has more turns and longer narrow passages. The actual time is higher than the optimal time because it includes mode changing, command selection, and computational time. The mean velocity of the wheelchair was 1 m s\(^{-1}\) for the first route. For the second route, the participants had a lower velocity of 0.88 m s\(^{-1}\). The maximum speed was limited to 1.3 m sec\(^{-1}\) for safety reasons. In general, a narrow performance gap observed among the participants signifies the system’s usability, and consistency to navigate and maneuver the wheelchair in open and small spaces.

### 5.3. Participant experience evaluation

At the end of the navigational session, the participants were given a set of questionnaires to express their navigational experience in four metrics of average workload, learnability, confidence and difficulty, as presented in Figure 13. The
metrics were measured on a scale between 0 and 5, from the least to the most. The workload metrics denotes the effort to accomplish the tasks. All of the participants agreed that it took a higher workload to complete route 2 than route 1 because route 2 has more turns and a narrower passage than route 1. Participant P3 and P5 recorded the most effort because route 2 has more turns and a narrower passage than took a higher workload to complete route 2 than route 1 accomplished the tasks. All of the participants agreed that it least to the most. The workload metrics denotes the effort to accomplish the tasks. All of the participants agreed that it took a higher workload to complete route 2 than route 1 because route 2 has more turns and a narrower passage than route 1. Participant P3 and P5 recorded the most effort because route 2 has more turns and a narrower passage than route 2. As for difficulty metrics, all of the participants agreed that route 2 is more difficult than route 1.

A t-test was performed to gauge the influence of routes on the level of difficulty. The null hypothesis stipulates that there is no significant difference between the means of difficulty for route 1 and route 2. The result of the test clearly disproves the null hypothesis and shows that the difference in mean difficulty of the routes is significant with (Mean = 3.2 vs 4.4, t(4) = −3.21, p = 0.016).

6. Conclusions

In this paper, EOG traces embedded in EEG signals are used to drive a wheelchair navigation system. A sliding window is used to capture important signatures in the EOG traces accurately without partial loss of information. Extracted features are used to infer the eye condition (i.e. whether the eye is open or closed) and gaze direction using a number of SVMs and an HMM. The HMM determines the state of the system and generates the commands that move the wheelchair. The wheelchair can be steered in six directions forwardly and backwardly. Two different modes of operation are made available to ensure safety and convenience to the user. The asynchronous system achieved an average classification rate of 98% in an online test, with an average execution time of less than 1 s.

An actual navigation session was performed wherein five participants undertook two navigation tasks by maneuvering the wheelchair through two designated routes. The participants managed to complete the tasks without collisions. In this session, the usability of the backward movement proved useful when the wheelchair was trapped in tight dead ends with no space to make a turnaround. A good average accuracy of 98% for route 1 and 97% for route 2 shows that the system is easy to use and stable. This system is still in the development phase and, therefore, has not been tested with real patients who suffer a severe motor disorder.

Acknowledgments

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