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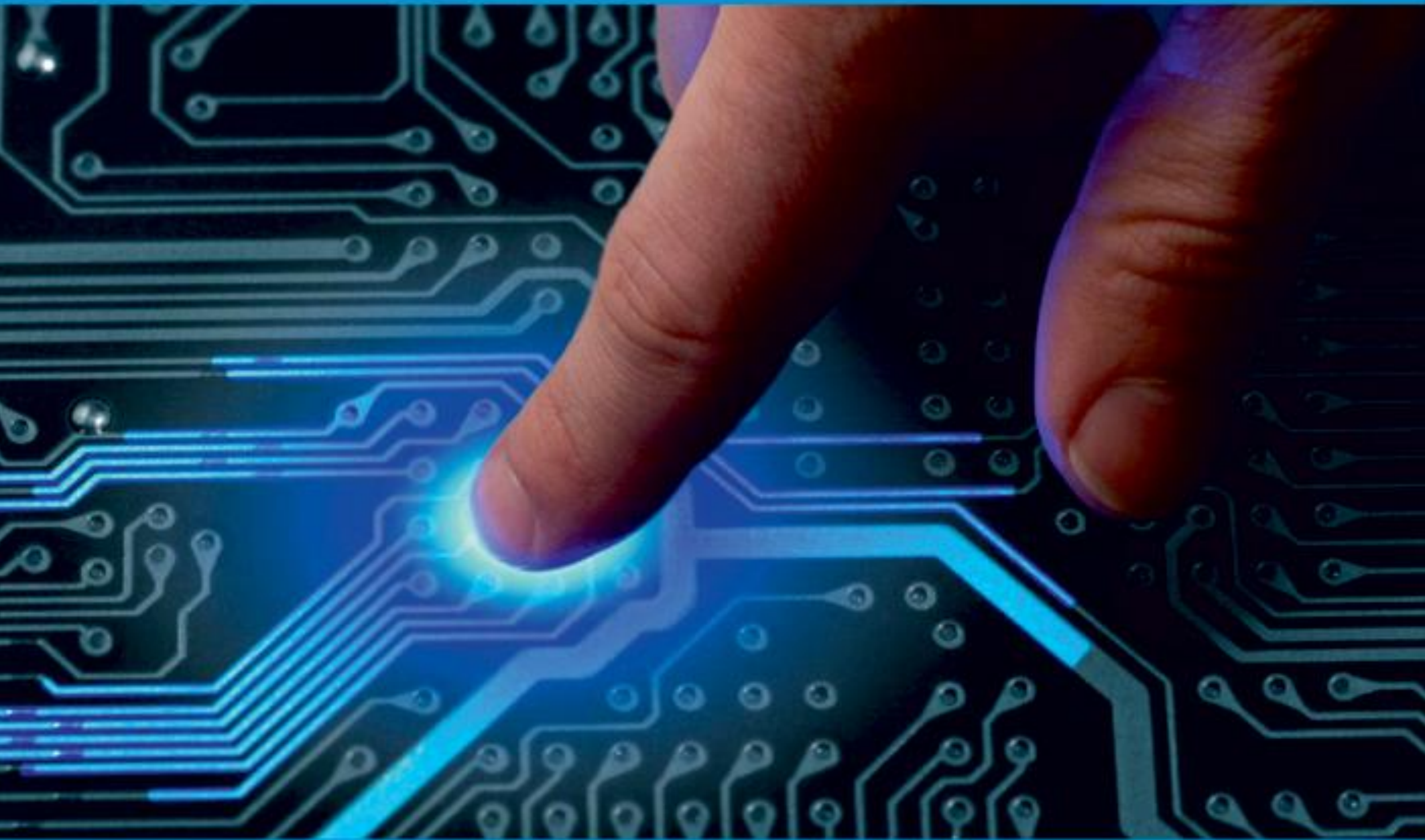

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A Hybrid Brain-Computer Interface and Computer Vision-Based Human-Vehicle Collaborative Simulated Driving System

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ABSTRACT: In order to make driving more comfortable and convenient, automatic cars have been designed. These vehicles, however, were unable to meet the variety of human goals. The combination of automated driving with brain-computer interface (BCI) control has garnered attention recently. In this study, a fusion technique has been presented to explore and validate the viability of human-vehicle collaborative driving, since the BCI system still has some limitations in real-time controlling. It was decided to create a hybrid BCI to understand human intentions. To keep the car on the road, an automated driving component based on computer vision was also developed. This research initially developed a technique for combining these two types of vehicle driving decisions. Both the hybrid electroencephalograph (EEG) signals and the visual data can be obtained simultaneously by this technique. Motor imagery and steady-state visual evoked potentials make up the hybrid EEG signals. To decide whether to operate a simulated car, the collected multisource data can be combined. The suggested approach was assessed using several destinations. The outcomes of the experiment confirm that combining computer vision and human intention is feasible. The information transfer rate was 85.80 bits per minute, and the task success rate was 91.1%.

KEYWORDS: steady-state visual evoked potential (SSVEP), motor imagery (MI), human-vehicle collaborative driving (HVCD), brain-computer interface (BCI), and computer vision.

I. INTRODUCTION

The U.S. National Highway Traffic Safety Administration has graded autonomous vehicles (ADVs) created by several firms, such as Google, Lexus, and Volvo, as having reached a high degree of self-driving capability [1]. The advancement of sensors, including laser radars, cameras, and global positioning systems (GPS), has made it possible for cars to automatically avoid obstacles, assess traffic conditions, and navigate. ADVs offer inexperienced driving and anti-fatigue. Additionally, they provide a cozy setting for human commuting.A path or destination should be manually set in ADVs. The purpose of automated driving is to prevent collisions, save time and energy, and assess road conditions [2], [3]. Nonetheless, exceedingly comfortable driving experiences are difficult to achieve and the variety of human intention is hard to satisfy.Human intentions and traffic conditions are taken into account simultaneously with HVCD. Brain-computer interface (BCI) allows one to access a person's mental state, and HVCD helps individuals with motor disabilities overcome their driving challenges.Human intentions have been ascertained through the widespread usage of electroencephalogram (EEG) signals. Numerous tests have confirmed advanced steady-state visual evoked potential (SSVEP) detection techniques [4]. SSVEP is a response to a flickering visual stimulus that is detected over the occipital cortex at a fixed frequency, usually greater than 6 Hz [5], [6]. It is possible to generate many SSVEPs, shift attention to stimuli at various frequencies, and identify the chosen option [7]. A user needs little training to become accustomed to an SSVEP-based BCI system because it is very simple to set up. SSVEP-based BCI systems are usable by the majority of subjects [8]. High information transfer rate (ITR) and signal-to-noise ratio can be attained by SSVEP-based BCI systems [9].

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II. METHODOLOGY

Fig. 1 shows the system structure in its entirety. Through BCI, the human intelligence component receives SSVEP and MI signals. The computer vision part gets access to road information obtained via a camera mounted in the front of the car from the vehicle simulation system. The element of fusion combines the judgments made based on the EEG readings with the outcomes of the computer vision. The ultimate collaborative choice is utilized to steer the vehicle simulation.But the subject can also go to the places by accident. Actually, every part of the system can make the random intended command and the consecutive.

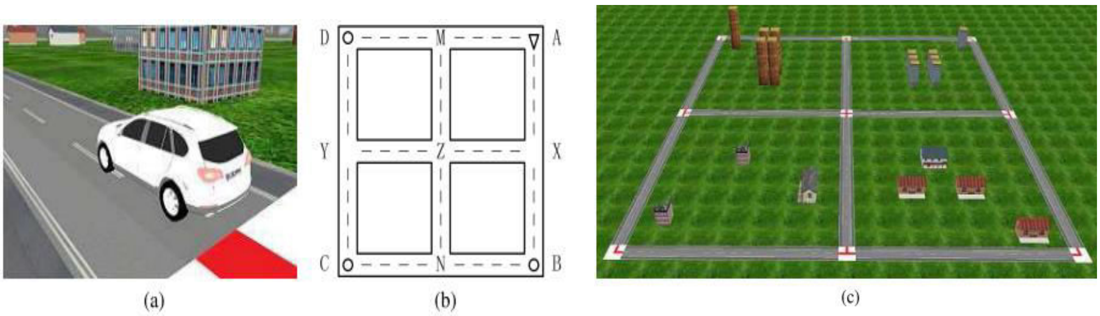

Figure 2. Traffic environment simulation. (a) Provides an illustration of the model car.

(b) Triangle at position A displays the car in the beginning. Three further locations are represented by the circles at points B, C, and D. Z is a cross intersection, while points M, N, X, and Y are T-intersections. (c) Provides an overview of the whole driving simulation scenario.

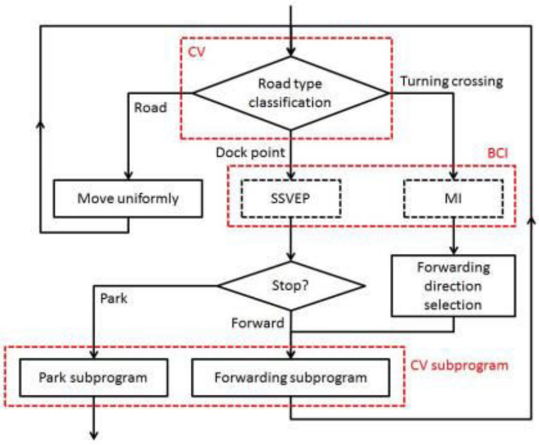

Figure 3: The system functioning procedure flowchart. The kind of road is recognized by the computer vision component. The choice for driving across an intersection will be made by the MI command. The SSVEP command will decide if the car is getting close to the turn point. The computer vision subprograms are in charge of all the vehicle behavior specifics.

A. SSVEP-Based BCI Component: The visual stimulus (150 × 150 pixels for each stimulator) is shown on an LCD display (27, 60 Hz refresh rate, 1920 × 1080 pixels screen resolution), as shown in Fig. 12. MATLAB processes the SSVEP data that were gathered from the Oz channel (as shown in Fig. 5). To find the SSVEP, canonical correlation analysis (CCA) is used.

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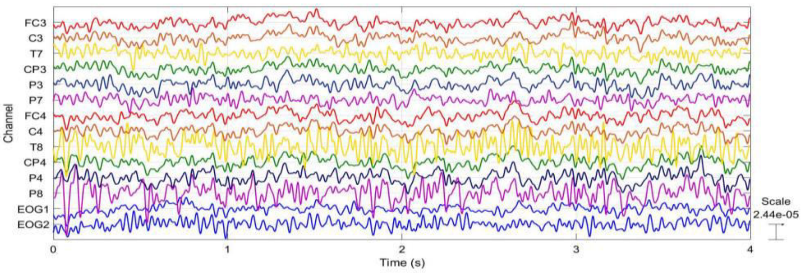
$$\rho(x, y) = \max_{U_k, V_k} \frac{E[x^T y]}{\sqrt{E[x^T x] E[y^T y]}} = \max_{U_k, V_k} \frac{E[U_k^T X Y^T V_k]}{\sqrt{E[U_k^T X X^T U_k] E[V_k^T Y Y^T V_k]}}. \quad (1)$$



The SSVEP signals obtained from the Oz channel are the set of variables, X ∈ RC×T, in this paper as seen in Figure 6. In this case, C stands for the number of channels,indicates the quantity of sample points.Y ∈ R2Nh×T, the other set of variables, was intended as the reference signals [40] are characterized by their

$$Y_{f_i} = \begin{Bmatrix} \sin(2\pi f_i t) \\ \cos(2\pi f_i t) \\ \vdots \\ \sin(2\pi N_h f_i t) \\ \cos(2\pi N_h f_i t) \end{Bmatrix}, t = \frac{1}{S}, \frac{2}{S}, \ldots, \frac{T}{S} \quad (2)$$

where the symbols fi, Nh, and S stand for frequency, harmonic number, and sampling rate, respectively.
A classifier may be used to represent the target frequency recognition approach as shown in the following example:

$$f_{\text{target}} = \arg\max_k \rho_k, k = 1, 2, \ldots, N \quad (3)$$

where N is the total number of sources of stimuli.

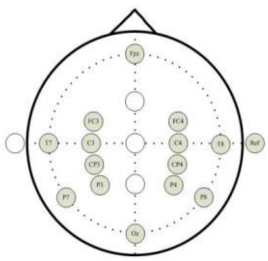


Figure 5: Electrode channels for EEG signal acquisition. The right earlobe is the location of the reference electrode. SSVEP signals are recorded on channel Oz, whereas MI signals are recorded on the other channels. The upper and lower eyelids, respectively, are where the EOG channels are stuck.

B. The MI-Based BCI: Elements since eye movement usually affects electro-oculogram (EOG) signals, we use wavelet CCA (wCCA) in this research to eliminate EOG artifacts from MI signals. The electrode location used to

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record the SSVEP signals is noticeable for being rather distant from the eyes. As a result, it is unclear how EOG affects SSVEP signals. As a result, we did not use the EOG removal technique for SSVEP. The k-nearest neighbor (kNN) feature vector is extracted using CSP, and then classification is performed to get the final control command. Fig. 4 shows the original signal samples for EOG and MI.

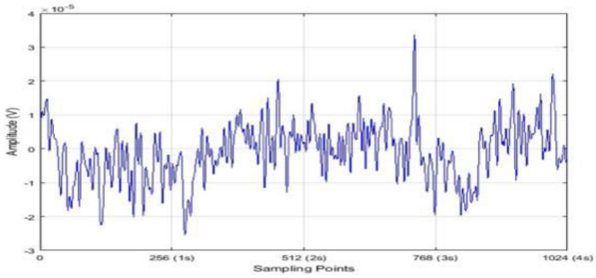

Fig. 6. SSVEP signals recorded from Oz channel. Take 4-s length sampling points as an example.

1) wCCA Data Preprocessing: To obtain zero mean data, we centered the obtained signals. To magnify the EOG signals, vertical EOG signals are added to the EEG signals. The first pair of the canonical variables, wl and wr, which include the majority of the EOG noise, are then obtained by utilizing the signals Sl from the left brain (i.e., T7, P7, FC3, C3, CP3, and P3) and Sr from the right brain (i.e., T8, P8, FC4, C4, CP4, and P4). We employed a wavelet hard threshold to decrease the EOG noise because wavelet transformation can detect the eye blink artifacts [39].

2) Feature extraction: CSP seeks to optimize the difference in the signal variance ratios by locating a spatial filter matrix W ∈ RC×C [18]. Assume that X1 and X2 are EEG signals from two MI tasks, where X1 and X2's normalized covariance matrices are denoted by C and T, respectively, by the number of EEG channels and samples, respectively.

$$\Sigma_1 = \sum \frac{X_1 X_1^T}{\mathrm{trace}(X_1 X_1^T)}$$
$$\Sigma_2 = \sum \frac{X_2 X_2^T}{\mathrm{trace}(X_2 X_2^T)} \quad (6)$$

3) Classification with kNN: An efficient instance-based technique for differentiating between mental states is the kNN. By computing the distance in the feature space, kNN determines how similar the test and training sets of data are to each other. The MI signals captured in the offline and online experiments are used as the training data and test data, respectively, after the noise reduction. The majority vote of its kNNs, which are made up of the training data, classifies the test data into the corresponding mental state. Based on the mental state, the final control commands are formed.

C. Computer Vision-Based Road Condition Recognition Component

By identifying the different sorts of intersections, the computer vision component completes the fundamental vehicle operation and perceives the state of the road. The focus of advanced driver assistance systems is mostly on affordability and industry requirements [41]. A multiclass support vector machine (SVM) classifier is trained using this approach. The road is divided into seven categories using the histogram of the oriented gradient (HOG) characteristic. The seven categories include road, left corner, right corner, left T-intersection, normal T-intersection, and cross intersection, in accordance with the photos from Fig. 9(b)–(k).

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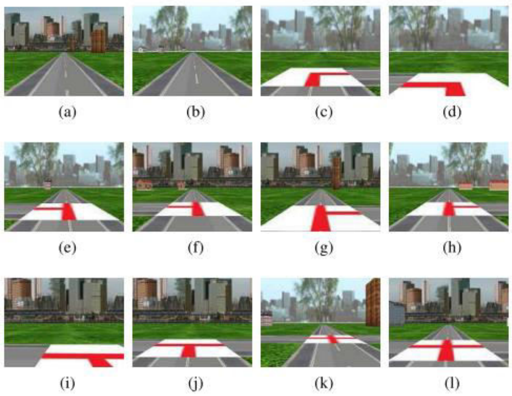

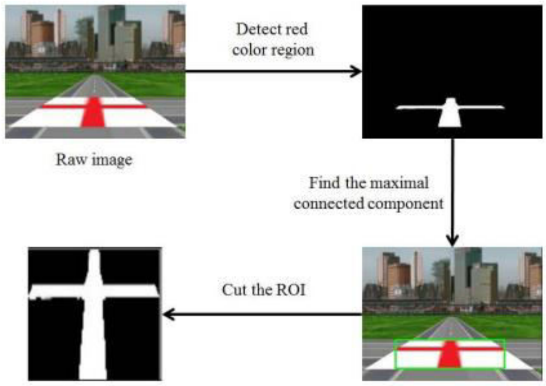

The color-based image preprocessing method's flowchart. First, the raw image is converted into a binary image using the color of the sign. The ROI, or maximum linked component, is retrieved and subsequently scaled for the extraction of HOG features. The geometric deformation of the sign in the picture is unavoidable as the routes of the car traveling to the junctions are random. As a result, the HOG feature makes sense and can strengthen the vision-based recognition component's resilience. The HOG window in this study is set to 100 × 100 pixels.

TABLE I
COMMAND DECISION BINARY VECTOR BIT MEANINGS

Bit	Set Mode	Meaning
1	1 0 0 0 0	Heading
2	0 1 0 0 0	Parking
3	0 0 1 0 0	Moving straight
4	0 0 0 1 0	Turning left
5	0 0 0 0 1	Turning right

Fig. 9 except Fig. 9(g) does not consider the right time to turn direction.

III. EXPERIMENT

A. Topics

The six healthy subjects for the studies were numbered 1 through 6 and consisted of three males and three girls. Both subject 5 (male) and subject 2 (female) had some prior MI experience. For the first time, they had to operate a simulation car using the SSVEP and MI BCI systems in this experiment. After being adjusted, all of the individuals showed normal visual acuity and showed no signs of brain illness.

B. Collection of SSVEP and MI EEG Signals

Using a 16-channel amplifier, SSVEP and MI EEG signals are recorded concurrently (g.USBmap, Guger Technologies, Graz, Austria). EEG signals (Oz for SSVEP, T7, T8, P7, P8, FC3, FC4, C3, C4, CP3, CP4, P3, and P4 for MI) are obtained from the electrodes as shown in Fig. 5. Resistances

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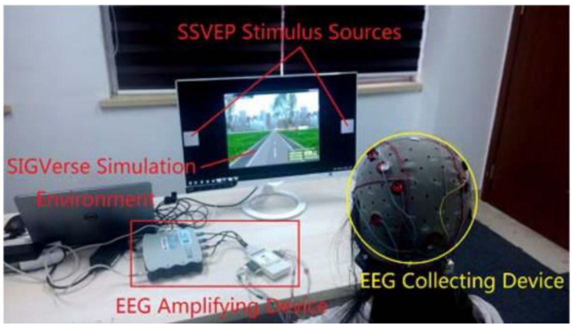

Figure 12: A calm interior environment with a subject wearing an EEG collecting equipment and a simulation environment with a source of screen stimuli are kept at or below 5k ~. The 256 Hz sampling frequency is applied to the signals. High-frequency sounds and power line interference are eliminated using a 50-Hz notch filter and a 5–60-Hz band-pass filter.Two groups were created from the signals that were gathered from every SSVEP and MI channel. For the SSVEP processing, the signals from the Oz channel are recorded. For MI processing, the residual signals are recorded.EEG signals were continuously recorded during the experiments whenever the car was traveling on the road, or just before a corner or intersection.Simultaneously, the server received the final judgments from SSVEP, MI, and computer vision labeled with their owners. In order to receive them for fusion, the server opened multi threads.

C. Methods of Experimentation

Before the testing started, the subjects received an explanation of the experimental protocol. To gather the fundamental EEG patterns for MI, each subject received at least 15 minutes of training. The MI classification machine was trained using the samples that were gathered prior to testing. The purpose of the pre-experiment was to acquaint the subjects with the apparatus. The participant in Figure 12 was directed to use the EEG collecting apparatus while sitting in a calm interior setting.To start or stop the simulated car, two distinct SSVEP stimulus sources flickered on the screen. Conventional BCI systems based on SSVEP require specific frequencies of visual inputs in order to produce control commands.Every participant in the simulation experiment had to finish three trials, each of which had to be done five times. In every experiment, the subjects drove the car to a different location from the same starting point. The vehicle's directions and starting place were predetermined.

IV. EXPERIMENTAL RESULTS

A. Results of Offline Experiments

1) Offline SSVEP Performance: Five elicitations of each stimulus SSVEP signal were required of each individual. The subject can move on to the next MI offline trial if they succeed each time. We thus chose six participants for additional research.

TABLE III
EXAMPLE OF CONFUSION MATRIX OF OFFLINE MI TRAINING RESULTS

	Left (P)	Right (P)	Rest (P)	Recall
Left (A)	8	1	1	0.8
Right (A)	1	7	2	0.7
Rest (A)	2	0	8	0.8
Precision	0.73	0.88	0.73	-

2) Offline MI Performance: The training set was obtained by repeating each type of MI ten times. The accuracy of the offline MI training is 77.2%±5.8%. Table III displays the comprehensive study for recall rate and pattern recognition precision.

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The subjects can elicit the correct MI signals with an accuracy of roughly 77.2%, according to the mean accuracy. Subject 6 performs the best, with a mean accuracy of almost 86.7%. Subject 5, on the other hand, performs poorly, with an accuracy of only 70.0%.

3) Computer Vision Performance When Offline: We test the computer vision component's performance in the experiment using cross-validation. Four samples from each class served as the testing set, while sixteen samples from each class were designated as the training set. Every category has a recall rate and precision rate of 1.0.
To find out if the classifier is sensitive to the samples, cross-validation was employed.

B. Results of the Online Experiment

Online SSVEP Performance: Table IV displays the accuracy of the SSVEP classification results from the online experiment. Overall, the subjects' mean accuracy was 97.7%±2.9%. The mean filter was also used to filter the categorisation findings. Results are averaged five times by the filter. Eighty percent of the signal sampling overlaps.

2) Online MI Performance: The accuracy of the MI performance during the online experiment is displayed in Table V. Every destination was processed five times throughout the task. Additionally, from the accuracy of every topic for various destinations, we can observe that destination 3 typically has lesser accuracy than destination 2.

TABLE V
ACCURACY OF THE ONLINE MI

Destination	B	C	D	Mean & SD.
Subject 1	79.1%	73.3%	43.3%	65.3%±19.2%
Subject 2	100.0%	96.7%	90.0%	95.6%±5.1%
Subject 3	93.3%	70.0%	51.0%	71.5%±21.2%
Subject 4	85.7%	83.3%	77.8%	82.3%±4.1%
Subject 5	72.7%	72.0%	60.0%	68.2%±7.2%
Subject 6	66.7%	100.0%	72.3%	81.3%±17.0%
Mean & SD.	82.9%±12.6%	82.6%±13.1%	66.6%±18.0%	**77.4%±11.3%**

TABLE IV
ACCURACY OF THE ONLINE SSVEP

Destination	B	C	D	Mean & SD.
Subject 1	100.0%	90.0%	90.0%	93.3%±5.8%
Subject 2	100.0%	86.0%	100.0%	95.3%±8.1%
Subject 3	100.0%	100.0%	100.0%	100.0%±0.0%
Subject 4	100.0%	100.0%	100.0%	100.0%±0.0%
Subject 5	91.7%	100.0%	100.0%	97.2%±4.8%
Subject 6	100.0%	100.0%	100.0%	100.0%±0.0%
Mean & SD.	98.6%±3.4%	96.0%±6.3%	98.3%±4.1%	**97.7%±2.9%**

3) Online Computer Vision Performance: In the online experiment, the computer vision component has a high accuracy of 98.9%±2.7%. The car was a little off the road due to the accumulation error that resulted from the 90 rotation. The computer vision component failed to recognize the T-intersection and drove outside while approaching it. In this case, the trial was marked as unsuccessful.

V. DISCUSSION AND CONCLUSION

A hybrid EEG-based and HVCD simulation system was presented in this work. The experimental findings show that computer vision and EEG can be combined to control the vehicle's movement and arrive at the desired location. The vehicle was given multi-control orders using SSVEP and MI. Because the EEG signal's detection accuracy is restricted, we employed a computer vision system to increase safety by preventing vehicles from leaving the road. The suggested system tries to integrate multisource information to manage the vehicle, taking into account the variance of human intents through SSVEP and MI signals. An HVCD simulation system is being proposed for the first time in this paper. Users can send control commands using EEG-based BCIs in our suggested simulation environment. The vehicle was directed by SSVEP signals to proceed or stop at the designated locations, and it was directed by MI signals to change directions at various kinds of intersections. Additionally, to process the intricate driving scenarios, we employed computer vision techniques. The car uses computer vision technology to make precise left and right turns. Our suggested fusion technique was predicated on the hierarchical choice. To arrive at a safe driving approach, it took into account both human variability in intention and computer vision recognition outcomes.

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