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Voice Navigation Effects on Real-World Lane Change Driving Analysis Using an Electroencephalogram

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ABSTRACT Improving the degree of assistance given by in-car navigation systems is an important issue for the safety of both drivers and passengers. There is a vast body of research that assesses the usability and interfaces of the existing navigation systems but very few investigations study the impact on the brain activity based on navigation-based driving. In this paper, a real-world experiment is designed to acquire the electroencephalography (EEG) and in-car information to analyze the dynamic brain activity while the driver is performing the lane-changing task based on the auditory instructions from an in-car navigation system. The results show that auditory cues can influence the speed and increase the frontal EEG delta and beta power, which is related to motor preparation and decision making during a lane change. However, there were no significant results on the alpha power. A better lane-change assessment can be obtained using specific vehicle information (lateral acceleration and heading angle) with EEG features for future naturalized driving study.

INDEX TERMS Auditory instructions, EEG, in-car navigation, lane change, real-world driving.

I. INTRODUCTION

The navigation system is the most popular and commonly used function of an in-vehicle information system (IVIS). In Taiwan, its output value to the automobile electronic industry has exceeded 1 trillion New Taiwan Dollars and reached 40.15 million units, meaning that almost every car has an IVIS (Communication Components Magazine, 2010). Although this technology is very convenient and helps the driver navigate to near or far destinations, the in-car navigation system has caused problems or accidents because of software errors (Navigation Systems Research Foundation, 2007) such as an unclear interface design [1] and distracted driving [2]. According to the National Highway Traffic Safety Administration (NHTSA), driver distraction accounts for 25 to 30 percent of all accidents in the United States. Another significant distractor in relation to accidents is the use of GPS which causes around 10% of accidents due to distraction. Although existing research on lane-changing behavior emphasizes explicit behavior and typical durations, there are few published results on how the brain is involved in executing a lane change from the driver's perspective. Hence, there is a need to explore human brain activity during this activity.

Another important issue in any study about driving is how to generalize the findings from a simulator to real life. There are some measurable differences between a simulator and real-life driving [3]–[6]. For example, Halvig et al. compared real-life driving and simulators with respect to driving performance, sleep-related physiology (using an EEG and electrooculography) and subjective sleepiness during night and day driving [5]. Generally, the simulator results were associated with higher levels of subjective and physiological parameters related to sleep than actual driving. Therefore, this study focuses on an on-road experiment and uses EEG recordings to explore the dynamic brain activity of the driver during a lane change along with the auditory instructions from the in-car navigation system.

II. BACKGROUND

A. THE DEFINITION OF LANE CHANGE

A lane change is defined as a driving maneuver that moves a vehicle from one lane to another where vehicles in both lanes are moving in the same direction of travel [7]. Researchers have used different types of information to develop a lane change model, including the position of the car [8], the locomotion of the car body [9] and the angle of steering [10]. Other researchers involved human or environmental factors, including traffic signals and obstacles [11], intent and distance between the other cars [12], the distance between other cars [13] and maintaining a smooth driving state [14]. To explore the decision making of the driver, Guo et al. [15] observed that when the driver performs a lane change, there is sine-wave steering pattern (decelerate-accelerate-decelerate). Also, drivers tended to turn the indicator signals on only 50% of the time at lane-change onset, reaching a 90% rate only 1.5–2s after onset [15], [16].

B. EYE MOVEMENT STUDIES ON LANE CHANGES

Since vision is the main cue for driving behavior, researchers have extensively utilized eye movements, or gaze, as a window through which to study how humans execute these car control behaviors [15]–[20]. In the lane change studies, most of the work focuses primarily on the monitoring and decision-making aspects which are the processes to determine when or how much time it will take to execute the maneuver [16], [20]. Both novice and expert drivers exhibited similar fixation patterns (time and frequency) on the rear mirror [21] and gaze patterns on the target lane [20]. A dual-purpose view of driver gazes for control and monitoring [22] can be used to augment as well as to generalize the current theories and models of vehicle control to include the necessary behaviors for monitoring and situation awareness. Moreover, these findings have been implemented in an integrated computational model of driver behavior with success [23] and facilitated the development of real-world systems for lane-change collision avoidance [24] to increase driving safety.

C. ELECTROENCEPHALOGRAPHY STUDIES ON LANE CHANGE

The Lane Change Task (LCT) is a simple and low-cost simulation tool to study the attention associated with performing a vehicle task while driving [25], [26]. A previous study showed that the reaction time of deviation when the study participant controlled the steer to make the car go back to the original lane increased with an increase in their drowsiness level [27]. Regarding EEG signatures associated with drowsy driving, theta power burst or longer episodes of theta activity significantly increase when the driver goes from an alert state to a poor/drowsy state during prolonged driving [28]. These findings are implemented in the online detection system, demonstrating their feasibility for detecting behavioral lapses [29]–[31].

The LCT was also used to study the driver's mental workload while driving [32], [33]. Participants were requested to perform the lane change task and a secondary task at the same time. The driving task load contributed more to the changes in alpha power, whereas the working memory load contributed more to the changes in theta power. These results indicate that EEG can provide sensitive information for workload detection of driver while he is performing the lane change.

From the current survey, no previous work studies the in-vehicle navigation effect on the lane change. The psychophysiological signals provide sensitive information for human functional states assessment in both laboratory and real-world settings and for building a new communication channel between driver and vehicle that allows for driver workload monitoring.

In summary, how to define the proper stage or execution time is the core problem for studying lane changing, although this is usually not addressed in the literature. The EEG feature could be a better approach as the changes can be observed before actual car movement takes place.

D. AIM OF THIS STUDY

To explore the in-car navigation effect on driving, an on-road experiment was designed in which the subject is required to perform a lane change while listening to auditory instructions from the in-car navigation system. The detailed aims of this study are: (i) to build a system that integrates vehicle information, imaging and electroencephalography to study on-road driving; (ii) to develop an evaluation model that is based on real-world vehicle information to mark the stages of lane change; (iii) to study the behavioral performance and dynamic brain activities during real-world lane change driving; and (iv) to explore the voice navigation effect on real-world lane change driving through EEG data.

III. MATERIALS AND METHODS

A. PARTICIPANTS

In this paper, 9 healthy adults aged from 22 to 30 (mean age 25.5 years) with normal vision and with more than three years of driving experience (mean experience of 8.2 years) participated in the experiment. All the participants were recruited from National Chiao Tung University and none of them suffered from any sleep or psychiatric disorders nor did they have a history of central or peripheral neurological impairments, brain injury, alcohol abuse, diabetes,

FIGURE 1. Realistic driving environment in the Hsinchu Fish Harbor. (A) real environment; (B) the bird's eye view of driving lane from GPS (Green rectangle illustrating the experimental road path).

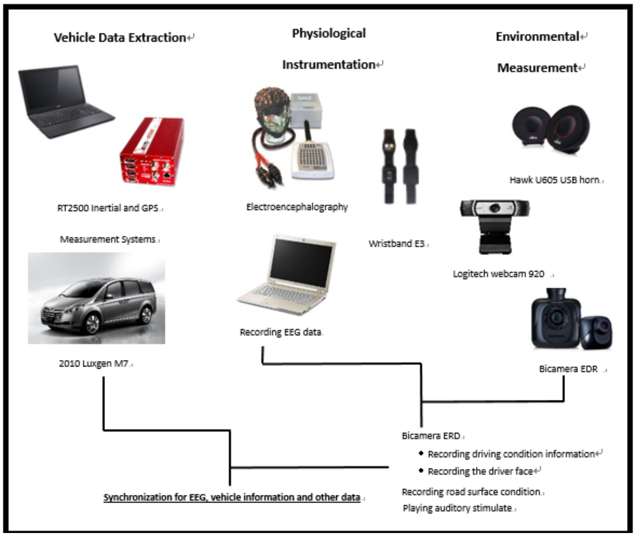

FIGURE 2. Integration system for studying the real-world driving.

or drug addiction. All subjects signed the consent and were informed about the experimental procedures and driving task process.

B. EXPERIMENTAL ENVIRONMENT

The experiment vehicle was a 2010 Luxgen M7 with an automatic transaxle. The experiment was conducted on a rectangular section of roadway in Hsinchu Fish Harbor, Taiwan, and a GPS signal was available for most of the experiment. The snap shot of the road and the GPS position data from a typical round on the rectangular section of the road is shown in green in Figure 1A and 1B. Figure 2 shows the study in process when the participant ready for the experiment in the car as shown in Figure 3 and when the participant is driving which consists of the experimental setup as shown in Figure 4.

C. LANE-CHANGE TASK

The real-life driving experiment used auditory stimulus and comprised several instructions from the vehicle navigation system which were suitable for Taiwanese. For safety compliance purposes, the vehicle speed was limited from 30km/s to 50km/s on the experiment route, the experiment was only

FIGURE 3. Study participant ready for the experiment in the car.

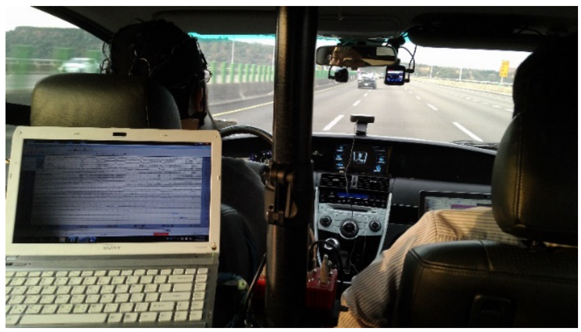

FIGURE 4. Experimental setup of the instruments during study.

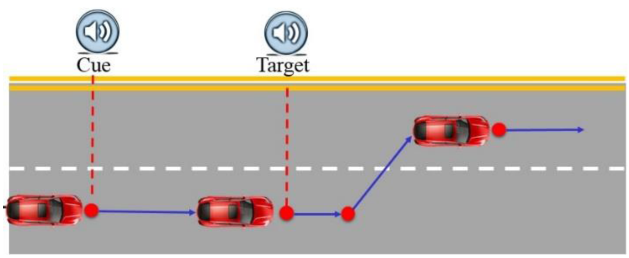

FIGURE 5. A bird's eye view of the event-related lane-change paradigm.

conducted during daylight hours and the participants were instructed to hold the steering wheel in both hands. During the experiment, the examiner randomly played two types of stimuli when the participant was driving along the longer sections of the route (L-Road). The stimuli comprised two instructions. The first was a cue type (CT): the cue was "change lanes after 500 meters"; the target was "change lanes" after 15 seconds. The other type was a non-cue type (NCT): the cue had no instructions; the target was "change lanes". Each stimulus event was defined as a "trial" which included the cue and target (Figure 5). The participant drove the vehicle in a clockwise direction, and the examiner played the stimuli twice when the participant was on an L-Road. When, the participant had completed the lane-change, the examiner played the next stimulus when there was no traffic.

D. EXPERIMENT PROCEDURE

Every participant spent 15 minutes reading the instructions and signing the informed consent form. Then, they were given an EEG cap to wear and were asked to sit on a chair while the conductive gel was applied. The electrodes were digitized by a 3D-digitizer. Self-reporting questionnaires, including Karolinska Sleepiness Scale (KSS) [34], [35] and Stress Visual Analog Scale (S-VAS) [36], were used for every participant to record their psychometric responses of fatigue and stress. The KSS was closely related to EEG and behavioral variables, indicating a high validity in measuring sleepiness. The KSS measured the subjective level of sleepiness at a time and would be recorded at primary experiment. This was a ten-point scale (1 = extremely alert, 3 = alert, 5 = neither alert nor sleepy, 7 = sleepy – but no difficulty remaining awake, and 9 = very sleepy – fighting sleep) There was a modified KSS that contains one other item: 10 = extremely sleepy, falls asleep all the time. The S-VAS had proven to be an effective tool to simply determine the stress level. It was usually a horizontal line which was 100 mm in length (0 = no stress, 100 = very severe stress), operationally. The participants marked on the line the point that they felt represents their sense of their current state.

First, the examiner guided the participant to the experiment station. The participant filled in the Visual Analog Scale (VAS) questionnaire at the start and end of the experiment. The participant also filled in the Karolinska Sleepiness Score (KSS) questionnaire every ten minutes during the experiment period. During the primary experiment, participants continued to drive around the rectangular roadway and engaged in the lane change task for about seventy minutes in a soundproof car as shown in figure 3 and 4.

E. VEHICLE INFORMATION ACQUISITION

To collect human driving data from real-life scenarios, a RT2500 inertial measurement unit and a GPS measurement system (RT2500-IGMS) were used as the data collection platform, as shown in Figure 6. Different sensors provide different types of data: (i) Lane change trajectory: the GPS/IMU integrated system records the position data of the host vehicle with time stamps (x, y, z, yaw, t) and with 250Hz frequency. Lane change trajectory key points can be extracted from this data; (ii) Steering angle: the heading angle and the lateral acceleration are obtained from the RT2500-IGMS. Steering angle data can be used to accurately check the start and end of each lane change operation; (iv) Panoramic camera: video was recorded around the host vehicle. The recorded images can be used to visually check each lane change trajectory segmented from the GPS position data for validation; (v) Coarse start/end time of each lane change trajectory: recorded automatically from the steering angle which helps to quickly extract lane change behavior.

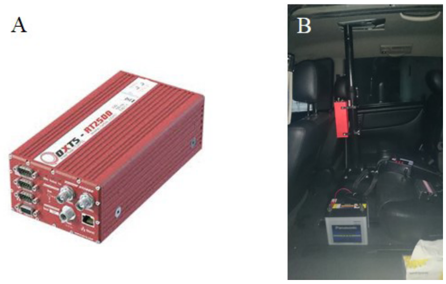

FIGURE 6. **(A) RT2500-IGMS (B) RT2500 installed in the vehicle.**

As illustrated in figure 2, the experimental instruments included two notebooks (notebook A, notebook B) for recording data, Empatica E3 wristband and event data recorder. Notebook A recorded the vehicle dates which were acquired from the RT2500-IGMS and dynamic image of the road from the webcam. Simultaneously, notebook B recorded the EEG data and played the auditory stimuli. And then, notebook A had transmitted the data markers which were synchronous indexes for vehicle data and webcam to notebook B with some time. Notebook B would record the markers to be ''log'' file form notebook A and EEG data for information aligning.

Empatica E3 wristband was a peripheral recording instruments. It could record the heart rate (PPG), skin conductivity (EDA), temperature, 3-axis accelerometer and coordinated universal time (UTC). Then, we could use the UTC for data synchronization with other information.

The experimental vehicle was installed a bi-camera event data recorder (EDR) for security concerns. One of the EDR recorded the traffic condition and another recorded the participant of face condition. If the accident happened at that day, we could get out the data form bicameral EDR to investigate the accident condition.

F. PHYSIOLOGICAL DATA RECORDING

The EEG signals were recorded by Ag/AgCl electrodes that were attached to a 32-channel Quik-Cap (Compumedical NeuroScan). Thirty electrodes were arranged according to a modified international 10-20 system [37], and two reference channels, A1 and A2, were placed on the left and right mastoids. All channels were digitized by a 3D-digitizer. The sampling frequency was 1000 Hz and the impedance of each electrode was kept below 10 kΩ. The signals were amplified by the Scan NuAmps 32 channel portable amplifier.

G. LANE-CHANGE POINT ANALYSIS

To study behavioral performance and dynamic brain activities under different conditions, appropriate behavioral markers from the vehicle information to define the lane-change time points were developed. The heading angle (X_h) and lateral acceleration (X_l) from RT2500-IGMS were used as the assessment indicator to determine the lane-change time point. Then, trial epochs from the first second are extracted before ''cue'' to 12 seconds after the ''target'' and preparation time

(CT: 15 seconds; NCT: 5 seconds) for X_h and X_l. In the case of NCT, the epoch had a total time of 18 seconds. The baseline of the heading angle (X_{bl}) was taken as the average of the 2 seconds before the target, and the absolute coordinate angle became the heading angle of the headstock deviation.

$$\boldsymbol{X}_H = \boldsymbol{X}_h - X_{bl}$$

From the heading angle analysis, the minimum of heading angle (X^H_{min}) at time ($t^H_{\min}$) between the target and 10[th] second is calculated. Simultaneously, the lateral acceleration reduced the traffic noise by a low pass filter, which was set $1 \sim 10$ Hz.

$$\boldsymbol{X}_L = lowpass_{10Hz}(\boldsymbol{X}_l)$$

The next step is to find the minimum lateral acceleration (X^L_{min}) at time ($t^L_{\min}$) between target and $t^H_{\min}$. Then, using $t^L_{\min}$, the first peak of the lateral acceleration was calculated as (V_{peak}) at time (t_{peak}) from $t^L_{\min}$ to the target. The threshold was set as the standard deviation as 2 seconds' target before (standard deviation of straight, V_{th}).

The final step is to calculate the discriminant function to find out the start cross time point (t_{start}):

$$\begin{cases} If\ |\boldsymbol{X}_L\ (t) - 0| < V_{th}; & \text{t from } t_{peak} \text{ to target, } t = t_{start} \\ If\ \boldsymbol{X}_L\ (t) = 0; & \text{t from} t_{peak} \text{ to target, } t = t_{start} \end{cases}$$

According to the flow path, all start cross time points for every trial were defined. The above example was left as the cross case. The right cross case was opposite for sign of heading angle and lateral acceleration.

H. EEG DATA ANALYSIS

The EEG raw data was first processed by a band-pass filter from 1 to 50 Hz. The filtered data was down-sampled from 1000 Hz to 500Hz to reduce the computational complexity of the EEG data. Then, the event file was added to EEGLAB in MATLAB for further analysis after removing the artifacts.

The recorded three-dimension coordinate was mapped to the EEG channels for the visualization model display and for fitting the advanced dipole before independent component analysis (ICA) was conducted. After ICA, the independent component signals were obtained with a scale map by ICA decomposition processing. The scale map included some topographical figures to show the source distribution on the brain surface. Furthermore, according to the exact channel location in the brain, the dipole fitting process provided by EEGLAB correctly finds the source position of each component through the Boundary Element Methods [39]. The dipole position is a three-dimensional coordination representing the location in the brain model. By using the scale map and the visualization model produced from the dipole fitting process, the region of interest component was selected for further analysis.

The components from each subject were selected based on the features of dipole position, scale maps, and power spectrum information. Component clustering was used to classify the components from all the subjects into several clusters for event-related spectrum perturbation (ERSP) analysis.

I. STATISTICAL ANALYSIS

A t-test was applied to compare the difference in the vehicle parameters (including preparation speed, response time, response speed, action time, action speed and LC distance) between CT and NCT. The Wilcoxon signed-rank was applied to identify the differences between the EEG signal (CT and NCT) in every brain area. In ERSP analysis, a matrix is obtained with a size equivalent to [frequency bins × time windows] for each brain area. There are two-time ranges: preparation time (from cue to target) and response time (from target to LC); four frequency band powers: delta band (1 - 3 Hz), theta band (4 - 7Hz), alpha band (8 – 12 Hz) and beta band (13 – 30 Hz) which combine to be 8 matrix blocks by the ERSP matrix. An 8 EEG index matric is built using the mean value of each matrix for every subject. Similarly, all the vehicle parameters (including preparation speed, response time, response speed, action time, action speed and LC distance) for every subject were available. To discuss the relationship between vehicle information and EEG signals, the correlation between the EEG index and the vehicle parameters were calculated in the frontal and central component.

IV. RESULTS

A total of 10 subjects finished the experiment; 9 data of all subjects were recorded and 1 datum of all subjects was lost during experimentation. All recorded information was synchronized between each other for all subjects.

A. BEHAVIORAL RESULTS BASED ON VEHICLE INFORMATION

Figure 7 displays the relationship between the vehicle parameters for CT and NCT with respect to: (a) response time (RT), (b) action time (AT), (c) lane change distance (DI), (d) preparation speed (PS), (e) response speed (RS), and (f) action speed (AS). As shown in Figure 7-A (vertical axis, millisecond; horizontal axis, left, CT group; right, NCT group), a comparison of RT was not significant in the CT group versus the NCT group ($p > 0.05$). As shown in Figure 7-B (vertical axis, millisecond; horizontal axis, left, CT group; right, NCT group), a comparison of AT was not significant in the CT group versus the NCT group ($p > 0.05$).

There was no significant difference for the mean of response time and action time between CT and NCT. In Figure 7-C (vertical axis, meter; horizontal axis, left, CT group; right, NCT group), a significant difference in DI can be seen in the CT group versus the NCT group ($p < 0.01$). In Figure 7-D (vertical axis, kilometer per hour; horizontal axis, left, CT group; right, NCT group), a significant difference in PS can be seen in the CT group versus the NCT group ($p < 0.01$). In Figure 7-E (vertical axis, kilometer per hour; horizontal axis, left, CT group; right, NCT group), a significant difference in RS can be seen in the CT group versus the NCT group ($p < 0.01$).

In Figure 7-F (vertical axis, kilometer per hour; horizontal axis, left, CT group; right, NCT group), a significant

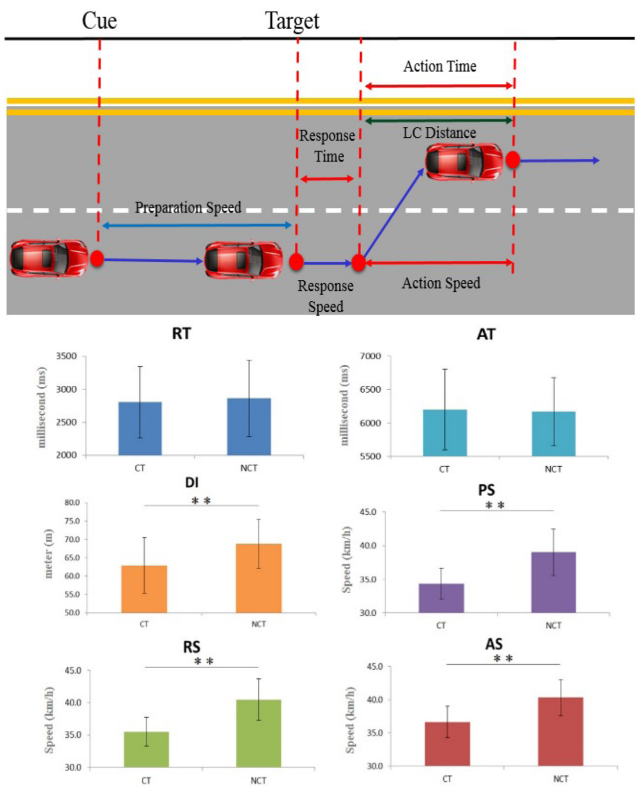

FIGURE 7. **Parameter of vehicle information during real world lane-change and a comparison of the parameters of vehicle information for two cases. **$p < 0.01$.**

difference in AS can be seen in the CT group versus the NCT group (*p* < *0.01*). There was a significant difference for the mean in relation to speed between CT and NCT. Because distance had an impact on speed, DI was found to be significant between CT and NCT. All correlation comparisons between each vehicle information under different cue types are shown in Table 1 and Table 2.

TABLE 1. **The correlations between each behavioral performance under cue-type condition.**

	Cue Type					
CT	RT	AT	DI	PS	RS	AS
RT	1	0.263	-0.0166	-0.3312	-0.5343	-0.4845
AT	0.263	1	0.8737**	0.0633	0.0837	0.1417
DI	-0.0166	0.8737**	1	0.4625	0.5203	0.6018
PS	-0.3312	0.0633	0.4625	1	0.944**	0.8334*
RS	-0.5343	0.0837	0.5203	0.944*	1	0.9215**
AS	-0.4845	0.1417	0.6018	0.8334**	0.9215**	1

RT= Response Time AT=Action Time, DI=Distance, PS=Preparation Speed, RS=Response Speed, AS=Action Speed, CT= Cue Type, *p<0.05, **p<0.01

In the CT condition, there is a significant positive correlation between AT and DI ($r = 0.87$, $p < 0.01$,); PS and RS ($r = 0.94$, $p < 0.01$); PS and AS ($r = 0.83$, $p < 0.01$); RS and AS ($r = 0.92$, $p < 0.01$). The vehicle speed of each lane-change stage has a higher relationship with each other when driving with the CT. Voice navigation seems to cast an influence on the driver's speed control in all the stages and on the finishing distance of the lane change.

TABLE 2. **The correlations between each behavioral performance under no cue-type condition.**

	Cue Type					
NCT	RT	AT	DI	PS	RS	AS
RT	1	0.3924	-0.2191	-0.6271	-0.56	-0.7439*
AT	0.3924	1	0.7116*	-0.0144	-0.0256	-0.1729
DI	-0.2191	0.7116*	1	0.6519	0.6349	0.5661
PS	-0.6271	-0.0144	0.6519	1	0.9902**	0.9457**
RS	-0.56	-0.0256	0.6349	0.9902**	1	0.9415**
AS	-0.7439*	-0.1729	0.5661	0.9457**	0.9415**	1

RT= Response Time AT=Action Time, DI=Distance, PS=Preparation Speed, RS=Response Speed, AS=Action Speed, CT= Cue Type, *p<0.05, **p<0.0

In the NCT condition, there is a significant positive correlation between AT and DI ($r = 0.71$, $p < 0.05$,); PS and RS ($r = 0.99$, $p < 0.01$); PS and AS ($r = 0.95$, $p < 0.01$); RS and AS ($r = 0.94$, $p < 0.01$); RT and AS ($r = -0.74$, $p < 0.01$). This result was also like CT. Moreover, there was a higher correlation between response time and action speed.

B. QUESTIONNAIRE ANALYSIS

Figure 8 shows the average trend of the fatigue level in the experimental period (70 minutes), which is continuously increasing. In the final moments of the experiment, the fatigue level is expected to decrease.

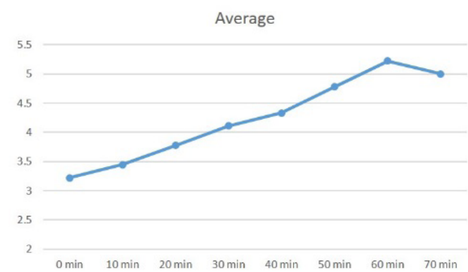

FIGURE 8. **The results of Karolinska Sleepiness Scale Questionnaires within ten-minute intervals during on-road driving.**

As shown in Figure 9, there was no statistical significance in the experimental start versus the end in the average value of S-VAS (*p* > *0.05*).

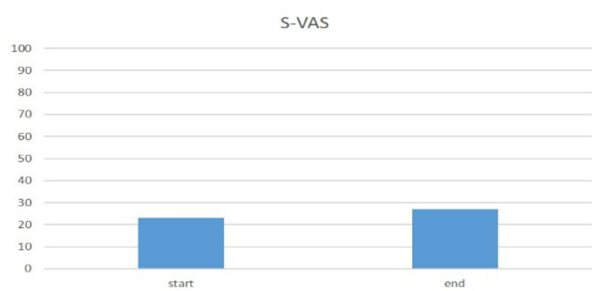

FIGURE 9. **The results of Stress Visual Analogue Scale Questionnaires for the start and end during on-road driving.**

C. ELECTROENCEPHALOGRAPHY DATA ANALYSIS

ERSP analysis could be used to investigate the EEG dynamics in the frequency domain. Figure 10 shows the ERSP

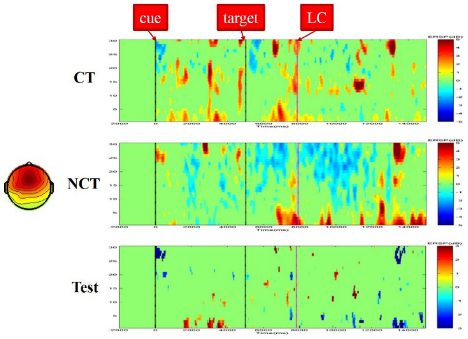

FIGURE 10. The frontal ERSP comparison between cue type (CT) and non-cue type (NCT).

in the frontal component between CT, NCT, and differences between CT and NCT by Wilcoxon signed-rank test to find the characters of power changes related. The vertical axis has a frequency range of 1 Hz ~ 30 Hz, the horizontal axis had a timeline of −2 second ~ 15 seconds. The important time points were 'cue' (0 seconds), 'target' (5 seconds), and 'LC' (lane change point was not fixed under a difference type).

Figure 11 shows the ERSP in the central component between CT, NCT, and is tested on all 6 subjects. All components are selected according to the scale map and visualization model produced from the dipole fitting process. The CT shows the alpha (8 Hz ~ 12 Hz) and beta (13Hz ~ 30 Hz) frequency band power response around the LC (cue: 0 seconds, target: 5 seconds, LC: 7.33 second). The NCT also shows the alpha (8 Hz ~ 12 Hz) and beta (13Hz ~ 30 Hz) frequency band power response around the LC (cue: 0 seconds, target: 5 seconds, LC: 7.41 second). The Wilcoxon signed-rank test showed there was significant difference in the CT versus the NCT ($p < 0.005$). The test shows that central beta band power increases more in the CT than the NCT between cue and LC, preparation time and action time (cue: 0 second, target: 5 seconds, LC: 7.37 second).

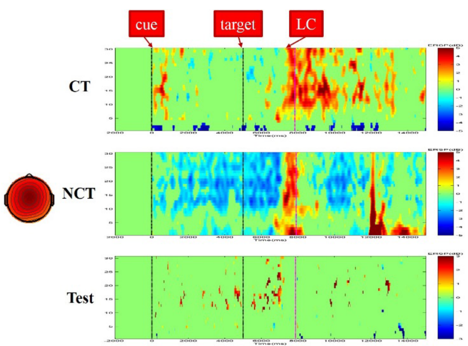

FIGURE 11. The central ERSP comparison between cue type (CT) and non-cue type (NCT).

D. CORRELATION ANALYSIS BETWEEN EEG AND VEHICLE INFORMATION

As shown in Table 3 to Table 10, the correlation analysis was performed to compare the EEG indexes and vehicle

TABLE 3. Correlation between frontal EEG and vehicle information from Cue to Target under Cue type condition.

Cue to Target (Frontal)						
CT	RT	AT	DI	PS	RS	AS
Delta	-0.5269	-0.0792	0.17	0.521	0.5255	0.3819
Theta	0.0957	0.2618	0.2727	0.2996	0.1981	0.1487
Alpha	-0.2766	0.1647	0.3	0.4783	0.4897	0.2944
Beta	-0.742*	0.0539	0.2363	0.3802	0.24898	0.3523

*p<0.05, **p<0.01

TABLE 4. Correlation between frontal EEG and vehicle information from Cue to Target under No-Cue type condition.

Cue to Target (Frontal)						
NCT	RT	AT	DI	PS	RS	AS
Delta	-0.5343	-0.6455	0.0635	0.4872	0.5005	0.6604
Theta	0.0329	-0.3257	0.0355	0.1923	0.2738	0.3451
Alpha	-0.2112	-0.5169	0.0101	0.3685	0.4118	0.4663
Beta	-0.4641	-0.755**	-0.7145	0.3292	0.3241	0.4449

*p<0.05, **p<0.01

TABLE 5. Correlation between frontal EEG and vehicle information from Target to LC under Cue type condition.

Target to LC (Frontal)						
CT	RT	AT	DI	PS	RS	AS
Delta	0.3588	0.729*	0.6192	0.4383	0.3432	0.1845
Theta	0.4104	0.5916	0.3414	-0.0731	-0.1466	-0.1154
Alpha	0.6161	0.7015	0.4665	0.1335	0.036	-0.0345
Beta	0.5211	0.3724	0.0144	-0.39	-0.4239	-0.415

*p<0.05, **p<0.01

TABLE 6. Correlation between frontal EEG and vehicle information from Target to LC under No-Cue type condition.

Target to LC (Frontal)						
CT	RT	AT	DI	PS	RS	AS
Delta	-0.6156	-0.6097	0.1362	0.5363	0.5363	0.7114
Theta	-0.1182	-0.2027	0.2213	0.3849	0.3849	0.4752
Alpha	-0.305	-0.5213	0.0646	0.478	0.478	0.5378
Beta	-0.731*	-0.729*	0.03	0.4648	0.4648	0.6736

*p<0.05, **p<0.01

TABLE 7. Correlation between central EEG and vehicle information from cue to Target under Cue type condition.

Cue to Target (Central)						
CT	RT	AT	DI	PS	RS	AS
Delta	0.1921	0.5469	0.3051	-0.3679	-0.4658	-0.4248
Theta	0.4124	0.2227	0.1578	0.0668	-0.2026	-0.1399
Alpha	0.1561	0.7323	0.3972	-0.5685	-0.5863	-0.4771
Beta	-0.2402	0.5225	0.2391	-0.5763	-0.4662	-0.4082

*p<0.05, **p<0.01

performance during each stage under different cue type conditions. The frontal beta showed a negative correlation with RT ($r = -0.742$, $p = 0.056$) after the cue and before the target in the CT condition, as shown in Table 3. The frontal delta showed a negative correlation with AT ($r = 0.729$, $p = 0.063$) after the target and before the LC in the CT condition, as shown in Table 5.

TABLE 8. Correlation between central EEG and vehicle information from cue to Target under No-Cue type condition.

Cue to Target (Central)						
NCT	RT	AT	DI	PS	RS	AS
Delta	0.1921	0.5469	0.3051	-0.3679	-0.4658	-0.4248
Theta	0.4124	0.2227	0.1578	0.0668	-0.2026	-0.1399
Alpha	0.1561	0.7323	0.3972	-0.5685	-0.5863	-0.4771
Beta	-0.2402	0.5225	0.2391	-0.5763	-0.4662	-0.4082

*p<0.05, **p<0.01

TABLE 9. Correlation between central EEG and vehicle information from Target to LC under Cue type condition.

Cue to Target (Central)						
CT	RT	AT	DI	PS	RS	AS
Delta	0.463	0.6582	0.4189	-0.3105	-0.4631	-0.3926
Theta	0.9381**	0.3366	0.1587	-0.1651	-0.3718	-0.2874
Alpha	0.5304	0.911*	0.6035	-0.4276	-0.5064	-0.3482
Beta	0.3743	0.4986	0.1244	-0.725	-0.6433	-0.5873

*p<0.05, **p<0.01

TABLE 10. Correlation between central EEG and vehicle information from Target to LC under No-Cue type condition.

Cue to Target (Central)						
NCT	RT	AT	DI	PS	RS	AS
Delta	0.3167	-0.4638	-0.45	-0.1298	0.0008	0.0624
Theta	0.2457	-0.7015	-0.6711	-0.0263	0.0896	0.0983
Alpha	0.4542	-0.2702	-0.5636	-0.3684	-0.3047	-0.349
Beta	0.5813	0.0363	-0.4086	-0.4669	-0.4258	-0.5522

*p<0.05, **p<0.01

The central alpha showed a positive correlation with AT ($r = 0.901$, $p < 0.05$) after the target and before LC in the CT condition, as shown in Table 9. The central theta showed a positive correlation with RT ($r = 0.938$, $p < 0.01$) after the target and before the LC in the CT condition, as shown in Table 9. The frontal beta showed a negative correlation with AT ($r = -0.7555$, $p < 0.05$) after the cue and before the target in the NCT condition, as shown in Table 4. The central theta showed a negative correlation with DI ($r = -0.8173$, $p < 0.05$) after the cue and before the target in the NCT condition, as shown in Table 8. The frontal beta showed a negative correlation with RT ($r = -0.7308$, $p = 0.0621$) after the target and before the LC in the NCT condition, as shown in Table 6. The frontal beta showed a negative correlation with AT ($r = -0.7287$, $p = 0.0632$) after the target and before the LC in the NCT condition, as shown in Table 6.

V. DISCUSSION

The on-road experiment was designed with the EEG recordings and in-car information to explore the dynamic brain activity while the driver performed the lane-change task followed by the auditory instructions from the in-car navigation system. By GPS measurement system, an on-road lane-change detection model (ORLCDM) based on two pieces of vehicle information (heading angle and lateral acceleration) which is sensitive to car locomotion was developed to detect the car movement as the driver starts to change lanes and finishes the change in the target lane. Although the ORLCDM can reach 85.53% of accuracy, the model still needs more parameters, such as the angle of the steer, the distance between other cars, night/day etc. [8], [9], [11]–[14], [43] to enhance its performance and generalization for each situation. Currently, this model provides a useful tool to define the different stages of on-road lane changes to explore behavioral performance and brain activities.

From the behavioral results, the auditory in-car navigation system had an influence on the real-world driver's performance, especially on speed control. There is a time difference between the auditory target shown and the lane change as judged by the ORLCDM. The subjects did not change lanes immediately but instead spent a similar amount of time scanning the environment to decide whether to turn the car. During this period, the drivers exhibited significantly different visual scanning in the rear-view/left/right mirror and current/target lanes to get sufficient information [15], [16], [20]. Therefore, these drivers could use a similar strategy and time to initiate a lane change, but the speed of the car was influenced by the auditory instructions from the navigation system. Although the difference is not reflected in the response time of the lane change, the distance to finish the lane change is shorter in the cue-type condition than it is in the non-cue type condition. The cue-type condition provides the driver with enough information to reduce speed for the incoming situation but the related brain processing should be examined by EEG analysis. There are some specific neural activities related to on-road lane change. Both cue types showed that the delta power at the frontal component increased after the target voice and before the lane-change. Both conditions also showed that there was an increase in alpha and beta power at the central component after the lane-change. There are no significant differences in either the frontal or central components for the two conditions. Currently, the role of the delta band in different cognitive processes is still under discussion [43]–[45]. Functional delta oscillations appear to attention and the detection of motivationally salient stimuli in the environment [46], [47]. Also, several studies suggest this reflects behavioral inhibition [47]–[49]. Other work indicates that synchronous delta activity plays an important role in coordinating the neural activity of the network during decision making [50]. In the current study, the increase in delta power is just before the lane change is initiated. Therefore, it could be related to the decision-making process which excludes interference from other senses when making the decision to execute a lane change (internal representation). Moreover, the frontal delta band is influenced by the cue instruction, and there is a positive relationship with the time to finish the lane change under the cue-type condition. The frontal delta could be a good index related to the decision making of an on-road lane change.

VI. CONCLUSIONS

In-car navigation systems influence on-road lane change behavior. They provide the driver with enough information to take preparatory action to move the vehicle into a different lane and help the driver to decide to make a lane change. The frontal delta and beta are unique for real-world lane change driving and these features can provide the index to test more lane-change performance under different individual status. The lane-change assessment developed in this study which is based on vehicle information (lateral acceleration and heading angle) can be used as a specific event maker for future naturalized driving study. Future study includes increasing the number of subjects to enhance reliability and develop the image analysis to compare the lane-change assessment.

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