Detection of Safety Checking Actions at Intersections Significant for Patients with Cognitive Dysfunction

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***Abstract*—Many elderly people have a high probability to become patients with cognitive dysfunction. They could show symptoms of attention disorder as well as execute function disorder. These symptoms may cause unsafe driving in their daily lives. The degree of these symptoms can be evaluated through neuropsychological examination. However, the correspondence relationship between these symptoms and unsafe driving is uncertain. To address this challenge, we are developing an unsafe-driving detection system, which requires a few small wireless sensors to be attached to a driver and a steering wheel. Because many patients with cognitive dysfunction show symptoms of attention disorder, it is generally assumed that they tend to be careless with safety checking actions. Based on this assumption, we analyzed driver's checking actions at intersections. In our experiments, 14 patients with cognitive dysfunction and 13 adults without cognitive dysfunction were evaluated while driving a real car. Video analysis of the experiment focused on left turn collision checking and left-right safety checking. Some results of the analysis indicate that the number of safety checking actions performed by patients with cognitive dysfunction is confirmed to be significantly lower than those by adults without cognitive dysfunction. Using the result of this analysis, we decided to use a sensor-based safety-checking action detection method based on calculations from wireless sensors. With this method, all safety checking actions at left-turn intersections were calculated. While the threshold value was decided between -37.5 to -27.5 degrees, some relationships regarding safety-checking between the patients with cognitive dysfunction and the adults without cognitive dysfunction are found using the chi-square test. The interactive evaluation system of safety-checking actions in intersections which enables the feedback for drivers can be constructed using the proposed sensors and evaluation method.**

Keywords - Cognitive dysfunction; Wearable Sensor; Safety Checking Action; Driving Skill.

I. INTRODUCTION

When a part of our brain is affected by apoplexy, a brain tumor or injury to the head, cognitive dysfunction symptoms, including attention disorder and execute function disorder, may appear. Although these symptoms can be improved through medical treatment, it may be dangerous for the patient to drive a car as part of his/her daily life, depending on the degree of the symptoms.

In Japan, under road traffic law, a driving license can be suspended or cancelled in cases of problems with recognition, judgement or operation which are identified through aptitude tests. However, there are no standard guidelines for judging the driving aptitudes of patients with cognitive dysfunction.

Shino et al. [1] revealed in their research that they found that the elderly drivers who belong to the Mild Cognitive Impairment (MCI) group had lower divided attention and alternating attention than the elderly of the non-MCI group. These elderly people were evaluated using Mini-Mental State examination Test (MMSE), Wechslor Memory Scale-Revised logical memory test (WMS-R) and the data from driving recorders.

Park et al. [2] investigated the association between unsafe driving performance and cognitive-perceptual dysfunction among elderly drivers. In this research, the authors revealed that unsafe driving performances are more prevalent among elderly drivers than among younger drivers and unsafe performances in steering operation are associated with cognitive-perceptual dysfunction. They compared these findings with the result from Cognitive-Perceptual Assessment for Driving (CPAD) and the data from virtual reality-based driving simulator research studies.

These research studies show that higher cognitive dysfunction is related to unsafe driving. Therefore, in some hospitals, neuropsychological examinations such as MMSE or WMS-R are used to evaluate the severity of the symptoms; however, the correspondence relationship between these symptoms and unsafe driving is uncertain [3].

Driving simulators are used to measure the reaction time to sudden dangers on the road and avoidance operations such as braking and steering [4]-[6]. However, such driving simulators do not provide a sense of acceleration and deceleration to the users, and the visual resolution and coverage angle of the display are limited. There simply is a certain gap between real and virtual driving.

To solve this problem, Tada et al. [7] used a real car and attached 3-dimensional acceleration and gyro sensors to the wrists of the drivers. The study revealed that there were some differences between the expert and the beginner drivers. By attaching these sensors to the toe and the head of the driver, it was clear that the general drivers' driving technique can be evaluated and more than 80% evaluation points corresponded with the point that was indicated by the safety driving instructor [8]. The system that was used in this experiment was commercialized [9]. However, this system was only used for evaluating the driving technique of general drivers under experimental conditions.

In order to adapt this system for cognitive dysfunction patients who want to restart driving, we have been developing an unsafe-driving detection system [10]. It is installed in real cars and captures the cognitive dysfunction driver's behaviors using wearable wireless motion sensors and a Global Positioning System (GPS) sensor. For lane changing operations, deceleration for planned slowdown [11], and safety checking when parking [12], the unsafe-driving detection system has demonstrated its ability to separate patients with cognitive dysfunction from adults without such dysfunction.

In this study, we focus on the differences in safety checking actions at intersections. Using the results of video analysis with patients' driving data acquired from experiments conducted on a specially designed private course, the method which enables us to separate the patients with cognitive dysfunction and adults without cognitive dysfunction was decided and the results are presented. In Section 2, we introduce several examples of research that support the background of the research field, and describe the positioning of our research. In Section 3, we describe the materials that were used in our experiment and the method concerning how to calculate an effective value to facilitate the analysis of driver behavior from the sensor data. In Section 4, we show the experimental design and the participants' information. In Section 5, video-based and sensor-based results are shown, respectively. In Section 6, we describe the results and considerations of the experiment. In Section 7, we conclude this research with future prospects.

II. RELATED WORKS

Using a real car, evaluations of unsafe driving caused by the symptoms of cognitive dysfunction have been conducted. To detect unstable driving, Sumida et al. [13] measured the triaxial angular velocity and acceleration of real cars at a driving school using a 3-dimensional acceleration sensor, a gyro sensor and GPS. Unstable driving was detected on both curved roads and straight roads. Chin et al [14] tried to facilitate safe behaviors with social support. In this research, only 3-dimensional acceleration sensors and gyro sensors were used to detect unsafe driving. In both studies, the authors used a real car with sensors. However, the motions of the car do not always represent unsafe driving. Bi et al. [15] revealed in their research that unsafe driving of elderly drivers can be detected with a sensor which included 3-dimensional acceleration and gyro sensors and was attached to both wrists of the drivers like a watch. However, the unsafe driving which can be detected with these sensors is limited to the behavior of some motions of the driver's arms.

III. THE CALCULATION OF SENSOR ANGLES TO DETECT SAFETY CHECKING ACTION

Figure 1 shows the small wireless wearable motion sensors used in our unsafe-driving detection system. The sensors are parts that were manufactured using the Objet system [9][10]. All sensors are synchronized and can measure triaxial angular velocity and acceleration. The black sensor box also holds the GPS sensor. Figure 2 shows the sensors attached to the driver's head, wrist and right leg toe, as well as the car's steering wheel and dashboard, to measure their movements. These sensors were used under the approval of the ethics committee of The Toyama Prefectural University, Japan. In this paper, we focus on the differences in safety checking actions at intersections, and only the sensor on the head and the car were used in this analysis. The relative yaw angle of the subject's head was used to evaluate the safety-checking action. This angle value was calculated from the head and car body yaw angle, and the calculation method of the yaw angle value is shown below.

Figure 1. Wireless wearable motion sensors.

Figure 2. Attached position of sensors.

The sensor measures the three dimensional angular velocity (ω_x, ω_y, ω_z) and the three dimensional acceleration (a_x, a_y, a_z) at the interval time Δt. We adopt the kalman filter method to calculate the attitude of the sensor to the ground from those data. By defining four real numbers (t, x, y, z) in the quaternion which represents the sensor direction as the system state of the kalman filter, the sensor direction can be calculated by the iteration of the following steps:

<Prediction step>

As the sensor attitude changes by the angular velocity of the sensor, the predicted sensor attitude $\boldsymbol{x}_{k|k-1}=(t_{k|k-1}, x_{k|k-1}, y_{k|k-1}, z_{k|k-1})^{\mathrm{T}}$ is given from the previous sensor attitude $\boldsymbol{x}_{k-1|k-1}=(t_{k-1|k-1}, x_{k-1|k-1}, y_{k-1|k-1}, z_{k-1|k-1})^{\mathrm{T}}$ by

$$\boldsymbol{x}_{k|k-1} = \boldsymbol{F}\,\boldsymbol{x}_{k-1|k-1}, \tag{1}$$

where $\boldsymbol{F}$ is the state transition matrix which is calculated from the angular velocity and the interval time.

<Update step>

As the predicted sensor attitude can be corrected by the observed gravity direction, the updated sensor attitude $\boldsymbol{x}_{k|k}$ is calculated by

$$\boldsymbol{x}_{k|k} = \boldsymbol{x}_{k|k-1}+\boldsymbol{K}\,\boldsymbol{y}, \tag{2}$$

where $\boldsymbol{K}$ is the kalman gain, and $\boldsymbol{y}$ is the measurement residual which is calculated from the acceleration and the predicted sensor attitude. The updated sensor attitude $\boldsymbol{x}_{k|k}$ becomes the previous values of the next step.

We can calculate the sensor attitude $\boldsymbol{x}_{k|k}$ (k=1,2,3⋯) by the iteration of the above steps from the initial sensor attitude $\boldsymbol{x}_{0|0}=(1,0,0,0)^{\mathrm{T}}$, and the yaw angle θ_k for each of the steps is calculated from the sensor attitude by

$$\theta_k = \arctan\frac{2\left(t_{k|k}y_{k|k} + x_{k|k}z_{k|k}\right)}{t_{k|k}^2 - x_{k|k}^2 - y_{k|k}^2 + z_{k|k}^2}\,. \tag{3}$$

This yaw angle is clockwise, so the value of the car body sensor is increased when the car turns right, and vice versa. As the yaw angle is based on the ground, the head direction in the car is calculated by subtracting the yaw angle of the car body sensor from the yaw angle of the head sensor.

IV. EXPERIMENT THROUGH A SPECIALLY DESIGNED DRIVING COURSE

A private course was designed at Toyama Driving Education Center, Japan, for the purpose of video analysis for safety-checking actions and acquiring the sensor data for objective evaluation. The experiment was conducted with the subjects equipped with wearable wireless sensors shown in Figure 1 while driving real cars on a private course. Figure 3 shows the top view of the private course designed for the experiment. The course includes several road types such as T-shaped, cross-shaped, and signalized/non-signalized, with/without stop sign, and roads with several kinds of speed limits. The course takes 10 – 15 minutes to drive. There are four types of turnings at T-shaped intersections (shown in Figure 4). In this study, type ①/② are called left/right turn at T-junction and type ③/④ are called right/left turn at branch. The intersections with turnings are selected for analysis because no safety checks were necessary at many of the intersections without turnings. Table 1 shows all types of intersections on the private course. In Table 1, ①, ②, ③, and ④ are denoted by LT, RT, RB, and LB, while the right and left turn at the cross intersections are denoted by RC and LC, respectively.

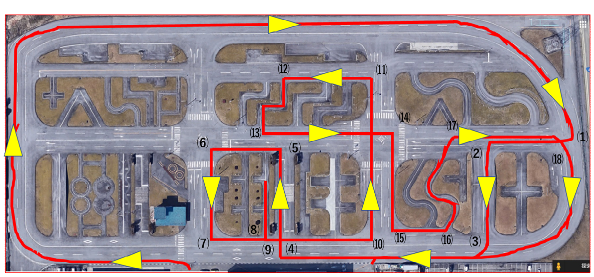

Figure 3. Specially designed private course.

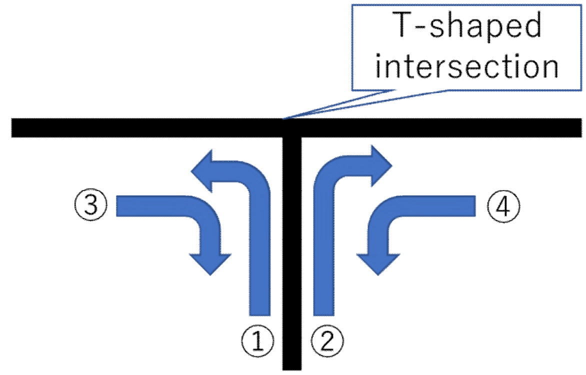

Figure 4. Types of in-out directions at T-shaped intersection on the course.

TABLE I. ATTRIBUTE OF EACH INTERSECTION

Intersection	1	2	3	4	5	6	7	8	9
Type	RB	LB	RT	RB	LT	LC	LT	LB	LT

Intersection	10	11	12	13	14	15	16	17	18
Type	LB	LC	LB	LT	RC	LT	LB	RT	RT

The subjects were males and females between 20 – 60 years old and consisted of 14 patients with cognitive dysfunction and 13 adults without cognitive dysfunction. All 14 patients had various cognitive dysfunction symptoms and were positioned border-line to be allowed to restart driving after the examination in the hospital. The experiments were conducted with all the sensors shown in Figure 1. Multiple video cameras were installed inside and outside the car to record the driving behavior in detail. These video cameras recorded a front, side, and back view of the cars and drivers.

V. ANALYSIS USING THE RECORDED VIDEO

When crossing an intersection, checking for left-turn collision accident and left and right checking are essential. The former is necessary only when turning left since we have left-hand traffic in Japan, and the latter is necessary at all intersections except when checking for the left at RB, and the right at LB intersections. Therefore, 45 checking actions are necessary on the private course. From the preview of the video, the following hypothesis was established: the number of safety actions carried out by patients with cognitive dysfunction is significantly lower than the ones by adults without cognitive dysfunction. Experiments were conducted under the approval of the ethics committee of the Toyama Prefectural University. The video analysis for all 45 checking points was performed by six adult evaluators with valid driving licenses who are accustomed to driving in their everyday lives. These evaluators belong to the same organization as the authors and they are not related to this study. Table 2 shows the results of each evaluation by video analysis with T-test. One of the results indicates a significant difference ($p < 0.05$) and 2 results indicate a tendency of difference ($p < 0.1$) between the patients with cognitive dysfunction and the adults without cognitive dysfunction.

TABLE II. T-TEST RESULT

evaluator#	T-test (for all checking on all intersections)	T-test (for left checking on left-turn)
1	t(25) = 2.105, p = 0.023	t(25) = 1.912, p = 0.033
2	t(25) = 1.665, p = 0.054	t(25) = 2.206, p = 0.018
3	t(25) = 1.458, p = 0.079	t(25) = 1.806, p = 0.042
4	t(25) = 0.455, n.s.	t(25) = 1.158, n.s.
5	t(25) = 0.517, n.s.	t(25) = 0.906, n.s.
6	t(25) = 0.122, n.s.	t(25) = 0.546, n.s.

As a result of video analysis, it was clear that when the drivers check for left-turn collision, they also do left forward checking. Table 2 also shows the result of the T-test which calculated the significance of drivers' behavior focusing on the safety checking for left on left-turn. This result indicates that focusing on left side checking on left-turn leads to a significant difference between the patients with cognitive dysfunction and adults without cognitive dysfunction on safety-checking. Almost all of the safety checking actions at intersections are done before the entrance into the intersections and there is a tendency for the head angle to become bigger as the drivers approach the intersection.

For the reasons mentioned above, the safety checking detection sequence for left-turn intersections was decided to be as follows.

Step 1. Determination of the time range before and after the intersection.
To extract the sensor data including the safety-checking motion for left/right-turn from the data of the whole course, the time range before and after the target intersection is determined from GPS data according to the following criteria.
[start time: T_s] The time of GPS data nearest to the point that is 30 m before entering the target intersection or the point that is 5 m after exiting the previous intersection closer to the target intersection.
[end time: T_e] The time of GPS data nearest to the point that is 5 m after exiting the target intersection.

Step 2. Estimation of the straight-running direction before entering the intersection.
When the driver performs the safety checking before entering the intersection, it is thought that the car is going straight or has stopped and the direction of the car does not change. To extract such straight-running range, the straight-running direction of the car is estimated by the following steps.

(1) Calculate the weighted average direction d_0 from the yaw angle of the car as follows:

$$d_0 = \frac{\sum_{\{k|T_s \leq T_k \leq T_e\}} w0_k \theta_k}{\sum_{\{k|T_s \leq T_k \leq T_e\}} w0_k}, \tag{4}$$

where

$$w0_k = \frac{T_e - T_k}{T_e - T_s} \exp\left(-\frac{\left(\frac{d\theta_k}{dt}\right)^2}{\sigma_0^2} \right), \tag{5}$$

and T_k is the time of the data and σ_0 is the experimentally determined value from the standard deviation of the car yaw angle. In this weight value, the component before the exponential emphasizes the first section of the time region and the component of the exponential emphasizes the direction at the time of straight-running.

(2) Calculate the modified weighted average direction d_1 as follows:

$$d_1 = \frac{\sum_{\{k|T_s \leq T_k \leq T_e\}} w1_k \theta_k}{\sum_{\{k|T_s \leq T_k \leq T_e\}} w1_k}, \tag{6}$$

where

$$w1_k = \exp\left(-\frac{(\theta_k - d_0)^2}{\sigma_1^2} \right), \tag{7}$$

and σ_1 is the experimentally determined value from the angle region of the next step. This calculation pulls the angle d1 to the most frequently appeared angle near d_0, and the most frequently appeared angle means that the car was going into that direction for the most part.

Step 3. Extraction of the time range of the straight-running before entering the intersection.
Due to the influence of the sensor noise, the calculation error and the natural small steering offset of the car, the calculated direction of the car is not completely constant even if the driver thinks that the car is going straight. So, we determine the time range of the straight-running from the point when the car direction enters within ±5 degrees to the point when the car direction becomes more than ±15 degrees.

Step 4. Extraction of the angle of left-checking
The head direction of the car can be calculated by subtracting the car yaw angle from the head yaw angle. We define the angle of left-checking as the minimum of the head direction in the range of the straight-running before entering the intersection and the angle of the right-checking as the maximum of that.

The safety-checking angle that was calculated according to the above sequence may have the drift error which was caused by the sensor. To decrease the effect of the drift error, drivers head angle was reset when drivers looked toward the front every time they came close to the intersections.

VI. DETECTION WITH UNSAFE-DRIVING DETECTION SYSTEM

We processed the sensor data with the method shown in Section V and obtained the left-checking angles of the left turn. There are 27 subjects and 12 left-turn intersections in the course, but one intersection of one subject was excluded because he took the wrong turn at the intersection. In addition, in order to exclude cases when the car did not go straight for a sufficient amount of time before the intersection, we decided not to include data collected in cases when Step 3 of the previously mentioned method was less than 3 seconds. There were 18 cases that were under 3 seconds out of the 323 left-turn intersections; therefore, 305 cases were analyzed.

Assuming a threshold head angle can determine the safety checking actions, the relationship between the safety checking count was measured by the threshold angle and the driver's status. Patients with cognitive dysfunction or adults without cognitive dysfunction were tested from the threshold angle values of -60 to -15 degrees. Figure 5 shows the result of the chi-square test. It indicates that there is some relationship while head angle values are between -27.5 to -37.5 degrees. The T-test was performed to the ratio at which the person did their safety checking at the angle over/under -32.5 degree. Consequently, a significant difference was confirmed between the patients with cognitive dysfunction and adults without cognitive dysfunction $t(20) = 1.8276$, $p = 0.0413 < 0.05$.

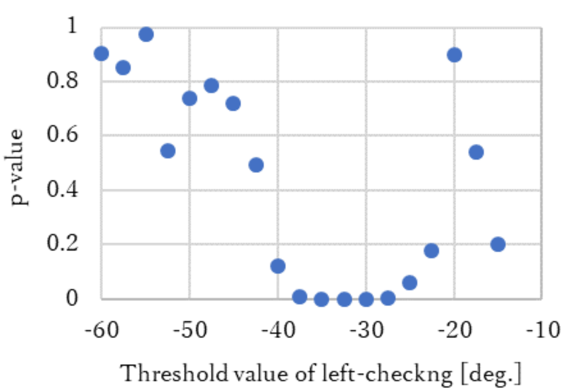

Figure 5. Wireless wearable motion sensors.

VII. DISCUSSION

According to the results from the experiment, we conclude that the patients with cognitive dysfunction and adults without cognitive dysfunction can be separated by the head angle value just before the intersections. However, there are some differences between the results of the video-based subjective evaluations and the results of the sensor-based evaluations. The designed private course had various kinds of intersections in terms of shape, signalized/non-signalized, with/without stop sign, road width, speed limits, the time allowance to do safety-checking, and so on. By focusing on each feature, the differences between the two groups can be even clearer. The data is not sufficient for making satisfactory combinations with these features. Therefore, a further study that focuses on the effective combination of the features is expected to contribute to the supplement amount of data for distinguishing the two groups. It can also be concluded that the head angle movement threshold value calculated from the sensors can be used to separate the two groups. This study has not yet clarified the reasons for -37.5 to -27.5 degree as the best angle for separation. This leads to the hypothesis that the driver's safety checking is less than these values or includes many indirect checkings by way of the mirror or the checkings done with more eye movements and less head movements. This can be examined in a further studies using an eye-tracking system to analyze the driver's safety-checking actions in detail. In addition, the proposed safety checking action detection method may need changes. The angle calculation method which is shown in Section III may have a calculation error, because it calculates under the assumption that gravity acceleration is always constant and the direction is always 90-degree angle to the ground. This can cause errors when the car is accelerating or turning. Also, the accuracy of each parameter explained in Section V for detecting the safety checking action, requires adequate improvements for the effective detection. At the moment, manual resetting of the driver's head angle on every intersection is required. In order to reset automatically, the average head angle before the intersections can be used in future works.

VIII. CONCLUSION

This paper presented an unsafe-driving detection system. We conducted experiments equipped with video cameras and wearable wireless motion sensors using real cars. It was discovered that the safety checking actions of patients with cognitive dysfunction can be significantly confirmed by conducting a subjective evaluation and sensor based calculation with a basic set of checking actions.

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