Modeling of Driver's Distraction State based on Body Information Analysis

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***Abstract* - For this study, we defined a "concentration state" as that when a driver performs only driving tasks and a "distraction state" as that when a driver performs a driving task and a mental arithmetic task simultaneously. Based on results of these driving tests, we elucidate the characteristics of safety confirmation behaviors by near-misses according to differences between two driving conditions when approaching an intersection. Specifically, using Bayesian Networks (BNs) to express the relation between safety confirmation behaviors graphically for driving scene and driver's internal state, we analyze correlations between characteristic body information (i.e., eye-gaze / face orientation) and operation information (i.e., steering wheel, accelerator, and brake) when switching from a "concentration state" to a "distraction state" based on viewpoints of driving style and driving workload sensitivity. Using evaluation experiments, by constructing internal state estimation models of subjects for whom driving style and driving workload sensitivity are mutually opposite, we try to analyze body information and the operation information by which the influence of a distracted state appears easily through the specification of unique behavior patterns associated with each driving scene.**

Keywords - body information; driver behavior; human engineering; near miss; non-regulated intersection

I. INTRODUCTION

According to accident statistics, at non-regulated intersections where numerous crossing accidents occur, non-confirmation of safety is common: cognitive distraction states account for approximately 3/4 of human error in crossing accidents. Of pedestrian accident factors that result in death, 35% are states of careless driving, classified as a "distraction state" or "state of fatigue" according to the level of driver arousal. To clarify the relevance between a "distraction state" and a driver's driving characteristics, we have been studying a possibility of modeling drivers' internal states when switching from a concentrating state to a distracted state [1]. Detection indices of the "distraction state" are restricted to physiological information and body information. Methods of detecting attentiveness and arousal level from face orientations and eyelids (e.g., blinking or eyelid opening) captured by an onboard camera [2] [3] and an approach to detect the reduction of driver arousal level from vehicle behaviors [4] have been put to practical use as techniques of fatigue state estimation for drivers. More recently, research and development projects to detect and use eye-gaze movements have been promoted actively for the detection of signals of inattentive driving and distraction states [5] [6]. Furthermore, as case studies dealing with facial expression changes during driving, studies dealing with the relation between the evaluation value of facial expression changes by a third party and the degree of fatigue have been reported as attempts at driver fatigue measurements [7] [8]. In these studies, various methods been attempted, with increasing capabilities demonstrated by the evaluation of facial expression changes.

In earlier studies [9] [10], to extract characteristic behavior patterns that occur when a driver becomes distracted, we used a mental arithmetic task to perform a driving experiment simulating a driver's distraction state. Then, we analyzed the relation between data of physical information such as the face orientation / eye-gaze movement obtained from experiments and a driver's driving characteristics. Results show that a clear difference might occur in the distribution of eye-gaze movement in a concentration state and distraction state. Furthermore, through analysis of correlation between the physical information and operating information of vehicles, we confirmed the possibility of modeling drivers' internal states when switching from a concentrating state to a distracted state.

For this study, we attempt to model driving behavior using Bayesian Networks (BNs) [11] for a dataset acquired in earlier research. Actually, BNs can represent a causal relation of several random variables as a graph structure. Furthermore, one can obtain the *a posteriori* probability distribution of other variables by setting the evidence of the causal variable. For this study, we set the evidence for the driving scene and the driver's internal state, and perform probabilistic inference. Then, we find a posterior probability distribution of each node of physical information, biometric information, and operation information, and analyze the characteristic driving behavior, which changes depending on the driving scene and the driver's internal state.

This paper is presented as follows. We review related work to clarify the position of this study in Section II. Section III presents a definition of the running route and near-miss events assuming the sudden appearance of a bicycle. In Section IV, we examine two cases of "concentration state" to assess driving tasks and "distraction state" to assess driving tasks and mental arithmetic tasks simultaneously. Additionally, we identify characteristic behavior patterns corresponding to the three driving scenes and analyze the correlation between physical information and operation information, each of which is likely to be affected by the distracted state using the constructed internal state estimation model. Finally, we present conclusions and intentions for future work in Section V.

II. Related Works

A cognitive distraction state is difficult to ascertain from external appearances because it is an internal state of a driver. No estimation method has been established. Proposed methods of distraction state detection [12] were classifiable into four types based on the modalities to be measured [13] [14]. Considering the burden on drivers, the use of "physiological information" and "subjective evaluation" of drivers is unrealistic for application to actual driving conditions. For "operating information" such as steering and braking, which are involved directly with risk, notifying the driver even after detecting the distraction state can occur too late for danger avoidance. The distraction states addressed in this study include a "thinking state" and a "blank state" in which attention resources are distributed, and "impatience, or a frustrated state" attributable to time constraints under driving tasks. Abe et al. examined a "thinking state" [15]. Honma et al. reported a "blank state" [16]. Each study examined the experimental verification of each state. Each confirmed the presence of distinctive situations in which oversight and delayed discovery of changes in the surrounding circumstances would occur easily.

In earlier studies of modeling driving behaviors, Kumano et al. modeled eye-gaze movement using Dynamic Bayesian Networks (DBNs) [17]. They constructed a model of eye-gaze behaviors using DBNs from elements such as body movements, driving operations, and driving situations for identifying three types of eye-gaze movements such as forward gazing, dead angle confirmation, and inattention. As a result of verifying observation parameters because of differences in eye-gaze behaviors, they demonstrated the possibility of acquiring a high discrimination rate using context information such as driving operations and driving situations. However, the internal state estimation of each driver has not been reached for prediction of risky driving.

However, in constructing real-time distraction detection systems, Ahlstrom et al. investigated the usefulness of a real-time distraction detection algorithm called AttenD [18]. They described that it is difficult to measure the driver distraction state. There is no commonly accepted ground truth for driver distraction [19]. The validation of AttenD was performed in the field using the general methodological setup of a field operational test. That earlier study found that true distraction is difficult to attain in an artificial setting such as a simulator. However, AttenD seems not to respond appropriately our target distraction states such as a "thinking state" or "blank state" as described above. Therefore, we are convinced of the necessity of modeling along with each cycle of recognition, judgment, and operation which is the basis of driving tasks.

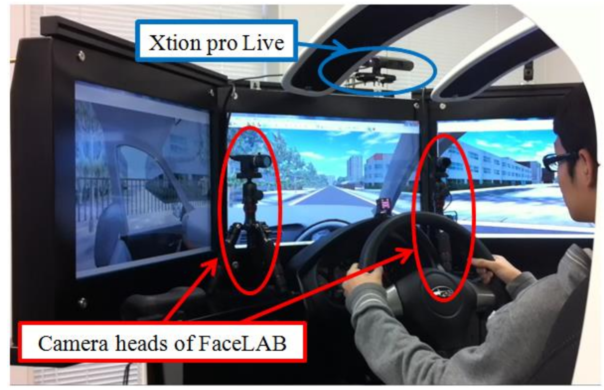


Figure 1. Experimental system for measuring driver behaviors.

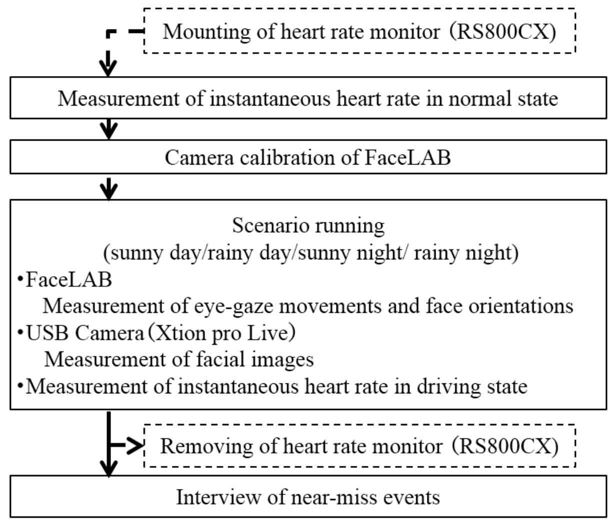
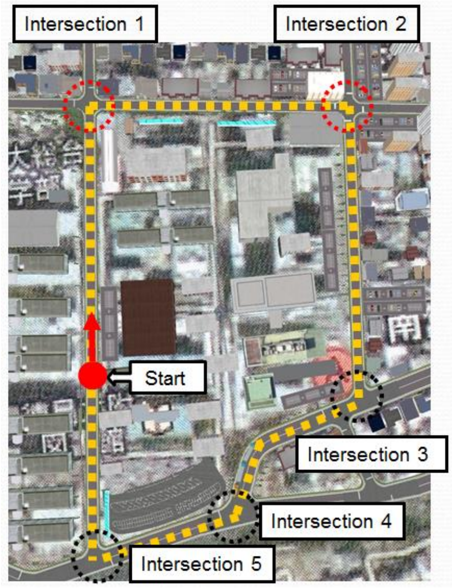
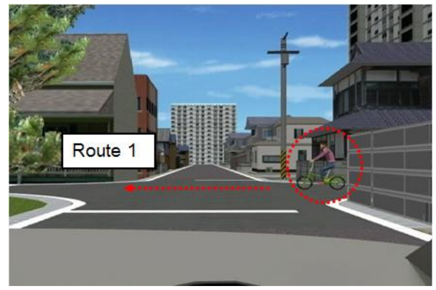


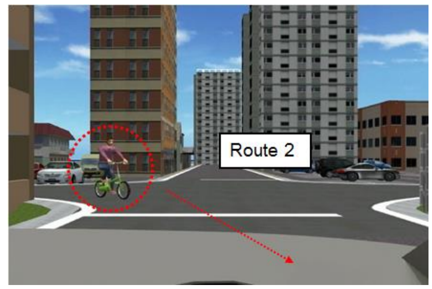
Figure 2. Outline of experimental protocols.



(a) Running route for simulation



(b) Sudden appearance of bicycle at intersection 1



(c) Sudden appearance of bicycle at intersection 2

Figure 3. Simulation course with near-miss events of two types (Route 1/Route 2).

III. METHODS

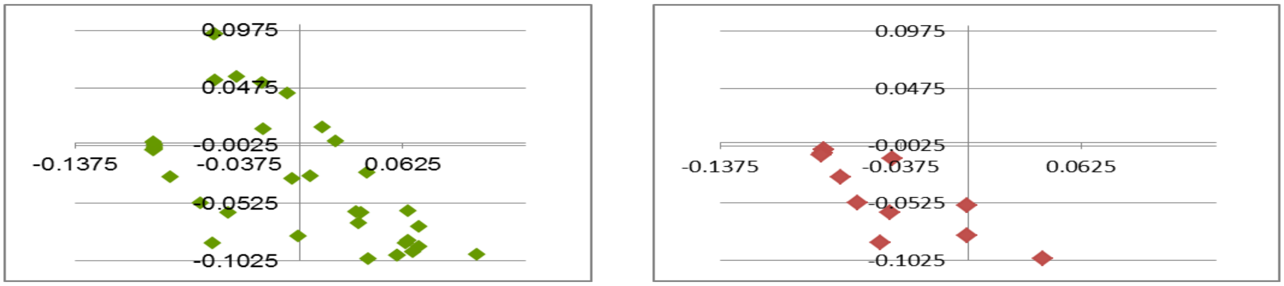
A. Experimental Systems

This study used a driving simulator (DS) to assess driving behaviors for freely set road environments and traffic conditions that affect driver behaviors. Figure 1 portrays the experimental system configuration used to measure driver behaviors. The DS used for experiments has platforms corresponding to compact and six-axis motion, which is equipped with ordinary cars. The DS has three color liquid crystal displays mounted in the front of the cabin, and has a function reproducing pseudo-driving environments that are freely configurable to horizontal viewing angles. As Figure 1 shows, to measure body information such as head poses, face orientations, and eye-gaze movements without restraining drivers, we installed cameras to the left and right in the center of the three-color liquid crystal monitors mounted in front of the cabin. Additionally, we set an infrared pod on top of the instruments in front of the cabin. Here the camera heads and infrared pod are input-based sensors of a head-gaze tracking device (FaceLAB; Ekstreme Machine Corp.).

B. Experimental Protocols

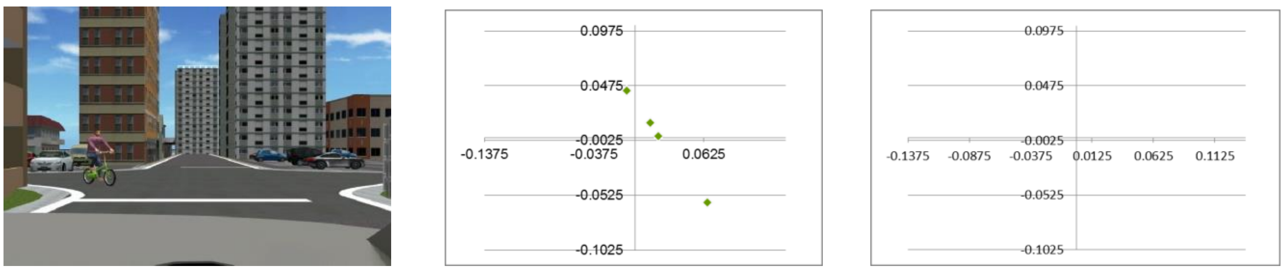
Figure 2 depicts the experimental protocol outline. The "concentration state" for driving represents driving states while performing only driving tasks. In contrast, the "distraction state" is defined as a "thinking state" during which driving tasks and simple mental arithmetic tasks are performed simultaneously. Similarly to experiments described by Abe et al. [15], mental arithmetic tasks used in our experiment included one digit addition, presented to drivers at 3 s intervals. Mental arithmetic results were to be reported verbally. The correctness of the results of each mental calculation was not reported to the driver during driving. Initially, as individual characteristics of each subject, we conducted an examination of the following questionnaire methods: attitude, oriented, and concept to work on driving were performed using the driving style check sheet [20]. Regarding the types of operation burdens that were strongly felt, they were performed using a driving load sensitivity check sheet [21]. In one running test, for each target subject wearing a heart rate monitor (RS800CX; Polar), we measured the instantaneous heart rate of a normal state during 1 min in advance. Next, to improve the measurement accuracy for face orientations and eye-gaze movements of each participant, we calibrated the cameras of the head-gaze tracking device (FaceLAB). We recorded a face video while driving with the USB camera (Xtion Pro Live; ASUS Corp.) to analyze the facial expressions of the subject. After these preparations, each participant ran three laps along the running scenario described later in Section Ⅲ.C, by synchronizing the time base of each measuring device. Finally, using a questionnaire that specifically examines traffic events occurring at intersections, subjective reviews, a four-stage check, were also conducted when a near-miss occurred.

After obtaining the approval of Akita Prefectural University Research Ethics Board, the experiment contents for all subjects were explained fully to participants in advance. We obtained written consent of participants. From



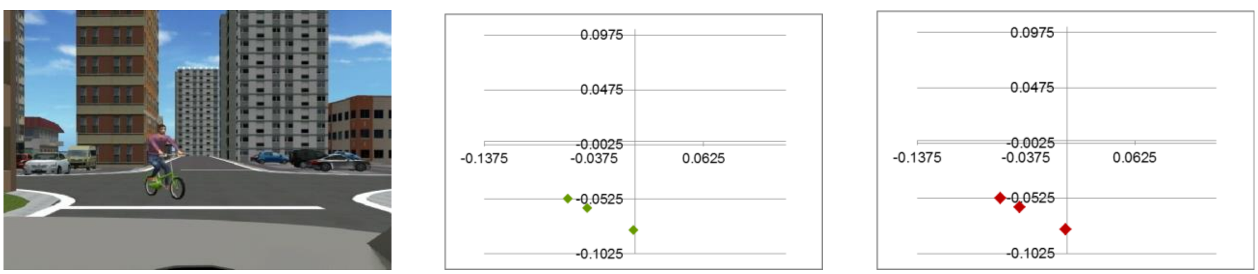
(a) Eye-gaze movements (b) Face orientations

Figure 4. Scatter diagram of the sections ranging from detection to gaze-tracking of sudden appearance of bicycle.



(a) Target scene (b) Eye-gaze movements (c) Face orientations

Figure 5. Detection case of sudden appearance of the bicycle for the first time.



(a) Target scene (b) Eye-gaze movements (c) Face orientations

Figure 6. Case in which eye movements and face orientations were plotted concurrently.

each, we also obtained an agreement to publish a face image along with the consent to experimental participation.

C. Near-miss events and running scenarios

Figure 3 presents a definition of the running route and near-miss events assuming the sudden appearance of a bicycle. The running route is a circuit course simulating non-controlled intersections near the Tokushima University campus, where joint research has been conducted. As targets, we set two types of sudden appearance of bicycles for intersection 1 and intersection 2 as shown in Figure 3. One near miss is defined as the sudden appearance of a bicycle along route 1, which is crossing from the right side to the left side of the vehicle. The other near-miss entails the sudden appearance of a bicycle along route 2, which is interfering with the vehicle path at intersection 2. With the main campus gate as a starting point, each subject traveled from the intersection 1 in order through intersection 5. In addition, intersection 1 and intersection 2 are non-controlled intersections that had poor visibility.

Subsequently, we present an overview of running scenarios in the following. The basic traveling scenario is configured to three laps of the running route described above. We conducted control of near-miss events for generation as follows. The first lap and the third lap were without near-miss events. The second lap includes the sudden appearance of bicycles along route 1 at intersection 1 and route 2 at intersection 2. Furthermore, it is necessary to control other traffic flows such as traffic turning right and straight oncoming vehicles at intersection 1, and that of cars crossing in front of one's own vehicle at intersections 2 and

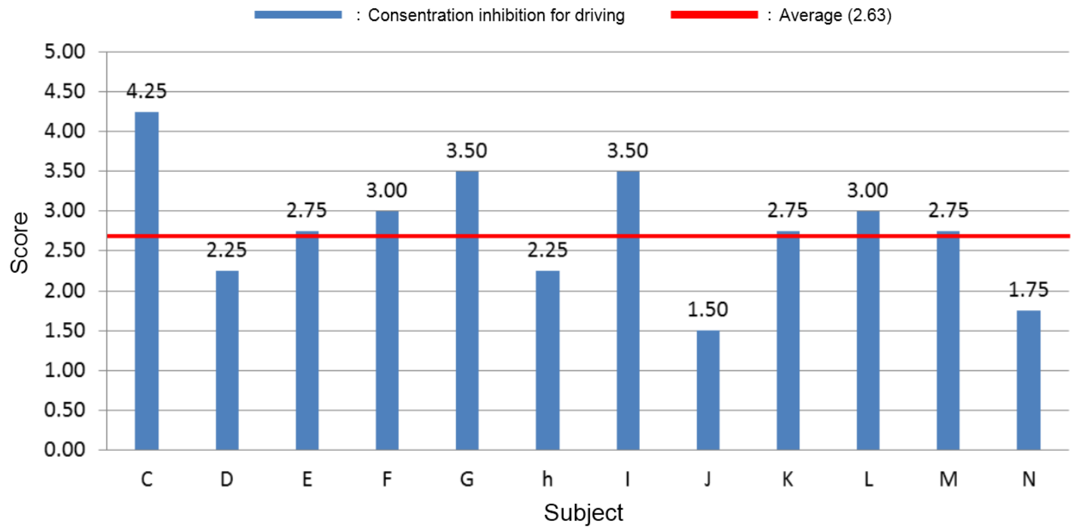


Figure 7. Calculation results of "concentration inhibition for driving" for all participants.

3. Based on the fundamental running scenarios described previously, we must assess behaviors in different weather (i.e., sunny or rainy) and time periods (i.e., daytime or nighttime). We prepared four driving environments: sunny day, rainy day sunny night, and rainy night.

IV. EXPERIMENT

For experiments, we examined two cases of "concentration state" to assess driving tasks and "distraction state" to assess driving tasks and mental arithmetic tasks simultaneously. Based on the running scenarios described in Section III.C, the experiments were conducted to three laps of the same route with one running environment, for driving environments of four types with varying weather and time zones. Furthermore, by changing the driving environments in the order of sunny day / rainy day / sunny night / rainy night, we examined the same conditions for all participants, all of whom were students of our university with ordinary vehicle driver licenses. These 10 men were designated as C, D, E, H, I, J, K, L, M, and N; 2 women were designated as F and G. During running experiments, we gave instructions to each driver to observe traffic rules and speed limits based on as pause, as stipulated in the Road Traffic Law.

A. Correlation between driving behaviors and driving load sensitivity

Our previous study [9] specifically examined time-series variation of eye-gaze movements and face orientations before and after encountering a near-miss. Consequently, we extracted behavioral patterns characterizing the "distraction state" on driving, and attempted to derive the effective findings for engineering modeling. In this section, narrowing down the time axis on the sudden appearance of the bicycle from microscopic points of view, we should analyze the temporal relation between eye-gaze movements and face orientations from the start point of viewing to the end point of tracking with respect to the sudden appearance of the bicycle. Figure 4 depicts scatter diagrams of eye-gaze movements and face orientations from the starting to the end point of tracking in the "concentration state." Comparison to the scatter diagram of face orientations shows that the scatter diagram of eye-gaze movements has been scattered widely. We recognized a tendency to control eye-gaze movements before face orientations when searching for the gazing target. Therefore, we subdivide the time axis from the start point of viewing to the end point of tracking, and analyze the eye-gaze movements and the face orientations by particularly addressing the timing to be shown on the scatter diagram. Figure 5 depicts the results by which only the eye-gaze movements appeared to scatter diagrams ahead. By contrast, Figure 6 presents results for which both eye-gaze movements and face orientations appeared simultaneously in scatter diagrams. In Figures 5 and 6, respectively, (a) is a scene image sudden appearance of the bicycle, (b) a scatter diagram of eye-gaze movements, and (c) is a scatter diagram of face orientations. As understood from Figure 5, when the driver was able to view the sudden appearance of the bicycle at first, we were unable to observe changes in the scatter diagram of face orientations. Subsequently, we confirmed the scatter diagram in which the eye-gaze movements and the face orientations were matched in Figure 6. Therefore, we believe that the driver had to view and track the sudden appearance of the bicycle for the first time at this timing.

Next, we consider the effect of the driving load sensitivity to eye-gaze behaviors in the "distraction state" and the "concentration state." In this study, particularly addressing

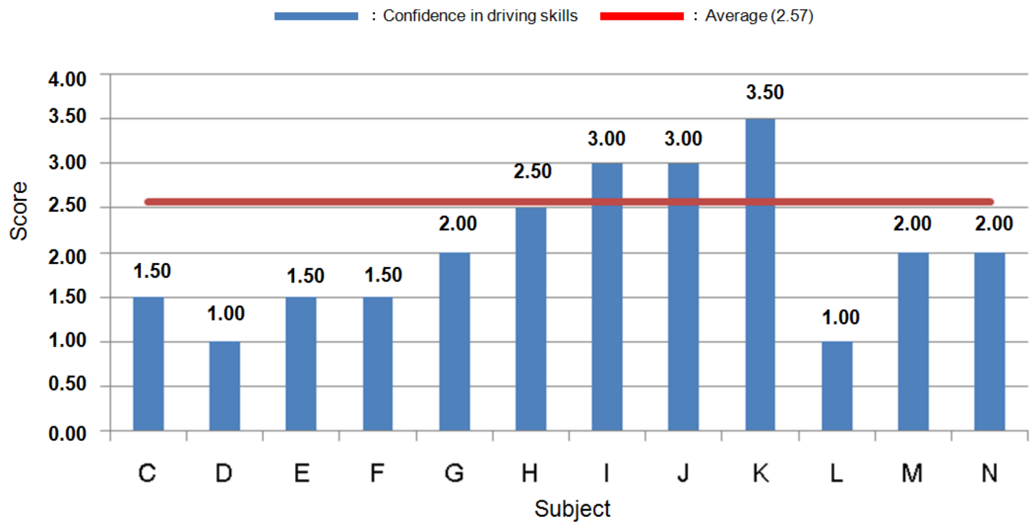


Figure 8. Calculation results of "confidence in driving skills" for all participants.

the "concentration inhibition for driving" from the 10 indices of the driving load sensitivity, Figure 7 depicts the result of whole participants. The value of the driving load sensitivity is calculated at 0.50 steps from 1.00 to 5.00, the average value (i.e., 2.63) in Figure 7, which indicates the survey result intended for the drivers of 20 years old to 74 years old conducted by Research Institute of Human Engineering for Quality Life. In the "concentration inhibition for driving" by performing mental arithmetic tasks and driving tasks simultaneously, we have classified "easily burdened group (i.e., C, E, F, G, I, K, L, and M)" and "not easily burdened group (i.e., D, H, J, and N)." Then, we analyzed gazing behaviors using heat maps of eye-gaze movements. Results show that for the easily burdened group the "concentration inhibition for driving" tended to fall into a "distracted state" by performing mental arithmetic tasks and driving tasks simultaneously. We inferred that the "easily burdened group" had unintentionally devoted attention resources to mental arithmetic tasks because their eye-gaze movements were distributed when approaching intersections.

Additionally, we consider the effect of the driving style to eye-gaze behaviors in the "distraction state" and the "concentration state." Particularly addressing the "confidence in driving skills" from the 9 indices of the driving style, Figure 8 depicts the result of whole participants. The value is calculated at 0.50 steps from 1.00 to 4.00, the average value (i.e., 2.57) in Figure 8, which indicates the survey result as same as the driving load sensitivity. In the easily burdened group (i.e., C, E, F, G, I, K, L, and M), we have confirmed subjects I and K having with the "confidence in driving skills." On the other hand, subjects C, E, F, G, L, and M don’t have the "confidence in driving skills." We have expected that a concentration state and distraction state strongly depend on both "concentration inhibition for driving" and "confidence in driving skills" of each driver.

B. *Modeling of internal states estimation*

BNs can be used as a probabilistic model to visualize complicated dependence of the target problem by a graph structure. They represent dependence between variables by non-circular effective links. BNs represent random variables by nodes. Furthermore, BNs combine nodes with directed links and define the mutual dependence of variables as probability distributions. The node under the directed link is called the parent node. The node at the end of the directed link is called the child node. A random variable we want to find is defined as X. The value of the observed variable is defined as e. A normalization constant is defined as π. The probability of propagation from parent node or child node is defined as π and λ. An arbitrary *a posteriori* probability is calculable locally using the following equation: by stochastic inference using BNs, the probability distribution of the target random variable is obtainable.

$$P(X_j | e) = \alpha\lambda(X_i)\pi(X_j) \quad (1)$$

The internal state estimation model handled in this research consists of 8 nodes: 2 nodes corresponding to the face orientation and eye-gaze movement of body information (Head and Eye), 1 node corresponding to the heart rate of the biometric information (Heart), 3 nodes corresponding to handles, accelerator, and brake of operation information (Handle, Accelerator, Brake), and 2 nodes corresponding to the driving scene and the driver's internal state (Scene, State). Table I presents the list of nodes. For each node from "Head" to "Brake," changes of values were recorded every 3 s because the mental arithmetic task given every 3 s in the driving experiment. "Scene" is an assigned number denoting the state according to the three driving scenes (straight line, intersection entry, and right turn) from characteristics of the simulation course.

For building the internal state estimation model, we use BAYONET, which is Bayesian Network building support software by NTT Data Matrix Systems. BAYONET has the function of learning the characteristics of the target dataset and automatically constructing a network. Now, based on the precondition that the driver's internal state and operation information are influenced according to the driving scene, the driving scene "Scene" is set as the parent node. Then the internal state "State" and the operation information "Handle, " "Accelerator," and "Brake" are set as child nodes. Then the directed link is set manually. Furthermore, based on the hypothesis that the driver's internal state is likely to appear in the physical information and in the biological information, the physical information "Head," "Eye" and the biological information "Heart" are set as parent nodes. The internal state "State" is set as a child node. The directed link is set manually.

We consider that the driver's internal state "State" is determined by the distribution of attention resources accompanying the performance of the driving task and the mental arithmetic task. Therefore, we quantify the distribution of attention resources for driving tasks and mental arithmetic tasks, and define the driver's internal state using these values. We use the number of occurrences of saccades every 3 s as the evaluation value of the attention resource distribution to driving tasks. Because saccades are a rapid movement of the eye-gaze movement from the gaze point to the gaze point, many saccades occurred during driving while devoting attention to the surrounding environment. The evaluation value of i-th driving task D_i is defined using the following equation. The number of occurrences of saccade S_i is normalized as a value of 0–1.

$$D_i = \frac{S_i - S_{\min}}{S_{\max} - S_{\min}} \qquad (2)$$

We use the time from the instant the question is presented to the end of the answer as the evaluation value of attention resource distribution to mental arithmetic tasks. A quicker answer reflects concentration on the mental arithmetic task and represents allocation of more attention resources. Therefore, the evaluation value is higher. However, in the case of no answer or a wrong answer, we set the evaluation value as the lowest because attention resources are not allocated to the mental arithmetic task. Specifically, it was set to the same value as the longest response time of each subject. The evaluation value of the mental arithmetic task at i-th point A_i is defined as shown in the following equation. In addition, T_i, which is the time from the question entry to the end of the reply, was normalized as a value between 0 and 1. A_i is set to approach 1 for rapid answers.

$$A_i = 1 - \frac{T_i - T_{\min}}{T_{\max} - T_{\min}} \qquad (3)$$

From the above, the *i*-th evaluation value of the driver's internal state $State_i$ is defined from the evaluation value of the driving task D_i and the evaluation value of the mental arithmetic task A_i using the following equation.

$$State_i = \frac{D_i + A_i}{2} \qquad (4)$$

TABLE I. DEFINITION OF BNs NODES

Node	Contents
HEAD	Displacement value of head pose movements for 3 s [m]
EYE	Displacement value of eye-gaze movements for 3 s [m]
HEART	Variation of instantaneous heart rate for 3 s [s^{-1}]
HANDLE	Operation value of steering for 3 s (-1 ~ +1)
ACCEL	Operation value of accelerator for 3 s (-1 ~ +1)
BRAKE	Operation value of brake for 3 s (-1 ~ +1)
SCENE	Driving scenes (1: straight, 2: approaching intersections, 3: turn right)
STATE	Internal states (1: concentration state, 2: neutral state, 3: distraction state)

C. *Analysis of internal states estimation model*

The state in which attention resources are not properly allocated according to the driving scene is called a distraction state. If a distraction state continues, then it engenders dangerous driving and a higher probability of causing an accident. Additionally, it is expected that a concentration state and distraction state defined as the driver's internal state depend on the driving skill of each driver. For this reason, we think that an analysis particularly addressing the driving style and driving workload sensitivity based on check sheets is important. As described herein, we specifically examine subject C, who has less opportunity to drive, and subject I, who drives on a daily basis. Figure 9 presents test results related to the driving style. Figure 10 shows test results reflecting the driving workload sensitivity. Average values shown in Figure 9 and Figure 10 are the values of results from about 540 men and women for a survey conducted by the Research Institute of Human Engineering for Quality of Life (HQL). In the driving style of Figure 9, subject C has high "passivity to driving" and "a propensity for anxiety." In addition, Subject I had a high tendency for "confidence in driving skills" and a "car as a status symbol." From this, they are found to have polar opposite driving styles. In terms of the driving workload sensitivity in Figure 10, both subjects had a high "concentration inhibition for driving."

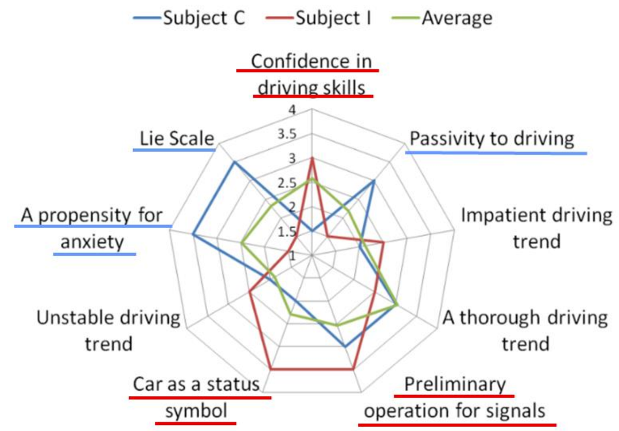


Figure 9. Driving style results of subjects C and I.

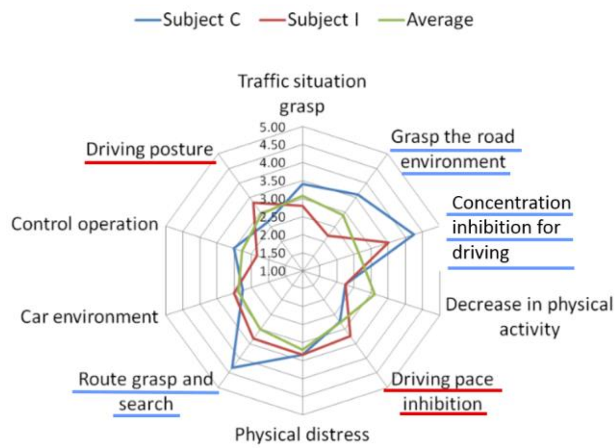


Figure 10. Driving workload sensitivity results of subjects C and I.

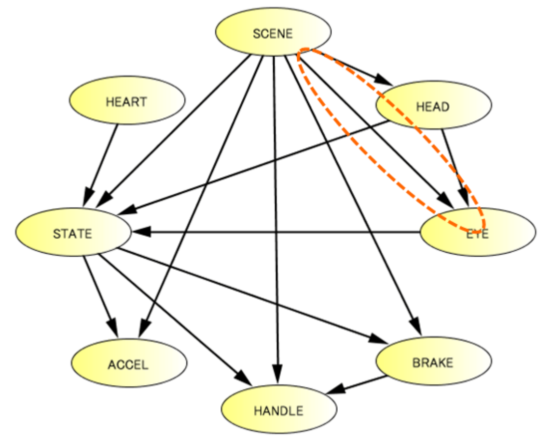


Figure 11. Internal state estimation model for risky driving (Subject C).

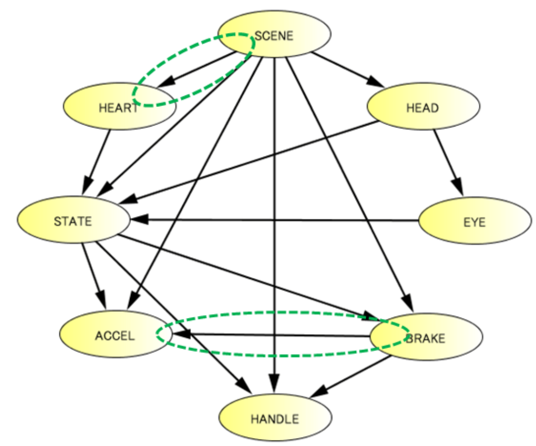
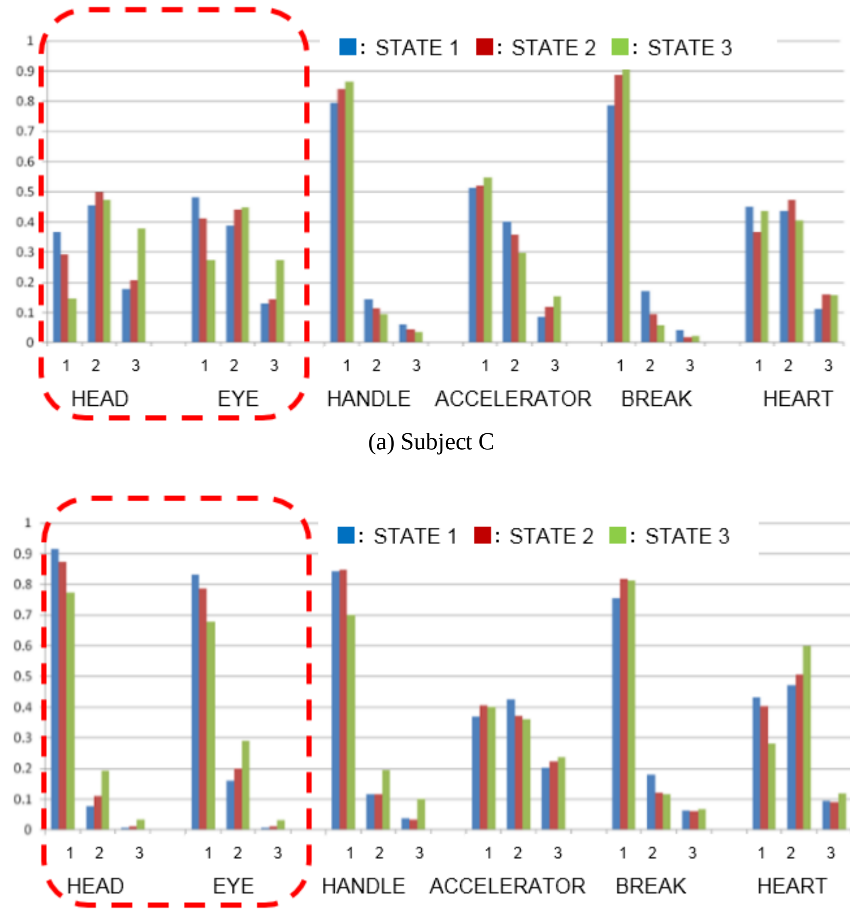


Figure 12. Internal state estimation model for risky driving (Subject I).

Subject I exhibited a tendency to have a higher "driving pace inhibition." In other words, we estimate that both subjects have characteristics that easily fall into a distraction state because of simultaneous performance of the driving task and mental arithmetic task.

The learning data used to construct the internal state estimation model are a joining of all data acquired in the four driving experiments conducted with different weather and time zones. The number of data of subject C was 634. The number of data of subject I was 619. In addition, these data were discretized in three stages using K-means method. The model of subject C is presented in Figure 11. The model of subject I is shown in Figure 12. Comparing Figure 11 with Figure 12 enables confirmation of the existence of a directed link unique to each subject. Because the directed links connect the nodes in a form optimized to raise the accuracy of the inference, significant correlation exists between the nodes to which the directed links are established. For example, in Subject C in Figure 11, a directed link from the "Scene" node to the "Eye" node is established, but in subject I in Figure 12, its directed link is not established. In other words, subject C's eye-gaze movement is more likely to be affected depending on the driving scene. Conversely, subject I's eye-gaze movement might be affected only slightly. In subject I in Figure 12, a directed link is established from the "Scene" node to the "Heart" node and from the "Brake" node to the "Accelerator" node, respectively, but in the subject C in Figure 11, its directed link is not established. Particularly because the directed link from the "Brake" node to the "Accelerator" node shows a clear causal relation between the brake and the accelerator operation amount, it can be regarded as the skill level of the driving operation. The feature shown above demonstrates that it is possible to construct an internal state estimation model that is unique to the subject because of differences in driving style and driving workload sensitivity.



(a) Subject C

(b) Subject I

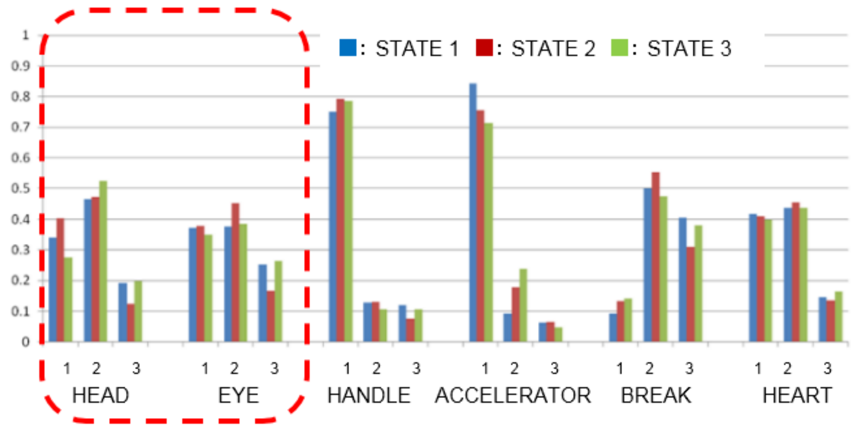
Figure 13. Probability distribution of respective nodes with evidence of the straight running period.

D. Stochastic reasoning by internal states estimation model

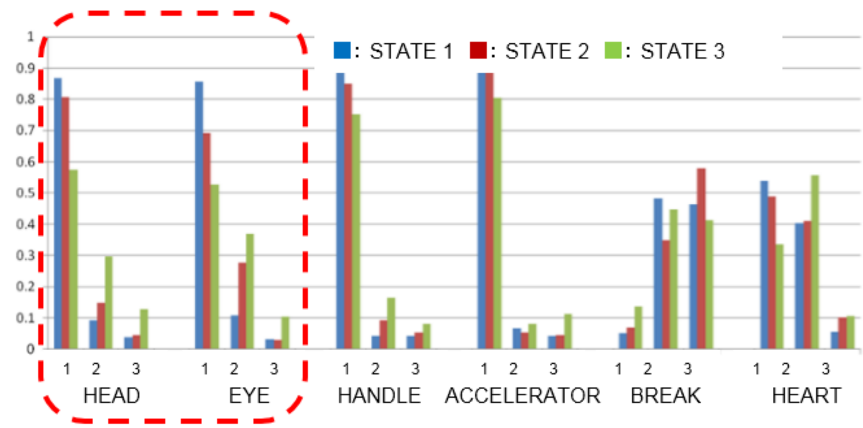
Next, we identify characteristic behavior patterns corresponding to the three driving scenes and analyze the correlation between physical information and operation information, each of which is likely to be affected by the distracted state using the constructed internal state estimation model. The three driving scenes are controlled by evidence of the "Scene" node. Scenes are classified into a straight section "Scene 1," an entrance section "Scene 2," and a right turn section "Scene 3." Subsequently, we gave evidence to the ‘State’ node representing the driver’s internal state for each driving scene, and compared the probability distribution of each node in the concentrating state "State 3" and the distracted state "State 1." Figures 13–15 present the posterior probability distributions of subjects C and I obtained by stochastic reasoning corresponding to three driving scenes. In the figure, values 1–3 indicated by each node on the abscissa show the magnitude of the movement amount and the operation amount. The ordinate axis shows values of their posterior probabilities.

In the straight section of Figure 13 and the approach section of Figure 14, devoting attention to the posterior probability distribution of the ‘Head’ node and the "Eye" node, subject C has a large face orientation and movement amount of the eye-gaze movement. Conversely, subject I's movement amount is small. Regarding the driving style, subject C has high "passivity to driving" and "a propensity for anxiety." Subject I has a high "confidence in driving skill," so it can be inferred that this is attributable to the difference in driving skill levels. In addition, in the right turn section of Figure 15, a tendency is apparent by which the face orientation and eye-gaze movement amount of subject I become greater than in the straight section of Figure 13. In other words, it can be inferred that subject I was driving while identifying points to be noticed according to each driving scene, in contrast to subject C, who did not.

In addition, when comparing concentrating state "State 3" and distracted state "State 1" in a distracted state in both driving scenes of both subjects, the amounts of movement



(a) Subject C



(b) Subject I

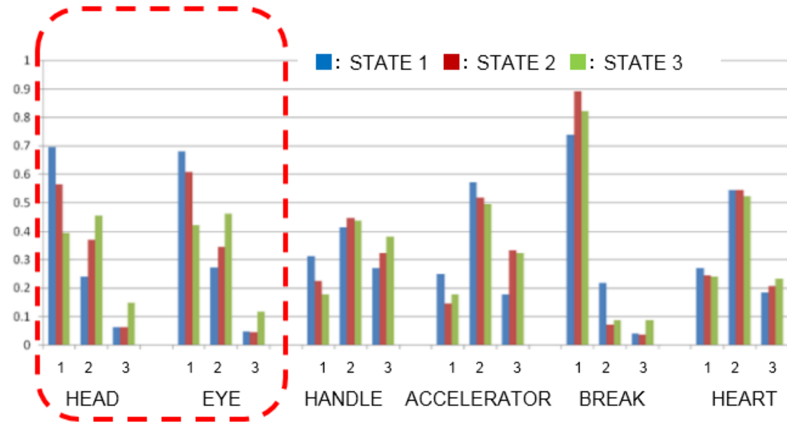
Figure 14. Probability distribution of respective nodes with evidence of approaching the intersection period.

of the face orientation and the eye-gaze movement are small (posterior probability of "Head 1" and "Eye 1": distracted state > concentrating state). However, in the concentrating state, for both driving scenes of both subjects, the amount of movement the face orientation and the eye-gaze movement is large (posterior probability of "Head 3" and "Eye 3": distracted state > concentrating state). These tendencies are regarded as evident in the change in the amount of the movement of the face orientation and the eye-gaze movement for both subjects as a result of depriving attention resources by the simultaneous execution of the driving task and the mental arithmetic task. Next, devoting attention to the posterior probability distribution of the 'Handle' node in the straight section of Figure 13 and the entry section of Figure 14, in the distracted state, the steering wheel operation amount of subject C is increased, whereas the steering wheel operation amount of subject I is decreased. Moreover, subject I, more than subject C, showed a difference in posterior probability when the concentrating state changed to the distracted state. This tendency suggests that the simultaneous execution of mental arithmetic tasks is strongly influential because subject I shows a burden from "distributing the concentration of the driving" and "driving pace inhibition."

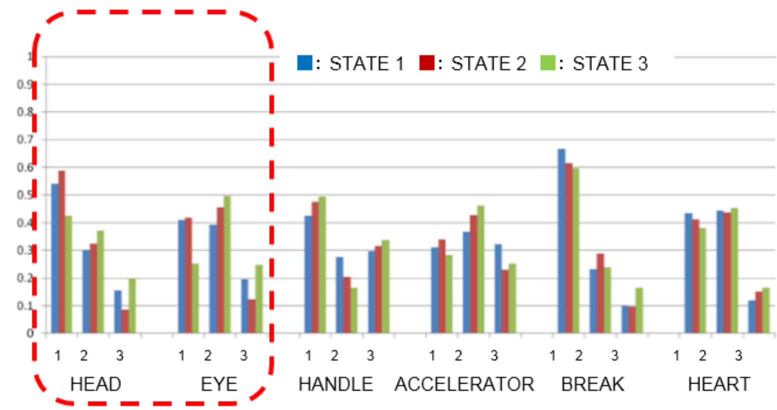
Finally, we specifically examine the probability distribution of the "Heart" node of the instantaneous heart rate. In the internal state estimation model of subject I presented in Figure 12, a direct link is established from the "Scene" node to the "Heart" node. For subject C presented in Figure 10, the directed link is not recognized. By devoting attention to this point and by comparing the posterior probability distributions of both subjects shown in Figures 13–15, subject I presents a marked difference between the posterior probability of the concentrating state and distracted state in each driving scene, but subject C shows no marked difference. This result is attributable to the presence or absence of an effective link in the internal state estimation model that is unique to each subject.

E. Validation of internal states estimation model

After constructing an internal states estimation model with three datasets of learning data out of the four running



(a) Subject C



(b) Subject I

Figure 15. Probability distribution of respective nodes with evidence of turning to the right period.

experiments conducted with different weather and time zones (sunny day / rainy day / sunny night / rainy night), probabilistic inference was conducted for the model using the remaining 1 dataset as test data. Then the accuracy of the model was verified through cross validation. Table II presents the results. Assuming that the number of verification data is *N* and that the correct number of inference results is *C*, then the correct answer rate is represented as *C* / *N*. Therefore, the average value was calculated and inferred by all combinations (model construction and test of four patterns). It is noteworthy that the "Scene" node and the "State" node were used as explanatory variables. The other six nodes were set as objective variables to find the correct answer rate.

As shown in Table II, particularly addressing Subject I, it indicates a high correct answer rate in all the nodes except the "Heart" node. Especially, in the "Eye", the "Head," the "Handle," and the "Brake" nodes directly connected to judgment / operation of driving behavior, the correct answer rate of more than 70% can be confirmed for each node. These numerical values show the possibility of extracting and defining a characteristic driving behavior pattern when shifting from the driving concentration state to the distracted state. Results suggest effectiveness of the internal state estimation model that is unique to the subject. However, the correct answer rates of the "Eye" node and the "Head" node of subject C tended to be lower than those of subject I because subject I was driving without glasses, whereas subject C was wearing glasses while driving. Therefore, we infer that the difference in detection accuracy between the eye-gaze movement and the face orientation was influenced.

TABLE II. RESULTS OF ACCURACY VALIDATION

Node	Subject C	Subject I
HEAD	0.48715	0.779525
EYE	0.417975	0.707025
HEART	0.49720	0.443275
HANDLE	0.70335	0.746700
ACCEL	0.52265	0.574150
BRAKE	0.71645	0.755225

V. CONCLUSION AND FUTURE WORK

For this study, we analyzed driver behavior changes to ascertain the time at which a driver becomes distracted. In an earlier study, we conducted a driving experiment simulating a distraction state and obtained a dataset. Additionally, we constructed a Bayesian model incorporating the driver's internal state as a node for two subjects, and executed probabilistic reasoning. We analyzed the relation between inference results and driving style / driving workload sensitivity. Results clarified the following points. Dividing "watching behaviors" when approaching the intersection and the "safety confirmation behaviors" after a temporary stop is effective for analyses of the behavioral patterns characterizing the "distraction state." It is possible to construct a specific internal state estimation model of the subject by differences in the driving style and driving workload sensitivity. In addition, results show a unique directed link of the subject. Although we analyzed only two subjects in the present study, we expect to evaluate more subjects and analysis items in future research. Additionally, it is considered that temporal information is necessary for dealing with driving behavior. Therefore, we plan to conduct research with modeling using DBNs.

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