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DEVELOPMENT OF DRIVER PSYCHOLOGY EVALUATION SYSTEM BASED ON DRIVING OPERATION INFORMATION

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Abstract. *In recent years, due to advances in traffic safety technology, the number of traffic accidents and the number of deaths have been decreasing in Japan. However, the number of traffic accidents is still very large. It has been pointed out that influences and responses to psychological stress are influenced by personal characteristics (accident likelihood), the main ones of which are a lack of emotional stability, aggression, social cooperativeness, etc. In this research, we first experimented to reproduce driving in a mentally unstable state by putting psychological stress on the driver, constructed a GMM driving psychology estimation model and an SVM classifier based on the obtained driving operation data, and then used these to estimate the psychology of a psychologically weak driver. In our experiment, encouraging results were obtained.*
Keywords: Driving support systems, Driver characteristic, Gaussian mixture model, Driver psychology

1. **Introduction.** In recent years, due to advances in traffic safety technology, the number of traffic accidents and the number of deaths have been decreasing in Japan. Nevertheless, the number of traffic accidents is still very large, numbering about 530,000 in 2015. There are various causes of these accidents, but the biggest one is ignoring the obligations of safe driving, such as safety uncertainty and speeding. This accounts for about 70% of the total cause of accidents. In many cases, these duty violations are known to be caused by the addition of psychological stress on the driver [1, 2, 3].

It has been pointed out that influences and responses of psychological stress are influenced by personal characteristics (accident likelihood), the main ones of which are a lack of emotional stability, aggression, social cooperativeness, etc. [2]. Traffic accidents are the result of reciprocal processes of human and environmental factors. Simultaneously with the appearance of human factors such as cognitive and judgmental errors, environmental factors trigger psychological stress and the mind becomes unstable, which causes unsafe driving and leads to an accident. Therefore, we aim to develop a psychological diagnosis type support system that estimates and detects driver psychology with accident likelihood for each driver, and gives appropriate advice according to it.

In this study, the true value of accident likelihood for each driver to be estimated is obtained by using the K-2 type driving suitability test of the National Police Agency. An experiment is designed that adds psychological stress to the driver and reproduces driving in a mentally unstable state. Based on the experiment results and the true value

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of accident likelihood by an aptitude test, we construct a psychological state estimation model of accident likelihood using Gaussian mixture models (GMM), and a psychological state classifier using a support vector machine (SVM). The accuracy of the estimation is verified by comparing the estimation results obtained by the constructed model with the true value obtained by the aptitude test. The remainder of the paper is organized as follows. In the next section, a new estimation method of driver psychological characteristics with accident likelihood is presented. Furthermore, in Section 3, some experiment results are demonstrated and good performance of our method is obtained. Finally, in Section 4, we state the conclusions and remarks of this paper.

2. A New Estimation Method of Driver Psychological Characteristics with Accident Likelihood.

2.1. Driver psychology and accident likelihood. Figure 1 shows a simple process of a violation in safe driving caused by psychological stress [2]. As shown in the figure, when impatience, irritation, and excessive anxiety are generated by applying physiological and psychological stress etc. to a driver while driving, it is possible that the driver may cause a change in the driving state and start driving dangerously. However, there are individual differences in the influence of psychological stress on driving. Previous studies have reported that drivers with psychological characteristics of emotional instability, aggression, and non-cooperativeness are susceptible to psychological stress and are liable to cause a traffic accident [2]. In this research, a driver in such a psychological state is called a psychologically weak driver.

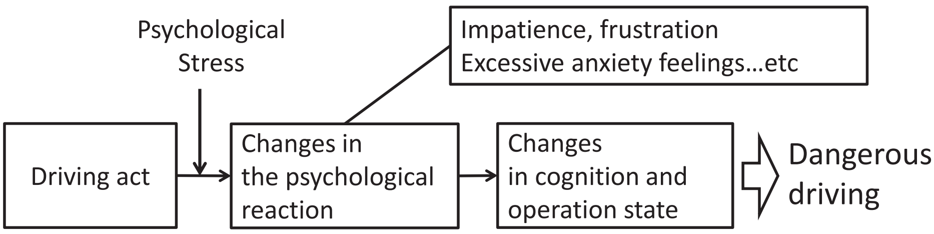

Figure 1. The process of violating safe driving [2]

Generally, traffic accidents are the result of the combination of human factors and environmental factors. For normal driving, the psychologically weak driver will not necessarily cause a traffic accident. However, in some driving environments, such as continuous red traffic signals, and traffic jams, the psychologically weak driver may feel psychological stress and the mind may fall into an unstable state. When psychologically weak drivers fall into such a mental state, they are liable to mistake signals, suffer misjudgment, make behavioral errors, etc., and these lead to accidents. In this research, we aim to estimate the psychological characteristics of each driver from driving operation data, by detecting a psychologically weak driver, and accordingly providing appropriate support.

2.2. Driver psychology estimation method proposal based on driving operation data. Conventionally, psychological tests of drivers are conducted using the K-2 type driver suitability test of the National Police Agency. This K-2 type driver suitability test is a paper test, which was developed by the National Police Agency and improved based on many accident records and drivers' test results. In this research, we will rely on the results of this K-2 type driving aptitude test and use it as a judgment criterion for identifying psychologically weak drivers.

Figure 2 shows the flowchart of the estimation of driver psychology by using driving operation data. As shown in the figure, a driving experiment is firstly carried out with a driving simulator (DS) to collect driving operation data. The operation environment

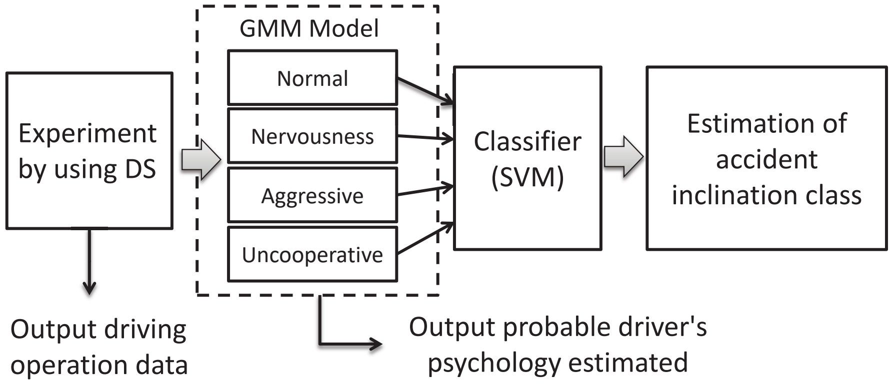

Figure 2. Flowchart of estimation for driver psychology and driving duty violation

of the DS for the experiment is designed to place psychological stress on the driver and make it easy for a psychologically weak driver easy to reproduce driving in an unstable mental state. And then, using the driving operation data collected, the driving psychology of the driver is estimated by the driving psychological estimation model. The driving psychological estimation model is constructed for each psychological characteristic by Gaussian mixture models (GMM) using the driving operation data of the psychologically weak driver and a normal person, who is identified in advance by the K-2 type driving aptitude test. Finally, we classify driving psychology using a support vector machine (SVM) which is a kind of classifiers. The SVM is constructed by machine learning using learning data that are the output of the GMM driving psychology estimation model of the normal person and the psychologically weak driver. The following sections discuss the design of the driving environment, the composition of the GMM driving psychology estimation model, and the configuration of the driving psychology classifier by SVM.

2.3. **Driving environment design.** In this research, in order to reproduce the psychologically unstable state of a psychologically weak driver, a dedicated driving environment on the DS was designed and built using the UC-win/Road 10.1.1 software by FORUM 8. This software provides functions such as the design of roads and terrain, installation of 3D buildings and traffic signals, control of signal patterns and traffic flow, as basic driving environments [4]. Here, based on the research so far, we designed a straight course of two lanes in a general urban area, including the following five types of driving sections, which places a strong mental burden on psychologically weak drivers.

1) Signal section with a continuous red signal: When the vehicle reaches a predetermined position before the intersection, the signal is intentionally switched to red. This scene appears continuously in multiple places. The traffic signals are set to the positions that can be sufficiently recognized from the host vehicle within 100 [m] before the intersection.
2) Tracking section of low speed parallel driving of the front vehicle: The respective front vehicles of the first traffic lane and the second traffic lane drive parallel at a low speed so as to block the road.
3) Overtaking section with slow front vehicle and street parking: After a vehicle brakes at the front, it drives at low speed. There are also a number of vehicles parked on the road.
4) Jump-out section of pedestrian and right-turning vehicle: There are a number of pedestrians who suddenly cross without warning and some oncoming vehicles that suddenly turn right. These are dangerous behaviors that cannot be predicted, and so place a mental burden on drivers.

5) Traffic congestion section: The driver is required to drive in a congested traffic environment that travels at a speed of about 15 [km/h] along a section of about 700 [m].

2.4. Estimation of driver psychology by Gaussian mixture models (GMM). The GMM is a statistical model that is represented by a linear combination of several normal distributions, and is used in voice recognition and other areas [5]. In addition, because the GMM is based on the normal distribution, the amount of calculation required is small, and it is suitable for low-performance real-time processing on a personal computer. The GMM consisting of M normal distributions can be represented in the distribution of each mixture weight α_m, mean vector $\boldsymbol{\mu}_m$, and the covariance matrix $\boldsymbol{\Sigma}_m$.

In this case, the output probability of the observation vector $\boldsymbol{o}$ is defined by the following equation.

$$P(\boldsymbol{o}|\alpha_m, \boldsymbol{\mu}_m, \boldsymbol{\Sigma}_m) = \sum_{m=1}^{M} \alpha_m N_m(\boldsymbol{o}), \tag{1}$$

where α_m shows the weight of normal distribution number m, and it satisfies the following equation.

$$\sum_{m=1}^{M} \alpha_m = 1. \tag{2}$$

In addition, $N_m(\boldsymbol{o})$ shows the probability density function represented by the following equation.

$$N_m(\boldsymbol{o}) = \frac{\exp\left(-\frac{1}{2}(\boldsymbol{o} - \boldsymbol{\mu}_m)^t \boldsymbol{\Sigma}_m^{-1} (\boldsymbol{o} - \boldsymbol{\mu}_m)\right)}{(2\pi)^{\frac{D}{2}} |\boldsymbol{\Sigma}_m|^{\frac{1}{2}}}, \tag{3}$$

where D shows the dimension of the observation vector $\boldsymbol{o}$, $|\boldsymbol{\Sigma}_m|$ shows the determinant of the covariance matrix, and $\boldsymbol{\Sigma}_m^{-1}$ shows the inverse matrix of the covariance matrix.

Since the GMM has the advantage that it can be approximated with arbitrary precision to a probability distribution with multi-modality, it is suitable for modeling data with large variation every time such as in driving operation data. The authors confirmed the effectiveness of the GMM to driver intention estimation [6] and driving cooperativeness estimation at intersections [7]. In this research, in order to estimate the driver's psychology from driving operation data, we will construct a psychological state estimation model for each psychological characteristic state using a GMM.

2.5. Recognition of psychological state by the SVM. The psychological state of the driver is estimated by each individual GMM psychological state estimation model and is represented by a probability. Here, the classification (clustering) of a driver's psychology is performed from the probability of output of each GMM using the SVM.

The SVM is either a linear SVM or a nonlinear SVM. When each class of learning data can be linearly separated, a linear SVM using a hard margin method is used, whereas when each class cannot be linearly separated a nonlinear SVM using a soft margin method is used. In this study, it is judged that learning data cannot be linearly separated, so a nonlinear SVM using a soft margin method is used. In addition, the kernel that can construct an optimal nonlinear mapping uses the Gaussian kernel (RBF kernel) with the parameter $\gamma = 0.04$.

Conventionally, the output of the SVM is the classes of psychological characteristics; however, Platt [8] proposed a method of assigning confidence, that is, the classes membership probability from the output of the SVM. In the method of Platt, the distance from the class to be classified to the predicted separation plane is first defined as the distance f, and then the value $P(f)$ obtained by converting the distance into the interval of $[0, 1]$ with the sigmoid function is used as the estimated value of the class membership probability.

$$P(f) = \frac{1}{1 + \exp(Af + B)}. \tag{4}$$

However, it is necessary to estimate the parameters A and B in advance with the maximum likelihood method. The advantage of the sigmoid function method is that the class membership probability can be directly estimated from the classification score. Therefore, if the parameters A and B are estimated, the procedure is simple. In this research, using the method of Platt, the output of the SVM is taken as the estimated value of the class membership probability.

3. **Experiment Results and Discussion.**

3.1. **Collection of driving operation data.** The driving experiment was carried out by using the DS on the course outlined in Section 2.3. The subjects were 23 men and women in their twenties, and gave their informed consent before the experiment was performed. The operation data recorded in the experiment consist of three parts: 1) steering operation amount [%], 2) pedal operation amount [%], 3) direction indicator information $[0, 1]$. Here, the pedal operation amount is negative when braking, and positive when accelerating. The vehicle information consists of three parts: 1) vehicle speed [km/h], 2) vehicle acceleration [$\mathrm{m/s^2}$], 3) vehicle position coordinate [m]. In addition, the sampling frequency of all the data is 20 [Hz]. After completion of the driving experiment, a written questionnaire was administered by using the SD method, in which drivers evaluated their degree of psychological stress in each driving section. In the questionnaire, a response of "not uncomfortable" is assigned 1 point, "slight discomfort feeling" 2 points, "discomfort feeling" 3 points and "very discomfort feeling" 4 points.

3.2. **Estimation of driver psychology by GMM.** First, in order to compose the GMM psychological state estimation model, the results of the K-2 type driving aptitude test of the subjects are analyzed and the psychologically weak drivers are identified according to the criteria of the National Police Agency. Based on the decision criteria of the National Police Agency, we classify the psychological state of the psychologically weak driver into three classes of emotional instability, aggression, non-cooperativeness, and include a normal class. These four classes are used to construct the GMM. Next, from the results of the K-2 type driving aptitude test corresponding to these four classes, the evaluation results of emotional stability deeply related to the psychological state of the psychologically weak driver are extracted. For each subject, the results of the questionnaires in the five driving sections were plotted against the evaluation results of emotional stability and are shown in Figure 3. The upper left of Figure 3 shows the result of the emotionally unstable class, the upper right shows the result of the aggressive class, the lower left shows the result of the uncooperative class and the lower right shows the result of the normal class. For Figure 3, after excluding outliers by the modified Thompson method, a correlation was obtained by subtracting the regression line. As a result, the minimum correlation coefficient among the 4 classes was $r = 0.638$, and it was confirmed that there was a correlation between them.

Based on this result, the driving operation data in the five driving sections of the correlated four classes of the psychologically weak driver were taken out and the GMM driver psychological estimation model was built for each class by the method shown in Section 2.4. Based on the degree of separation between the classes, the five amounts, that is, the vehicle speed, the acceleration, the steering wheel amount, the time change of the pedal stepping amount and the jerk were selected and the 5-dimensional driving characteristic amount was used. Figure 4 shows examples of the GMM driver psychology

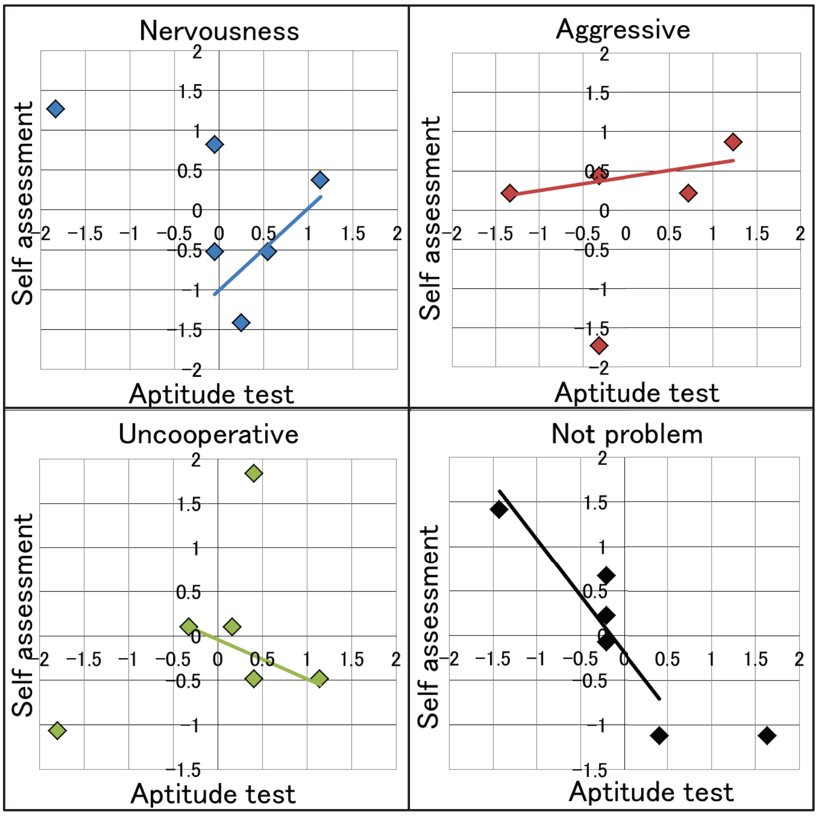

FIGURE 3. Aptitude test and self-assessment

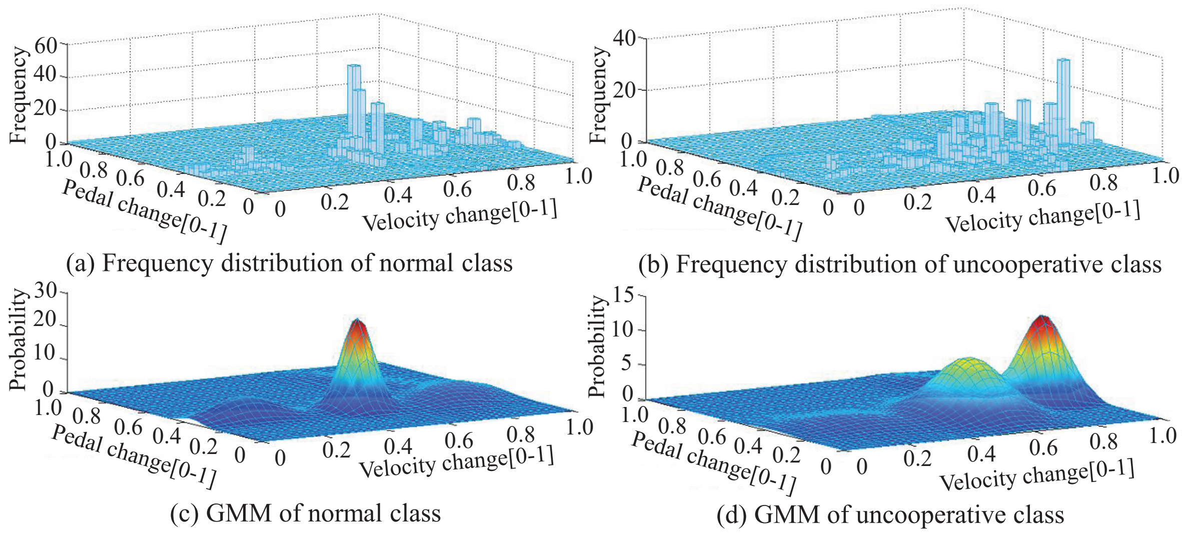

FIGURE 4. Example of normal class GMM and uncooperative class GMM

estimation model of the normal class and uncooperative class in the signal section. Figure 4(a) shows the frequency distribution of the normal class, 4(b) shows the frequency distribution of uncooperative class, 4(c) shows the GMM driver psychology estimation model of the normal class and 4(d) shows the GMM driver psychology estimation model of the uncooperative class. And the GMM shown in Figure 4 are the plot in only two dimensions (vehicle speed, pedal operation change amount) out of the five-dimensional GMM. As shown in the figure, the frequency distribution of driving operation data can be approximated by a normal distribution and modeled. It was also confirmed that the constructed GMM driver psychology estimation model of the normal class has a different

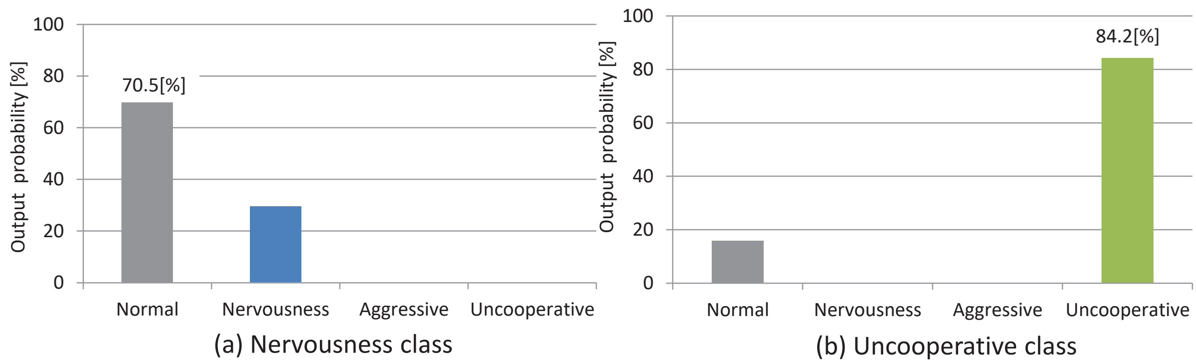

Figure 5. GMM output of the uncooperative class

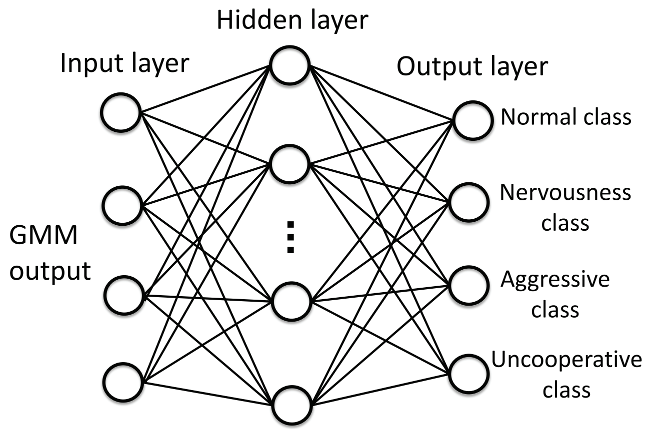

Figure 6. Results of classification obtained by SVM

distribution from that of the uncooperative class. In addition, inputting the driving operation data of one subject in the uncooperative class in to the constructed GMM driver psychology estimation model produces estimation results, some examples of which are shown in Figure 5. Figure 5(a) shows the output of the GMM driver psychology estimation model of emotional instability class, and 5(b) shows the output of the GMM driver psychology estimation model of the uncooperative class. As can be seen by comparing 5(a) and 5(b) in the figure, the probability of uncooperative was the highest for the outputs of both GMMs, which was 84.2 [%], and the psychological state of the subject was correctly estimated.

3.3. **Results and evaluation of classification by SVM.** Figure 6 shows the SVM classifier constructed by the method introduced in Section 2.5 using the leave-one-out cross-validation (LOOCV) method. Its input is the output of each class's GMM, and the output is the membership probability of each class. Here, a threshold is applied to the class membership probability. In other words, the threshold value was set with reference to the scoring method of the K-2 suitability test, with no gradient to be 0.4 or less, a weak gradient to be 0.4-0.7, and a strong gradient to be 0.7-1.0. Table 1 shows an example of the estimation results using the class membership probability of the above SVM for the driving operation data in the signal section of 14 subjects. The driving operation data for these 14 subjects are the driving operation data belonging to each class by the modified Thompson method with outliers deleted as shown in Figure 3. The left side of this table shows the number of subjects for each class and the right side shows the estimated number of subjects for each class. The horizontal axis of the table represents the estimated class and the vertical axis represents the true class set from the results of the K-2 aptitude test. For example, the estimation results of five subjects with true values of normal class can

Table 1. Estimation results by SVM

True class		Estimated class				
Class	Number	Normal	Nervousness	Aggressive	Uncooperative	Other
Normal	5	3	0	0	0	2
Nervousness	2	0	1	0	0	1
Aggressive	4	0	0	3	0	1
Uncooperative	3	0	0	0	2	1

be estimated to be clearly normal class for three subjects, but the remaining two have a lower probability of belonging to the normal class. For these two subjects, for example, the subject with subject number 18 has a maximum affiliation probability of 0.556 and basically belongs to the normal class. However, because the probability of belonging to the normal class is in the range of 0.4-0.7 and the probability of belonging to the nervous class is 0.333, it was presumed the subject shows the tendency of a psychologically weak driver. In a similar way, it is possible to estimate ambiguous drivers belonging to other classes and having weak tendencies.

4. **Conclusion and Remarks.** In this research, we first experimented to reproduce a mentally unstable driving state in drivers by placing psychological stress on them, and constructed the GMM driving psychology estimation model and the SVM classifier based on the obtained driving operation data, and then used these to estimate the psychology of a psychologically weak driver. The results obtained are as follows.

1) Using the results of the K-2 type driving aptitude test conducted by the National Police Agency, the driver's psychology is classified into four classes of nervous class, aggressive class, uncooperative class, and normal class according to the psychological characteristics of the psychologically weak driver prone to having an accident.
2) For each of the classified classes, a five-dimensional GMM driving psychological estimation model was constructed using driving operation data. Then, we constructed an SVM classifier that classifies driver psychology using the output probability of the GMM driving psychological estimation model, and confirmed its effectiveness.
3) In the estimation model constructed in this research, driver psychology could be estimated with an accuracy of about 80% in the driving environment of the signal section.

In the future, improvement of accuracy can be achieved by reviewing the experimental design and increasing the number of subjects.

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