Assessment and Prediction of Older Drivers’ Driving Performance

Yasuhiko Nakano, Satoshi Sano, Yuzuru Yamakage, Takao Kojima, Chika Kishi, Chisa Takahasi, Yurie Iribe, Haruki Kawanaka and Koji Oguri

Abstract — Traffic accidents involving older drivers have been increasing all over the world. In order to assess older driving performance and predict the risk of traffic accidents, we analyzed data from specific license renewal tests that are obligatory for Japanese drivers aged 70 years old or older, which includes a driving simulator test and an on-road test. As a result of the analysis, we found that aging affects several test results, such as the percentage of correct answers and the reaction times in multiple judgment tasks tests. In order to be able to classify a driver as a high accident risk, we performed an outlier analysis using a one-class SVM to investigate performance characteristics, and also performed a logistics regression analysis. Using parameters strongly related to cognitive decline, we found a viable way to classify impaired drivers. Driving is a complex task requiring integration of cognition, judgment, and operation skills. Deterioration of these skills is likely to increase the risk of traffic accidents. Although our final objective was to support elderly drivers suffering such deterioration, we initially studied a measurement method to detect the area and extent of deterioration effectively.

Keywords—Older Driver; Driver Performance; Alzheimer’s disease; One-class SVM, Logistic regression analysis; Driving simulator test; On-road Driving test;

I. INTRODUCTION

Both the world’s adult population and the older population itself are aging. The proportion of persons aged 80 years or older within the older population increased from 7 percent in 1950 to 14 percent in 2013, and there will be 830 million persons aged 80 years or older by the end of the century; seven times as many as in 2013 [1]. In the United States, there were 33 million licensed older drivers in 2009, which is a 23 percent increase from 1999 [2][3]. In 2011, vehicle crash death rates per capita-mile increased at ages 70-75 among males and at ages 65-69 among females [4]. Driving is a complex task requiring integration of cognition, judgment, and operation skills. Many of the skills required to operate a vehicle safely may be compromised with age or as a consequence of the various medical conditions that often accompany aging [5]. Alzheimer’s Disease (AD), the most common cause of dementia, has been estimated to affect as many as 11.6% of people age 65 and older and 47.8% of people age 85 and older [6]. A survey has suggested that many drivers diagnosed with AD continue to drive and have a higher risk of crashing, but are reluctant to give up driving. Safety considerations imply that a diagnosis of AD preclude continuation of driving [7]. In contrast, Drachman [8] and O’Neill [9] have suggested that any limitation of driving privileges should be based on driving ability rather than on clinical diagnoses such as AD. G.K. Fox [10] has reported that 63.2 percent of drivers diagnosed with AD failed an on-road evaluation, which was an important result. Conversely, 36.8% were judged safe to drive. These results indicate that there may be some who are capable of driving normally among those diagnosed with AD. Therefore, it is inappropriate to confiscate a person’s license immediately just because they are diagnosed with AD. We suggest a more graded and flexible approach to be preferable. In this study, to investigate the driving characteristics of elderly drivers, we analyzed data from license renewal tests for 610 elderly (aged 70 years or older) Japanese drivers. Then, to discern their specific driving risks, we performed a significance test on the elderly age group by gender and cognitive impairment. We detected subjects who exhibited different characteristics from typical elderly people (outliers). That is, we investigated whether a cognitively impaired person could be classified according to an abnormal value detection technique. Finally, we used logistic regression analysis to try to classify cognitive impairment and predict whether a driver was a higher accident risk. Driving is a complex task requiring integration of cognition, judgment, and operation skills. Deterioration of these skills is likely to increase the risk of traffic accidents. Although our final objective was to support elderly drivers suffering such deterioration similarly to Nakano et. al [11], in this study we studied a measurement method to detect the area and extent of deterioration effectively.

II. METHODS

In order to assess driving performance and predict the risk of traffic accidents, we analyzed data from a specific set of obligatory license renewal tests of drivers aged 70 years or older, which included a driving simulator test and an on-road test [12][13].

A. The basic statistical analysis of elderly license renewal tests

In Japan, mandatory license renewal testing for drivers aged 70 years or older began in 2001. Since 2009, cognitive impairment screening testing (CIST) is mandatory for drivers 75 years old or older. CIST is based on a seven-minute screening developed by Solmon [14], which can
classify subjects into three categories: impaired, slightly impaired, and not impaired. The test is designed to avoid classifying a healthy elderly adult as a cognitively impaired person to the extent possible. Although the driver’s license cannot be revoked as a direct result of the test, the test is used to monitor deterioration of cognitive ability.

In 2011, we gathered 1,000 scale data points from such license renewal tests in Aichi Prefecture, Japan, and for this study analyzed the effective data of 610 people from this group, in which the three tests detailed below were all included. Some prior research analyzes elderly drivers' characteristics, e.g., Tamida [15] and [16]. Although Tamida mainly reported driver behavior in on-road testing using a driving recorder, there are no arguments about the validity of the driving simulator test or the relationship between cognitive impairment and these tests.

We used data from the driving simulator test (Fig. 1), an on-road test that takes place on a driving school test course, and a cognitive impairment screening test, and then analyzed the data itself and correlated these in terms of age, gender, and cognitive impairment. The results are summarized as follows;

![Fig. 1 Driving simulator test](image1)

1) Cognitive impairment screening test
A cognitive impairment test identifies a cognitive impairment based on a seven-minute screening [14]. Subjects are classified as levels 1, 2, or 3, which correspond to cognitively impaired, slightly impaired, or not impaired, respectively.

2) Driver aptitude test
A driving simulator is used to determine driver aptitude (Fig. 1). Although there are four kinds of tests, we considered only three because the fourth is almost same as the others. These three tests are the simple reaction test, the selective reaction test, and the distribution of caution and multiple task test, and are explained briefly below.

![Fig. 2 Driving simulator](image2)

(a) Simple reaction  (b) Selective reaction  (c) Multiple task test

![Fig. 2](image2)

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a) Simple reaction test
This is a test of fundamental reflex operation capability. The simulator runs a straight line of road displayed on a monitor as in Fig. 2 (a), at a fixed speed. When the signal light turns red, the driver’s reaction is to release the accelerator and depress the brake (Red-Change). The speed of the reaction and the correctness of the reaction are measured (Table I, II).

<table>
<thead>
<tr>
<th>Event</th>
<th>Driving task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal</td>
<td>Reaction</td>
</tr>
<tr>
<td>Red-Change</td>
<td>Red</td>
</tr>
<tr>
<td>Yellow-Lift</td>
<td>Yellow</td>
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<tr>
<td>Green-Keep</td>
<td>Green</td>
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</table>

b) Selective reaction test
This test measures reactions to changes in signal lights on the road. Subjects drive on the straight road displayed on the monitor as in Fig. 2 (b) at a fixed speed, and react to light signal color changes. When the signal light turns red, the driver’s reaction is to release the accelerator and depress the brake (Red-Change). When the signal light turns yellow, the driver’s reaction is to release the accelerator (Yellow-Lift). When the signal light turns green, the driver’s reaction is to continue pressing the accelerator (Green-Keep). The test measures the reaction time and the correctness of the reaction (Table I, II).

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<td>Signal</td>
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<td>Red-Lift</td>
<td>Red</td>
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<tr>
<td>Red-Change</td>
<td>Reaction time</td>
</tr>
<tr>
<td>Yellow-Lift</td>
<td>Reaction time /Correct rate</td>
</tr>
<tr>
<td>Green-Keep</td>
<td>Correct rate</td>
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</tr>
<tr>
<td>Green-Keep</td>
<td>Correct rate</td>
</tr>
</tbody>
</table>

3) On-road test
The subject gets into a real car with an instructor and drives the training course at a driving school according to the instructor's directions. The subject drives through a crossing with a signal or a stop sign, travels a curved road, performs
lane changing, and parks in a garage. The instructor observes the driver’s behavior, such as the operation of the accelerator and brakes, stopping behavior at a signal, and blinker signaling, etc. In this study, four typical tasks were observed: responding to a crossing signal, responding to a stop sign, performing a lane change, and driving a curved road. We decided to judge driving ability by the number of times the tasks were completed correctly and when a required safety act was completed correctly.

B. **Outlier detection a one-class support vector machine (SVM)**

A one-class SVM is a method of solving the teacher-less study problems relevant to the presumed problem of probability density distributions. Specifically, it is the technique of finding a smooth boundary surrounding a domain where data are observed by high probability instead of modeling the density distribution of the data [17]. In case there is no correct answer to the boundary that could clearly separate the issue, a one-class SVM can identify the “outliers” among the positive examples [18]. This method is often used for document classification [19] [20]. We decided to predict the higher risk subjects who had a greater tendency to differ from the group by detecting the abnormal values in elderly driver test data. Scholkopf’s [21] method is as follows; after transforming the feature via a kernel, K(x_i, x_j), outlier data from the original space are moved around the origin of the new space. Using these characteristics, we can distinguish typical subjects and outliers (abnormal, higher risk subjects).

\[
K(x_i, x_j) = \exp(-\gamma ||x_i - x_j||^2) \tag{1}
\]

\[
\gamma \text{ is a kernel function. The decision function is then}
\]

\[
f(\phi(x)) = \text{sgn}(w^T\phi(x) - \rho) \tag{2}
\]

Function sgn is the signum function and is set to 1 when \( u > 0 \), and -1 for all other values. \( w \) is a dignity vector and \( \rho \) is a bias term. In order to seek a discernment hyperplane by which the teacher data of the rate \( v \in (0, 1) \) decided beforehand remains on the origin side, following equation (3) is solved for the dignity vector \( w \).

\[
\min \frac{1}{2}||w||^2 + \frac{1}{n}\sum_{i=1}^{l} \xi_i - \rho \tag{3}
\]

subject to \( w^T \Phi(x) - \rho - \xi_i, i = 1, 2, ..., l, \xi_i \geq 0 \).

\( \xi_i \) is a slack variable.

The kernlab library ksvm of R was used for the calculations by one-class SVM in this study.

C. **Classification of cognitive impairment using logistic regression analysis**

Logistic regression analysis is an analytical method that uses a model which makes a categorical variable an objective variable and explains the objective variable by other variables. Using logistic regression analysis, the three following statements were assumed; (a) The aim is to classify an objective variable as two values of a direction with doubt of cognition, and a healthy person. (b) Prior probability is not known beforehand. (c) Do not necessarily follow a normal distribution. As a dependent variable, the parameter out of which the significant difference was produced by the t test of the basic statistical analysis was used, and the logistic model was built. A logistic model (logit model) can be denoted as follows.

\[
l = \ln\left(\frac{p}{1-p}\right) = b_0 + b_1x_1 + \cdots + b_px_p \tag{4}
\]

\[
p = \frac{1}{1+\exp(-l)} = \frac{1}{1+\exp(-b_0 - b_1x_1 - \cdots - b_px_p)} \tag{5}
\]

\( l \): logit (Logarithm odds), \( p \): Probability of cognitive impairment, \( b_0 \): Constant, \( b_1 - b_p \): Partial regression coefficient

Since the logarithm odds ratio was modeled by the linear sum of the input variable in the above mentioned model (equation 4), a good result is not obtained in data in which linear separation is impossible. However, it can be improved by modeling a logarithm odds ratio with a nonlinear function (equation 6).

\[
l = \ln\left(\frac{p}{1-p}\right) = 1 + b_1x_1 + \cdots + b_px_p + b_{12}x_1x_2 + \cdots + b_{(p-1)p}x_{p-1}x_p \tag{6}
\]

III. **RESULTS**

A. **The basic statistical analysis of elderly license renewal tests**

The age structure of the subjects taking the elderly license renewal test and the number of subjects that have been identified as impaired are shown in Table IV. The largest number of drivers tested was in the age group of 75-80 years old. The next largest group was 70-75 years, and the group aged 80-85 years numbered almost the same. There were far fewer drivers 85 years of age or older who came to be tested. Cognitively impaired subjects were on the order of 5-10% of the total number in all age groups. This percentage is a little less than those of [6]. We expect that the reason for this was that the drivers who come to renew their driver’s license tend to be in good health.

<table>
<thead>
<tr>
<th>TABLE IV. DISTRIBUTION OF SUBJECTS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td><strong>Male</strong></td>
</tr>
<tr>
<td><strong>Female</strong></td>
</tr>
<tr>
<td><strong>Total</strong></td>
</tr>
<tr>
<td><strong>Percentage</strong></td>
</tr>
</tbody>
</table>

In (), cognitive impairment (Level 1, 2)
Concerning the difference of 5% significance level by age group, we examined the data of the group aged 70 years or more in the current data (Fig. 5, Fig. 6). The analytical method we used was the Turkey method. As a result, there are significant differences in reaction time for Red-Lift and Red-Change in the multiple task test. To analyze differences between multiple values, a significance test was carried out by performing multiple analyses on just the items that had significant differences in the analysis of variance, ANOVA. For reference, box plots are shown as well.

Concerning gender differences, there are significant differences in the reaction time and correct rate of Red-Lift and Yellow-Lift of collision in the case of the multiple task test (5% significance level). Concerning the difference between impaired and not-impaired, there are significant differences in the reaction time of Red-Lift, Red-Change and the correct rate of selective task test, and also significant differences in the reaction time of Red-Lift, Red-Change and Yellow-Lift and the correct rate of Red Judge and Yellow-Judge of the multiple task test. Red Change is shown for reference as a typical example in Fig. 7.

### B. Outlier detection using one-class SVM

The kernlab library ksvm of R was used for calculation of the one-class SVM in this study. A Radial Basis Function (RBF) was used for the kernel. It sought sigma by an automatic presumption function, and ν was specified from 0.01 to 0.3 in units of 0.01. We thought a higher risk driver could be classified as an outlier (abnormal person). We also think a lot of cognitively impaired subjects should be classified as an outlier. As a reference, we defined the classification of cognitive impairment as follows (equation (7), (8)). The following values were calculated when ν was moved respectively.

\[
\text{Sensitivity} = \frac{\text{Number of cognitively impaired identified}}{\text{Number of cognitively impaired in test set}}
\]

\[
\text{Specificity} = \frac{\text{Number of non–cognitively impaired identified}}{\text{Number of non–cognitively impaired in test set}}
\]

where categories means impairment (Level 1, 2)

First, using all 22 items that consisted of 17 items from the driving simulator test and 5 items from the on-road test as determined parameters, we estimated the outliers. With no discrimination between cognitive impairment and non-
impairment, drivers were extracted by indicating the properties that were significantly different from the average. In the percentage of correct answers and the reaction times in the simulator tests, subjects that were significantly distant from the average were extracted. Though there was not much difference in scores in the on-road tests, there was a subject who scored nothing for all tests including the stop sign, the lane change, and driving a curved road.

We defined “Sensitivity” as a probability that can be determined regarding cognitive impairment and “Specificity” as a probability that can be determined regarding non-impairment (equation 7, 8). There is a trade-off between Specificity and Sensitivity due to a change of $\nu$ as shown in Fig. 8. Sensitivity is shown to be 0.8 but Specificity is worse at 0.6. The results of extracting outliers using the 10 item parameters derived from significant differences in cognitive impairment are shown in Fig. 9. Specificity is improved in particular, as both are about 0.8. The rate at which someone who is not impaired is accidentally classified as having an impairment is decreased considerably compared with Fig.8. A subject assigned as level 1 was classified correctly either way.

C. Classification of cognitive impairment using logistic regression analysis

We used the two values of cognitive impairment or non-impairment as the target variable, and 10 parameters that have significant differences coming from a t-test of the basic statistical analysis as the dependent variable. We constructed a logistic model to classify the two values. The results are shown in Fig. 10. In the figure on the left of Fig., 10, the model was a linear sum of a parameter. The right figure shows a non-linear function model using the same parameters. In the total number of subjects 610, there were 40 cognitively impaired subjects, of which 39 subjects were Level 2, and one subject was Level 1. There were 570 subjects determined to be unimpaired.

Because of this unbalanced data ratio, the logistic analysis results may be biased towards the characteristics of the majority of subjects. Therefore, the analysis was performed after balancing the data. (The number of the smaller ones was used.) After randomly selecting unimpaired subjects, logistic regression analysis was performed three times. The final results were obtained by averaging the three values (Table V, VI)

**TABLE V. RESULT OF LINEAR REGRESSION**

<table>
<thead>
<tr>
<th>Prediction</th>
<th>FALSE</th>
<th>TRUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>True</td>
<td>0</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>14</td>
</tr>
</tbody>
</table>

**TABLE VI. RESULT OF NON-LINEAR REGRESSION**

<table>
<thead>
<tr>
<th>Prediction</th>
<th>FALSE</th>
<th>TRUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>True</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

The results for the linear case are as follows. Sensitivity = $26/40 = 65\%$; Specificity = $34/40 = 85\%$. In the case of the non-linear model, cognitive impairment was fully identified, and Sensitivity and Specificity scores were 100% in this case. The non-linear model takes into account the secondary model parameters. In particular, the contribution of the related parameters of the percentage of correct answers and the number of collisions were high.

IV. DISCUSSION

The method of evaluating elderly drivers is important. When classifying cognitively impaired subjects, it is very important to not misjudge the unimpaired as cognitively-impaired and to correctly identify cognitive impaired subjects to the extent possible. Subjects who differ greatly from the group should be classified as cognitively impaired. We found there are cognitively impaired subjects who have retained the capability required to drive safely. These results support the prior research on this subject [10]. In future research, it will be necessary to classify a person who
has a higher risk of crashing with certainty and to observe and predict a person who has a mild risk.

V. CONCLUSION

In order to support elderly drivers with deteriorated driving ability, we initially studied a measurement method to detect the area and extent of deterioration effectively. Techniques of assessing and predicting Japanese elderly drivers’ driving performances and accident risks were examined based on the analysis of data from license renewal tests developed by the National Police Agency of Japan. As a result, we found that aging affects the percentage of correct ty (IIHS). FATALITY FACTS mobile, - statistics 1999. [cited 2014, 7]. Available from URL: http://www.iihs.org/research/fatality.aspx?topicName=Older people. 2010. "Alzheimer's disease and driving," Journal of the royal society of medicine. 1992 April; 85(4): pp. 199–202


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