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Published in IET Intelligent Transport Systems
Received on 31st January 2013
Revised on 15th May 2013
Accepted on 28th May 2013
doi: 10.1049/iet-its.2013.0027

ISSN 1751-956X

Elderly driver retraining using automatic evaluation system of safe driving skill

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Abstract: In Japan, although the rapid aging of the population has caused serious traffic problems, only a few studies have investigated the behaviour of elderly drivers in real traffic conditions. The authors have been developing a system to automatically evaluate safe-driving skill through small wireless wearable sensors that directly measure the driver's behaviour. The authors aim is to promote safe driving by providing a personalised training program according to the individual's own shortcomings in driving behaviour. By employing the sensors together with GPS and driving instructors' knowledge, our system can automatically identify shortcomings in driving skill with an accuracy of over 80%. In February 2010, the Kyoto Prefecture Public Safety Commission, in Japan, certified our system as the first and only support tool for its 'mandatory retraining course for elderly drivers' that all elderly drivers, aged over 70 years, are required to take when renewing their driver's license. In this study, the authors discuss the effectiveness of our system and investigate elderly drivers' behaviour through a large-scale demonstration experiment, involving 749 elderly drivers, in the mandatory driver-retraining course on public roads. The authors results reveal that although elderly drivers are able to maintain a safe vehicle speed, their tendency to not scan around their vehicle to ensure safety makes their driving risky.

1 Introduction

The rapid aging of Japan's population has caused serious traffic problems in the country. In 2011, elderly population aged over 65 years in Japan was 29.75 million, constituting 23.3% of the total population and marking a record high [1]. This percentage of the elderly in the population is the highest in the world. In the past decade, the number of traffic accidents caused by elderly drivers aged over 65 has increased almost 1.33 times, whereas the total number of traffic accidents has decreased by 27% during the same period [2]. Despite the great efforts that have been made to improve vehicles and road safety equipment, the number of traffic accidents, especially those involving elderly drivers, is still at a generally high level. In addition to focusing on vehicles and roadside safety, driving behaviour should also be considered in schemes to reduce traffic accidents. However, only a few studies have been conducted to investigate elderly drivers' behaviour in real traffic conditions.

According to a traffic accident report by the National Police Agency [2], the lack of scanning behaviour to confirm safety (e.g. turning at a crowded intersection without checking the entire area) is the most frequent cause of traffic accidents in Japan (31.4% of all traffic accidents, 34.6% of those by elderly drivers). The statistics show that drivers can reduce their traffic risks significantly by improving their own driving behaviour, for example scanning around for any potential hazards as well as covering the brake with their foot when approaching a blind intersection (bad visibility because of buildings, other structures etc.). Our objective in this research is to develop an automated evaluation system of each driver's safe-driving skill to promote safer driving by offering personalised training programs based on his/her own evaluation results. In this paper, we defined defensive driving skill to prevent traffic accidents at potentially dangerous spots as 'safe-driving skill'.

For the purpose of driving assistance, there are many kinds of systems such as lateral control assistance system in car driving [3], driver's strain estimation [4], hazard alert system using infrastructure-to-vehicle or vehicle-to-infrastructure communication [5]. However, despite the fact that the lack of scanning behaviour to confirm safety is the most frequent cause of traffic accidents in Japan, none of them measure and evaluate driver's scanning behaviour.

Event data recorders (EDRs) are widely used to record vehicle information and videos of driving scenes related to dangerous driving situations [6]. According to Takeda *et al.* [7] and a risk consulting company, traffic accidents were reduced more than 30% by installing EDRs in vehicles to record drivers' daily driving behaviour and by later providing them safety guidance based on the recorded behaviour (but not prompt feedback). This result supports our expectation that giving personalised training programs could be an effective way to reduce traffic accidents.

We have been developing an automatic evaluation system of driving skill by using wearable sensors to directly measure drivers' head motion and pedal operation behaviours whereas not introducing any significant stress on the drivers. Employing the sensors together with GPS and driving instructors' knowledge, our system automatically evaluates each driver's safe-driving skill by analysing how he/she behaves (as well as 'not' behaves) for safety at dangerous spots (e.g. accident-prone areas).

Since 1998, all elderly drivers aged over 70 have to take a mandatory retraining course when renewing their driver's license in Japan. Renewal of one's driver's license is usually required every three years. In February 2010, the Kyoto Prefecture Public Safety Commission certified our system as a support tool for the mandatory retraining course. At present, our system is the first and only driving behaviour measurement/evaluation system that can be used in a mandatory retraining course in Japan. In this paper, we discuss the effectiveness of our system and investigate elderly drivers' behaviours on public roads through a large-scale demonstration experiment in the 'mandatory retraining course for elderly drivers' with 749 elderly drivers.

2 Proposed system's basic idea

When a single traffic accident occurs, we can find a vast amount of information on a potentially dangerous situation. For example let us assume that a driver enters a blind intersection (potentially dangerous spot) at excessive speed without scanning around. If there is fortunately no approaching vehicle on the intersecting road, then no collision or sudden braking will occur. Each accident that actually occurs is just the tip of the iceberg, and thus we should focus on hidden 'potentially dangerous situations'. Our basic idea is that detecting potentially dangerous situations and giving prompt feedback to drivers is essential for improving traffic safety.

EDRs have been widely used to record dangerous driving situations [6]. As key information to detect such danger, most EDRs focus on sudden changes in vehicle motion (e.g. sudden braking). However, since potentially dangerous situations do not directly correlate to sudden changes in vehicle motion, EDRs misjudge potentially dangerous situations as 'not dangerous'. To achieve our concept's purpose, it is necessary to directly measure the driver's behaviour and to evaluate the appropriateness of the driver's behaviour from the viewpoint of preventing traffic accidents.

Eye-cameras have been widely used to record drivers' gaze positions [8–10]. However, since an eye-camera greatly restricts a driver's movements, continuous use of a recorder equipped with one could become very stressful to drivers. Moreover, since eye-mark recorder data requires a high processing cost for use in driver training, providing prompt feedback is difficult. In addition, there is no methodology currently available for automatically detecting potentially dangerous situations using eye-camera data.

Meanwhile, over the last few years, various studies have been conducted on estimating drivers' gaze positions using a video-based approach [11–14], which enables us to measure driver behaviour without introducing significant stress to drivers. Nevertheless, none of these efforts provided an automated methodology for detecting potentially dangerous situations as effectively as an eye-camera-based approach.

As another approach, Takeda *et al.* [7] recently tried to detect potentially dangerous situations using a custom-equipped vehicle with many kinds of sensors installed in it. However, since Takeda's method relied on manual detection by an operator, it is expensive and time-consuming. Therefore providing the driver prompt feedback is impossible.

To achieve automatic detection of potentially dangerous situations, we have been developing an automatic evaluation system of safe-driving skill. Our system employs wearable sensors and driving instructors' knowledge to directly measure drivers' behaviour and to promptly evaluate the appropriateness of the measured behaviour. Since our system runs its evaluation procedure within a few seconds, we can promptly feedback to the driver evaluation results that consider potentially dangerous situations. In the following section, we describe the details of our system.

3 Driving behaviour measurement using wearable sensors

3.1 Wearable sensors

We use three small wireless wearable sensors that contain a three-axis gyro chip and a three-axis accelerometer chip to measure driver behaviour. A driver wears a cap with one sensor as shown in Fig. 1 to detect scanning behaviour from head motion. Another sensor was placed on the subject's right shoe, and the other was placed on the vehicle's dashboard. The sensor is so small (39 mm $(W) \times$ 44 mm $(H) \times$ 12 mm (D), 20 g) that it never disturbs the driver while driving. The sensors on cap, shoe and dashboard measure the driver's head motion, toe motion and vehicle motion, respectively. The sensors send measured data sampled at 25 Hz to a PDA (72 mm $(W) \times$ 115 mm $(H) \times$ 17.8 mm (D), 170 g) through a Bluetooth connection. Transmitted motion data from the sensors are stored in memory with timestamps. A PDA also receives and stores GPS location data at 1 Hz. Since the wearable sensors and PDA are both small, wireless, and battery-powered, we can easily adapt our system to various kinds of vehicles and drivers.

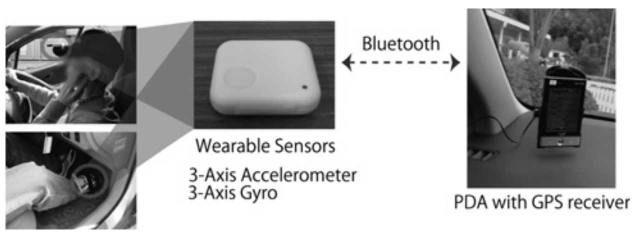

Fig. 1 *Driving behaviour measurement using wearable sensors*

3.2 Detecting scanning and pedal operation behaviours

When measuring head/toe motions using a three-axis gyro/accelerometer sensor on a moving vehicle, the measured data would be a linear combination of head/toe motion and vehicle motion. In this paper, to reduce vehicle-caused noise, we implement our automated method by employing independent component analysis (ICA) [15].

ICA is a method to extract statistically independent components from their linear mixtures without using any prior information [16]. Let us assume that the m-dimensional vector of sensor data $\boldsymbol{x}(t) = [x_1(t), \dots, x_m(t)]^{\mathrm{T}}$ is generated by an unknown linear mixture model

$$\boldsymbol{x}(t) = A\boldsymbol{s}(t)$$

where $\boldsymbol{s}(t) = [s_1(t), \dots, s_n(t)]^{\mathrm{T}}$ is the n-dimensional $(n \le m)$ vector whose elements are called sources. Based on the assumption that $\{s_i(t)\}$ are mutually independent signals, ICA finds demixing matrix $\boldsymbol{W}$ by minimising statistical dependence among output signals $\boldsymbol{y}(t)$

$$\boldsymbol{y}(t) = \boldsymbol{W}\boldsymbol{x}(t)$$

Here, if $\boldsymbol{W}A = \boldsymbol{I}$, $\boldsymbol{y}(t)$ equals $\boldsymbol{s}(t)$. In this paper, we employ the fastICA algorithm [16] to estimate $\boldsymbol{W}$, where $\boldsymbol{W}A = \boldsymbol{I}$. Since the cap-mounted sensor data $x_{\mathrm{cap}}(t)$ include linear mixtures of head motion $s_{\mathrm{head}}(t)$ and vehicle motion $s_{\mathrm{car}}(t)$, by applying ICA to $\boldsymbol{x}(t) = [x_{\mathrm{cap}}(t), x_{\mathrm{car}X}(t), x_{\mathrm{car}Y}(t), x_{\mathrm{car}Z}(t)]^{\mathrm{T}}$, we can estimate $s_{\mathrm{head}}(t)$. Here, $x_{\mathrm{car}X}(t)$, $x_{\mathrm{car}Y}(t)$, $x_{\mathrm{car}Z}(t)$ denote tree-axis (X, Y, Z) vehicle-mounted sensor data. In the same way, we also apply ICA to the toe-mounted sensor data.

After applying ICA, by integrating head motion data we calculate the driver's head-rotation angle. When integrating head-motion data, to ignore small head motions not related to scanning behaviour, we only use head-motion data whose absolute value exceeds a pre-set threshold. In this paper, using 209.7 min of manually annotated data, we experimentally defined the threshold value as 20°/s. In addition, to tackle the cumulative error, if no head motion is measured for 3.0 s while driving, we reset the head-rotation angle to zero. The above reset policy is based on the assumption that drivers would usually look ahead while driving.

After calculating the head-rotation angle, to identify whether the detected head-rotation is actually scanning behaviour, we use support vector machine (SVM) [17]. In this paper, we trained the SVM classifier using the manually annotated data. We also trained an SVM classifier using the same data to clarify drivers' pedal-operation behaviour (acceleration/brake pedal).

4 Automatic evaluation method of safe driving skill

4.1 Evaluation criteria of safe driving skill

As a result of interviews with three professional driving instructors, we found that they usually evaluate a driver's skill from the following viewpoints.

1. Scanning behaviour

To prevent traffic accidents at potentially dangerous spots, perceiving potential hazards by widely scanning around with head movement is essential. To collect sufficient information to confirm safety, the driver should appropriately scan around according to the situation. For example checking the left blind spot for pedestrians or cyclists by rotating one's head to the left-back side is necessary when turning left at a crowded intersection; however, the same behaviour could be a risky distraction in another situation such as driving straight. A driving instructor evaluates one's scanning behaviour for whether he/she scans with the appropriate orientation whereas taking enough time to collect information in the traffic environment (i.e. not done in a perfunctory manner). In addition, since scanning only after entering potentially dangerous spots is useless for preventing accidents, the timing of scanning is also regarded as an important condition.

2. Vehicle speed

Another important condition in evaluating driving skill is the maintenance of appropriate speed. Even if a driver can detect hazards in advance, excessive speed makes it difficult to avoid them. Moreover, approaching potentially dangerous spots slowly gives a driver enough time to carefully scan hazards.

3. Pedal-operation behaviour

From the viewpoint of active safe driving, there is a big difference in driving skill between drivers who cover the brake with their foot in advance of approaching potentially dangerous spots and drivers who do not.

Based on the interview results above, in this paper, we defined a checklist of 'minimum' required safe-driving behaviours at potentially dangerous spots (i.e. minimum requirements for all drivers to prevent accidents there) using the following evaluation criteria: (1) orientation of scanning, (2) number of scanning motions, (3) scanning time (i.e. whether the driver takes enough time to detect hazards), (4) timing of scanning, (5) vehicle speed, and (6) pedal-operation behaviour. Here, different types of potentially dangerous spots would have differently prepared checklists of minimum required safe-driving behaviours. Therefore in this paper, for each potentially dangerous spot, we manually defined a checklist of minimum required safe-driving behaviours based on driving instructors' knowledge.

4.2 Evaluation procedure of safe-driving skill

The procedure for evaluating safe-driving skill was accomplished as follows.

(A) By analysing GPS data, detect the driver's approach time to pre-defined potentially dangerous spots. Here, since GPS signal includes inevitable errors, our system uses a map matching algorithm to improve location estimation accuracy. Then, start the evaluation procedure for every detected spot.

(B) Apply ICA to wearable sensor data to reduce vehicle-caused noise. Then by using SVM, detect the driver's scanning behaviour and pedal-operation behaviour from the wearable sensors' data.

IET Intell. Transp. Syst., 2014, Vol. 8, Iss. 3, pp. 266–272
doi: 10.1049/iet-its.2013.0027

(C) Calculate scanning orientation and scanning time from the detected scanning behaviour data. Calculate vehicle speed from the GPS data.
(D) Evaluate the driver's skill by comparing driving behaviour detected in (B) and (C) to the pre-defined checklist for the spot. If all of the evaluation criteria are satisfied, evaluate the behaviour as 'good'. If not, display a message requesting improvement related to the unsatisfied criteria. Then, score the driver's skill at the spot according to the achievement ratio of the pre-defined checklist.

Since our system runs its evaluation procedure automatically, we can promptly feedback evaluation result to the driver after finishing driving as post-learning. Fig. 2 shows an example of our system's evaluation results. Our system can integrate the driver's evaluation result at each pre-defined potentially dangerous spot and then score his/her total driving skill at five levels (A: excellent – E: worst).

5 Experiments

5.1 Relationship between head motion and scanning behaviour

To prevent traffic accidents at potentially dangerous spots, collecting potential hazards by widely scanning around the area with head movement is essential. Based on this idea, our system detects a driver's scanning behaviour for confirming safety by applying ICA and SVM to head motion data measured by the cap-mounted wearable sensor. In this section, we discuss the accuracy of our detection method by comparing its detection results with eye-camera data.

We performed an experiment with ten subjects aged from 26 to 52 on public roads in Osaka, Japan. We had each subject drive a vehicle (1500 cc, automatic transmission) and measured his/her behaviour at an accident-prone intersection (potentially dangerous spot) on a public road. Each subject wore an eye-camera (NAC Inc., EMR-8B) to measure his/her gaze position and a wearable sensor to measure his/her head motion while driving.

First, we manually checked eye-camera data and detected 109 scanning behaviours for checking the safety of the area (e.g. checking wing mirrors, looking at pedestrians standing at the corner of the intersection). Meanwhile, our method detected 107 candidates, and 89 matched the results of the eye-camera data (precision ratio: 83.2%, recall ratio: 81.7%). The results show that we can detect the driver's scanning behaviour for checking the safety at potentially dangerous spots by measuring and analysing head-motion data.

5.2 Study to validate proposed method

In this section, we discuss the validity of our system by comparing its evaluation results with an evaluation made by a professional driving instructor. We performed an experiment with 23 subjects (aged from 40 to 69) on public roads in Kyoto, Japan. In the experiment, we used a driving school's vehicle (1500 cc, automatic transmission) and asked each subject to drive a predefined 3.4-km course. All subjects in the experiment were not familiar with the course. The subject wore a cap with one sensor to measure head motion. Another one was placed on the subject's right shoe to measure pedal operation, and the other was placed on the dashboard to measure vehicle motion. In addition, the position and speed data of the vehicle were obtained by GPS with a frequency of 1 Hz. We also used video cameras to record the driver's head/foot motions as well as the surrounding traffic environment, and then this video footage was presented to a professional driving instructor, whose subjective evaluation of each driver's skill was adopted as ground truth data. Note that the video data were used only to evaluate the validity of our system, which works without video cameras.

In this paper, we focused on eight intersections (seven non-signalised intersections and one signalised intersection) selected as potentially dangerous spots by a professional driving instructor. Some subjects could drive only part of the course because of limitations of the driving instructor's schedule, but we were still able to measure 138 driving behaviour sets for 23 subjects at eight potentially dangerous spots.

First, we asked the driving instructor to give a subjective evaluation of the subjects' safe-driving skill based on the evaluation criteria described above. In the subjective

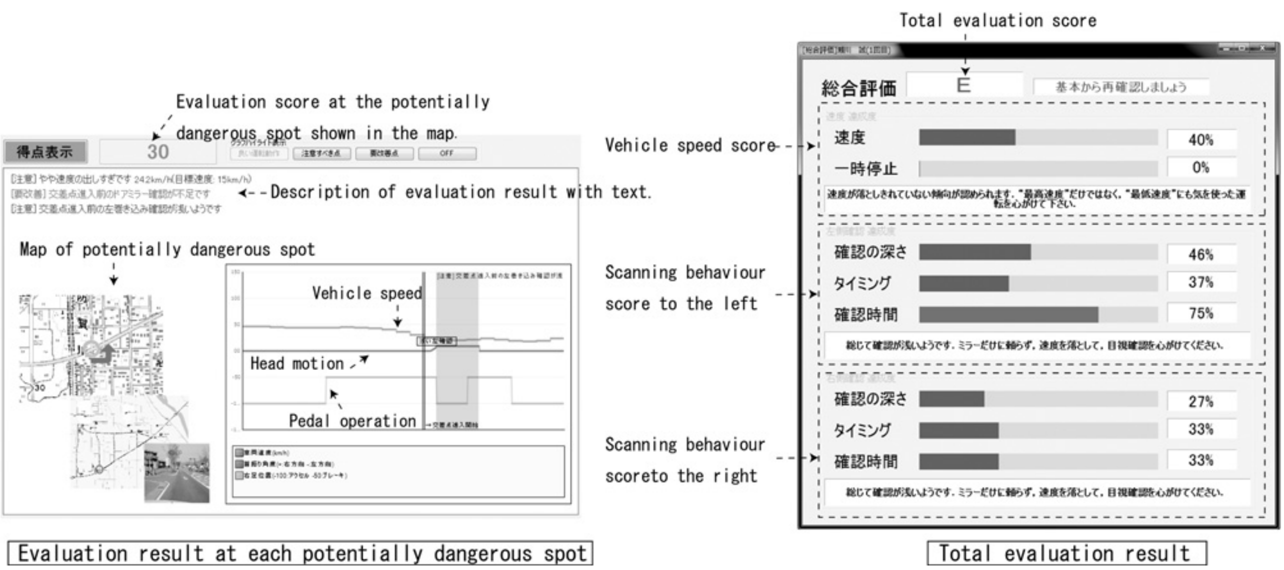

Fig. 2 *Example of evaluation results of proposed system*

Table 1 Accuracy of proposed system

Type of shortcoming	No. of detected by instructor	No. of detected by our system	No. of correctly detected	Precision ratio, %	Recall ratio, %
no scanning behaviour	48	45	40	88.9	83.3
insufficient scanning	68	65	52	80.0	76.5
scanning time is not enough	19	17	16	94.1	84.2
timing of scanning is bad	2	2	2	100.0	100.0
looking away	2	2	2	100.0	100.0
excessive speed	30	30	30	100.0	100.0
ignoring stop sign	8	8	8	100.0	100.0
not covering brake	5	4	4	100.0	80.0
Total	182	173	154	89.0	84.6

evaluation procedure, we only showed the driving instructor our experiment's video data and never shared our system's evaluation results. The video data consisted of the front view, driver's face and driver's feet. As a result of the subjective evaluation, 52 driving behaviour sets were evaluated as 'good', whereas 84 behaviour sets were evaluated as 'risky'. The driving instructor also pointed out 182 shortcomings of 84 risky behaviour sets (see Table 1 for details).

Turning to the evaluation results of our system, 50 driving behaviour sets were evaluated as 'good' and 86 were evaluated as 'risky'. Among the 50 driving behaviour sets evaluated as 'good' by our system, 45 sets matched the instructor's subjective evaluation (precision ratio: 90.0%, recall ratio: 86.5%). Likewise, among the 86 driving behaviour sets evaluated as 'risky' by our system, 79 matched the instructor's subjective evaluation (precision ratio: 91.9%, recall ratio: 94.0%).

Here, let us look deeper into 'risky' driving behaviour sets from the viewpoint of the kinds of shortcomings that make behaviour risky. As shown in Table 1, although most of the shortcomings identified by the instructor were potentially dangerous behaviours that conventional methods (e.g. EDRs) could not detect (e.g. no scanning behaviour when approaching potentially dangerous spots), our system could point out most of them with an accuracy of over 80%.

5.3 Large-scale demonstration experiment in mandatory retraining course for elderly drivers

Since 2009, we have trained over 3000 licensed drivers (including professional drivers) by giving personalised safe-driving advice according to the evaluation results of our system. In February 2010, the Kyoto Prefecture Public Safety Commission certified our system as the first and only support tool for the mandatory retraining course for elderly drivers, which must be taken by all elderly drivers aged over 70 when renewing their driver's license. This has become an opportunity to examine our system's ability to train a large number of elderly drivers. In this section, we investigate 749 elderly drivers' behaviours through a large-scale demonstration experiment in the mandatory retraining course.

In the demonstration experiment, we first had each elderly driver drive a predefined 3.5-km course on public roads without giving them any preliminary information. Therefore they did not know pre-defined potentially dangerous spots on the course. Then we measured his/her driving behaviour using the wearable sensors. After a group of drivers finished driving the course, a driving instructor gave them a 1-h safe-driving lecture using each driver's skill-evaluation results as a textbook (Fig. 3).

To evaluate the effectiveness of our system from the viewpoint of driving instructors, we interviewed three driving instructors who were in charge of the demonstration experiment. In the interviews, all of them evaluated our system as an effective support tool for personalised driving lectures, saying, 'One of the major problems of a conventional retraining course for elderly drivers is how to quantitatively show a driver his or her shortcomings in safe-driving skill in an easily understandable way. Thanks to the system, making the drivers understand their shortcomings has become easy' and 'Elderly drivers have a tendency to overestimate their driving skill. Since the system

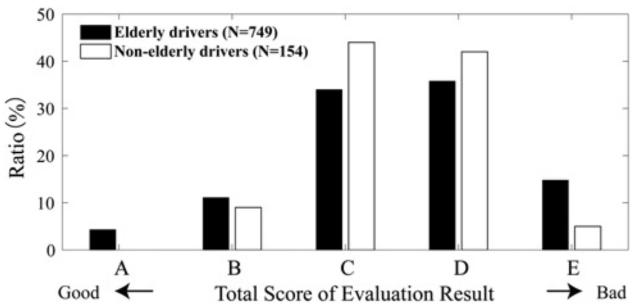

Fig. 4 *Comparison of total evaluation results of elderly and non-elderly drivers*

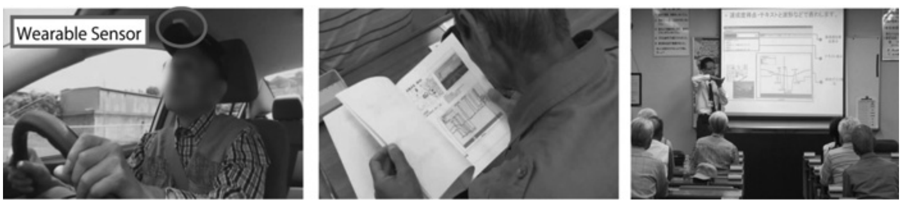

Fig. 3 *Mandatory retraining course for elderly drivers*

doi: 10.1049/iet-its.2013.0027

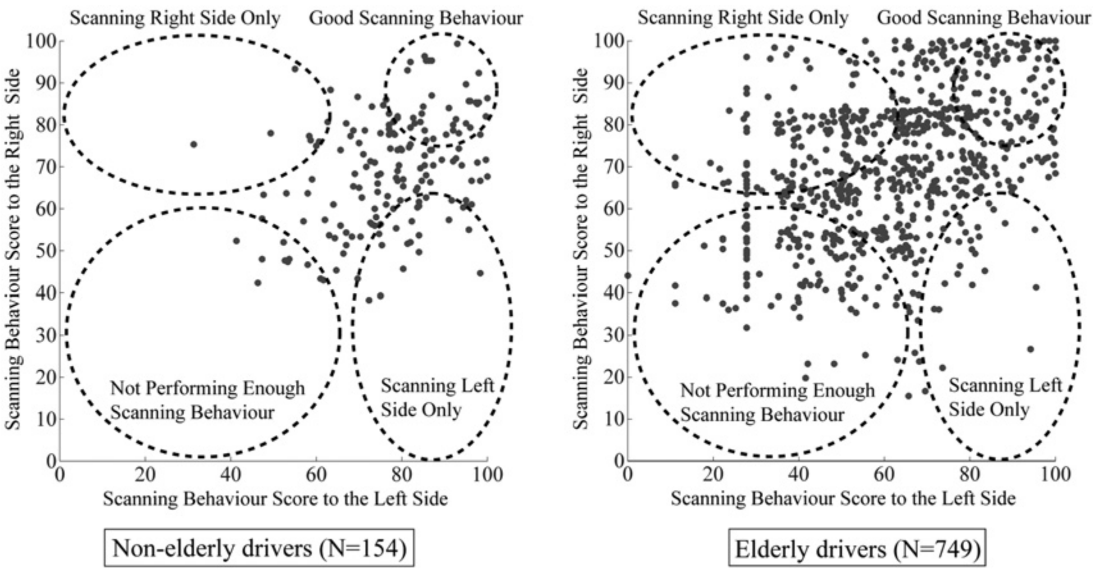

Fig. 5 *Comparison of scanning behaviour scores*

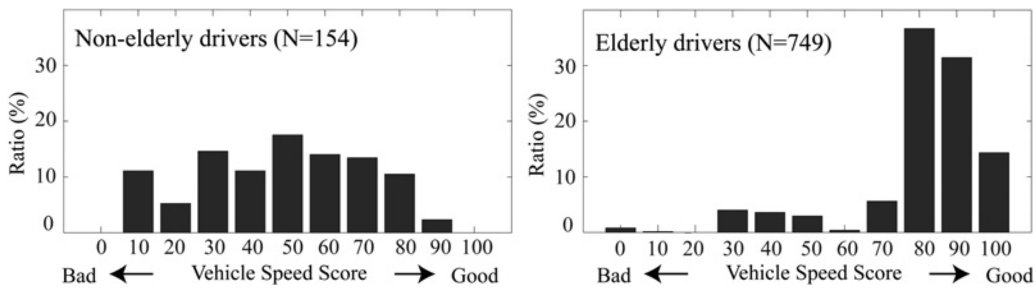

Fig. 6 *Comparison of vehicle speed scores*

quantitatively evaluates their driving skill, I can easily explain why their driving behaviour is insufficient for avoiding risk'.

Fig. 4 shows the distribution of total scores of all drivers' skill-evaluation results ('A' denotes 'excellent' and 'E' denotes 'worst'). For comparison, we also show the evaluation results of 154 non-elderly drivers who took the retraining course using the same curriculum. A striking diversity of driving skill was found among drivers, especially among elderly drivers; whereas some elderly people could drive very safely, others drove in a risky manner. The important point is that nearly 15% of the elderly drivers were evaluated as worst (E) (three times the rate of non-elderly drivers). This result reflects the actual high accident rate of elderly drivers.

Let us now look at the results in detail. Fig. 5 shows the distribution of 'scanning behaviour score' corresponding to evaluation criteria (1)–(4) as described in the section on 'Evaluation Criteria of Safe-driving Skill'. The *X*- and *Y*-axes of Fig. 5 represent the scores of scanning behaviour to the left and right sides, respectively, and each dot in the figure represents each driver's score. Here, the diversity of scanning skill among elderly drivers is much greater than that among non-elderly drivers: Some elderly drivers performed good scanning behaviour, some scanned to either the right or left side only, and some never performed any scanning behaviour. The results indicate the importance of giving elderly drivers a personalised driving lecture according to each driver's skill.

In contrast, when focusing on the ability to maintain appropriate speed (Fig. 6), whereas most of the elderly drivers could maintain a safe vehicle speed, nearly half of the non-elderly drivers had a tendency to drive at excessive speed.

The results shown in Figs. 5 and 6 taken together reveal a key characteristic of elderly drivers: Although they can generally maintain a safe vehicle speed, their tendency to neglect proper scanning makes their driving risky.

6 Conclusions

When a single traffic accident occurs, we can find a vast amount of information on a potentially dangerous situation. Our basic idea is that to improve traffic safety, it is necessary to detect potentially dangerous situations and to give prompt feedback to drivers. Although entering a blind intersection without scanning around is obviously very dangerous behaviour, if there is fortunately no approaching vehicle on the intersecting road, no collision or sudden braking will occur. To detect these kinds of potentially dangerous situations, we have to focus on driver's behaviour as well as vehicle motion. To put this idea in practice, we have been developing an automatic evaluation system of safe-driving skill. Specifically, we aim to promote safe driving by providing the driver a personalised training program based on his/her own shortcomings in driving behaviour. In this paper, we discussed the effectiveness of our system by comparing its evaluation results with the results of an evaluation made by a professional driving instructor. Although conventional EDRs cannot detect potentially dangerous situations, our system can achieve this, with accuracy of over 80%, by employing wearable sensors along with GPS and driving instructors' knowledge.

In February 2010, the Kyoto Prefecture Public Safety Commission certified our system as the first and only support tool for its 'mandatory retraining course for elderly drivers' that all elderly drivers must take when renewing their driver's license. Through a large-scale demonstration experiment involving 749 elderly drivers in the mandatory driver-retraining course, we investigated elderly drivers' behaviour in real traffic conditions and revealed the diversity of driving skill among elderly drivers. Our findings indicate the importance of giving elderly drivers a personalised driving lecture according to each driver's skill. Our results also revealed that although elderly drivers are able to maintain a safe vehicle speed, their tendency to neglect proper scanning to confirm safety makes their driving performance risky. Although the accuracy of our system is not enough to be an assessment tool of elderly drivers' ability, through interviews with the driving instructors in charge of the demonstration experiment, we confirmed that our system could be an effective support tool for personalised safe-driving lectures. As the next step, to improve accuracy of our system, we plan to use video-based estimation method of drivers' gaze positions [11–14] together with our sensors.

Driving behaviour has many aspects. Among them, we mainly focused on gazing because the lack of scanning behaviour to confirm safety is the most frequent cause of traffic accidents in Japan. As a future work, to cover more aspects of driving behavior, we plan to measure traffic environment around vehicle, lateral position of vehicle on the lane, distance from leading vehicle using image processing technology and vehicle motion data via controller area network (CAN) bus. In addition, since driver's perception and reaction times varies with age, some elderly drivers might look around for adequate time but still not see the danger whereas others might do it. Therefore developing an evaluation method considering each driver's perception and reaction time is also our future work.

7 Acknowledgment

This work is supported by the Strategic Information and Communications R&D Promotion Programme (SCOPE) of the Ministry of Internal Affairs and Communications, Japan.

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