Examining the Environmental, Vehicle and Driver Factors Associated with Crossing Crashes of Elderly Drivers Using Association Rules Mining

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Abstract: This study identifies the crash pattern and examines the environmental, vehicle and driver factors associated with crossing crashes of elderly drivers in Japan. The 5 years crash data in Toyota City is used for empirical study. Association rules mining is applied to discover various factors associated with crossing crashes of elderly and non-elderly drivers, respectively. The major findings indicate that 1) elderly drivers are more likely to lead to crossing or right turn crashes, compared to non-elderly drivers; 2) there are more factors including crash location (intersection without signal), lighting (daylight), road condition (dry, other), weather condition (clear, raining), vehicle type (light motor truck) and traffic violation (fail to confirm safety) associated with the large proportion of crossing crashes due to elderly drivers. The findings of this study can be used by traffic safety professionals to implement some counter measures to reduce the crossing crashes due to elderly drivers.

Keywords: Elderly Drivers, Crossing Crash, Association Rules Mining, Toyota City

1. INTRODUCTION

The vehicle crashes due to elderly drivers are a major concern for roadway traffic safety issue in Japan, since the proportion of vehicle crashes due to elderly drivers has been increased up to 20%, although the number of vehicle crashes has a trend to decrease from 2005 to 2015 (The Tokio Marine Research Institute, 2015). Meanwhile, it is reported that the population distribution in Japan is shifting towards a larger representation of elderly people, and it is estimated that the proportion of people (≥ 65 years old) is up to 31.6 % in 2030, while this figure is 26.8% in 2013 (Statistics Bureau, Ministry of Internal Affairs and Communications, 2013). Therefore, the population of elderly drivers can be expected to be increased continuously over the next two decades.

To ensure the driving safety of elderly drivers, some incentive measures are implemented in Japan. For example, the local government distributes discount coupons for public facilities or free bus tickets to the elderly drivers who have returned their licenses voluntarily. However, it is reported that some elderly drivers are unwilling to return licenses voluntarily, since there are not sufficient public transportation facilities near home, and private cars are indispensable for their daily life. As a result, the return rates of licenses in metropolis such as Tokyo and Osaka are larger than that in local cities in Japan, where the bus transportation system is not sufficient and residents are living in the suburban areas.

To reduce the vehicle crashes due to elderly drivers, Japan National Policy Agency had revised the Road Traffic Law, and requires the elderly drivers (≥ 75 years old) who made some types of traffic violations to go hospital for checking their cognitive ability to judge whether they are still suitable for driving or not (Japan National Policy Agency, 2017). These types of traffic violations are related to the cognitive problem of elderly drivers. However, it is reported that the number of doctors cannot fulfill the huge demand of cognitive ability check for elderly drivers, and it is estimated that this demand will increase in the next decade.

As the traditional measure for preventing and reducing the vehicle crashes due to elderly drivers, the education program is considered as an ideal and effective way. To make the education program more efficiently and effectively, it is necessary to understand the distinctive crash pattern of elderly drivers, compared to non-elderly drivers.

This study aims to identify the distinctive crash pattern due to elderly drivers, compared to non-elderly drivers, and examine the environmental, vehicle and driver factors associated with crossing crashes due to elderly drivers. The 5 years vehicle crash data from 2009 to 2013 in Toyota City, Japan is used for empirical study. Association rules mining is applied to discover various factors associated with crossing crashes of elderly and non-elderly drivers, respectively. Based on findings of this study, knowledge of crash characteristics such as environmental, vehicle and driver factors can be used to guide the design of counter measures to improve driving safety of elderly drivers.

The rest of this paper is organized as follows. Section 2 gives a brief literature review concerning the crash pattern analysis of elderly drivers and the methodology called association rules mining used in previous studies. Section 3 introduces association rules mining methodology implemented in this study. Section 4 describes the dataset used for empirical study and the results of basic statistical analysis of the different crash pattern between elderly and non-elderly drivers. Section 5 reports the results of association rules mining and discusses the different characteristics between elderly and non-elderly drivers. Finally, this study is concluded in Section 6 with a discussion about future research issues.

2. LITERATURE REVIEW

To propose effective counter measures to reduce the crashes among elderly drivers, it is essential to understand the crash types in which they are involved and the circumstances that lead to their crashes. It is known that elderly drivers are over-involved in angle, overtaking, merging and intersection crashes, and especially in the occasions when the elderly driver was turning left (Mayhew *et al.*, 2006). Meanwhile, elderly drivers are significantly over-represented in intersection-related crashes. For example, it is reported that between 48% and 55% of fatal crashes involving drivers 80 years old or older occurred in intersections, more than twice the driver age 50 or less (23%) (Staplin *et al.*, 2001). This might result from the fact that age-related cognitive, visual and physical can impact their ability to perform driving tasks and navigate the types of complicated roadway situations where elderly drivers` crashes often occur (Anstey *et al.*, 2005).

To propose the effective education program for elderly drivers to reduce the traffic crashes, it is important to understand the distinctive crash pattern of elderly drivers compared to non-elderly drivers. Previous studies have indicated that the crash pattern involved in elderly drivers are different from that of non-elderly drivers (Institute for Traffic Accident Research and Data Analysis, 2007; Matsuura, 2016). Elderly drivers are more likely to be involved in the crashes occurring in the intersection without signal, and crossing crashes take the largest proportion among the crash types. It is well recognized that crossing crashes usually lead to severe injury for drivers involved in crashes. To understand the reasons of crossing crashes, previous studies have investigated the association factors of crossing crashes (Preuseer *et al.*, 1998; Wang and Abdel-Aty, 2007; Matsuura, 2016). These studies utilized the crash data to reveal the associated factors of crossing crashes, and based on these findings we can give some counter measures to prevent the crossing crashes due to elderly drivers.

These previous studies are based on the traditional statistical methodology which has a rather limited ability to reveal the associated relation between factors and crashes. One traffic crash is defined as a rare, random, multifactor event always due to preceded by a state in which road users fail to cope with the current environment, and one crash results from a series of directly or indirectly associated events (Montella, 2011). So the data mining technology can help us to find some valuable insights in the research field of traffic safety by performing knowledge discovery from a large traffic crash dataset, compared to the traditional statistical methodology.

Among data mining methods, association rules data mining is an ideal methodology, since it might help us to discover new dependence between various factors and crash pattern based on the traffic accidents data. Recently, some previous studies have applied this methodology in roadway traffic safety. For example, Pande and Abdel-Aty (2009) developed closely associated crash characteristics in the form of rules based on the association rules mining methodology. Mirabadi and Shatifian (2010) applied this methodology to extend knowledge discovery and reveal association patterns of railway crashes in Iran. Montella (2011) applied this methodology to investigate the contribution factors to different crash patterns at urban roundabouts. Based on the literature review, we found that this methodology is seldom applied in the field of crash pattern analysis of elderly drivers.

To find the counter measures to reduce the vehicle crashes due to elderly drivers, it is necessary to investigate the characteristic of crash pattern of elderly drivers from various viewpoints by the association rules mining methodology which can help us to discover the knowledge behind the crash dataset. Based on this motivation, this study applies association rules mining to investigate various factors related to crossing crashes of elderly drivers using the vehicle crashes dataset in Toyota City, Japan.

3. METHODOLOGY

This study used association rules mining technology to perform the empirical analysis. Recently, this methodology is prevailed and applied in the research field of traffic safety in previous studies (Wang and Qin, 2015; Das *et al.*, 2017). A brief introduction of this methodology is described here. The more detailed introduction to this methodology can be found in the study proposed by Hahsler *et al.* (2005).

The data mining methodology on the transaction data using the association rules mining was proposed by Agrawal (Agrawal *et al.*, 1993). This methodology is an association discovery approach used to discover the relative frequency of sets of items (i.e. crossing crash in this study) occurring alone and together in a given event (i.e. a crash observation in this study). The rules have the form "X→Y" in which X is the antecedent and Y is the consequent. In association rules, each rule can be expressed by 3 indexes, i.e. support, confidence and lift. Support is the percentage of this rule existing in the dataset. Confidence is the ratio of support to the percentage of antecedent in the dataset. Lift is a mathematical measurement to quantify the statistical dependence of a rule by ratio of confidence to the percentage of consequent. The computation method of these indexes related to association rules are listed as follows.

$$S(X) = \sigma(X)/N \tag{1}$$
$$S(Y) = \sigma(Y)/N \tag{2}$$
$$S(X \to Y) = \sigma(X \cap Y)/N \tag{3}$$
$$C(X \to Y) = S(X \cap Y)/S(X) \tag{4}$$
$$L(X \to Y) = C(X \cap Y)/S(Y) \tag{5}$$

where,

$S(X)$: support of antecedent X,

$\sigma(X)$: number of observation with antecedent X,

$S(Y)$: support of consequent Y,

$\sigma(Y)$: number of observation with consequent Y,

$S(X \to Y)$: support of the association rule $\{X \to Y\}$,

$\sigma(X \to Y)$: number of observation with antecedent X and consequent Y,

N : total number of observation in the dataset,

$C(X \to Y)$: confidence of the association rule $\{X \to Y\}$ and

$L(X \to Y)$: lift of the association rule $\{X \to Y\}$.

The lift of rule indicates the frequency of co-occurrence of the antecedent and the consequent to the expected co-occurrence under the assumption that they are independent. A value smaller than one indicates negative between them. A value equal to one indicates independence, and a value bigger than one indicates positive dependence. The higher value of lift indicates the greater dependence (Cios *et al.*, 2007). The association rule in this study might involve multiple explanatory variables being set as antecedents. As a result, it can discover many valuable relations between single or multiple factors related to crossing crashes due to elderly drivers. A rule with one antecedent and one consequent is defined as a 2-product rule. Just like this, a rule with two antecedents and one consequent is defined as a 3-product rule.

For example, in a rule: "violation=disobey stop sign → crossing crash" (support=2%, confidence=70%, lift=3.5), support indicates that percentage of observations including both violation called disobey stop sign and crossing crash is 2% in the whole dataset; confidence indicates that the percentage of observations including both violation called disobey stop sign and crossing crash is 70% of the dataset including violation called disobey stop sign; lift indicates that violation called disobey stop sign is positively associated with crossing crash.

To implement this data mining technology, the Apriori algorithm proposed by Agrawal and Srikant (1994) is applied in this study, which is a level-wise, breadth-first algorithm counting transactions. The free statistical software R has a package called "arules" to make an analysis of association rules mining by this algorithm.

4. DATA PREPARATION

This study used 5 years of vehicle crash records (2009-2013) obtained from Traffic Safety and Crime Prevention Division, Social Affairs Department of Toyota City. The data was stored as a sorted format by occurring time in Microsoft Excel Worksheet tables. Each crash record indicated only one actor of vehicle crashes. Therefore, there were two records for one crash which indicated two actors sorted by the severe level of fault. Each crash record had many attributes describing timestamp, environmental factors, traffic conditions and driver characteristics. This study only prepared a dataset including the crash records of drivers who had more severe fault for each crash. Crashes occurring in the intersection or segment were used in this study, since crossing crashes rarely occurs in other locations such as parking lot or square.

The total number of observation in the crash dataset is 9,706 (from 2009 to 2013) including 1,313 crashes due to elderly drivers (≥65 years old) and 8,393 crashed due to non-elderly drivers (<65 years old). Figure 1 illustrated distribution of crashes in Toyota due to elderly and non-elderly drivers, respectively. It indicates that most of crashes occurred in the urban area of Toyota City. This might indicate the trend that the level of social activity is greater in areas with dense population, which leads to an increased risk for accidents (Nieminen *et al.*, 2002).

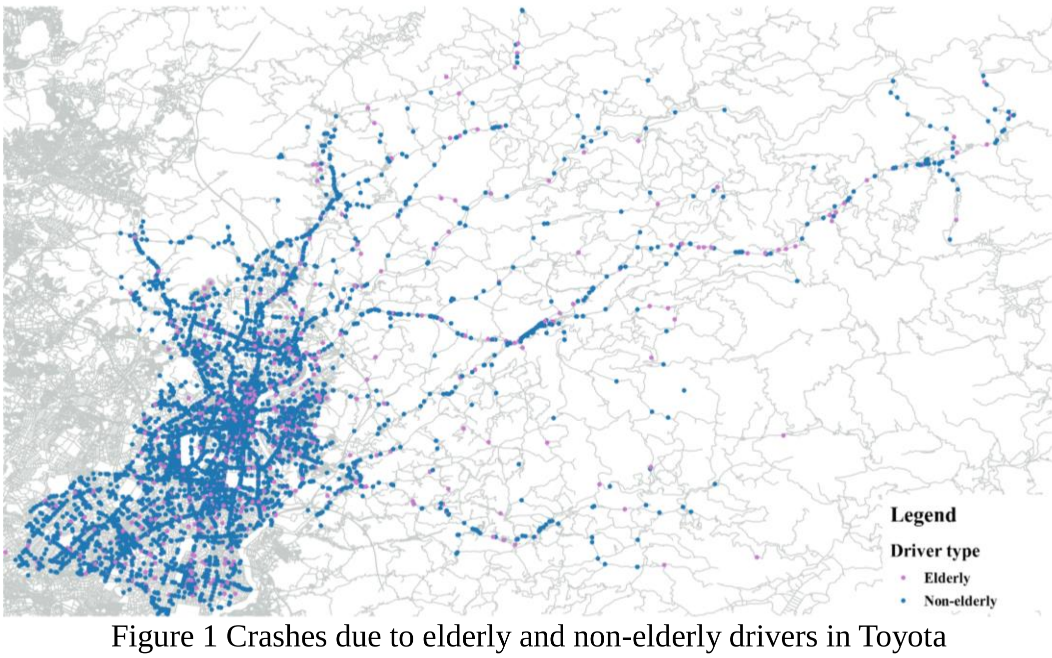

Figure 1 Crashes due to elderly and non-elderly drivers in Toyota

Traffic crash database contains many attributes related to the detail of crashes. We conducted a detailed literature review to investigate the significant factors associated with traffic violation and crash type. The crashes of elderly and non-elderly drivers were examined in terms of frequency of the location, environmental, vehicle and driver factors that were involved to know which factors were more likely to characterize the crash pattern of elderly drivers. Table 1 lists descriptive statistics of significant variables.

Table 1 Description statistics of significant variables

		Elderly drivers		**Non-elderly drivers**	
		Percentage	**99% CIs**	**Percentage**	**99% CIs**
Crash location	Intersection with signal	22.2	19.2-25.1	19.0	17.9-20.2
	Intersection without signal	**39.2**	**35.7-42.7**	**34.1**	**32.8-35.4**
	Segment	**38.6**	**35.1-42.1**	**46.9**	**45.5-48.3**
	Total	100.0		100.0	
Lighting	**Daylight**	**61.5**	**58.0-64.9**	**50.0**	**48.6-51.4**
	Dawn	24.1	21.1-27.2	21.3	20.2-22.5
	Night	**14.4**	**11.9-16.9**	**28.7**	**27.4-29.9**
	Total	100.0		100.0	
Road condition	Dry	89.5	87.3-91.7	87.0	86.1-88.0
	Other	10.5	8.3-12.7	13.0	12.0-13.9
	Total	100.0		100.0	
Weather condition	Clear	77.1	74.2-80.1	74.5	73.3-75.7
	Raining	10.3	8.1-12.4	11.8	10.9-12.7
	Other	12.6	10.2-14.9	13.7	12.7-14.6
	Total	100.0		100.0	
Vehicle type	**Light motor truck**	**17.1**	**14.4-19.7**	**4.5**	**3.9-5.0**
	Light motor car	18.1	15.3-20.8	21.9	20.7-23.1
	Ordinary motor truck	**4.6**	**3.1-6.1**	**10.2**	**9.4-11.1**
	Ordinary motor car	60.2	56.8-63.7	63.4	62.0-64.8
	Total	100.0		100.0	
Traffic violation	**Inattention**	**22.0**	**19.1-25.0**	**30.8**	**29.5-32.1**
	Fail to confirm safety	**60.9**	**57.5-64.4**	**55.1**	**53.7-56.5**
	Incorrect operation	5.6	4.0-7.3	5.6	4.9-6.2
	Fail to observe objects	2.5	1.4-3.6	2.8	2.3-3.3
	Disobey traffic lights	3.0	1.8-4.2	2.2	1.8-2.6
	Disobey stop sign	2.3	1.2-3.3	1.3	1.0-1.6
	Other	3.7	2.3-5.0	2.2	1.8-2.6
	Total	100.0		100.0	
Crash type	Hit pedestrian	8.1	6.1-10.0	5.5	4.8-6.1
	Hit fixed object	4.8	3.3-6.3	2.9	2.4-3.3
	Head on	5.2	3.6-6.8	3.3	2.8-3.8
	Rear end	**24.6**	**21.5-27.7**	**44.1**	**42.7-45.5**
	Crossing	**29.0**	**25.8-32.2**	**23.0**	**21.8-24.1**
	Right turn	**10.4**	**8.3-12.6**	**7.0**	**6.3-7.7**
	Other	17.9	15.2-20.6	14.3	13.3-15.3
	Total	100.0		100.0	

Note: Rows in bold indicate statistical significance (i.e., no overlap in the confidence level).

Location: elderly drivers were not surprisingly, significantly more like to crash in intersections without signal, consistent with the fact that they are the dangerous parts of the network because they present a driver with many points for possible conflict with other road users, often at high speeds and with minimal time to respond, and a lack of adequate in-vehicle crashworthiness opportunities (Oxley *et al.*, 2006). In contrast, non-elderly drivers were significantly involved in crashes occurring in the segment. It might indicate the driving region of non-elderly drivers is wider than elderly ones, and the risk of crashes occurring in the segment was increased.

Environmental factors: elderly drivers were significantly more likely to crash in the lighting of daylight, while non-elderly drivers were more likely to crash in the lighting of night. Meanwhile, there were no significant differences between elderly and non-elderly drivers in the road condition or weather condition being present when the crashes occurred.

Vehicle factor: elderly drivers were significantly more likely to cause crashes of light motor trucks, where non-elderly drivers were significantly more likely to cause crashes of ordinary motor trucks. This significant difference between two types of drivers might indicate that the main purpose of driving ordinary motor trucks is transporting industrial commodities, which are seldom used by elderly drivers after retirement. In contrast, it is inferred that elderly drivers are more likely to drive light motor trucks for agricultural works in suburban area of Toyota, compared to non-elderly drivers.

Driver factor: for the traffic violation that was attributed to the cause of crash, elderly drivers were significantly likely to fail to confirm safety, while non-elderly drivers were likely to be inattention. These differences might indicate that elderly drivers are paying attention to drive, however they are likely to fail to confirm safety due to aging effects. For the type of crash, elderly drivers were significantly likely to cause crossing or right turn crashes, while non-elderly drivers were likely to cause rear-end crashes consistent with the previous study (Matsuura, 2016).

To summarize, the crashes of elderly and non-elderly drivers differenced in location, lighting, vehicle type, traffic violation as well as the type of crash. Elderly drivers are more likely to crash in intersections without signal and in the lighting level of daylight. They are also more likely to cause crashes of light motor trucks, make traffic violation in which they failed to confirm safety and be involved in crossing and right turn crashes.

5. RESULTS AND DISCUSSION

This study utilized package of “arules” in open source statistical software R to conduct the association analysis (Hahsler *et al.*, 2005). To know the difference between elderly and non-elderly drivers, we applied this analysis methodology to sample data of them, respectively. The association rules of environmental, vehicle and driver factors with crossing crashes are extracted from the generated rules using the Apriori algorithm. Creating association rules for elderly and non-elderly drivers includes 5 steps: 1) generate rules with equal to or more than 2 items; 2) determine threshold values; 3) eliminate the rules with lift values outside of the threshold; 4) eliminate the rules that have both support and confidence values lower than the thresholds; 5) eliminate the redundant rules referring to the items of antecedent. To find the association rules highly related to crossing crashes of elderly and non-elderly drivers, the threshold value for support is set to be 1%, and that for confidence is set to be 70%.

The association rules of environmental, vehicle and driver factors and crossing associated with crashes for elderly and non-elderly drivers are listed in Table 2. As the first rule related to elderly drivers, traffic violation of Disobey stop sign was highly associated with crossing crashes (support=0.023, confidence=1.000, lift=3.446). The explanation of first rule is: 2.3% of vehicle crashes were due to Disobey stop sign and led to crossing crash; out of traffic violation of Disobey stop sign, 100% were crossing crashes; the proportion of crossing crashes with Disobey stop sign was 3.446 times the proportion of crossing crashes in the complete dataset.

For elderly drivers, there were 2 rules having the highest lift value (3.446): "Violation=Disobey stop sign → Crossing crash", "Violation=Disobey traffic lights, Location=Intersection with signal, Lighting=Daylight → Crossing crash". These two rules indicated the single factor or combination of factors which had largest proportion of crossing crash inside crash type for elderly drivers. For non-elderly drivers, the highest lift value (lift=4.355) is found for a 2-product rule: "Violation=Disobey stop sign → Crossing crash" indicating that the proportion of crossing crashes involving disobey stop sigh is more than four times for proportion of crossing crash inside the crash type.

Table 2 Association rules of crossing crashes for elderly and non-elderly drivers

Antecedent	Types	Support	Confidence	Lift
Elderly drivers				
Violation=Disobey stop sign	2-product	0.023	1.000	3.446
Violation=Disobey traffic lights	2-product	0.027	0.897	3.093
Location=Intersection with signal	3-product	0.027	0.972	3.350
Lighting=Daylight	4-product	0.023	1.000	3.446
Lighting=Daylight	3-product	0.023	0.938	3.231
Weather=Clear	4-product	0.018	0.958	3.303
Vehicle=Ordinary motor car	3-product	0.014	0.900	3.102
Weather=Clear	4-product	0.011	0.933	3.216
Lighting=Daylight & Location=Intersection without signal				
Type=Light motor truck	4-product	0.037	0.738	2.545
Violation=Fail to confirm safety	5-product	0.033	0.754	2.600
Road=Dry	5-product	0.033	0.741	2.555
Road=Other	4-product	0.017	0.710	2.446
Violation=Fail to confirm safety	5-product	0.014	0.731	2.518
Weather=Raining	4-product	0.024	0.705	2.428
Violation=Fail to confirm safety	5-product	0.021	0.730	2.515
Non-elderly drivers				
Violation= Disobey stop sign	2-product	0.013	1.000	4.355
Violation= Disobey traffic lights	2-product	0.020	0.904	3.936
Vehicle=Ordinary motor car	3-product	0.011	0.914	3.982
Location=Intersection with signal	3-product	0.020	0.908	3.955

Note: One 6-product rule related to elderly drivers was not shown in Table 2.

Compared to data mining results related to non-elderly drivers, the different factors associated with relatively large proportion of crossing crashes included location (intersection without signal), lighting (daylight), road condition (dry, other), weather (clear, raining), vehicle type (light motor truck) and traffic violation (fail to confirm safety). These different factors might indicate the different characteristics between elderly and non-elderly drivers, and elderly drivers might lead to crossing crashes associated with more factors, compared to non-elderly drivers. These findings can help us to make some counter measures to improve the traffic safety by educating them. An interesting finding was that the traffic violation fail to confirm safety was highly associated with crossing crashes in some occasions, and these occasions should be set as the education targets for elderly drivers, since elderly drivers were likely to make a traffic violation involving fail to confirm safety shown in Table 1.

The reasons for the different association rules applied to elderly driver and non-elderly ones are listed as follows. Firstly, the proportion of crossing crashes concerning elderly drivers are larger than that of non-elderly drivers. In this paper the threshold value of confidence applied to association rules mining is set as 70%, and the association rules concerning non-elderly drivers cannot be extracted from the dataset. Secondly, the elderly driver has a large proportion of traffic violation called fail to confirm safety. Here, the violation called fail to confirm safety is highly related to the crossing crashes, which is concluded in the previous study (Matsuura, 2016).

6. CONCLUSIONS

The current study used the crash data due to elderly and non-elderly drivers for 5 years (2009-2013) in Toyota City to identify crash pattern and investigate the significant environmental, vehicle and driver factors associated with crossing crashes of elderly drivers. A data mining technology called association rules mining is applied in this study, which can identify valid and understandable pattern underlying in a large crash data set. The association rules mining is implemented using package “arules” included in the statistical software R.

Results of basic statistical analysis have indicated elderly drivers are more likely to crash in the intersection without signal and in the lighting of daylight. They are also more likely to cause crash of the light motor truck, make traffic violation in which they failed to confirm safety and be involved in crossing and right turn crashes. Results of association rules mining have indicated that there are more factors associated with crossing crashes of elderly drivers, compared to non-elderly drivers. These factors include crash location (intersection without signal), lighting (daylight), road condition (dry, other), weather condition (clear, raining), vehicle type (light motor truck) and traffic violation (fail to confirm safety). These results might reveal the different characteristics of crash pattern of elderly drivers due to their aging effects.

The results of this study can help us to extend the knowledge to driving safety issue of elderly drivers. Based on results of this study, some counter measures to reduce crossing crashes due to elderly drivers will be discussed in future works.

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