Behavior Analysis about Pedestrians Facing the Backward Focusing on Actuating Factors of Driver and Pedestrian from Near-miss Incident Database

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Abstract

The measures against pedestrian accidents are necessary and indispensable in considering autonomous driving and assist system without accidents. In order to further reduce pedestrian accidents, it is thought that to pay attention to pedestrians is necessary that facing the backward. In this research, pedestrian behavior is analyzed from near-miss incident database collected by a drive recorder installed in taxis. In addition, we added an index on the timing of their occurrence, information on where pedestrians were initially, pedestrians and vehicles’ avoidance behavior, and the risk level of scenes. As a result, most of the scenes could be classified using pedestrians and vehicles behavior and relationships. The results have been organized as a form that allows us to look at factors likely to be related to typical scenes and factors. The results show that the characteristics of incidents on narrow roads and wide roads, and it is important to capture the moment of pedestrian behavior changing timing.

I. Introduction

Reducing traffic accidents is an important issue. In order to aim at traffic accident zero, it is necessary to grasp what kind of accident has occurred. In recent years, the number of fatalities, accidents and injuries has been gradually decreasing due to traffic accidents in Japan. Focusing on fatalities, accidents with pedestrians has a high proportion, so it is important to consider measures. Among them, the crossing collision is the most and largest frequent accident and various measures are considered for that case. The situation for these next frequent accidents are in facing or facing backward to the pedestrian. The number of these accidents is not so much, but the rate of fatal accidents is high. It is necessary to focus on these types of accidents in order to aim to reduce further accidents. Furthermore, it would be useful to be able to predict potential risks by pedestrians towards automated driving and driving support systems and forecasting.

In this research, we focused on the accident when the pedestrian facing backward. The target scenes are extracted and analyzed from the database of the drive recorder in order to understand what is happened in these accident situations. For these purposes, we analyze the accident based on the behavior of the pedestrian about what happened when the event occurred and before then. Furthermore, we will organize the characteristics of each cause of the accident, and aim at data organization that can be used as a basis for what kind of measures are necessary.

II. Accident with Pedestrians Facing Backward

In this paper, we focus on the accident scene involving the pedestrian faced backward when accidents occurred. This chapter describes the current situation of accidents in Japan, the meaning of selecting this scene, database for analyzing this scene, and how to proceed with the analysis with this database.
A. Accident Statistics

By Japan National Police Agency (2019) the outbreak situation of the traffic accident in 2018 [1], there are about 430,000 incidents, and 3532 fatalities in Japan. From this data, we will examine the tendency of accidents and accidents involving pedestrian as shown in Fig.1. The number of traffic accident is a downward trend from 1990’s, but there are still a lot of accidents. There are about 49000 incidents and casualties (includes minor injuries) and 1186 fatalities in the accident involving pedestrians in 2018, and the fatalities of pedestrians is 34% of the whole. The most frequent accidents are pedestrians crossing. And the next one, there are many pedestrians facing or facing backwards in the number of incidents, and many pedestrians stopped on the road and facing backward in the number of fatalities.

The accidents involving pedestrian crossings are expected to continue to decrease, such as the spread of ADAS. On the other hand, it is thought that measures are necessary in the future about involving pedestrian accidents facing backwards where there are not a lot of measures as crossing.

![Fig.1: Characteristics of accidents involving pedestrian in Japan (2018) [1]](image)

(b) change in number of incidents
(c) change in number of fatalities

In this way, the accident with pedestrians in Japan was summarized to some extent. Especially in the case of crossing accidents, which account for the majority of accidents, driving assistance to avoid collision with pedestrians is also spreading to the world. It seems measures will be taken in the future and the number of accidents related to this situation will decrease.

Under this premise, in order to further reduce accidents involving pedestrian, it is thought that to pay attention to pedestrians is necessary who are facing the backward and face-to-face. The cause of these accidents may be narrow road where pedestrians and vehicles are not divided, pedestrians cross or stop regardless of the intersection. In this study, we consider the accident patterns facing backwards, where mutual behavior is difficult to predict. Therefore, we proceed with analysis using a database that can be analyzed in more detail.

B. TUAT Near-miss Incident Database

In this research, pedestrian behavior was analyzed from TUAT near-miss incident database e.g. Nagai et al. [2], Kamata et al. [3], collected by a drive recorder installed in taxis. In this database, there are collected data like date and time, GPS position data, Vehicle speed, vehicle acceleration, brake pedal operation, camera movie of front view when taxi drivers’ slam on the brake timing. So the feature of collision with facing backward pedestrians by using near miss incident database (Later this database is called TUAT_NIDB) were analyzed. That data can notice the driving state before near crash incident occurred. In addition, we want to consider the dangerous scene that of human images in words associated the numerically data of the database. As shown in Table1, 178 scenes were extracted from about 100,000 data in TUAT_NIDB

![Fig. 2: Database viewer and data example](image)

<table>
<thead>
<tr>
<th>type</th>
<th>case</th>
</tr>
</thead>
<tbody>
<tr>
<td>incident to human</td>
<td>about 9000</td>
</tr>
<tr>
<td>Road (not an intersection)</td>
<td>about 2300</td>
</tr>
<tr>
<td>facing backwards</td>
<td>178</td>
</tr>
</tbody>
</table>

Table 1: Number of near-crash incident data
As an example of research using this database, Matsui et al. [4], analyze the most common accidents, crossing accidents. Hayashi et al. [5], model typical behavior of pedestrians in facing backwards. In this study, we analyze the general trends and characteristics of accident involving pedestrians facing backwards to reduce more accidents.

III. Analysis Method using TUAT_NIDB

The authors analyzed behavior of pedestrians facing backward from TUAT_NIDB in reference [6]. As shown in the Table 2, it was classified based on behavior at the time of avoidance, road surface shape, etc. For further details, pedestrians and drivers behavior about avoidance, and so on were clarified to estimate the characteristics in the overtaking situations with pedestrians facing the backward. In order to grasp the risk of overtaking pedestrians typically, focusing on road shape, environment and relative position between pedestrians and vehicles. The classification of these scenes was added the surrounding environment information such as other traffic, participants and road structures based on the position and the behavior, pathway of the pedestrians and vehicles, in anticipation to use the future driving behavior database. Since these information were not registered in the database, the items listed in Table 1 were classified while checking the video registered in the database and the results were considered we eventually chose the things that were important. Items in Table 1 were divided into items relating to the positional relationship between pedestrians and vehicles when it could be confirmed, the subsequent behavior of the driver, the behavior of the pedestrian, and the situation of other traffic environments. And we decided classification method focused on pedestrian and driver behavior based on this list. The representative scene was extracted using these analyzed data. Most of the scene in this analysis could be classified into three representative examples from the movement of pedestrians facing backwards and vehicles, (i) pedestrian is on the path of vehicle from the start scene and (ii) drivers operate a steering and approached close to the pedestrian scene and (iii) pedestrians come into the vehicle path scene.

However, this analysis lacks information on environment and pedestrian detection. It was not possible to analyze the relationship in detail between the pedestrian detection and the actual risk level.

In this paper, we added timing related to pedestrian behavior (detected, on the path), risk level information (index level), and information on the environment (number of parked vehicle, pedestrian) as shown in Table3. The index added were the risk level of incident, and the number of other traffic participants (vehicles and pedestrians), the timing when pedestrians can be found in recorded movie, when the pedestrian enters the path of the vehicle.

The other items are originally tagged in TUAT_NIDB and classified as low, medium, high, and bumpy. The amount of other traffic participants (vehicles and pedestrians) is classified as nobody, a little, and a lot. In addition, it was analyzed to make it easier to clarify the relationship between each factor including these added indexes and other factors. Their relationships were considered focusing on the movements of pedestrians, the environment of roads and the level of risk. The indexes (number of parked vehicle, pedestrian) was not classified in the low level case.

About pedestrian detectable timing, the first frame timing that was able to be confirmed on the image that the target pedestrian is walking were recorded from the trigger of the database. This time was indexed in 10-5 [s], 5-3 [s], 3-1 [s], and less than 1 second.

About the timing when the pedestrian on the pass, The time from the trigger of the database is recorded for the first frame in which the pedestrian entered the vehicle's planned trajectory. This was arranged in the same way as a previous index.

<table>
<thead>
<tr>
<th>Table 2: The proposed classification index</th>
<th>Table 3: The added classification index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No.</td>
</tr>
<tr>
<td>pedestrian position</td>
<td>location from vehicle</td>
</tr>
<tr>
<td>driver behavior</td>
<td>approaching timing</td>
</tr>
<tr>
<td>avoidance behavior</td>
<td>C</td>
</tr>
<tr>
<td>route changing</td>
<td>D</td>
</tr>
<tr>
<td>speed change</td>
<td>E</td>
</tr>
<tr>
<td>foreseeability</td>
<td>F</td>
</tr>
<tr>
<td>avoidance target line</td>
<td>G</td>
</tr>
<tr>
<td></td>
<td>H</td>
</tr>
</tbody>
</table>

| No. | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|------------------------------------------|----------------------------------------|
| from near-accident database | incident level | I | others | low | middle | hi | crash |
| number of parked vehicle | J | others | no vehicle | few | many |
| number of pedestrian | K | others | no pedestrian | few | many |
| Time from | L | others | 10-5 [s] | 5-3 [s] | 3-1 [s] | 1-0 [s] |
| trigger | M | others | on the path | left side | right side | left side | right side | left side | right side |

| No. | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
|------------------------------------------|----------------------------------------|
| from previous incident | number of parked vehicle | I | others | no vehicle | few | many |
| pedestrian detected | J | others | no pedestrian | few | many |
| Time from | K | others | 10-5 [s] | 5-3 [s] | 3-1 [s] | 1-0 [s] |
IV. Analysis Result

In this section, the graph arranges all the indexes to organize the relationship between the indexes. First, the results for all 178 data used this study were shown and analyzed the features. The following shows the result of extracting only the data that belongs to the specific index, in order to find the indexes that is closely related to the chosen index.

A. Classification result (All data: 178 cases)

The analysis results of all 178 cases are shown in Fig. 3. The index of A to M correspond to Table 2 and Table 3. At first, it can be seen that the driver did nothing such as avoiding other traffic. The pedestrian did not change the speed but did not move as expected, such as changing its direction or did not change the movement. The driver avoided it by braking. In fact, there were 35 or 34 such scenes when the pedestrian came in and when the pedestrian did not change the movement.

![Fig.3: Characteristics of all data (n=178)](image)

B. Classification result (Comparison within items)

In this section, the analysis results were organized based on the relationship between pedestrians and vehicles and the behavior of pedestrians to investigate relationship with other indexes. The analysis results for (a) A1, (b) A2, (c) A3, (d) F1 and F2, (e) F3, (f) F4, (g) H1, (h) I3 and I4, (i) L3 and L4, (j) H3 and H4, (k) I1, (l) L1 were shown in Fig. 4.

There were 54 scenes belonging to A1 scene where pedestrians were found in initially on the path of the vehicle. In this case, pedestrians often do not change their behavior until trigger timing. There were 80 scenes belonging to A2 scene where pedestrians were on the left (closer) side. This scene occurs more often on wider roads than other scenes. There were 44 scenes belonging to A3 scene where pedestrians were on the right (far) side. In this case, the distribution of foreseeability is different from the others.

There were 56 and 40 scenes belonging to F1 and F2 scene where the movement of pedestrians could be predicted. In this case, risk index is lower than others. There were 34 scenes belonging to F3 scene where the movement of pedestrians could be predicted but the timing was sudden. In this case, naturally, the distribution of on the path timing index (M) and route changing index (D) is biased. There were 48 scenes belonging to F4 scene where pedestrians move unexpectedly. In this case, it seems to be more common on relatively narrow roads.

There were 90 scenes belonging to H1 scene in narrow road with one lane. This case account for half of the whole. There were 11 and 3 scenes belonging to I3 and I4 scene that has hit or high risk level. In this case, it was difficult to grasp the trend because the number of cases was small, but there were many other traffic participants. There were 36 and 4 scenes belonging to L3 and L4 scene where the brake trigger came in immediately after it became possible to confirm that the pedestrian was walking. In this case, the person who stopped in front starts walking suddenly, which was not seen from the driver until just before in environmental conditions may be included here.

There were 18 and 8 scenes belonging to H3 and H4 scene in wide road with two or more lanes. Distribution of pedestrian’s position index (A) and on the path timing index (M) is characteristic. There were 94 scenes belonging to I1 scene classified low risk level. In this case, it was similar to the trend of all data. There were 11 scenes belonging to L1 scene where it was possible to find pedestrians early. This scene seems to be a bit more on narrow
roads.

(a) A1 (n=54)  (b) A2 (n=80)  (c) A3 (n=44)

(d) F1,2 (n=56,40)  (e) F3 (n=34)  (f) F4 (n=48)

(g) H1 (n=90)  (h) I3,4 (n=11,3)  (i) L3,4 (n=36,4)

(j) H3,4 (n=18,8)  (k) I1 (n=94)  (l) L1 (n=80)

Fig.4: Result for each Index
C. Consideration

When focusing on pedestrian location index (A), there are many cases that have been on the left from the beginning. Pedestrians who are on the road from the beginning do not change much behavior. When focusing on foreseeability index (F), none of them were so common, and only sudden changes did not lead to risk.

On the other hand, when focusing on wide roads (H3, H4), there are many cases where comes close from the left side index (A2). Detectable timing index (L) and on the path timing index (M) is shorter compared to narrow roads. This time, it has not been fully examined, but there seems to be a case that became such a result because the vehicle speed was faster even the view was open and it was easy to find even if the pedestrian was far away.

Think about the consequences of high risk cases (I3, I4), the tendency of detectable timing index (L) was not so different, and the tendency of foreseeability index (F) and route changing index (D) was different. In other words, the tendency of (F) has a higher influence on the risk evaluation value than (L). It is suggested that behavior changing timing rather than pedestrian detectable timing was more likely to affect the risk. In addition, the analysis method used in this study by visual observation from the video image, it should be noted that it was difficult to judge that the movement of the pedestrian changed unless changing the direction of the pedestrian's foot near the vehicle. It is suggested that the actual driver can be judged from other movements because it was often faster to start stepping on the brakes than judging from the video image.

V. Conclusion

In order to reduce accidents with pedestrians, we focused on the scene where pedestrians are facing backwards. The drive recorder data, which shows the situation before and after incident, was used to examine the factors. It was analyzed using TUAT near-miss incident database which has a large number of incidents in Japan. 178 cases were extracted from more than 100,000 data included that database. The indexes were created and categorized that seemed to be related to the scene where pedestrians were facing backwards. The classification results are shown below.

On wide roads, pedestrians tend to come from the left (near) side, and the time between pedestrian detectable and avoidance of brake triggers tends to be short.

In high risk cases, it was suggested to be most susceptible to the timing of pedestrian changes in movement.

In the future works, we need to tag the factors more in detail and analyze them to assess collision risk and use this database for predicting or modeling the behavior of pedestrians. In addition, we will consider how to organize other than characteristic and typical scenes.

References