Classification of Crash Pattern Based on Vehicle Acceleration and Prediction Algorithm for Occupant Injury

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ABSTRACT: Injury prediction based on data from event data recorder in automatic collision notification is expected to reduce trauma deaths. Known to affect on injury, the crash pattern is required to be classified to accurately predict injury. We performed crash simulations with a full-vehicle finite element model, and determined typical vehicle acceleration profiles of each crash pattern. A method to classify a crash pattern by comparing vehicle acceleration with the typical profiles was found to be effective. We also performed multi-body simulations with a vehicle interior and a dummy model, and developed injury prediction algorithms of each crash pattern.

KEY WORDS: safety, event data recorder, injury prediction, algorithm, crash pattern classification [C1]

1. Introduction

Measurements in active safety and passive safety have been effective in reducing morbidity and mortality in road traffic crashes. In Japan, the number of trauma death in a year decreased to less than 5000 (1). In order to achieve “Zero Death”, further measurements, especially at post crash including Emergency Medical Service (EMS), are required (2). Advanced Automatic Collision Notification (AACN), which consists of injury prediction based on data from an Event Data Recorder (EDR) and automatic notification shortly after accident, is expected to optimize EMS and reduce trauma deaths (3). Techniques to classify crash patterns have been developed to detect a certain phenomenon to effectively activate occupant protection devices. However, in order to predict occupant injury, the overall crash from the beginning to completion is necessary to be considered.

In this study, we tried to develop 1) a method to classify a crash pattern based on vehicle acceleration which an EDR records through the overall crash, and 2) an injury prediction algorithm considering the effect of crash pattern.

2. Crash Pattern Classification Based on Vehicle Acceleration

In developing a method to classify the five patterns of frontal crash, firstly, we examined characteristics of vehicle acceleration according to each crash pattern. Secondly, we suggested a method to classify which crash pattern’s characteristics vehicle acceleration in an accident had, and evaluated the accuracy of our method to vehicle-to-barrier crashes and vehicle-to-vehicle crashes.

2.1. Vehicle Acceleration in Frontal Crashes

A number of studies have investigated vehicle acceleration in crashes, and revealed that the crash direction, the velocity, the vehicle, and the partner affect on its characteristics. Woolley et
al.\(^{(8)}\) suggested a function modeling vehicle acceleration to time history according to the vehicle deformation phenomenon. Crosby et al.\(^{(9)}\) showed that the time history was estimated by the vehicle weight, the residual deformation, the change in velocity, and so on. Elmarakbi et al.\(^{(10)}\) performed finite element simulations with a full-vehicle model to evaluate the effect of crash partner, which was a pole in the study.

Our method to classify the pattern of a crash is to be used in AACN where vehicle acceleration itself is recorded in EDR. It is necessary not to estimate the acceleration as in Ref. (8) and (9), but to investigate it, which varies depending on the crash pattern, in advance. Crashes of various patterns occur in the real world, while crash experiments with vehicles in laboratory are limited. Therefore, we used a finite element model of one type of vehicle to perform the five crash patterns at two levels of crash velocity. By analyzing the accelerations from the simulations, we tried to determine a typical vehicle acceleration profile of each crash pattern.

2.1.1. Methods

In order to obtain vehicle acceleration and compartment intrusion in various frontal crashes, crash simulations with a full-vehicle finite element model were performed. LS-DYNA ver. 971 was used as a solver of finite element simulation in this study. The vehicle model is 3.29 m in length, 1.48 m in width, 1.54 m in height, and 935.8 kg in weight, which is typical Japanese light-vehicle, and consists of 373528 nodes and 371052 elements. The ratios of beam and shell element numbers to solid are 12.5 and 36 %, respectively. The frontal part of this model is bilaterally asymmetric, and the rear part is simplified. Incidentally, the driver seat is in the right hand side of the model.

As mentioned in Introduction, a NHTSA report\(^{(7)}\) showed that about 80 percent of frontal crash accidents were roughly divided into five crash patterns. Therefore, we designed vehicle crash simulation models in each one of the five patterns: Full-Wrap (FW), Offset (OF), Oblique (OB), Pole (PL), and Under-Ride (UR), as shown in Fig. 1. A vehicle model with initial velocity collides against a barrier model, which is a fully-restrained rigid wall or pole in FW, OB, PL, and UR simulations, and a deformable cuboid whose back side is restrained in OF.

![Fig. 1 Five crash patterns of vehicle-to-barrier simulations](image)

Time history of acceleration, \(a(t)\), at the right side sill of vehicle model on its local coordinate system is obtained as the vehicle acceleration. The acceleration is filtered with CFC 60 in accordance with SAE J211. An accelerometer at the location might not break in a frontal crash, which makes it possible to record acceleration in whole the crash phenomenon. In this study, only translational deceleration on the longitudinal direction was considered and called as acceleration, though it was actually deceleration. The technical requirements for EDR include \(\Delta V\) of only longitudinal direction, while does triaxial acceleration under certain specified conditions\(^{(11)}\). Therefore, we focused on the single direction at the single point to show the possibility of crash pattern classification by using simple equipment at low cost.

These simulation models had been validated to experiments of each crash pattern previously as shown in Fig. 2. In each experiment, the vehicle closing velocity was different from each other because of experimental limitations. In each crash pattern except UR, \(a(t)\) in the simulation is qualitatively similar to that in the experiment. In OF, OB, and PL, it is quantitatively similar too. In UR, the trend that acceleration keeps decreasing is in common.

![Fig. 2 Vehicle acceleration vs. time in the simulations and experiments](image)

The initial velocity of vehicle model was set at two levels, 50 and 65 km/h. In our experimental simulations, compartment intrusion occurred in the range of 50 to 65 km/h, and vehicle accelerations in each crash pattern had common approximate profiles. Thus, we considered that a typical acceleration profile of each crash pattern in the range could be determined.

To analyze crash phenomenon, acceleration vs. displacement, \(a(s)\) is commonly used as Ref. (9). By calculating according to Eq. (1), (2), and (3), time history of velocity, \(v(t)\), \(\Delta V\), and time history of displacement, \(s(t)\), are obtained, and by deleting time of \(a(t)\) and \(s(t)\), \(a(s)\) is finally obtained. While finite element simulations provide the velocity and displacement of a node, in this study, the equations were used because only \(a(t)\) from EDR is available for crash pattern classification.
\[ v(t) = \int a(t) \, dt \] 
\[ \Delta V = \max[v(t)] - \min[v(t)] \] 
\[ s(t) = \int (v(t) + \Delta V) \, dt \] 

2.1.2. Results

The vehicle crash simulations of 10 cases (five crash patterns, two crash velocities) were performed, and vehicle acceleration vs. displacement, \( a(s) \), was obtained as shown in Fig. 3. To compare \( a(s) \) among the two velocities, the acceleration and displacement values were normalized by \( \max[a(t)] \) and \( \max[s(t)] \) respectively. In frontal crashes, crash energy is absorbed by firstly the front part of vehicle, especially the side members, and secondly the cabin. \( a(s) \) has two phases according to the absorption mechanism in all crash patterns except UR where the side members do not engage the crash.

Typical vehicle acceleration vs. displacements, \( a(s)_{\text{TYP}} \), was determined by lining \( N \) characteristics points, \( C_n \), as shown in Fig. 3. FW and UR’s \( a(s) \) have three \( C_n \), and that of OF and PL have four, and that of OB has five respectively. The coordinate values of \( C_n \), \( a_n \), and \( s_n \), were derived by averaging each value of flexion points of the two normalized \( a(s) \) in each crash pattern. The flexion points were picked up to represent the two phases described previously. In addition, times at the flexion points for a \( C_n \) were similar. The average gap was about 5 ms.

As suggested in the literature, \( a(s)_{\text{TYP}} \) depends on the vehicle of this study. Each vehicle might have its own \( a(s)_{\text{TYP}} \). Additionally, \( a(s)_{\text{TYP}} \) might change in other crash pattern, such as different wrap ratio of OF crashes, as the five here might not represent all frontal crashes. It would be necessary to investigate vehicle acceleration in other frontal crashes. By the investigation, we may find that, for example, 20 and 40 percent-wrap of FWs would have similar acceleration profiles and \( a(s)_{\text{TYP}} \) in common.

Times at the flexion points of two \( a(s) \) in a crash pattern, which were picked up to define characteristic points, \( C_n \), in \( a(s)_{\text{TYP}} \), were similar. In each crash pattern acceleration vs. time might have characteristic points at certain times even in any velocity of crash, which indicated the existence of \( a(t)_{\text{TYP}} \).

2.2. Crash Pattern Classification

In the previous section, we revealed that the five crash patterns have their own typical vehicle acceleration vs. displacement profile, \( a(s)_{\text{TYP}} \). We tried to develop a method to compare vehicle acceleration in a crash with \( a(s)_{\text{TYP}} \) and to classify its crash pattern. We also evaluated our method’s reliability to 10 vehicle-to-barrier crashes and one vehicle-to-vehicle crash.

Fig. 4 shows the flow of crash pattern classification when a crash happens. The second step, calculating \( a(s) \) is done by Eq. (1), (2), and (3) as Section 2.1. The third step is the key in classification of crash pattern, and we suggested its method in this section.

![Flow of crash pattern classification](image_url)

2.2.1. Methods

The difference, \( D \), of \( a(s) \) in a crash with \( a(s)_{\text{TYP}} \) of a crash pattern is defined as the average of \( N \) shortest Euclidean distances, \( d_n \), between characteristic points, \( C_n \), and \( a(s) \) as shown in Fig. 5. Eq. (4) and (5) describe \( d_n \) and \( D \) respectively. As this definition, a point of \( a(s) \) whose distance to a \( C_n \) is the shortest could be different in comparing with other \( a(s)_{\text{TYP}} \). The pattern of a crash is classified as that of the minimum \( D \) among the five, which means our method gives a crash pattern as an output, even if there will no similar crash pattern among the five.

![Measuring difference between a(s) and a(s)_{TYP}](image_url)
\[ d_n = \min \left\{ d(t) - a_{TYP}^{s}, (t) - s_{TYP}^{s} \right\} \] (4)

\[ D = \sum d_n / N \] (5)

The reliability of our method was validated to ten vehicle-to-barrier crashes which were the vehicle crash simulations in the previous section, and one vehicle-to-vehicle crash which was a reconstruction experiment of a real world accident. The ten simulations consist of the five crash patterns and two levels of crash velocity, while experiments in the same patterns were limited in those velocity levels. The real world accident was a full frontal crash, which was relatively easy to be reconstructed in testing sites, and its occurrence situation, vehicle damage and occupant’s injuries were reported in details. We conducted the experiment where a vehicle of the same type as the finite element vehicle model in this study and the accident collided against a full-wrap deformable barrier which was rigidly connected to the edge face of a truck to be equivalent to the front of crash partner in the accident. Accelerations were measured at the right side sill. The deformation of vehicle, especially the side member, which resembled to that in PL crashes, was successfully reconstructed in the experiment.

To evaluate reliability, two indexes: accuracy and precision, are commonly used. Accuracy evaluates correctness of classification results to true values, while precision evaluates dispersion among results. These indexes are defined as Eq. (6) and (7) respectively where U is the class of all crashes, A is the class of crashes of a pattern, and B is the class of crashes classified as the pattern.

\[ \text{Accuracy} = \frac{(A \cap B) + A \cup B}{U} \] (6)

\[ \text{Precision} = \frac{(A \cap B)}{B} \] (7)

2.2.2. Results

Our classification method correctly classified crash patterns in eight out of the ten simulations of vehicle-to-barrier crash. The exceptional two cases were FW and PL at 65 km/h of crash velocity, and both were classified as OB. The accuracy and precision were calculated from the results, and more than 80% in all crashes and 100% in all crashes except OF, respectively. OF’s precision was 50%.

One reconstruction experiment of vehicle-to-vehicle crash where the vehicle deformed as in PL crashes was classified as PL by our method. In fact, \( a(t) \) measured in the experiment resembled PL’s \( a(TYP) \), which is a transformed form from \( a(s) \) and explained in Subsection 3.1.1. in detail, as shown in Fig. 6.

\[ \text{Exp. } a(t) \]

\[ \text{PL. } a(TYP) \]

Fig. 6 \( a(t) \) in the reconstruction experiment and \( a(TYP) \) of PL: accelerations are normalized by their max. respectively.

2.2.3. Discussion

The method to classify a crash pattern based on the vehicle acceleration did classify vehicle-to-barrier crashes, which indicated its effectiveness. Furthermore, the crash pattern of a vehicle-to-vehicle crash was classified correctly, which indicated the possibility that EDR with a single acceleration sensor could provide the pattern of a frontal crash in AACN. As we discussed in Subsection 2.1.3, each vehicle might have its own \( a(TYP) \). If \( a(TYP) \) of a vehicle are known in advance, a crash pattern will be predictable as we showed here. In this study, only the five crash patterns were concerned, though other crash pattern might have different \( a(TYP) \) as we discussed in Subsection 2.1.3. The indication above suggested that patterns of frontal crashes should be grouped according to acceleration profiles not appearance as in this study, and the number of group might not be five. Furthermore, using multiple axial acceleration sensors at multiple points, which is technologically-feasible as included in the requirements for EDR under certain specified conditions (13), is expected to expand the target of crash patterns and improve the reliability. In such case, our method here could take place, as other direction acceleration can be obtained in the crash simulations and analyzed as in Section 2.1, and included as other factors to evaluate \( D \) as in this section.

The number of cases in the validation was limited because of the lack of available real crashes. Additionally, we notice some issues with our classification method itself. The precision of OF’s \( a(TYP) \) was relatively lower than that of the other four. In the simulations of OF, the vehicle acceleration varied because of the buckling behavior of the deformable barrier model. The variation is required to be considered in determining \( a(TYP) \) and comparing with \( a(s) \) of crashes. Secondly, the difference between \( a(s) \) and \( a(TYP) \) was evaluated in terms of only several points not the whole acceleration. Multiple indexes, such as \( \Delta V \), are necessary to be introduced in evaluating the difference. Thirdly, indication of the existence of \( a(TYP) \) might make it possible to classify a crash pattern by using \( a(t) \) rather than \( a(s) \), which requires several extra processes.

3. Prediction of Occupant Injury According to Crash Pattern

In the previous chapter, we confirmed that the vehicle acceleration depends on the crash pattern and also developed a method to classify the pattern of a crash based on its acceleration. The vehicle acceleration significantly causes occupant injury as \( \Delta V \) was found to have a strong correlation in a statistical analysis (4). Severity of an injury could be different according to the crash pattern, which indicates that predicting injury with consideration of the crash pattern is expected to make the reliability of prediction higher. Therefore, we tried to develop a prediction algorithm with the consideration. Firstly, we examined relations between injury values of each occupant’s body segment and \( \Delta V \) according to the crash pattern. Secondly, we suggested equations to predict probability of severe injury as a function of \( \Delta V \), and compared it to one real world accident where the driver injured.
3.1. Occupant Injury in Frontal Crashes

Ref. (4) and (5) showed that occupant injury correlated to the crash pattern based on statistical analyses of a real world accident database where a crash pattern was described by Collision Deformation Classification (CDC) (12). However, the database might not provide the correlation accurately, because by using CDC the crash pattern is defined based on the vehicle deformation rather than the vehicle acceleration which causes occupant injury most significantly. Experiments with cadavers could evaluate the effect of acceleration on injury (13), but it is extremely difficult to conduct. Therefore, numerical simulation is now widely used. Miyazaki et al. (14) used a human multi-body model with 5th, 50th, and 95th percentile of Japanese male’s body shape in frontal crash simulations. The models didn’t consider the deflection of thorax which has a strong correlation with thorax injury (15). Finite element method enables to make a human model with a higher biofidelity, and has been used to evaluate injury in detail. Choi et al. (16) developed a finite element model of elderly male driver and simulated fractures of the ribs. Sato et al. (17) developed a finite element driver model for rear-end impacts and investigated the local deformation of the intervertebral discs. However, such a model with complex attributes needs regulations for each simulation and is unsuitable for great amount of simulations covering most frontal crashes. Therefore, we used a numerical model of Hybrid III 50th percentile, which is not too complicated and designed to measure injury values including thorax deflection. The dummy have another advantage that it is available for real world experiments in more various situations than that with cadavers and volunteers.

3.1.1. Methods

Vehicle interior of driver seat and occupant model shown in Fig. 7 were used to predict occupant injury in frontal crashes of the five patterns by using MADYMO R7.2 as a multi-body simulation solver. The occupant is the model of Hybrid III 50th percentile dummy which MADYMO provides. Time history of translational acceleration on travel direction (X in Fig. 7), a(t), is given to the right side sill which each part of the vehicle interior model is linked to, and the dummy is subjected to inertia load. The translational and angular accelerations on the other directions are not considered here. Response of the dummy model unchanged when lateral translational acceleration was additionally input in simulations of OF and OB where the vehicle rotates in the real world. The dummy wears the seatbelt and the airbag deploys in all cases of the simulations. The time of inflating the steering wheel is identical among the five. Fig. 8 shows, despite a same ΔV, a(t) is significantly different from each crash pattern. The maximum accelerations of FW, OB, and PL are similar and larger than that of OF and UR. The acceleration in OF generates in relatively late of crash phenomenon.

For each crash pattern, we performed 16 cases where ΔV ranged from 10 to 25 m/s every 1 m/s. In terms of prediction in AACN, detecting severe injuries is important. The range might cover the threshold of severe injury. Input a(t) of each crash pattern is shown in Fig. 8. Those simplified acceleration to time histories are defined based on a(s)TYP which we created in the previous chapter. As the results in Subsection 2.1.2 showed, at any velocity, times at flexion points of a(s) could remain constant. Therefore, a(s)TYP of each crash pattern was created, as we discussed in Subsection 2.1.3. Time of a C of a(s)TYP, t*, is defined as the average of the two flexion points’ time. By lining Cn(a, t), a(s)TYP is determined. Secondly, to create a(t) of a ΔV, each an of a(t)TYP is multiplied by a certain scalar to make the integration of a(t) agree with the ΔV, while t* does not change. As Fig. 8 shows, despite a same ΔV, a(t) is significantly different from each crash pattern.
The correlations between the injuries and \( \Delta V \) for each crash pattern, \( \text{Injury}(\Delta V) \), were approximated. Linear and exponential approximation were respectively used at low and high \( \Delta V \) for the head and thorax injuries as Eq. (8) and (9) where \( p, q, r, \) and \( s \) are coefficients. Deflected values from the trends were eliminated from the approximations, which resulted in strong correlations \((R^2>0.90)\). The approximations were drawn in Fig. 10 with solid and broken lines.

\[
\text{Injury} = q + p \cdot \Delta V \quad (8) \\
\text{Injury} = s \cdot \exp(r \cdot \Delta V) \quad (9)
\]

Additionally, its disregard of vehicle deformation and intrusion might cause the constancy of the maximum force of femur at high \( \Delta V \). Validation to crashes at multiple \( \Delta V \) is required to be conducted.

The existence of different \( \text{Injury}(\Delta V) \) among the crash patterns supported the necessity of different injury prediction according to crash pattern. By using the equations representing the correlations, \( \text{Injury}(\Delta V) \), injury value of occupant’s each body segment could be estimated instantaneously.

3.2. Prediction Algorithm for Occupant Injury

Fig. 11 shows the flow of prediction algorithm for occupant injury considering the difference of crash patterns when a crash happens. \( \Delta V \) and \( a(s) \) are calculated from \( a(t) \) by Eq. (1), (2), and (3) as Section 2.1. The occupant injury is predicted based on \( \Delta V \) and the crash pattern which is classified according to \( a(s) \) as suggested in Chapter 2. In AACN, the probability of injury occurrence, which is an indicator to make medical decisions, is required to be presented instantly as URGENCY \(^5\). The equations of injury value of each body segment as a function of \( \Delta V \) in the previous section, \( \text{Injury}(\Delta V) \), could not predict the probability of injury occurrence. The simulation, which the equations were based on, represented one single occupant, Hybrid III 50th percentile dummy, though the real world consists of various attributes. To solve this limitation we introduced injury risk curves of each injury index \(^{10,19,20}\), which represent correlations between the probability of injury occurrence and each injury value.

To evaluate reliability of the algorithm, comparing predicted injury probability to injuries in real world accidents is required. The accidents must be that of vehicle of the same type as our model, because \( a(t) \) used in Subsection 3.1 as the inputs depends on our vehicle model. Furthermore, EDR or an acceleration sensor must be on the accident vehicle. Fortunately or unfortunately, there were a few available records of accident where a vehicle of the same type involved and a driver injured. We conducted a crash experiment to reconstruct the acceleration of one of the accidents.

3.2.1. Methods

The injury prediction equation, \( P(\Delta V) \), was obtained by assigning the equation of injury index value, \( \text{Injury}(\Delta V) \), to the risk curve of severe injury (Abbreviated Injury Scale, AIS 3+), \( P(\text{Injury}) \). Equation (10) represents the risk for HIC 15 for head
AIS $3^+$ (18). Equation (11) and (12) represent the risks for the 3 ms cumulative acceleration and deflection for thorax AIS $3^+$ respectively (19). Equation (13) represents the risk for the maximum force for thigh AIS $3^+$ (20). All $P(\text{Injury})$, whose predictor is injury value of Hybrid III 50$^\text{th}$ percentile dummy, were developed based on cadaver tests and presented in the literatures respectively.

$$P = \frac{1}{[1 + \exp(3.39 + 200 \times \text{HIC} - 0.00392 \times \text{HIC})]}$$

$$P = \frac{1}{[1 + \exp(3.1493 + 0.063 \times \text{Acc}[\text{G}])]}$$

$$P = \frac{1}{[1 + \exp(3.7124 + 0.0475 \times \text{Def} \times \text{mm})]}$$

$$P = \frac{1}{[1 + \exp(4.9795 + 0.326 \times \text{Force}[\text{kN}])]}$$

The reliability of this prediction algorithm was evaluated to one real world accident. The accident was the same with one vehicle-to-vehicle crash used for the validation in Section 2.2. In the accident, it was reported that the driver, female in her fifties, suffered lung injury (AIS 3) and chest bruise (AIS 1). As mentioned in Subsection 2.2.1, we conducted an vehicle-to-deformable barrier crash experiment to reconstruct the accident and obtained vehicle acceleration. The deformation of the vehicle in the accident was successfully reconstructed in the experiment, which means that the measured $a(t)$ could resemble that in the accident. Therefore, we predicted injuries of the driver based on the $a(t)$ and compared it with the reported injuries. Based on the $a(t)$ pattern of the crash, we classified it as PL by our method in Chapter 2, and $\Delta V$ was calculated as 12.2 m/s. The probability of AIS $3^+$ occurrence is estimated by $P(\Delta V)$ of PL based on $\Delta V$ as shown in Fig. 11. To compare the predicted injury, we determined the probabilities of head, thorax, and thigh AIS $3^+$ in the crash were 0, 100, and 0% respectively. The reliability of our prediction algorithm was compared with that of URGENCY (5) for Maximum AIS (MAIS), the highest single AIS code with multiple injuries in frontal crashes. The URGENCY was developed based on NASS-CDS database from 1997 to 2007 including cases without seatbelt use and airbag deployment, and $\Delta V$ is the only predictor.

3.2.2. Results

The injury prediction equations of each crash pattern, $P(\Delta V)$, were developed by assigning the correlation of injury index value vs. $\Delta V$ into injury risk curves. As shown in Fig. 12(a), the probabilities of head AIS $3^+$ occurrence at a $\Delta V$ were different among the five crash patterns. However, when it comes to P for the other body segments’ injury, only OF and UR were different from the other crash patterns. $P(\Delta V)$ for head injury increased steeply at the range of $\Delta V$ from 20 to 25 m/s, though in case of $\Delta V$ below about 15 m/s it remained about 5%. At a $\Delta V$, $P$ for head injury of PL was highest and that of OF was lowest. $P(\Delta V)$ for thorax injury was identical among FW, OB, and PL, and that of OF showed the lowest probability. $P(\Delta V)$ for deflection based thorax injury was lower than that of acceleration based injury. $P(\Delta V)$ for thigh injury kept being lower than 1.5%.

The reliability of this prediction algorithm was evaluated to one real world accident where the crash pattern was PL and thorax AIS 3 occurred. $P(\Delta V)$ predicted the injury more closely than URGENCY (5). At $\Delta V$ of 12.2 m/s, PL lines for thorax injury were closer to 100%, and that for head injury was nearly 0% as shown in Fig. 13. $P(\Delta V)$ for thigh injury was not evaluated its reliability, since it had a very weak correlation with $\Delta V$ as shown in Fig. 12.

Fig. 12 $P(\Delta V)$ for AIS $3^+$ injuries of each crash pattern

(a) Head injury
(b) Thorax injury (acc. based)
(c) Thorax injury (def. based)
(d) Thigh (left) injury

Fig. 13 $P(\Delta V)$ of PL for AIS $3^+$ injuries and URGENCY of frontal crashes for MAIS $3^+$, and a real world accident classified as PL crash

3.2.3. Discussion

Injury prediction equations, $P(\Delta V)$, of the five crash pattern were obtained and found to have different correlations with $\Delta V$, which supported the necessity of consideration of crash pattern in injury prediction. The steep curve of $P(\Delta V)$ for head injury and very small probability of thigh injury showed that improvement of $P(\Delta V)$ were required. In other word, the simulation model, which $P(\Delta V)$ depended on, needed improvement as we discussed in Subsection 3.1. Additionally, the risk curves, which also influenced on $P(\Delta V)$, are necessary to be consider, because their own reliabilities were questioned in Ref. (19) and (21) which $P(\Delta V)$ of head injury was originally suggested.

$P(\Delta V)$ could closely predicted injury of a real world accident than URGENCY of frontal crashes, which indicated that considering the difference of crash patterns was effective. However, only one case was far from enough to evaluate the reliability. In addition to the improvement of our $P(\Delta V)$ itself, a number of real accident cases were indispensable to enhance the reliability. When vehicle acceleration is not recorded in a case, we need it in some way. In such a condition, available cases are limited to ones with good structural engagement and reconstructible in testing fields. Age and sex of drivers, which are injury factors as reported in Ref. (4), should have been considered.

We have taken a stance that the factors could be simply weighted on average driver (22).
4. Conclusions

We found characteristic relationships between vehicle acceleration and displacement at one location of vehicle in frontal crashes, and developed a method to classify a crash pattern based on vehicle acceleration by focusing on those relationships. The method successfully classified patterns of vehicle-to-barrier crashes and a vehicle-to-vehicle crash, though its accuracy is necessary to be validated in a number of cases. These findings indicate that EDR with a single acceleration sensor could provide the pattern of a frontal crash.

We also found relationships between occupant injury values and \( \Delta V \) according to crash patterns, and developed an injury prediction algorithm. The injury prediction equations of each crash pattern where \( \Delta V \) was only the parameter provided the probability of injury of each body segment. Our algorithm predicted the injury in a real world accident a little more accurately than an existing algorithm, URGENCY, though more cases are required to validate the accuracy. These findings indicate that EDR with a single acceleration sensor could predict occupant injury with consideration of crash patterns.

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