Identification of Factors Influencing Injury Severity Prediction (ISP) in Real World Accident Based on NASS-CDS

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ABSTRACT: To improve the accuracy of Injury Severity Prediction in the event of vehicle crash, a new algorithm is proposed using the US vehicle accident database (NASS-CDS). This proposed algorithm work over the base algorithm (introduced by kononen et al) in which, some of the additional variables were introduced and some of the existing variable’s classifications were modified. Results suggest that the proposed algorithm has some advantage over the base algorithm.

KEY WORDS: Safety, automatic crash notification, injury database, injury criteria, intelligent vehicle, [C1]

1. Introduction

Development of accurate injury severity prediction (ISP) algorithm for Advanced Automatic Crash Notification (AACN) system is important in reducing more number of accident deaths and as well as excessive resources. AACN is the successor of Automatic Collision Notification (ACN). Flow service of AACN was shown in Figure 1. In the event of crash, telematics systems use Event Data Recorder (EDR) data from vehicle to transmit important injury related crash information to the call center. Public Safety Answering Point (PSAP) receives information from the call center and dispatch appropriate Emergency Medical Services (EMS) to the crash location. With appropriate field triage decisions, more number of crash victim’s lives could be saved. According to CDC expert panel report (13), seriously injured crash victims who are transported to a Level 1 trauma center have, 25% decreased mortality compared to those treated at a regular hospital. Several ISP algorithms have been developed in the past (457). Algorithm proposed by Kononen, et al. is based on telematics transmission and voice communication. Variables considered are as follows, delta-V, seat belt used status, principal direction of force (PDOF), vehicle type, number of crash events (single / multiple), occupant age and gender. Collecting more and accurate crash information, which are available immediately after a crash, play an important role in improving the ISP accuracy. Kusano, et al. (5) identified that PDOF could be a misleading indicator for determining impact direction (front, left, right rear) especially over the range of 30 to 60 degrees, angular frontal–side impacts at the two front corners of the car since it may be difficult to classify directions in which group (front/side) it will belong to. Therefore, classification of impact direction from existing four main directions to six directions including two additional angular directions at the two front-end corners of vehicle may improve the accuracy of ISP. Ridella, et al. (6) described that for occupants above 65 years of age, the percentage of serious injury crashes increase gradually and this study try to evaluate that parameter for improving AACN prediction accuracy. Bahouth, et al. (9) showed that the number of crash events and order of occurrence of those events influences the degree of injury. Again, this information could enhance the degree of accuracy for the ISP algorithm. Gabriel et al. (10) analyzed model year effect (1994-2007) on occurrence of severe injuries and concluded that the mortality rate of front seat occupant have decreased for newer vehicles compare to older vehicles.

Many researchers have used interaction terms in bio-statistical models; however fewer applications in the serious injury risk prediction models. In this study, interaction terms are evaluated for accuracy improvement. Significance of interaction terms are
2. Data and Methods

2.1. Approach

Kononen et al. developed an algorithm to predict the occurrence of minor/serious injury during vehicle crash. This published algorithm is open and can be used for further modification. It will be referred as “public algorithm” corresponding to the “base model” in the following sections of this paper. The objective of this study is to improve the prediction accuracy of this base ISP algorithm. This study focused on the following two aspects to improve the accuracy of ISP algorithm
1. Better classification of existing variables
2. Introduction of new additional variables

2.2. Case Selection

In the present analysis, National Automotive Sampling System (NASS-CDS) accident data from calendar year (CY) 2009-2013 is used. The selection criteria for those accident cases are tabulated in Table 1. Incomplete accident cases with unknown values for critical parameters (say: Delta-V, Vehicle curb weight, age, gender, belt status, Model year, etc.) are not considered for this study. Since the crash behavior of heavy vehicles (Curb weight >4,500 kg) will be very much different from the passenger vehicles, they are not considered for this study. Since the crash behavior of heavy vehicles (Curb weight >4,500 kg) will be very much different from the passenger vehicles, they are not considered for this study. The accident samples are limited to planar collisions (i.e., excluding rollovers and the rare crashes coded with the primary general area of damage as top or bottom). In the present study,
1. CY 2009-12: Accident cases are considered for variable sensitivity study and for building logistic model
2. CY 2013: Accident cases are chosen only for verification. They are not used in building logistic model

| Variable name          | Classification                        | Type   |
|------------------------|---------------------------------------|--------|
| Delta V (mph)          | -                                     | continuous |
| Impact direction       | (front, right, left, rear)            | categorical |
| Vehicle type           | (car, suv, van, pickup)               | categorical |
| Belt use               | Yes or No                             | binary  |
| Multiple event         | Yes or No                             | binary  |
| Gender                 | Male or Female                        | binary  |
| Age                    | >55 or <55 years                      | binary  |

This study attempts to improve the ISP accuracy by modifying some of the variable’s classification as shown in Table 3 and by introducing new variables as shown in Table 4. Justification for the modification and addition of new variables are discussed in the results section.

Table 1. List of filters/constraints used to prepare input dataset

| No. | Description                                      |
|-----|--------------------------------------------------|
| 1   | Unknown Delta-V removed                          |
| 2   | Model Year <2000 removed                         |
| 3   | Vehicle Curb weight >4,500 kg removed            |
| 4   | Crashes coded with the primary general area of damage as top or bottom and rollovers removed |
| 5   | Unknown age, gender, or belt status removed      |
| 6   | ISS=0, MAIS=0 & 7 cases with no injury or unknown injury severity, are removed |
| 7   | No Imputations                                   |

Table 2. Seven variables considered by Base Model

Table 3. Variable’s classification modification in Proposed Model

Table 4. Five new variables introduced in Proposed Model

2.3. Variable selection

This study uses the findings of the base model (Kononen et al.) and tries to explore the possibility of improving it. Variables proposed by the base model for prediction of minor/serious injuries are tabulated in Table 2.

2.4. Logistic regression method

Logistic regression is one of the most popular mathematical modelling techniques used to find the relationship of independent variable to a dichotomous dependent variable. As shown in Figure 2, logistic function z represents the summation of independent variables and they can vary from \(-\infty\) to \(\infty\). Output variable f(z) varies from 0 to 1. In this analysis, ISS (Injury Severity Score) considered as dichotomous variable. If the injury severity score falls in the range of 1-6, it considered as minor injury (MAIS=1) and if the ISS >6, it considered as serious injury (MAIS=5). The injury severity score is divided into three categories: (i) ISS=0 to 1, (ii) ISS=2 to 4 and (iii) ISS=5 to 6. The relationship between the independent variable and the binary dependent variable is given by the logistic function z as follows:

\[ z = \frac{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)}} \]

where \(\beta_0, \beta_1, \ldots, \beta_k\) are the coefficients to be estimated, and \(X_1, X_2, \ldots, X_k\) are the independent variables.
level for any one of the occupants within the accident vehicle under consideration has ISS>15, it is considered as serious injury; otherwise it will be judged as minor injury. In terms of probability, CDC panel recommends probability limit greater than 0.2 as a cut off value for serious injury.

![Logistic Function](image)

**Fig. 2** Logistic Function

### 3. Results

This section tries to explain about the justification aspects for variable classification modification and new variable addition. Accident analysis was carried out using NASS CDS data and explained the effect of proposed variables on serious injury. All logistic regression calculations are performed by XLSTAT\(^{(1)}\). All decisions on injury severity (ISS>15) are based on vehicle level. For example, if any one of the occupants within the vehicle incurs serious injury it will be considered as a seriously injured case.

#### 3.1. Accident Analysis Results

Detailed accident analysis has been carried out and each predictor variable effect on serious injury occurrence has been discussed in detail in following sections.

##### 3.1.1 Impact direction (4 to 6 PDOF classifications)

Direction of impact is an important variable in identifying injury probability. According to base model, impact direction’s classifications are as follows: left, right, front and rear. Classification of front-side impact directions might increase the chance of identifying minor/serious crash occurrence. Hence, there is a possibility of intermediate levels between front and side impact directions as shown in Figure 2. Based on accident analysis study, PDOF is classified into six directions and corresponding angles are shown in Table 5.

![Schematic diagram of angle of impact](image)

**Fig. 3** Schematic diagram of angle of impact

#### Table 5. Impact direction determination from PDOF

| PDOF (angle of impact) | Base algorithm (deg.) | Proposed algorithm (deg.) |
|------------------------|-----------------------|---------------------------|
| Front                  | -45 ~ 45              | -25 ~ 25                  |
| Front-left             | -                     | -55 ~ -25                 |
| Left                   | -135 ~ -45            | -160 ~ -55                |
| Rear                   | -135 ~ 135            | 160 ~ 180                 |
| Front-right            | -                     | 25 ~ 55                   |
| Right                  | 45 ~ 135              | 55 ~ 160                  |

##### 3.1.2 Age of occupants (2 to 3 age classifications)

Figure 3 shows the percentage of serious injury in the older occupants starting from age>55 years. It shows (a) the percentage of serious crashes (ISS>15) remains almost constant in the age range between 55 and 65 years, and (b) it increases gradually above 65 years and this is on par with the previous studies mentioned in the introduction section. At present, after the crash age information may or may not be obtained via voice communication with the TSP call centers.

![Percentage of ISS>15 serious crashes involving older age group >55 years](image)

**Fig. 4** Percentage of ISS>15 serious crashes involving older age group >55 years.

##### 3.1.3 No. of crash events (2 to 3 event classifications)

Percentage of accidents with seriously injured occupants, are plotted for single and multi-crash events as shown in Figure 4(a). Results show that the percentage of accidents with seriously injured occupants increased sharply moving from single to multi-event. As mentioned in the introduction section, number of events influences the degree of injury. Hence, this study tried to explore the possibility of one more level between them and the results are plotted in Figure 4(b). Results show that, percentage of accidents with seriously injured occupants is different for 2 & 3+ crash events.
3.1.4. Model Year (MY)

Figure 5 shows the percentage distribution of serious accidents (ISS>15) versus MY distribution. It is clear that newer-MY vehicles are likely to be safer than those of older-MY vehicles. New vehicles performance has been increased significantly over last decade. Road traffic safety rules and regulations imposed on vehicles result in reducing more number of accident deaths.

3.1.5 Time of Crash

Figure 6 shows the time of crash histogram chart for serious accidents. It shows that percentage of serious accidents during 0-6AM is almost double than that of any other time span. Further, analysis was carried out to clarify the inherent facts and characteristics in such late night crashes. Referring to Figures 7-9, “0-6AM” period has, (a) the average delta-V of the crashes were not high compared to those occurred in other time span (b) comparatively less braking operation, and (c) comparatively more skidding behavior. Cases of (b) and (c) may occur due to less visibility at night. Less braking combined with more skidding, will lead to more out-of-position occupants. There may be other factors for the occurrence of high level of injury (ISS>15), namely presence of alcohol, drowsiness, etc. Hence, to categorize minor/serious injuries, time can be treated as a representative variable for those causes.
3.1.6 Near Side Presence

In case of frontal impact, the front passengers will be near-side occupants and rear passengers will be treated as far-side occupants. Similarly, for right side impact, all passengers on the left (including the driver) will be counted as far-side occupant and vice versa for left side impact. In general, more number of severe injuries is expected on the near-side occupant due to direct contact.

3.1.7 Number of impacts x unbelted status

As mentioned in the section 3.1.3, as the number of impacts increases, the probability of serious injury increases. This section tries to explore the sensitivity of belted status & multi-impact with the serious injury occurrence. Figure 10 shows the percentage of serious accidents with belted status and multi-impact combinations. Results suggest that unbelted occupants during multi-impact will suffer more severe injury than other combinations.

3.1.8 Relative location (near-side/far-side) x belt status

In general, far-side occupants are less injured than near side occupants and belted occupants are comparatively safer than unbelted ones. Therefore, inclusion of the coupling effects of these two conditions will most likely lead to better separation of serious/minor injury classification. Figure 11 show that, nearside - unbelted occupants have greatest risk of sustaining serious injury.

3.2 Logistic Regression Results

Based on accident analysis results, all the above-mentioned variables are used in building logistic regression model. In this section, base and proposed logistic models are presented with their respective sensitivity, specificity, ROC (Receiver Operating Characteristic) and false cases, for both weighted and un-weighted data. For binary variables, dummy variable “0” taken as reference. For finding the statistical significance, p < 0.05 is used. Finally, the results of the proposed model are compared with the base model.

3.2.1 Base Model Logistic regression

Table 6. Results of logistic regression (Base model)

| Base Model, n=4211, 2009-2012 | Value | Pr. > Chi² | Odds ratio (95% Conf. Int) |
|-------------------------------|-------|------------|--------------------------|
| Intercept                     | 11.792| < 0.0001   | 20.09 (14.86, 27.14)     |
| Ln Delta-V                    | 3.000 | < 0.0001   | Reference                |
| Rear                          | 0.000 | reference  |                          |
| Left                          | 1.765 | < 0.0001   | 5.843 (2.97, 11.49)      |
| Front                         | 0.612 | 0.053      | 1.845 (0.99, 3.43)       |
| Right                         | 1.358 | 0.000      | 3.890 (1.93, 7.82)       |
| Any one of the occupants unbelted | 0.000 | reference  |                          |
| All occupant belted           | -1.180| < 0.0001   | 0.307 (0.23, 0.40)       |
| Car                           | 0.000 | reference  |                          |
| Pickup                        | -0.213| 0.394      | 0.808 (0.49,1.32)        |
| Utility                       | -0.436| 0.013      | 0.646 (0.45,0.91)        |
| Van                           | -0.028| 0.932      | 0.972 (0.51,1.85)        |
| Single event                  | 0.000 | reference  |                          |
| Multiple Events               | 0.575 | < 0.0001   | 1.776 (1.37,2.29)        |
| All the occupants Age<55     | 0.000 | reference  |                          |
| If Any one of occupant Age>=55| 0.966 | < 0.0001   | 2.627 (1.99,3.46)        |
| No female present             | 0.000 | reference  |                          |
| If any female Present         | 0.078 | 0.552      | 1.081 (0.83,1.4)         |

With un-weighted data, logistic regression for base variables was performed and the results are tabulated in Table 6. Note that in Table 6, vehicle type and gender are not significant but they were kept in the model to improve the curve fitting as mentioned in Kononen’s study. The characteristic values like sensitivity, specificity, ROC and false cases values are as follows: 59.12%, 92.03%, 0.871 and 455 respectively, are shown in Table 8.

3.2.2 Proposed model logistic regression

With un-weighted data, logistic regression was performed for new variables, modified variables, together with base variables and the results are tabulated in Table 7. Sometimes an original base variable may not continue as a significant variable when it is included in the full model, which includes interaction terms...
related to it. In proposed model, not all variables are statistically significant. However, they are kept in model based on the principle of hierarchy, which requires all lower order components of the significant product terms to remain in all further higher models in the hierarchy.

It is clear that from Table 7, all interaction terms used in this analysis are statistically significant and they contributed to improve the fitting of the curve. For proposed algorithm, model characteristics are i) sensitivity=62.39%, ii) specificity=92.63%, iii) ROC=0.884 and iv) false cases=421, as shown in Table 8. By comparing the results of the proposed and base models, one can observe improvements in its characteristic values such as sensitivity, specificity, ROC and false cases values. Even a small change in accuracy of prediction can significantly affects the identification of serious and minor injury occurrence. This can be useful in saving more number of vehicle crash victims. Hence, it is very important to improve the prediction accuracy of ISP algorithm.

Table 7. Results of logistic regression (Proposed model)

| Proposed Model, n=4211, 2009-12 | Value   | Pr. > Chi² | Odds ratio (95% Conf. Int) |
|----------------------------------|---------|------------|----------------------------|
| Intercept                        | -12.380 | -          | -                          |
| LN Delta-V                       | 3.041   | < 0.0001   | 20.92 (15.2,28.6)           |
| Model Year (MY)                  | -0.108  | < 0.0001   | 0.898 (0.85,0.93)           |
| Age Modified                     | 1.055   | < 0.0001   | 2.872 (2.20,3.73)           |
| Rear                             | 0.000   |            | reference                   |
| Left                             | 1.277   | 0.004      | 3.587 (1.50,8.54)           |
| Front-left                       | 0.472   | 0.303      | 1.603 (0.65,3.93)           |
| Front                            | 0.003   | 0.994      | 1.003 (0.44,2.26)           |
| Front-right                      | 1.475   | 0.000      | 4.372 (1.97,9.67)           |
| right                            | 0.496   | 0.258      | 1.643 (0.69,3.88)           |
| Any one of the occupants unbelted| 0.000   |            | reference                   |
| All occupants belted             | -1.721  | 0.000      | 0.179 (0.07,0.44)           |
| Car                              | 0.000   |            | reference                   |
| Pickup                           | -0.298  | 0.250      | 0.743 (0.44,1.23)           |
| Utility                          | -0.449  | 0.012      | 0.638 (0.44,0.90)           |
| Van                              | -0.176  | 0.603      | 0.839 (0.43,1.62)           |
| Single Event                     | 0.000   |            | reference                   |
| Multi-impact 2 Events           | 0.206   | 0.257      | 1.228 (0.86,1.75)           |
| Multi-impact 3+                  | 0.531   | 0.005      | 1.700 (1.17,2.45)           |
| No female Present                | 0.000   |            | reference                   |
| If any female Present            | 0.116   | 0.393      | 1.122 (0.86,1.46)           |
| Time of accident (6-24hr)        | 0.000   |            | reference                   |
| Time of accident (0-6hr)         | 0.530   | 0.003      | 1.698 (1.22,2.4)            |
| None of them Present nearside    | 0.000   |            | reference                   |
| If anyone Present nearside       | 1.107   | 0.001      | 3.026 (1.54,5.94)           |
| In case of Multi-impact, if anyone unbelted | 0.000 |            | reference                   |
| In case of Multi-impact, all occ. belted | 0.593 | 0.033      | 1.809 (1.05,3.11)           |
| Presence of Nearside occupant unbelted | 0.000 |            | reference                   |
| Presence of Nearside occupant belted | -1.039 | 0.019      | 2.827 (1.18,6.75)           |

Table 8. Results of weighted/ un-weighted logistic regression for base and proposed model

| Model | Characteristics       | without weight n=4211 | weight <3000 n=4188 | weight T<4000 n=4198 | weight <5000 n=4204 |
|-------|-----------------------|------------------------|----------------------|----------------------|----------------------|
| Base  | False cases           | 455                    | 363                  | 367                  | 368                  |
|       | Sensitivity           | 59.128                 | 35.42                | 34.60                | 34.60                |
|       | Specificity           | 92.06                  | 96.70                | 96.60                | 96.66                |
| Proposed | False cases   | 421                    | 350                  | 348                  | 347                  |
|       | Sensitivity           | 62.39                  | 41.41                | 41.68                | 41.68                |
|       | Specificity           | 92.63                  | 96.46                | 96.50                | 96.53                |

3.2.3 Logistic regression with weighting factors (RATWGT-ratio inflation factor)

This section explains the effect of weighting factor / ratio inflation factors on logistic model. Figure 13 shows the distribution of weighting factors for the dataset NASS-CDS CY 2009-12 (n=4211). It is obvious from Figure 13 that most of the data with weighting factors below 2000 leads to a cumulative percentage of more than 99%. Hence, in order to find out the
effect of weightage for the present set of NASS-CDS data different level of weighting factors were selected including the original data without weightage. Weighted logistic regression analysis was carried out for the base and proposed model. Their model characteristics are shown in Table 8. By comparing weighted and un-weighted estimations from Table 8, following points are common for both base and proposed models: 1) false cases are less for weighted estimations, 2) Sensitivity is more for un-weighted estimations. 3) Specificity is more for weighted estimations. By comparing base and proposed models from Table 8, following points are common for both weighted and un-weighted estimations: 1) false cases are less for proposed models, 2) sensitivity is more for proposed models and 3) specificity variation appears to be same.

3.2.4. Performance verification (CY2013 data)

The present algorithm was verified by 2013 NASS-CDS database. There were total 758 vehicle (after filter) crashes. When predicted by the base model, there were 98 false cases. The proposed model false cases came down to 88 and the overall false case reduction is 10.2%. However, when weighted logistic regression prediction equation (corresponding to RATWGT<5000) is used, it has still lowered to 76 false cases.

Table 9. Verification results for CY2013

| For CY 2013: n=758 | Un-weighted | Weighted RATWGT<5000 |
|--------------------|-------------|----------------------|
| False cases        | 88          | 76                   |
| Sensitivity        | 50%         | 33%                  |
| Specificity        | 92%         | 96%                  |

It is clear from Table 9 that 1) False cases are less for weighted estimations 2) Sensitivity is more for un-weighted estimations 3) Specificity is more for weighted estimations.

4. Discussion and future works

Logistic regression analysis was carried out for the above-mentioned dataset (n=4211, 2009-12) with “proposed variables" and “airbag deployed" status as an additional injury predictor. Results shows that “airbag deployed" is not statistically significant (p=0.165 for un-weighted, p=0.44 for weighted) and number of false cases has increased slightly. Though airbag has proven capability to reduce injury severity, it was not a significant parameter in ISP algorithm. This phenomenon may occur due to airbag deployment issues under certain conditions (multi-impact, non-standard impact, high-speed impact, etc.) and could be due to inclusion far-side occupants. The present ISP algorithm focuses on “any serious injured occupant within the whole vehicle”. Hence, “airbag deployed" parameter was not omitted for this present study. Airbag deployment could be very effective over certain range of impact conditions and directions. Hence, there is lot of scope for ISP algorithm improvement by treating different range of impact conditions separately rather than a single global ISP algorithm. It will be addressed in our future studies.

5. Summary and Conclusion

Modifications are proposed to improve the accuracy of the ISP algorithm for AACN system using NASS CDS 2009-12 database. Algorithm based on Kononen’s variable is the starting or base model for the present modification study. The summary of the present study is as follows:

- Proposed model with five new and three modified variables is effective in improving the accuracy of ISP.
- Weighted logistic regression model will reduce more number of false cases compared to that of the un-weighted model.
- The developed algorithm and its efficacy are verified with CY2013 data.
- Still there is possibility for further improvements to enhance the accuracy and the robustness of the proposed prediction model by adding more crash information, which are available instantly.

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