Factors Influencing Specificity and Sensitivity of Injury Severity Prediction (ISP) Algorithm for AACN

Chinmoy Pal 1) Tomosaburo Okabe 2) Vimalathithan Kulothungan 3)
Narahari Sangolla 4) Jeyabharath Manoharan 5) Wang Stewart 6) John Combest 7)

1)-2) NISSAN Motor Co. 1-1 Aoyama, Morinosato, Atsugi, Kanagawa, Japan (E-mail: c-pal@mail.nissan.co.jp)
3)-5) Renault Nissan Technology Business Center, Chennai, TN, India
6) University of Michigan, International Center for Automotive Medicine, Michigan, USA
7) Nissan Technical Center North America, Farmington Hills, Michigan, USA

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ABSTRACT: To improve the accuracy of Injury Severity Prediction in the event of vehicle crash, a new methodology is proposed using the US vehicle accident database (NASS-CDS). This proposed method is an extension of the base algorithm introduced by Kononen et al. in which, some of the additional variables were introduced and branched logistic regression methodology was used. Results suggest that the proposed branching method has some advantage over the base algorithm due to better linearization of the complex multidimensional non-linear relationship of the input and output variables.

KEY WORDS: Safety, AACN, Crash, Injury Severity Prediction Algorithm, Accident Analysis, Branching Logistic Regression,

1. Introduction

Advanced Automatic Crash Notification (AACN) system can predict the serious injury probability for the occupants during an event of crash. Hence, this system assists in arranging appropriate mode of transport for the crash victims to the suitable hospital. MacKenzie et al. (13) found that death risk could be lowered by 25% for seriously injured occupants, if they are treated in Level 1 trauma center. Over-triage cause unnecessary expenditure and resources in the trauma system but under-triage are life threatening. Efficiency of the AACN system depends on the accuracy of injury severity prediction (ISP) algorithm. Several ISP algorithms have been developed in the past (4,7,12). Kononen et al. (4) ISP algorithm uses both telematics transmission and voice communication for its prediction. This study tries to use the findings of Kononen et al. and investigate the possibility of improvement.

Occupant height and weight may have some influence on the injuries. Mock et al. (2) identified that increase in occupant weight is associated with increase in mortality during automotive crashes. Pal et al. (15) identified that, occupant weight is an influential parameter for lower extremity injuries and occupant height is a significant parameter for thorax and head injuries during side impact. Adrian Lund (5) found that, occupants of lighter vehicles have more death rate than heavier vehicles. Chen et al. (6) found that Vehicle weight, footprint, and height have more important role in injury risk (particularly fatality risk) for one-vehicle crashes than in two-vehicle crashes. They have also concluded that occupants of heavier, larger-footprint and shorter vehicles may sustain less injury for one-vehicle crashes. Peter Cummings et al. (9) found that death risk is less for drivers with airbag, in comparison with drivers without airbag. According to NHTSA report (10), airbag effectiveness will be high for cases with pure frontal crashes (12’o clock) and less for cases with partial frontal crashes (10’o clock to 2’o clock, excluding 12’o clock). Craig (11) found that airbag effectiveness to reduce injuries differs with occupant height and injury probability may increase with occupant height. ΔV is one of the most influential parameter of ISP algorithm. Kononen et. al used the natural logarithm of the total ΔV and not much detail studies were carried out to capture the influence of ΔV combination on ISP accuracy. This study tries to investigate the possibility of introducing the above variables for ISP algorithm.

Logistic regression methodology was currently used to predict the serious injury probability based on available crash variables (by telematics transmission) and occupant details (by voice communication). Popular methods available for binary output responses are decision tree, logistic regression, etc. Logistic model tree concept comes from the idea of combining decision tree and logistic regression. Logistic model tree approach is a compact classifier with good accuracy (3). Ameen Abu-Hanna et al. (14) developed a hybrid model using local logistic regression model for different sub groups, which provides more data insights and better performance compared to traditional global logistic regression model. Hence, it is necessary to investigate the possibility of ISP algorithm accuracy improvement through local logistic regression for specific branches of dataset.

In the present analysis, NASS-CDS dataset (8) with calendar year 2005-12 was used to carry out logistic regression analysis. The main objectives of this study are (a) to highlight the effect of additional variables, (b) to choose the best-fit model for the most influential combination for ΔV, (c) to study the effect of logistic tree models on sensitivity and specificity (refer appendix).
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 modifications. It will be referred as “public algorithm” corresponding to the “base model” in the following sections of this paper. This study focused on improving the accuracy of ISP algorithm by adding new variables and by using logistic tree regression methodology. This study uses the base model findings 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 1.

Table 1. Seven variables considered by Base Model (BM)

| Variable name      | Classification | Type       |
|--------------------|----------------|------------|
| ΔV (Kmph)          |                | Continuous |
| Impact direction   | (front, right, left, rear*) | Categorical |
| Vehicle type       | (car/PV*, 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     |

*Reference dummy in logistic regression

This study tries to improve the accuracy of ISP algorithm by adding new variables tabulated in Table 2 for the proposed model (PM). It also focuses on improvement through logistic tree methodology by splitting the full dataset into different branches of subset as stated in Table 3.

Table 2. New variables for Proposed Model (PM)

| Variable name          | Classification | Type       |
|------------------------|----------------|------------|
| Wheel-base             |                | Continuous |
| Vehicle curb weight    | <110kg* or >=110 kg | Binary     |
| Airbag deployment      | Yes or No*     | Binary     |
| Occupant-height        | <180 cm* or >=180 cm | Binary     |

*Reference dummy in logistic regression

Table 3. Dataset branching strategy in proposed model (PM)

| Branch | Dataset branching criteria |
|--------|---------------------------|
| 1      | No of events : Single & Multi |
| 2      | Occupant age: <55 & >55 |
| 3      | Vehicle type : Cars & other vehicle type |
| 4      | Impact direction (Front & Right) |

2.2. Case Selection Criteria

In the present analysis, National Automotive Sampling System Crashworthiness Data System (NASS-CDS) accident data from calendar year (CY 2005-12) is used. The selection criteria for those accident cases are tabulated in Table 4. Accident cases with unknown values for critical parameters are not considered for this study. Since the crash behavior of heavy vehicles (Curb weight>4500 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).

Table 4. List of filters/constraints for input dataset

| 1 | Unknown ΔV removed |
| 2 | Model year < 2000 removed |
| 3 | Vehicle curb weight >4,500 kg removed |
| 4 | Area of damage: top/ bottom and rollovers removed |
| 5 | Unknown age, gender, or belt status removed |
| 6 | ISS=0, MAIS=0 & 7 cases, are removed |
| 7 | No Imputations |

Presence of driver alone cases within the NASS-CDS dataset is shown in Figure 1. According to which, 71% of vehicles within our selected dataset have only drivers. If this occupant information is available through belt signals, or occupant detection sensors, or voice communication, it may serve as vital information for ISP algorithm improvement. This study focus on those cases with vehicles having only drivers.

Fig 1. Percentage of driver alone accidents for different impact directions (front, side and rear)
3.1.1 Airbag Deployment

Airbag deployment event is not that significant for full dataset through logistic prediction using variables in Table 1 & Table 2, even though the A/Bag deployment event is one of the activation processes for AACN. Airbag has proven capability to reduce injuries in vehicle tests; hence, it is worth investigating the effect of air bag. Airbag may be effective in protecting occupants in certain range of velocity as shown in Figure 2.

| ΔV range | A/B deployed cases | A/B not deployed cases |
|----------|--------------------|------------------------|
| 3-17     | 674                | 572                    |
| 18-32    | 1473               | 525                    |
| 33-47    | 564                | 104                    |
| 48-62    | 199                | 41                     |
| >63      | 107                | 20                     |

Fig 2. Change in percentage of serious accidents for A/bag deployed and not deployed with respect to ΔV

3.1.2 Wheel base and vehicle curb weight

Figure 3 and Figure 4, shows the change of serious injury (ISS>15) percentage with respect to wheelbase and vehicle curb weight for frontal and side impact respectively. Percentage of serious injuries decreases with increase in wheelbase and curb-weight. In general longer wheelbase vehicles are likely to have more crush length and high curb weight, which in-turn will protect them from both frontal and side impacts.

3.1.3 Occupant Height and Weight

Figure 5 and Figure 6, shows the change of serious injury percentage with respect to two groups of driver heights (<180cm and >180cm) and weights (<110kg and >110kg) for frontal dataset. They indicate that, very large drivers above standard AM50 dummy specifications may be influential for the increase of serious injuries ISS>15 in frontal impacts.

3.2 Base model (BM)

Table 5 shows the logistic results of specificity, sensitivity and the total number of false cases for base model using variables in Table 1. It is to be noted that the specificity is very high (96.27%) and the sensitivity is comparatively low (35.22%). Base model’s result break-up for front, side and rear driver alone are shown in Table 5. It shows that sensitivity is quite high (56.68%) for side impact crashes compared to frontal crashes (26.18%).

To save more number of seriously injured occupants, this study investigated the possibility of improvement in sensitivity without sacrificing specificity in the following sections where a couple of new variables, as discussed above, are added to the base model with branching logistic regression.
Table 5. Base Model Characteristics

| Models                      | Sensitivity (%) | Specificity (%) | False cases |
|-----------------------------|-----------------|-----------------|-------------|
| Base Model (n=8642)         | 35.22           | 96.27           | 841         |
| Frontal driver alone (n=4283) | 26.18           | 97.40           | 337         |
| Side driver alone (n=1319)  | 56.68           | 91.34           | 179         |
| Rear driver alone (n=509)   | 0               | 100             | 11          |

3.3 Proposed model (PM)

This model uses the base model variables (Table 1) plus those new variables from Table 2 (frontal impact: wheelbase and side impact: curb weight). For this study, driver-alone present dataset was chosen, which covers 71% of overall dataset as shown in Figure. 1. Individually logistic regression analysis was carried out for front, side and rear driver-only datasets and the results are tabulated in Table 6. It was observed that, velocity terms “longitudinal component of ΔV (V1) and lateral component of ΔV (V2)” was more effective in frontal driver-alone dataset, (ΔV^{2.5}) was found to be effective in side driver-alone dataset and (ΔV^2) was significant for rear driver-alone datasets. Comparing Table 5 and Table 6, the proposed model exhibits,

- Considerable improvement for frontal impact cases
- No improvement for side impact cases
- Marginal improvement for rear impact cases

Table 6. Proposed Model Characteristics for driver alone cases

| Driver alone dataset | Sensitivity (%) | Specificity (%) | False cases |
|----------------------|-----------------|-----------------|-------------|
| Frontal cases (n=4283) | 26.50           | 98.06           | 310         |
| Side cases (n=1319)   | 54.55           | 92.31           | 172         |
| Rear cases (n=509)    | 36.36           | 99.00           | 12          |

3.4 Tree type logistic regression

In this section, dataset was split into different sub-segments based on criteria mentioned in Table 3 and individual logistic model was built for those sub-segments using the variables of the proposed model.

3.4.1 Logistic tree for frontal driver alone cases

Frontal driver alone dataset was split based on number of impact events (single & multi) and logistic regression was carried out for those subsets individually. For better understanding, results of single and multi-impact datasets are merged together for tracking the overall improvement as shown in Fig. 7.
Fig 9. Logistic branch: Vehicle type (frontal driver alone cases)

It was observed, that the velocity terms “square of longitudinal component of ΔV (V1²)” and lateral component of ΔV (V2²)” are effective for single impact event and “longitudinal component of ΔV (V1)” and lateral component of ΔV (V2)” are significant for multi crash event. Overall, the sensitivity increases (26.05% to 29.02%) without affecting specificity (98.06% to 98.08%) as shown in Figure 7. The significance and coefficients of variables changes with the dataset branching type.

Similarly frontal driver alone dataset was split based on occupant age (<55 & >55) and vehicle type (cars & other vehicle types), the results are shown in Figure 8 and Figure 9 respectively. It was observed that the overall sensitivity could be increased from 26.50% to 30.6% through age based logistic branch (as shown in Figure 8). Overall sensitivity could be increased from 26.50% to 31.86% through vehicle type logistic branch methodology (as shown in Figure 9). It is observed that, velocity terms “V1 & V2 combinations” may be effective for frontal driver alone conditions.

3.4.2 Logistic tree for Side driver alone cases

Side driver alone dataset was split based on number of impact events (single & multi) and logistic regression analysis was carried out for those two subsets. For better understanding, the results of single and multi-impact datasets are merged together for measuring the overall improvement as shown in Figure 10.
It was observed, that the velocity terms “natural log of ΔV (LnΔV)” is effective for single impact event and “square root of ΔV (ΔV^0.5)” is significant for multi crash event. As shown in Figure 10, sensitivity increases (54.55% to 61.50%) with marginal decrease in specificity (92.31% to 91.34%). Contribution level of variables and velocity transformation change with different branches of dataset.

Similarly side driver alone dataset was split based on impact direction (Left and Right) and vehicle type (cars and other vehicle types); the results are shown in Figure 11 and Figure 12 respectively. It was observed that the overall sensitivity could be increased from 54.55% to 63.10% through impact-direction based logistic branch as shown in Figure 11. Overall sensitivity increased from 54.55% to 59.36% through vehicle type logistic branch methodology as shown in Figure 12. It is observed that, velocity term “ΔV combinations” may be effective for side driver alone conditions.

4. Discussion

4.1 Variable contribution

Variable contribution may differ under different conditions. From Figure 2, it is clear that airbag may be effective in reducing injuries within the velocity range of 30 to 65 kmph. Logistic results for branched frontal driver alone datasets are tabulated in Table 7 and it is observed that the airbag is significant for Vel > 30kmph. However, airbag was not effective if we consider the whole dataset with full range of velocity. It is also evident from Table 7, that wheelbase, vehicle type, crash events, occupant weight will be effective under certain conditions. Significance level of “Belted status” also changes under different conditions. Kononen et al. have not considered roll over cases, vehicles with curb weight >4500 kg and model year <2000 in their study. Hence, if the whole dataset is branched in an appropriate rational way, there may be opportunity for improvement in ISP estimations.

Table 7. Logistic results p-value for variables in frontal driver alone cases

| Velocity terms | Vel < 30kmph | Vel > 30kmph | Age <55yrs | Age >55yrs |
|----------------|--------------|--------------|------------|------------|
| Original Wheelbase | 0.80         | 0.04         | 0.00       | 0.54       |
| Belted status (Yes or No*) | <0.0001     | <0.0001      | 0.03       |
| Vehicle type (car/PV*, suv, van, pickup) | 0.82         | 0.05         | 0.01       | 0.16       |
| Multi event (Yes or No*) | 0.01           | 0.19         | 0.00       | 0.86       |
| Gender (Male* or Female) | 0.99         | 0.64         | 0.67       | 0.99       |
| Age (>55* or <55 ) years | <0.0001     | 0.02         | NA         | NA         |
| Height (<180* or >=180) cm | 0.66         | 0.38         | 0.81       | 0.29       |
| Weight (<110* or >=110) kg | 0.18         | 0.07         | 0.22       | 0.08       |
| Airbag deployed (Yes or No*) | 0.33         | 0.05         | 0.19       | 0.01       |

(Green: significant (P<0.05) & yellow: likely significant (P between 0.05 to 0.1))

*Reference dummy in logistic regression

5. Summary and Conclusion

A comprehensive analysis is carried out to identify the factors influencing specificity and sensitivity using NASS CDS (2005-12) database. Algorithm based on Kononen’s variable is the starting point for the present study. Summary of the present study is as follows:

(a) New predictor variables such as wheel-base/curb-weight, airbag deployment status, height and weight of the driver may have some influence on ISP assessment.

(b) The influence and contribution of variables will change in different branches of dataset. One should make a note of the fact that the percentages of improvement may change with different types of sample or similar accident database of other countries.

(c) Change in velocity terms “ΔV1 (longitudinal-component)” and “ΔV2 (lateral-components)” combinations appears to have more influence for frontal dataset and “total ΔV” combination may have more influence for side impacts.
(d) Six different branched logistic regression equations are proposed. Branching algorithm for driver-alone dataset may improve the accuracy of the algorithm of injury severity prediction.

**Appendix**

**A-1. Specificity and Sensitivity**

![Fig A1. Logistic Function and cut-off probability p.](image)

Specificity and sensitivity are the two different popular quantitative measures for clinical triage. As shown in Fig. A1, a case is considered serious (positive) depending on a predefined cut-off probability value\(^{(6)}\). CDC expert panel recommended ISS=15 (with \(p=0.2\)) as the cut-off value for injury classification. Identification of “all minor cases as minor” and “all serious cases as serious” is not always being possible in reality. There will be a tradeoff between the correct and wrong predictions. Therefore, sensitivity and specificity are the two statistical indicators in medical field normally used to define the accuracy of a model prediction. Ideally speaking, these two indicators should be as high as possible (close to 100%) in order to achieve good prediction accuracy. Table A1 shows the injury classification along with the definitions of sensitivity and specificity as defined in Table A2.

**Table A1. Classification table of injury**

| Injury | Predicted |
|--------|-----------|
| ISS<15 (Minor) | A |
| ISS>15 (Serious) | B |

| Actual | Predicted |
|--------|-----------|
| ISS<15 (Minor) | A |
| ISS>15 (Serious) | B |

**Table A2. Definition of specificity and sensitivity**

| Specification | \(A/(A+B)\) | \(D/(C+D)\) | \(B+C\) |
|---------------|---------------|---------------|------------|
| Ratio of minor injury cases correctly identified as minor | | | Total no. of wrongly identified cases (should be as low as possible) |
| Ratio of serious injury cases correctly identified as serious | | | |
| No. of False cases /Mis firing | | | |

A-2. Over-triage and Under-triage

Over-triage “B” occurs when a minor injury case predicts as serious injury. Minor injured occupant will be taken to a high-level trauma center for better treatment. This leads to unnecessary costly and high-level of care for minor injury cases. It is waste of resource and money. Under-triage “C” occurs when a serious injury case predicts as minor injury and they will be treated at a low-level trauma center. The required treatment for serious injured case may not be available in low-level trauma center, so the chance of mortality increases. The over-triage and under-triage cases must be as kept small as possible. Injury trauma researchers need to develop a good logistic prediction model, with low rates of over-triage and under-triage, simultaneously. In other words, the prediction model should have both high levels of sensitivity and specificity values.

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