Development of a Pedestrian Injury Prediction Model for Potential Use in an Advanced Automated Crash Notification System

Giulio Ponte[a], Tetsuya Nishimoto[b]

[a]Centre for Automotive Safety Research, The University of Adelaide, Australia [b]Biomechanics Research Unit, College of Engineering, Nihon University, Japan

Abstract

Advanced Automated Crash Notification (AACN) systems can inform emergency services of a serious road crash with minimal delay, giving the precise location of the crash, and transmitting key information from the vehicle's event data recorder, including: the crashed vehicle's delta-V, occupant seatbelt use, airbag deployment and travelling speed. This information can be used to determine the likelihood of serious injury within the crashed vehicle using a suitable injury prediction algorithm. The focus of this paper is to present a proof of concept AACN pedestrian injury prediction model using South Australia crash data.

Background

In the period 2000 to 2013, there were 1,788 people killed and 17,405 people seriously injured in road crashes in South Australia (SA), from a population of approximately 1.7 million people. Pedestrians accounted for 11.5% (N=205) of the fatalities and 8.7% (N=1507) of the serious injuries. Also over this period, consistent with the safe systems approach to road safety, there has been a steady decline in pedestrian casualties.

Lowering of urban speed limits has resulted in reductions in pedestrian casualties in SA (Anderson, 2008) and improvements in vehicle design, have also led to improved injury outcomes for pedestrians (Strandroth, Rizzi, Sternlund, Lie and Tingvall, 2011). Post-crash notification of collisions involving pedestrians is one area in road safety that is still overlooked. Currently, a physical phone call must be made to emergency services and details and location of any pedestrian collision vocally conveyed from a caller to a call taker, before an emergency medical response can be activated. This can cause delays with emergency response, particularly if there is a delay in an emergency call being made, or there are issues with conveying the precise location of the crash.

Advanced Automatic Collision Notification (AACN) systems have the potential to automatically notify emergency medical services of a crash and transmit the precise location of that crash, along with various data that might be captured by a vehicle's event data recorder (EDR). Data captured on EDRs may include delta-V, vehicle pre- and post crash speed and potentially, other vehicle variables consistent with the specifications given by the National Highway Traffic Safety Administration (National Highway Traffic Safety Administration, 2006). Generally, only crash events of a sufficient magnitude (for example a crash that might involve the deployment of an airbag) would trigger an event to be recorded by an EDR.

Advanced Automated Crash Notification (AACN) systems have been developed that can do this, and vehicle speed transmitted from the systems can be used to predict occupant injury levels (Champion et al., 2004; Kononen, Flannagan & Wang, 2011; Nishimoto et al., 2017). This theoretically may improve occupant injury outcome by way of improved emergency activation and response. Pedestrians and other vulnerable road users may also benefit from the development of an AACN injury prediction model and some initial research has already commenced in Japan (Nishimoto, Mukaigawa, Tominaga, Kiuchi, 2015).

Detection of pedestrian crashes however, is difficult, it requires specialised contact sensors similar to those discussed in Fredriksson, Haland and Yang (2001) and Ito, Mizuno, Ueyama, Nakane and Wanami (2014) or non-contact pedestrian detection sensors such as those discussed in Oikawa, Matsui, Doi and Sakurai (2016). Some pedestrian impact sensors already exist in vehicles that deploy the vehicle's bonnet to mitigate pedestrian head injury in a pedestrian collision, for example the current Mazda MX-5 (Mazda, n.d.).

Knowing that vehicle speed in a pedestrian collision influences pedestrian injury severity (Davis, 2001; Rosén & Sander, 2009) and vehicle speed can assist with injury prediction by emergency medical services if it can be transmitted easily from a vehicle event data recorder (EDR), post-crash, to emergency services (Champion et al., 2004; Kononen, et al., 2011; Nishimoto et al., 2017, an AACN system based based on pedestrian crash data could potentially be a beneficial future vehicle technology. The aim of the present study was to develop a proof of concept AACN pedestrian injury prediction model using two sources of road crash data from SA; mass police reported crash data and the CASR at-scene indepth crash data.

Data

Mass crash data

SA Police must be notified of, and attend, any crash involving injury or significant property damage. Additionally, SA Police are responsible for preparing a vehicle collision report (VCR) that includes various driver and vehicle details, the severity of injury sustained by people involved and provide an estimate of the speed of vehicles involved in the collision. Data from the VCRs are re-coded with additional crash information into the South Australian Traffic Accident Reporting System (TARS), maintained by the SA Government Department for Planning, Transport and Infrastructure.

Mass crash data from the South Australian Traffic Accident Reporting system (TARS) for the years 2000 to 2013 was used in this study as one data source. Cases were only included if a police reported vehicle speed was available (N=4,312). The speed data from TARS is the police estimated speed of a vehicle prior to the collision with a pedestrian, and can be made by police judgment or based on driver or witness statements. In some situations the speed in TARS may be the vehicle travel speed or the vehicle impact speed, depending on any evasive action taken or reported by a driver. Injuries from TARS were disaggregated into serious injuries (hospital admission; N=1,065 and fatal; N=119) and minor injuries (hospital treated; N=2,360 and private doctor treated; N=768).

At-scene in-depth crash data

Independently of SA Police, The University of Adelaide's Centre for Automotive Safety (and the Road Accident Research Unit and Traffic Accident Unit before it) has been involved in at-scene in-depth crash investigation since the 1960's (McLean and Ryan, 1965, Baldock et al., 2009). The benefit of at-scene in-depth crash investigation is that very detailed information is collected and is used to reconstruct crashes, allowing for determination of vehicle speeds with greater precision (Kloeden, McLean, Moore and Ponte, 1997). Additionally, hospital records are examined to code injury severity according to the Abbreviated Injury Scale (AIS).

As mentioned, the CASR in-depth reconstructed speed data includes vehicle travel speed and vehicle impact speed for each pedestrian collision. The speeds are based on all at-scene evidence available immediately after the crash such as skid marks, scuff marks and pedestrian throw distances or, in the absence of all other information, based on driver or witness estimates (21% of cases). In some crashes, in the absence of any evasive action by a driver, the travel and impact speeds are equivalent.

Crashes investigated as part of CASR's at-scene in-depth crash investigation program (1999-2005) were used as the second data source. Cases in which vehicle travel speed could be determined and injury severity was coded according to maximum abbreviated injury score (MAIS) were used. The CASR in-depth speed/injury dataset consisted of total of 84 pedestrian crashes; MAIS 1 (N=35), MAIS 2 (N=23), MAIS 3 (N=8), MAIS 4 (N=7), MAIS 5 (N=7) and MAIS 6 (N=4).

The in-depth crash database maintained by the Centre for Automotive Safety Research (CASR) contains a detailed sample of crashes in SA. The TARS mass crash database contains details of all crashes that have occurred in SA. Hence, data from CASR can be matched with data in TARS to determine the correlation between AIS and TARS recorded injury as well as reconstructed CASR vehicle speeds and the estimates of vehicle speed in TARS.

In-depth injury data compared to TARS recorded injury data

The abbreviated injury scale (AIS) is used to code and rank individual body injuries sustained in traumatic events such as road crashes. Consistent with this, the CASR in-depth study database contains quantitative injury data coded using AIS, from which the highest valued or maximum AIS, (MAIS - indicating the highest threat to life body injury) can be derived.

The relationship between MAIS from the CASR in-depth database and TARS injury categories is shown in Figure 1. A considerable proportion (80%) of the pedestrian MAIS 1 injuries in the CASR in-depth sample corresponded to minor casualties in TARS database (private doctor and treated at the hospital) with the remaining 20% of MAIS 1 injuries corresponding to TARS admitted to hospital category of injury.

A majority of number MAIS 2 injuries (87.5%) were associated with TARS admitted to hospital injuries. Generally, MAIS 2 – 5 injuries were associated with TARS admitted to hospital category and the remaining MAIS 4 + injuries ultimately resulted in a fatality.

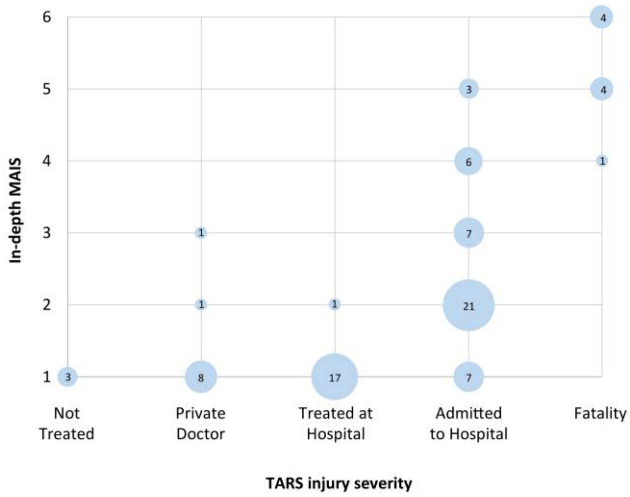

Figure 1. In-depth injury severity vs TARS injury severity

In-depth speed compared to TARS recorded vehicle speed

It was not clear whether the speed data in TARS was more aligned with vehicle travel speed or impact speed, so a comparison was made with cross-matched CASR travel and impact speeds. Figure 2 (a) shows the CASR in-depth traveling speed compared to TARS speed while Figure 2 (b) shows the CASR in-depth impact speed compared to TARS speed. While not showing exceptional correlation, TARS speed does correlate better with the CASR in-depth travel speed values (R^2 =

0.6163 for travel speed compared with R^2 = 0.4537 for impact speed). It was assumed then that travel speed was the reported variable in TARS.

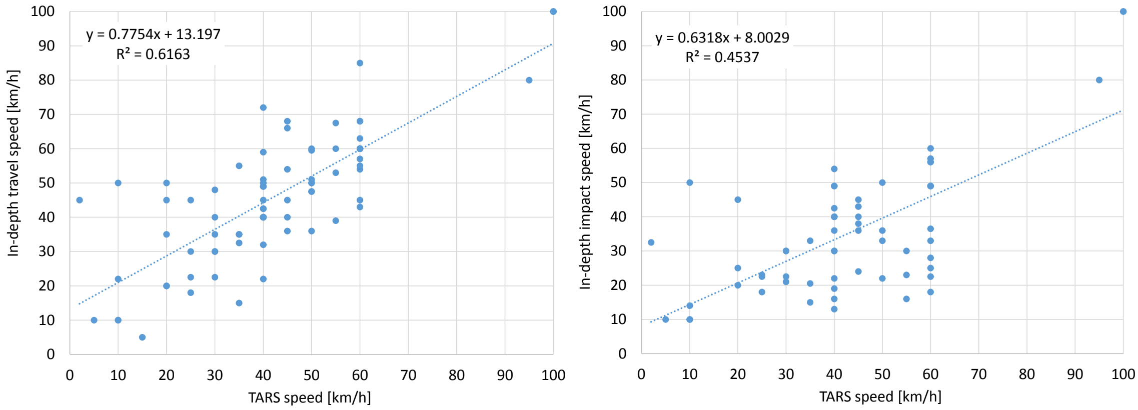

Figure 2. (a) In-depth travel speed vs TARS speed (N=84);
(b) In-depth impact speed vs TARS speed (N=62)

Method

Using the two sources of data, three pedestrian injury prediction models were developed using a logistic regression model. While it is acknowledged that several factors influence risk of injury to a pedestrian in a collision (e.g. age, gender, vehicle year etc.), for this study vehicle travel speed (a function of impact energy) was used as the single pedestrian injury risk predictor variable. The probability of injury (injury risk) for each model was p(Y=1 | x), where travel speed was the predictor variable.

$$p = \frac{1}{1 + exp[-(\beta_0 + \beta_1 x)]} \qquad (1)$$

The response variables for the various injury prediction models were:

- Model 1; Y=1 for MAIS 2+ (N=49) and Y=0 for MAIS 1 (N=35)
- Model 2; Y=1 for MAIS 3+ (N=26) and Y=0 for MAIS 1 and 2 (N=58).
- Model 3; Y=1 for TARS serious injury (N=1,184) and Y=0 (N=3,128) for TARS minor injury.

Results

Logistic regression results

The coefficients, standard errors and p-values resulting from the logistic regression are shown in Table 1, 2 and 3. The three regression models were found to be acceptable predictors of pedestrian injury ($p < 0.005$).

Table 1. Logistic Regression Model 1, MAIS2+ (N=84)

Risk factors	Coefficients	Standard Error	p-value
Intercept (β_0)	-2.419	0.809	0.003
Travel Speed (β_1)	0.062	0.018	<0.001

Table 2. Logistic Regression Model 2, MAIS3+ (N=84)

Risk factors	Coefficients	Standard Error	p-value
Intercept (β_0)	-3.455	0.916	<0.001
Travel Speed (β_1)	0.054	0.017	0.002

Table 3. Logistic Regression Model 3, Serious Injury+ (N=4,312)

Risk factors	Coefficients	Standard Error	p-value
Intercept (β_0)	-1.934	0.066	<0.001
Travel Speed (β_1)	0.031	0.002	<0.001

Injury risk curves for pedestrian accidents

By varying the vehicle speed, each of the logistic regression models can be used to construct risk curves that show the relationship between vehicle travel speed and the probability of a pedestrian collision resulting in a specific injury level. The injury-risk curves for each of the three models (and the corresponding 95% confidence intervals for the data) are shown in Figure 3 (a), (b) and (c). In a pedestrian collision where a vehicle involved had been travelling at 60 km/h, the likelihood of MAIS 2+ injury (model 1) would be around 79% [95% confidence interval: 63% to 88%] and the likelihood of MAIS 3+ injury (model 2) would be around 45% [95% confidence interval: 31% to 60%]. For model 3 a 60 km/h travel speed corresponds to a 48% risk of a serious injury [95% confidence interval: 46% to 52%].

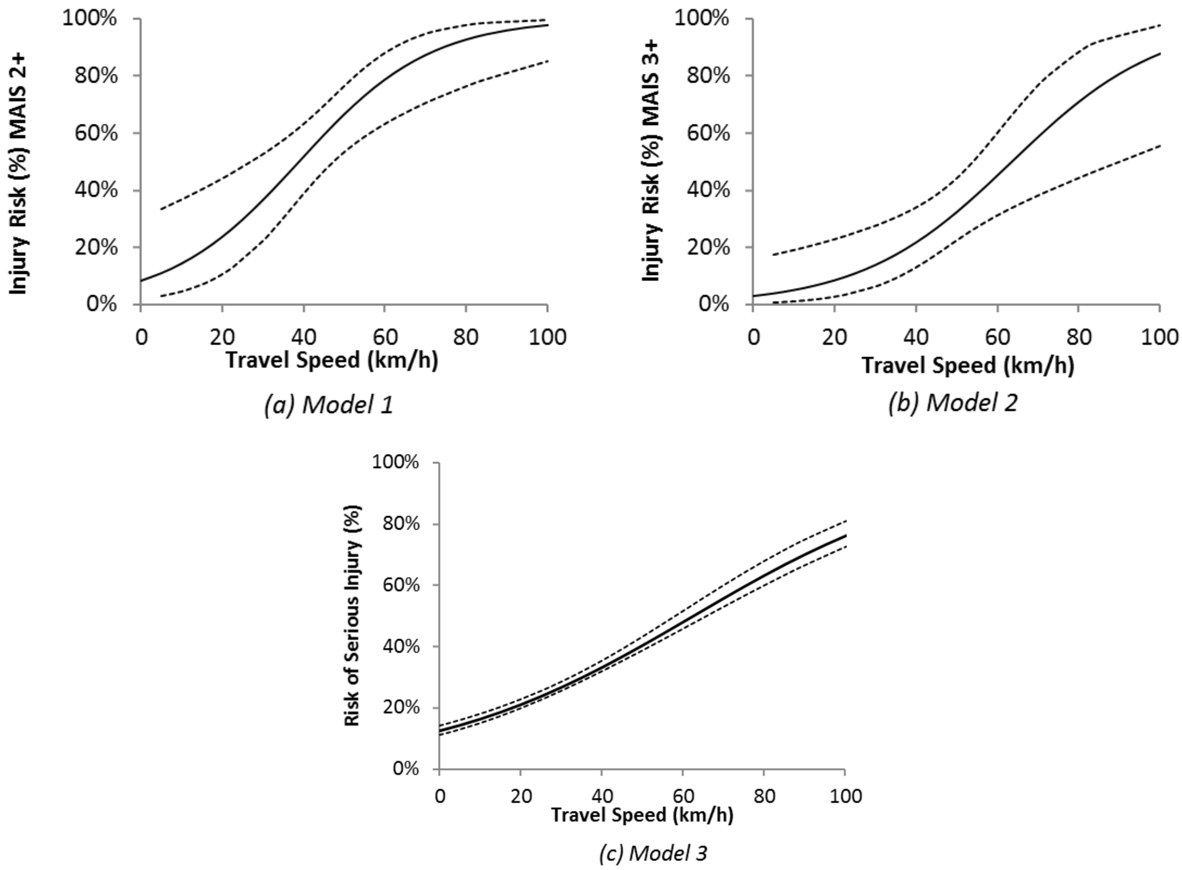

Figure 3. Pedestrian injury risk curves with 95% Confidence Intervals (Pezzullo, 2015) according to travel speed in-depth data for MAIS2+ (a), MAIS3+ (b) and TARS data (c)

Selecting and testing a suitable injury prediction model

The CASR in-depth data is based on good quality data in terms of injury classification and speed reconstruction, but the injury prediction algorithms are limited in real-world use due to the small sample of crashes. The TARS sample is significant in size, but the quality of the data is limited.

Ideally, a suitable injury prediction model would use a large sample of good quality data. Mass road crash data is routinely available, so the TARS injury prediction model (model 3) was selected as the as the suitable injury prediction model, and was evaluated using against the CASR in-depth crash data using receiver operator characteristic (ROC) analysis.

The test data consisted of the 84 pedestrian crashes in the CASR in-depth crash database that could be matched with the TARS sample of pedestrian crashes (as described previously). Since model 3 was developed to predict the probability of a serious casualty resulting from a pedestrian collision, the sensitivity and specificity can be calculated based on how effective model 3 is at classifying injury. Table 4 shows the classification matrix for the ROC analysis for the four categories of prediction that can be made by model 3.

Table 4 Classification matrix for ROC analysis

		Model 3 Injury Prediction	
		Predicted Positive	**Predicted Negative**
Actual Injury Severity	**Actual Positive** MAIS2+	True Positive (TP) *Pedestrian serious casualty correctly predicted to be a MAIS2+*	False Negative (FN) *Pedestrian serious casualty incorrectly predicted to be a MAIS1 (under triage)*
	Actual Negative MAIS1	False Positive (FP) *Pedestrian minor casualty incorrectly predicted to be a MAIS2+ (over triage)*	True Negative (TN) *Pedestrian minor casualty correctly predicted to be a MAIS1*

The sensitivity (true positive rate) of the algorithm (equation 2) is the rate of the true positives compared to true positive and false negatives, that is, how often the model correctly predicts actual serious casualties. The specificity (true negative rate) of the model (equation 3) is the rate of the true negatives compared to true negatives and false positives, that is, how often the algorithm correctly predicts minor, rather than serious, casualties The false positive rate, can be determined using equation 4.

$$Sensitivity = \frac{TP}{TP + FN} \qquad (2)$$

$$Specificity = \frac{TN}{TN + FP} \qquad (3)$$

$$1 - Specificity = 1 - \frac{TN}{TN + FP} = \frac{FP}{TN + FP} \qquad (4)$$

The ROC curve of sensitivity (vertical axis) against 1- Specificity (horizontal axis), or the true positive rate against the false positive rate, is shown in Figure 4. The injury prediction model has a sensitivity value of 1.0 only when 1-specificity also has a value of 1.0 in Figure 4. This represents a scenario in which all genuine pedestrian serious casualties in the CASR in-depth sample were correctly predicted by the TARS model to be serious casualties, however, this also resulted in all genuine pedestrian minor casualties incorrectly predicted by model 3 as serious casualties. Under this situation there would be a high level of over-triage, or lack of triage, as all injuries are predicted to be urgent.

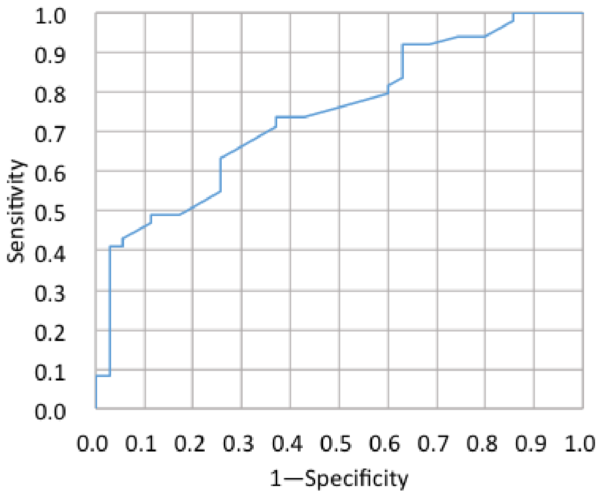

Figure 4. ROC curve for model 3, tested using matched in-depth cases

A decrease in the sensitivity of the model from a value of one introduces a level of under-triage while concurrently decreasing over-triage. Hence, depending on what levels of under and over triage can be tolerated, the ROC curve indicates various levels of triage threshold. The accuracy of the model can be determined by analysing the ROC curves, or more specifically the area under the curve (referred to as AUC). The AUC can vary from 0.5 (values occurring by chance alone) 0.7-0.9 (moderately accurate), greater that 0.9 (high accuracy) and up to 1 (perfect test) (Fischer, Bachman and Jaeschke, 2003).

The ROC curve in Figure 4 is not a smooth curve due to the limited number of CASR in-depth cases (N=84) available for verification of the model 3. Nevertheless, the AUC was determined to be 0.743 for the model 3, hence can be considered moderately accurate.

Injury thresholds for model 3 for use in AACN systems

Before the predictive model can be used in an AACN system, the optimal injury thresholds for notifications need to be determined so that occurrences of under-triage and over-triage are minimised. The under triage rate and over triage rates can be calculated using equations (5) and (6) respectively where the denominators and numerators are previously defined in Table 4.

$$Undertriage\ rate = \frac{FN}{TP + FN} \qquad (5)$$

$$Overtriage\ rate = \frac{FP}{TN + FP} \qquad (6)$$

Further, the ‘fitting rate’, (equation 7) is the ratio of algorithm’s prediction of genuine serious casualties (TP) and minor casualties (TN) to all predictions including those resulting in over and under triage.

$$Fitting\ rate = \frac{TP + TN}{TP + TN + FN + FP} \qquad (7)$$

Determining the notification thresholds on the basis of an under triage rate and over triage rate is important. In this study, the notification threshold is determined on the basis of an acceptable under-triage of pedestrian serious casualties of 10% or less in the prediction model. In this situation, fewer than 1 in 10 pedestrian casualties might be classified erroneously as a minor casualty when they might genuinely be a serious casualty.

The under triage rate and over-triage rate curves for each of the model 3 is shown in Figure 5. The two rate curves in the figure are approximately inversely proportional to each other. Also shown in the figure is the fitting rate curve. For the injury prediction model, an under-triage rate of 10% corresponds to a notification threshold of 23% for prediction of a serious casualty. The over triage rate is subsequently around 84% and the hit rate around 63%. In an AACN system using model 3 to predict the likelihood of a serious pedestrian casualty, the 23% threshold for the serious casualty rate (for a 10% under-triage rate), corresponds to a vehicle speed of 23 km/h.

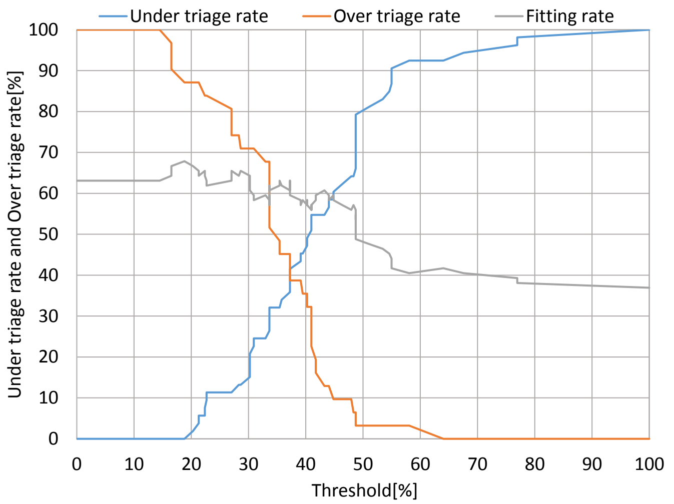

Figure 5. Relationship between threshold and triage rates for the model 3

Discussion

Automatic Collision Notification and Advanced Automatic Collision Notification systems are still emerging vehicle technologies. Several types of systems have been developed and deployed to various degrees, throughout different countries, to better assist vehicle occupants in post-crash emergency response scenarios. Arguably, road user groups such as pedestrians, cyclists and motorcyclists are in greater need of immediate post-crash emergency response, particularly as they are more vulnerable to injury and are not given the same protection as vehicle occupant in a carefully designed vehicle with a full suite of primary and secondary safety systems. As a consequence, vulnerable road users such as pedestrians are generally over-triaged by post-crash emergency responders, as there is no way of knowing the severity of a pedestrian collision with a vehicle.

An AACN system that can determine that a pedestrian collision has occurred, immediately notify emergency services of that collision and the precise location will certainly aid in quicker response. In addition, if adopted by emergency services, this basic crash information theoretically could be supplemented by one of three models proposed in this research, to predict the likely probability of an MAIS 2+ (model 1) or MAIS 3+ (model 2) or likelihood of a serious casualty according to the model 3. This information can be useful for emergency triaging, particularly when there might be competing demands for emergency service attendance for multiple incidents at different locations. An AACN system for pedestrians (and indeed all vulnerable road users) may also assist those injured by those drivers involved in hit and run incidences; with the accident, location and speed of the vehicle being transmitted even in the absence of the vehicle and driver.

The critical part in the future development of an AACN system for pedestrians is pedestrian detection. As mentioned earlier, pedestrian impacts are generally are not severe enough to deploy a vehicle safety system that might trigger an event data recording, so specific pedestrian impact detection devices are (such as those mentioned previously are required. Potentially, if integrated with vehicle EDRs, camera based autonomous emergency braking systems (where a time to collision might be such that the collision cannot be avoided) or forward collision warning systems (where the system detects a pedestrian, but the driver may not be able to stop in time and the collision still occurs) may also be useful as pedestrian detection systems for the activation of an AACN system.

The injury prediction models presented here are certainly not without limitations. The authors acknowledge that the data from the CASR in-depth crash investigations, while high in quality, are few in number. The mass crash data is limited in accuracy although being reasonably large in sample size. However, an attempt was made at validating the model 3 (the TARS model) with the CASR in-depth data, and the AUC of the ROC curve was determined to be 0.743 for TARS model, which is moderately accurate according to Fischer et al., (2003).

Internationally, accepted levels of under-triage rates are between 5% and 10% and the desired level of over-triage is 50%. (American College of Surgeons, 2014; Josten et al., 2012). For model 3, an under-triage rate of 10% resulted in an over triage rate exceeding 70%. This is greater than the recommended 50% over triage rate. The risk with such a high over-triage rate is that emergency medical resources will potentially be tasked to attend considerably more pedestrian serious casualties than might occur in reality. This is not too problematic, as pedestrian crashes in the absence of any AACN are generally over-triaged due to a pedestrian’s inherent vulnerability to injury.

Future Research

The authors of this paper have already commenced new work in this area of research, developing a multiple risk factor injury prediction model, replacing the police estimate of speed with known factors such as posted speed limit, pedestrian age, pedestrian gender, lighting conditions, distance from city, vehicle year, etc. The benefit of doing this is that other jurisdictions around Australia may also be able to add mass crash data to the model, provided some consistency in variables are recorded. This would enable the development of a national model for use in a pedestrian AACN system in Australia.

Conclusions

This research indicates that the development of proof of concept pedestrian injury risk prediction model is feasible using South Australian crash data and provides a starting point for further development for use in a pedestrian AACN system. A validated and refined model, when combined with an AACN system, could be used to provide an initial guide to assist with medical triage and could theoretically reduce the time to initial post-crash medical treatment for those with serious injuries and subsequent emergency transport to medical facilities (for those with predicted minor injuries, time to treat could increase). Such a system, if widely implemented, would potentially reduce pedestrian collision serious injuries and fatalities.

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References

American College of Surgeons (2014). Resources for Optimal Care of the Injured Patient (p23-29). Accessed July 2017 https://www.facs.org/~/media/files/quality%20programs/trauma/vrc%20resources/resources%20for%20optimal%20care.ashx

Anderson, R. W. G. (2008). Pedestrian collisions in South Australia (CASR039). Adelaide: Centre for Automotive Safety research.

Baldock, M. R. J., Woolley, J. E., Ponte, G., Wundersitz, L. N., Lindsay, V. L., 2009. In-depth crash investigation at the centre for automotive safety research. 3rd expert symposium on accident research. 15-23. Bergisch Gladbach: Bundesanstalt für Straßenwesen.

Champion, H. R, Augenstein J, Blatt, A. J, Cushing, B., Digges, K., Siegel, J. H, Flanigan, M. C., 2004. Automatic crash notification and the URGENCY algorithm: Its history, value and use. Topics in emergency medicine. 26 (2), 143-156.

Davis, G., 2001. Relating severity of pedestrian injury to impact speed in vehicle-pedestrian crashes. Transportation research record. 1773, 108-113. DOI: http://dx.doi.org/10.3141/1773-13.

Fischer, J. E., Bachmann, L. M., Jaeschke, R., 2003. A readers' guide to the interpretation of diagnostic test properties: clinical example of sepsis. Intensive care med 29. 1043–1051.

Fredriksson, R., Haland, Y., Yang, J., 2001. Evaluation of a new pedestrian head injury protection system with a sensor in the bumper and lifting of the bonnet's rear part, 17th International technical conference on the enhanced-safety of vehicles, Amsterdam, The Netherlands, 47.

Ito, D., Mizuno, K., Ueyama, T., Nakane, D., Wanami, S., 2014. Bumper contact sensor for pedestrian collisions based on analysis of pedestrian kinematic behaviour. International journal of crashworthiness. 19 (5), 514-523. DOI: 10.1080/13588265.2014.917493.

Josten, C., Siebert, H., Ruchholtz, S., (2012). Whitebook Medical Care of the Severely Injured, 2nd Revised and Updated Edition. Accessed July2017: https://www.facs.org/~/media/files/quality%20programs/trauma/vrc%20resources/resources%20for%20optimal%20care.ashx

Kloeden, C. N., McLean, A. J., Moore, V. M., Ponte, G., 1997. Travelling speed and the risk of crash involvement. Volumes 1 and 2 (CR172). Canberra, Federal office of road safety, transport and communications.

Kononen, D. W., Flannagan, C. A., Wang, S. C., 2011. Identification and validation of a logistic regression model for predicting serious injuries associated with motor vehicle crashes. Accident analysis and prevention 43, 112-122.

Mazda (n.d). Impact-absorption bonnet and bumpers. Accessed July 2017 http://www.mazda.com/en/innovation/technology/safety/passive_safety/bonnet_bumper/

McLean, A. J. and Ryan, G. A., 1965. Traffic accidents in metropolitan Adelaide. Australian road research. 2 (5), 43-62.

National Highway Traffic Safety Administration, 2006. Final Regulatory Evaluation: Event Data Recorders (EDRs), Office of Regulatory Analysis and Evaluation, National Center for Statistics and Analysis. Vol. 49 CFR Part 563 [Docket No. NHTSA-2006-25666], 1-62, Washington DC, USA. Accessible at: http://www.nhtsa.gov/Laws+&+Regulations/Vehicles.

Nishimoto, T., Mukaigawa, K., Tominaga, S., Kiuchi, T., 2015. Development of AACN algorithm for pedestrian and cyclist, Journal of society of automotive engineers of Japan. 46 (6), 1123-1129. (in Japanese).

Nishimoto, T., Mukaigawa, K., Tominaga, S., Lubbe, N., Kiuchi, T., Motormura, T., Matsumoto, H., 2017. Serious injury prediction algorithm based on large-scale data and under-triage control. Accident Analysis and Prevention 98, 266-276. http://dx.doi.org/ 10.1016/j.aap.2016.09.028

Oikawa, S., Matsui, Y., Doi, T., Sakurai, T., 2016. Relation between vehicle travel velocity and pedestrian injury risk in different age groups for the design of a pedestrian detection system. Safety science 82, 361-367.

Pezzullo, J., 2015.Logistic Regression. Accessed August 2016 http://statpages.info/logistic.html

Rosén, E., Sander, U., 2009. Pedestrian fatality risk as a function of car impact speed. Accident Analysis and Prevention 41, 536-542. http://dx.doi.org/10.1016/j.aap.2009.02.002

Strandroth, J. ,Rizzi, M., Sternlund,S., Lie, A. Tingvall, C. 2011."The correlation between pedestrian injury severity in real-life crashes and Euro NCAP pedestrian test results." ESV 2011, No. 11-0188.