SIDE IMPACT SEVERITY

The use of discriminant analysis to classify injury

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ABSTRACT

This paper discusses the problems associated with traditional impact severity measures for side impacts. Discriminant analysis is described and used to determine the important variables relating to injuries. Variables such as ETS and intrusion have high serious injury classification rates despite not being optimum in engineering terms. The resulting discriminant functions are insensitive to the sample of occupants.

INTRODUCTION

Traditional measures of impact severity such as delta-v and ETS are based on an understanding of accident dynamics obtained from measurements of acceleration, velocity and deformation recorded in crash tests. Analyses of vehicle and occupant motions during a frontal impact reveal that usually a restrained occupant is only just starting to get maximum restraint from his belt at the time when the vehicle has virtually completed its deceleration phase. The resulting injuries to the occupant are likely, therefore, to be closely related to the residual state of the car. Side impacts are more complex; equivalent analyses suggest that the order of events is reversed with a struck-side occupant interacting with an intruding side structure early in the impact sequence well before the gross vehicle structures see the impact forces. Crash tests indicate that the final injuries may be associated with instantaneous measurements such as the road speed of the bullet vehicle or the velocity change of the part of the occupant's body as it is struck by car side structure. Such measurements may be easily obtainable within the confines of the crash test laboratory, but are much more difficult to assess for real-world collisions - few studies reconstruct accidents to the extent of calculating the road speed of the bullet vehicle and there is no procedure available that can calculate the occupant contact velocity change from residual deformation measurements.

The most commonly accepted impact severity measure is delta-v, the velocity change of the vehicle during the impact, and this is commonly used to relate experimental results to field data. Delta-v is not, however, a measure of the conditions prior to impact as it is dependent on vehicle characteristics such as stiffness and mass. Therefore, it is not strictly a measure of impact severity. Marquant (1977) points this out saying that an ideal impact severity measure would predict the injuries resulting from a collision to a given vehicle. Nevertheless delta-v has frequently been used to assess the likelihood of injuries of a particular severity arising in a side impact. Jones (1982) estimates the mean delta-v for levels of chest injury in side impacts and shows an increase from 21 kph for AIS 1 injuries to 30 kph for AIS 2 injuries and above for restrained struck-side occupants. Rouhana (1985) gives comparable results describing the relation between maximum AIS and CRASH3 estimates of delta-v. Human tolerance to injury varies substantially and it may not be reasonable to expect an impact severity measure to predict whether an injury will or will not occur. An estimate of the probability of injury may be more realistic and would be solely based on parameters describing the pre-impact conditions. Amongst these would be measures of the vehicle structural performance, mass and the impact velocity, parameters used to evaluate delta-v, a fact recognised by Schmid (1984). Measurements of the residual crush or the intrusion into the occupants survival space have been considered as impact severity measures by Cesari (1976) amongst others but the close relation with parameters such as delta-v and ETS makes interpretation of the results difficult. Strother (1984) suggests that the association of injury and intrusion represents a mutual link with some other crash severity measure rather than a causal link. Some investigators have used more sophisticated analytic techniques to investigate the links between injury and impact severity in side collisions. Mills (1984) used probit analysis to predict injury as a function of delta-v although on a small sample while Gimotty (1982) used NCSS data to derive a logit model to examine the relative influence of several categorical variables on overall injury severity. Gimotty found that the best prediction of OAIS was a function based on lateral delta-v and age.

It is clearly difficult to relate the data concerning injury causation from field studies to that obtained from crash tests. A part of the problem has been the lack of accurate, sufficiently detailed field data. Few researchers have been able to take into account the interactions of a wide variety of occupant specific measures such as measurements of intrusion into the occupant space close to the level at which the injuries occurred. In addition the relative effects of accident parameters such as delta-v, ETS, deformation energy and maximum crush have not been compared.

The use of a single measurement of impact severity is not likely to adequately describe the likelihood of injuries. For example, the plot of the AIS of the most severe chest injury of struck-side occupants against vehicle delta-v shown in Fig.1 has the suggestion of a relation. There is, however, considerable scatter and the nature of the relationship is difficult to establish. Similarly, the plot of the same injuries against the residual intrusion at torso level shown in Fig.2 suggests a trend, but again with considerable scatter. In addition the intrusion to a vehicle is probably related to the delta-v and a clearer model might be obtained if the two were not considered in isolation.

It would be incorrect to use multiple regression techniques to examine these relations in more detail as AIS is defined as an ordinal variable and is not usable in arithmetic procedures. The mean delta-v can be calculated for each AIS band providing some useful data on the relationship but there remains the problem of relating this to the level of intrusion. The process of examining the variables of interest pair by pair could be continued, but a sharper technique that could inspect the interactions of many variables together is desirable.

Fig 1: Maximum AIS of chest injuries by delta-v

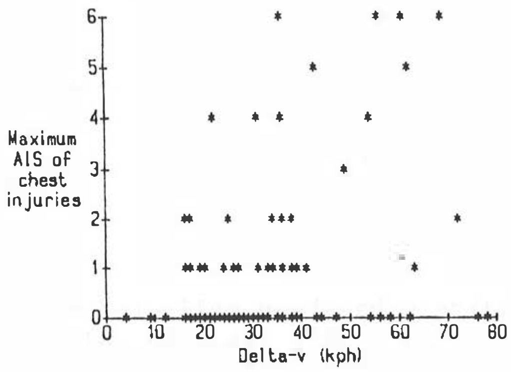
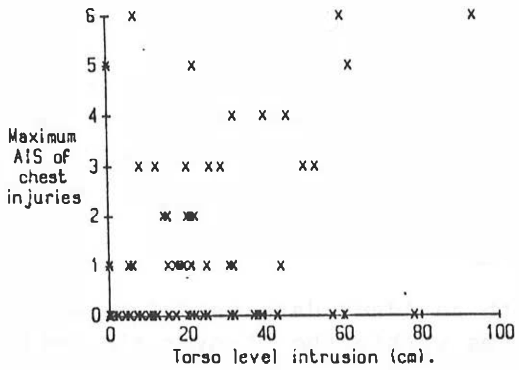


Fig 2:Maximum AIS of chest injury by torso level intrusion.



Several such techniques exist, the continuous variables could be transformed to categorical variables and a log-linear model fitted to the data. This technique has promise, but by condensing data some information is discarded. Also the relationships within highly multi-variate data sets are only rarely reduced to a useful extent. The technique used to assess the relationship between injury outcome and the various accident parameters in this analysis is discriminant analysis.

DISCRIMINANT ANALYSIS TECHNIQUES

Discriminant analysis is a statistical procedure that can be used to distinguish between cases described as falling within the values of a categorical variable using a linear combination of interval variables. The mathematical basis of the procedure is well described by Tatsuoka (1971). The procedure was initially developed for use with a polychotomous dependent variable and interval level independent variables but dichotomous independent variables have also been found to perform reasonably well. For example, a group of car occupants can be classified according to the presence or absence of chest injury, a dichotomous categorical variable. Several interval level variables such as delta-v, intrusion, occupant age, restraint use are suspected to influence the injury outcome. Discriminant analysis can be used to derive a linear function of the independent variables such that those cases in the group with injury have as different as possible a set of values of the function from those cases without injury. In addition, the range of values within each group of cases will ideally be as close together as possible. An iterative procedure can be used to include the variables one by one to obtain the best solution. The procedure used produced a function that classified the highest proportion of occupants with injury into the correct group. The resulting function will be optimised for the variability of the particular group of car occupants described within the sample. If the function were to be evaluated for a second set the fit would not be quite as good. Applying the function to a second group of cases can be used to assess the accuracy of the function, however this effectively means an artificial partitioning of the data set and the final function is probably better evaluated on a larger data set. An alternative method is to assess the predictive ability of a function using random subsets.

Discriminant analysis in its simplest form can therefore be used to identify the key variables that can be used to successfully classify an accident according to the likelihood of injury.

ACCIDENT DATA

The in-depth accident data used for this analysis has been collected by several teams within the UK over the period since 1983. The case selection procedures and investigation methodologies have been described in more detail by Galer (1985), Otubushin (1986) and Mackay (1985). The sample of accident data currently available comprises data on 2700 vehicles and 4200 occupants. The in-depth studies collect a large amount of detailed data particularly in terms of the amount and location of crush to the vehicle and the degree of intrusion into each seating position. This data has been combined with information on the occupant injuries and is available for analysis. Weighting factors have not been used to recreate the original distribution of accident severities as this is not required by the discriminant analysis. In fact the procedure employed, implemented within the statistical package SPSS/PC+ [Norusis (1986)], uses a chi-squared test as part of the optimisation process. Chi-squared tests are sensitive to sample size and so will tend to indicate relationships within large samples erroneously. In addition the discriminant process is used to examine the relations between variables for each occupant and is therefore independent of the accident sampling procedure.

RESULTS

The group of occupants selected for analysis were all seated on the struck side of vehicles with the most severe impact in energy terms either to the right or left sides and with a direction of force within 45° of a pure lateral impact. None were ejected from the car and no selection was made on restraint use as this was to be incorporated as one of the independent variables. There were 382 occupants from the initial sample that satisfied these criteria. Table 1 shows the distribution of the AIS of the most severe injury sustained by each occupant. 201 (53%) sustained an injury below AIS 2 which was used as the dividing line between serious and non-serious injuries for the dichotomous dependent variable to be used in the analysis.

Maximum AIS	0	1	2	3	4	5	6	n/k	TOTAL
No. of Occupants (%)	79 (21%)	122 (32%)	79 (21%)	36 (9%)	17 (5%)	20 (5%)	18 (5%)	11 (3%)	382 (100%)

Table 1: AIS of most severe injury sustained by each occupant

The group of independent variables to be tested were chosen from the variables routinely recorded for each occupant as part of the in-depth accident investigation procedures and are described in detail in Appendix 1. These variables were selected to represent the traditional impact severity measures resulting from the use of CRASH3, (delta-v, ETS, energy, other vehicle delta-v), measures of the vehicle sizes (mass, other vehicle mass, mass ratio), measures of the deformation of the vehicle (maximum crush, intrusion at 3 vertical levels) and the age of each occupant. Dichotomous variables included described the nature of the striking object and occupant restraint use, the direction of force was also included despite not being a strictly suitable type of variable. It would have been desirable to have included within the group a variable equivalent to the travelling velocity of the striking object, however the accident investigations did not incorporate the on-scene studies necessary to gather this data. Similarly a measure of vehicle side structure deceleration would have been advantageous.

The variables were initially used separately to construct discriminant functions that would examine the ability to predict the occurrence of serious and non-serious injuries. The results are shown in Table 2 which lists the variables, the percentage of occupants without and with serious injuries correctly classified together with the overall percentage of correct classifications. The variable that allocated the largest number of cases to the correct injury group was the ETS calculated from CRASH3. 74% of all cases were correctly identified but the variable was better at classifying occupants who did not sustain serious injuries than those who did. ETS was able to classify 82% of those who did not sustain serious injury and 65% of those who did. Each of the measurements of intrusion, the maximum crush and the energy were able to allocate over 70% of occupants to their correct category although the head and foot level intrusion measurements were noticeably poorer at predicting when serious injury would occur than when non-serious injury would occur. If the group allocation had been made purely on the basis of chance 50% of the occupants would be expected to be correctly grouped. Delta-v ranked relatively high as a predictor of injury correctly allocating 66% of all occupants and 57% of those with serious injury to the correct group, an improvement of 7% above the level of random allocation.

Most variables were not particularly good at predicting when an occupant would sustain serious injury, the best was restraint use being correct in 79% of the cases with serious injury. This variable was poor at predicting non-serious injury and failed to show a statistically significant difference between the two groups. Several variables were good at predicting when non-serious injury would occur while being poor at predicting serious injury. The predictive abilities of the mass ratio and mass of the striking object were identical as they are linearly related.

Variable	% of cases in each group classified correctly		
	No serious Injuries	Serious Injuries	All injuries
Delta-v	76	57	66
ETS	82	65	74
Energy	86	51	70
Other vehicle delta-v	69	60	65
Mass	48	54	51
Other vehicle mass	92	12	57
Mass ratio	92	12	57
Head level intrusion	89	52	73
Chest level intrusion	82	62	73
Foot level intrusion	83	56	71
Age	43	59	51
Direction of force	41	58	48
Other vehicle car?	65	50	58
Other vehicle HGV?	92	13	57
Other vehicle pole?	90	25	61
Maximum crush	82	63	73
Restraint use	23	79	53

Table 2:
Most severe injury prediction rate of independent variables alone

The optimum discriminant function was obtained for each variable separately to assess the strength of the association with the injury variable. The variables were then ranked on their ability to correctly classify occupants into groups with and without AIS 2+ injuries. An algorithm was developed to discover the combination of variables within a discriminant function that made the best prediction of serious injuries while also predicting well non-serious injuries. The best predictor was combined with the next best and the prediction evaluated. If the prediction rate of serious injuries improved the variables were retained otherwise the next best was substituted. It was sometimes necessary to explore several alternative avenues to find the optimum group of variables. Combinations of up to 4 variables were tested for their ability to predict the presence of an injury of AIS 2 or above.

The only group to show any improvement above the best single variable was the combination of ETS and chest level intrusion. The final function for predicting the injury severity group was,

$$F = -1.76 + (0.052 \times ETS) + (0.025 \times \text{chest intrusion})$$

This function gave only a marginal improvement on the use of ETS alone raising the serious injury prediction rate from 65% to 67% and decreasing the non-serious injury prediction rate by 2% to 80%. The overall rate was 74%. The injury prediction rate, being relatively high and 17% better than a random allocation, shows the advantage in using discriminant functions to classify injuries.

It is useful to examine potential reasons for the wrong classification of cases. The dependent variable is based on the most severe injury to the occupant. This injury could occur in any part of the body and it is to be expected that different mechanisms might relate to injuries in each area. Each of these mechanisms would have a different relationship to the independent variables tested and would all have a potentially confounding involvement in any model predicting injuries. The discriminant function based on the maximum injury severity would therefore be modelling the net effect of each of these mechanisms and would be expected to predict only a relatively low proportion of serious injuries. The other major potential reason for the shortfall in prediction rate might be the absence of an important variable amongst those tested. For example, it has already been suggested that the travelling velocity of the striking vehicle may be an important parameter in injury prediction and if such a variable were available for a discriminant analysis the classification rate might well improve.

To investigate the relationships between injuries and other accident parameters in more detail head, chest and leg injuries were examined separately. Variables were derived for each body area that indicated the presence of any injury above AIS 2 in severity. The distribution of the injury severities for each of these body areas is shown in Table 3.

Injury severity AIS	Body region		
	Head	Chest	Legs
0	235 (62%)	247 (65%)	214 (56%)
1	53 (14%)	62 (16%)	99 (26%)
2	47 (12%)	21 (6%)	32 (8%)
3	16 (4%)	20 (5%)	36 (9%)
4	9 (2%)	11 (3%)	1 (0.3%)
5	9 (2%)	11 (3%)	0 (0)
6	13 (3%)	10 (3%)	-
TOTAL	382 (100%)	382 (100%)	382 (100%)

Table 3: Severity of injuries to head, chest and legs

HEAD INJURIES

A head injury was defined as occurring if any part of the face or head sustained an injury of any severity. The ability of each variable alone to predict these injuries was examined and the results are shown in Table 4.

The variable with the best overall prediction rate for all occupants was the intrusion measured at head level, 77% of all occupants were allocated to their correct groups but only 49% of those with head injuries of AIS 2 head injuries and above were correctly predicted.

Variable	% of cases in each group classified correctly		
	No serious Injuries	Serious Injuries	All injuries
Delta-v	77	54	71
Lateral delta-v	76	54	70
ETS	79	53	72
Energy	81	45	72
Other vehicle delta-v	63	53	61
Mass	50	55	51
Other vehicle mass	92	12	72
Mass ratio	92	12	72
Head level intrusion	85	49	77
Chest level intrusion	76	60	72
Foot level intrusion	77	55	72
Age	44	64	50
Direction of force	41	60	46
Other vehicle car?	62	51	59
Other vehicle HGV?	91	14	72
Other vehicle pole?	86	26	71
Maximum crush	75	57	70
Restraint use	81	28	65

Table 4: Head injury prediction rate of independent variables alone

The variable with the highest correct prediction rate for those with serious injuries was age which enabled 64% to be correctly determined. However, age was not good at predicting non-serious injuries, and there was not a statistically significant difference between the mean ages for the two groups of occupants with and without serious head injury. Age was not therefore a good overall predictor and only classified 50% of all occupants correctly. The intrusions measured at each level were better overall predictors correctly allocating up to 85% of those with no serious injuries and up to 60% of those with serious injuries. The three measures of intrusion showed a high level of correlation with each other so it is to be expected that if one predicts injuries well then all three will. The chest level intrusion was the best of the three at predicting injuries.

ETS delta-v and the lateral component of delta-v were virtually equal in all their classification rates. Most variables gave an improvement in serious injury prediction rate above an allocation based purely on chance although many were poor at classifying those without serious injury.

The hierarchical procedure for identifying the best function for predicting groups was used and, as found for maximum injury severity, there was only a small improvement over the best single variable. The function was evaluated to be,

$$F = -1.71 + (0.056 \times ETS) + (0.018 \times \text{foot level intrusion})$$

This function classified 65% of occupants with a head injury correctly an improvement of 15% above chance classification and 10% above the rate using chest level intrusion alone. Equivalent functions replacing head and chest level intrusion for foot level intrusion were evaluated giving serious injury prediction rates of 59% and 61% respectively, both improvements on the predictions of the intrusion variables alone. It is not surprising that a measure of intrusion appears in the discriminant function considering the effectiveness of chest intrusion alone, although foot level intrusion was the poorest of the three.

When SPSS/PC+ performs a discriminant analysis it excludes cases with missing values, the small number of cases with foot level intrusion missing will not be exactly the same as those with chest or head level missing so there will be a variation in the final prediction rate that can be viewed as an error term. This variation combines with the high correlation between intrusion measurements and the typical downward arc of the head trajectory. This combination of effects is seen as the reason for the higher prediction rate of the function including foot level intrusion.

CHEST INJURIES

75 (19%) of occupants sustained a chest injury of AIS 2 or greater, the chest being defined as extending down to but not including the diaphragm. The distribution of all severities of injury is shown in Table 3.

Table 4 shows the proportion of correct classifications achieved by the discriminant functions based on each independent variable. The variable that had the highest proportion of occupants with injuries correctly classified was restraint use with a correct serious injury prediction rate of 80%. This variable was particularly poor at predicting those without serious injuries however, and was not amongst those groups of variables that improved the prediction rates when combined. It should be noted that it is difficult to identify restraint use by examination of belts in the lower energy side impacts. The variables describing maximum crush, chest level intrusion, delta-v and its lateral component also gave good classification rates for those with serious injuries.

Variable	% of cases in each group classified correctly		
	No serious Injuries	Serious Injuries	All injuries
Delta-v	79	64	76
Lateral delta-v	84	61	79
ETS	81	58	76
Energy	82	46	75
Other vehicle delta-v	57	46	55
Mass	50	55	51
Other vehicle mass	91	11	76
Mass ratio	91	11	76
Head level intrusion	87	56	81
Chest level intrusion	80	63	77
Foot level intrusion	77	56	73
Age	65	51	62
Direction of force	60	47	58
Other vehicle car?	61	52	59
Other vehicle HGV?	91	16	77
Other vehicle pole?	85	26	74
Maximum crush	76	60	73
Restraint use	22	80	36

Table 5: Chest injury prediction rate of independent variables alone

The process for finding the group of variables that formed the discriminant function with the highest serious injury prediction rate together with a good overall rate resulted in the following function:-

$$F = 2.62 + (0.042 \times ETS) + (0.029 \times \text{chest intrusion}) + (0.027 \times \text{age})$$

This function correctly classified 77% of those in the sample with serious injury, 81% of those with no serious injury and an overall rate of 80%. Although age did not rank highly in the list of good single injury predictors its addition increased the final rate by 10% to 77%. Other variables that were highly ranked either made no difference to or decreased the prediction rates.

LEG INJURIES

Leg injuries were defined as occurring to the pelvis, thigh, lower leg or foot. The distribution of severities of leg injuries is shown in Table 3. It should be noted that AIS 6 is not defined for leg injuries. 69 occupants sustained serious injuries representing 18% of all occupants. Table 6 shows the classification rates of each independent variable separately.

Of the variables 10 resulted in discriminant functions with overall correct classification rates above 70%. The best was energy correctly classifying 80% of all occupants followed by ETS, head level intrusion and foot level intrusion each predicting 79% correct. The best variable at classifying serious injuries on the other hand described whether the striking object was a truck or not. This variable correctly classified 98% of all occupants with serious injury. Restraint use was also able to classify occupants with serious injuries well, the rate was 80%. The variables describing restraint use and whether the striking vehicle was a truck did not show a statistically significant difference in mean values between the two groups. The optimum discriminant function was found to be:-

$$F = -1.7 + (0.058xETS) + (0.020 \times \text{foot intrusion}) + (-0.84 \times \text{ovhgv})$$

The function was able to correctly classify 72% of those with serious injury and 83% of those with no serious injury. The addition of a truck as a striking vehicle resulted in a 6% improvement in the correct injury classification rate.

Variable	% of cases in each group classified correctly		
	No serious Injuries	Serious Injuries	All injuries
Delta-v	80	56	75
Lateral delta-v	87	56	80
ETS	82	63	79
Energy	85	57	80
Other vehicle delta-v	73	50	79
Mass	54	52	53
Other vehicle mass	91	12	77
Mass ratio	91	12	77
Head level intrusion	84	53	79
Chest level intrusion	80	66	77
Foot level intrusion	82	65	79
Age	43	61	46
Direction of force	42	62	46
Other vehicle car?	59	44	56
Other vehicle HGV?	12	98	27
Other vehicle pole?	87	32	77
Maximum crush	81	65	78
Restraint use	23	81	35

Table 6:
Leg injury classification rate of independent variables alone

TOLERANCE OF RESULTS

The discriminant functions that classified the injuries best were inherently optimised for the relationships between injury and cause amongst the occupants studies. To examine the sensitivity of the discriminant variables each group was used to classify 10 randomly chosen subsets of the data. The variation in the percentage of cases correctly classified was measured and the 95% confidence limits calculated as a percentage. These limits are shown in Table. 7.

Body area	Average % of serious injuries correctly classified	95% confidence limit $\pm$%
Head	63.5	4.2
Chest	77.0	5.5
Legs	64.0	8.9

Table 7: Accuracy of discriminant functions

The correct classification rates of head and chest injuries varied little regardless of the subset of occupants used to evaluate the function. The variation was greater for those with leg injuries but remained small.

DISCUSSION

It is important to establish whether the discriminant functions found for each of the body areas do in fact reveal anything of the relation with the other accident parameters, or whether the results are merely the product of a statistical exercise. It is rare that any multi-variate technique will prove a causal link between variables, usually it is an association that is demonstrated together with the likelihood of the result arising by chance. Log-linear models such as logit or probit analysis have this problem just as much as regression procedures or categorical statistics such as chi-squared. It is the responsibility of the researcher to examine the statistics and interpret them in the light of other analyses and her experience. When fractions of variables are combined in a linear format as in the discriminant functions any direct causal link becomes increasingly difficult to understand. A good impact severity measure is likely to give the probability of injury in a particular impact in terms of parameters describing the energies involved in the impact, parameters describing how the loads have been transmitted through the car structure to the occupant and the susceptibility of the occupant to injury. The discriminant functions derived have some of these properties. Each involves the ETS which is calculated from the deformation energy by CRASH3 and a term describing the intrusion at a particular level into each occupants seating position.

The function for chest injuries also has a term based on the occupants age, a parameter closely related to her susceptibility to injury. That for leg injuries has a term that indicates a truck as the striking object and relates to the stiffness of the object. It is considered that the discriminant function can be viewed as representing an impact severity scale that is not directly measurable in a physical sense and can only be derived as a mathematical function of real variables. Such scales are widely produced by techniques such as factor analysis and multiple regression.

The final discriminant functions that were evaluated only rarely gave some improvement above the best single variable at classifying occupants who sustained serious injury. The best single variables however were frequently poor at classifying those who did not sustain serious injuries and often failed to distinguish between the groups at a statistically significant level. They also did not always appear to relate closely to any common understanding of accident events. These predictors were therefore considered to be somewhat spurious and more credence was given to the final discriminant functions. These all classified occupants sustaining serious injury at levels often substantially above those possible from chance. The function classifying head injuries gave the lowest improvement in classification rate above that of chance. The head is relatively mobile and is able to strike a large range of structures in side impacts. The trajectories of chest and leg injuries are far more predictable and classification rates of 27% and 22% above those possible from a random allocation of groups were achieved. The function for chest injuries also has a term for the age of the occupant which gave a clear improvement on the function excluding age. This supports the suggestion of an age effect upon the injury tolerance of casualties, a cross-tabulation of the age groups shows a significant difference in the distributions at the 5% level. The function for leg injuries surprisingly also contained a term for a truck as the striking vehicle that gave a noticeable improvement in injury classification rate. A cross-tabulation of leg injuries with a truck as the striking object showed a trend of leg injuries becoming less frequent. This trend was only significant at the 10% level though.

All of the final functions had the ETS and an intrusion measurement as terms. ETS always made the largest contribution to the final value of the function as it had the largest standardised coefficient, although all three coefficients for chest injuries were similar.

Better classification rates might be obtained if variables describing the occupant contact delta-v and impact velocity of the striking object were available, but it does appear that good predictions are obtainable with the more measurable variables. It is likely that the classification abilities of ETS and residual intrusion are high as they are good proxies for the two unmeasurable variables.

CONCLUSION

Discriminant analysis appears to be a useful technique in classifying injuries on the basis of readily measurable variables. One by one the independent variables can be used in functions that classify injury groupings often more successfully than would be achieved by chance. They can however give spurious functions which do not seem to arise when they are combined in the best functions. The classification rates vary little when evaluated on random subsets of occupants. The variables featured in the resulting functions are consistent with those that would be expected from engineering analysis. In particular the functions show the useful classification ability of ETS and intrusion despite these variables not being the best measurements from experimental crashes.

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REFERENCES

Marquant, J.F., Collision severity measured by delta-v, 21 AAAM Conference Proc. 1977.

Jones, I.S., Injury severity versus crash severity for front seat car occupants involved in front and side collisions. 26 AAAM Conference Proc. 1982.

Rouhana, S.W. et al, Lateral impact - an analysis of the statistics in NCSS, 29th Stapp Car Crash Conference, 1985.

Schmid, W., A model to assess risk of injury in traffic accidents as a function of regularised test impact speed. SAE Paper publ. in Mathematic Simulation of Occupant and Vehicle Kinematics, pp.146.

Cesari, D. et al, Influence of intrusion in side impact. Sixth ESV Conference, 1976.

Strother, C.E. et al, Injury and intrusion in side impacts and rollovers, Advances in belt restraint systems: design, performance and usage. SAE pubn. pp.141.

Mills, P.J. et al, The probability of injury to car occupants in frontal and side impacts. 28th Stapp Car Crash Conference, 1984.

Gimotty, P.A. et al, Models for the prediction of severe injury. Proc. 26th AAAM Conference, 1982.

Tatsuoka, M.M., Multivariate analysis techniques for educational and psychological research. ISBN 0-471-84590-6.

Galer, M.D. et al, The causes of injury in car accidents - an overview of a major study currently underway in Britain. 10th ESV Conference, 1985.

Otubushin, A. et al, Crashed vehicle examination techniques. Paper for the 1986 SAE Congress.

Mackay, G. M. et al, The methodology of in-depth studies of car crashes in Britain. Paper for the 1985 SAE Congress.

Norusis, M.A., SPSS/PC+ Advanced Statistics, SPSS Inc., ISBN 0-918469-15-5.

APPENDIX 1

Independent variables used in the analysis.

DELTA-V - Total velocity change of the vehicle during the impact estimated from the vehicle residual damage using CRASH3.

LATERAL DELTA-V - The perpendicular component of the delta-v.

ETS - Velocity calculated using CRASH3 assuming that all of the vehicle damage resulted from the car striking an undeformable object.

ENERGY - Deformation energy of the vehicle calculated using CRASH3.

OTHER VEHICLE DELTA-V - Delta-v of striking object calculated using CRASH3, only available for a small group of occupants.

MASS - Overall mass of the case vehicle including all occupants and luggage.

OTHER VEHICLE MASS - Overall mass of striking object.

MASS RATIO - $\frac{\text{mass of striking object}}{\text{mass of case vehicle}}$

CRUSH - Maximum crush of the vehicle regardless of location.

HEAD INTRUSION - Reduction in interior dimension of car measured laterally at head height for each occupant.

CHEST INTRUSION - Reduction in interior dimension of car measured laterally at the height of the facia for each occupant.

FOOTWELL INTRUSION - Reduction in interior dimension of car measured laterally at the footwell for each occupant.

AGE - Age of occupant.

DOF - Direction of force upon the car recorded as being lateral or $\pm$ 30°.

OTHER VEHICLE CAR - Was the striking object a car?

OTHER VEHICLE HGV - Was the striking object a heavy goods vehicle or large bus?

OTHER VEHICLE POLE - Was the striking object a pole or tree?

BELT - Was the occupant restrained?

Dependent variables used in the analyses:
MSERINJ - Set to 0 unless maximum AIS is 2 or greater.
HFSERINJ - Set to 0 unless maximum head or face AIS is 2 or greater.
CHSERINJ - Set to 0 unless maximum chest AIS is 2 or greater.
LGSERINJ - Set to 0 unless maximum leg AIS is 2 or greater.