Investigation of Brain Injury Mechanisms in Vehicle Crashes

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ABSTRACT: In recent years, an angular-velocity-based brain injury criterion, BrIC, has been proposed by the National Highway Traffic Safety Administration (NHTSA) for consumer vehicle safety assessment tests. In this study, the cumulative strain damage measure (CSDM), as one of the brain injury metrics, was calculated based on data obtained for a total of 360 anthropomorphic test devices (ATDs) in vehicle crash tests conducted by NHTSA and the Insurance Institute for Highway Safety (IIHS) using the Simulated Injury Monitor (SIMon ver. 4.0), a human brain finite element model developed by NHTSA’s research institute. Self-Organizing Maps (SOMs) and hierarchical clustering were used to classify test data composed of the brain injury risk level based on CSDM and its corresponding head kinematic parameters. Results demonstrated that, in addition to the peak values of angular velocities, the peak values of angular accelerations around three axes are also influential parameters for accurately predicting brain injury risk based on CSDM.

KEY WORDS: Safety, occupant safety, impact biomechanics, brain injury mechanism [C1]

1. Introduction

The level of head injury risk of occupants in vehicle crashes has generally been evaluated with the Head Injury Criterion (HIC) using only three components of linear head accelerations of ATDs. Therefore, it is not possible to evaluate or estimate the brain injury risk caused by head rotational motions. Although various criteria including ATD head rotational parameters have been proposed for evaluating brain injury risk, there is no single criterion that has been found to be suitable for this purpose in vehicle crash tests.

Takahounts et al. proposed a kinematically based brain injury criterion, BrIC, as a brain injury risk predictor that was calculated with the peak values of angular velocities around three axes. It was correlated with CSDM, which is the volume ratio of the human brain exceeding the prescribed strain criteria calculated with SIMon (1). Mueller et al. validated that BrIC can identify an injurious loading to an ATD head. They classified narrow offset crash tests into three groups based on events of the ATD head during the crash: airbag restrained, hard contact with vehicle interior parts and unrestrained. BrIC values were compared among those three groups. The results showed that the airbag restrained group had maximum BrIC and the hard contact one had minimum BrIC. They concluded that BrIC may need to be re-examined (2). Our previous study pointed out that using the peak value of angular acceleration probably improves the accuracy of a predictor when a brain injury risk based on CSDM is evaluated because SIMon results showed the volume fraction of the brain experiencing a 0.25 or higher strain threshold increased with increasing peak angular acceleration (3).

The purpose of this study was to examine the effect of head kinematic parameters, such as angular velocities, angular accelerations or linear accelerations, on CSDM using data obtained on 360 ATDs in vehicle crash tests conducted at NHTSA (4) and IIHS (5). The levels of brain injury risk based on CSDM ($P_{CSDM}$) and their corresponding sets of head kinematic parameters were classified with SOMs, a kind of neural network algorithm, in combination with hierarchical clustering to analyze data visually.

These methods make it possible to examine the correlation between $P_{CSDM}$ and head kinematic parameters efficiently even under different vehicle crash test conditions. The test conditions were frontal and lateral impacts having four different conditions each (e.g., fixed rigid barrier, moving deformable barrier, etc.). In addition to various test conditions, there were different sizes of dummies and corresponding seating positions. In order to identify the kinematic parameters from such a wide variety of conditions to predict brain injury risk accurately, a comprehensive rational methodology is needed that enables extraction of some global common features to explain all of the test results and also simultaneously facilitates identification of specific characteristics matching local crash phenomena (6).

In this report, the relationship between $P_{CSDM}$ and head kinematic parameters of all the ATDs were visualized using SOMs and they were classified into some clusters. The clusters were then characterized based on the level of partial correlation coefficients between $P_{CSDM}$ and head kinematic parameters. A comparison of the characteristics of relevant clusters indicated that some head kinematic parameters influenced $P_{CSDM}$ as common global phenomena and other ones as local phenomena.
2. Method

2.1. Data set and variables

Vehicle crash test data for 360 ATDs obtained from NHTSA’s and IIHS’s web sites were used in this study. Table 1 shows the test conditions and the corresponding number of ATDs. The SIMon code developed by NHTSA was used here.

Table 1 Test conditions and number of ATDs

| Crash test condition | Number of ATD |
|----------------------|--------------|
| Frontal RB           | 59           |
| Offset DB            | 15           |
| Small Overlap RB     | 109          |
| Oblique Offset MDB   | 56           |
| Lateral              |              |
| FMVSS 214 MDB        | 55           |
| IIHS MDB             | 28           |
| Pole                 | 34           |
| Vehicle-to-Vehicle   | 4            |

RB: Rigid barrier, DB: Deformable barrier, MDB: Moving DB

Linear accelerations and angular velocities around three local axes measured at ATDs’ head were input to SIMon. Figure 1 shows this three local coordinate axis.

![Fig. 1 Local three coordinate axis at ATD’s head](image)

A strain threshold of 0.25 was used to calculate the CSDM value for each test (1). Table 2 shows the nine parameters used in this study. The levels of AIS3+ brain injury risk were calculated using the risk curves (1).

Table 2 Parameters used in analysis

| Variable            | Explanation                                                                 |
|---------------------|-----------------------------------------------------------------------------|
| $P_{CSDM}$          | The level of brain injury risk of AIS 3+ based on CSDM                        |
| $P_{BrIC}$          | The level of brain injury risk of AIS3+ based on BrIC                        |
| $\log{Acc_x}$, $\log{Acc_y}$ | Logarithm of peak linear accelerations around x, y axes measured at ATDs’ head |
| $\log{Acc_z}$       | Logarithm of peak linear accelerations around z-axis measured at ATDs’ head  |
| $\log{Ang_x}$, $\log{Ang_y}$ | Logarithm of peak angular accelerations around x, y axes measured at ATDs’ head |
| $\log{Ang_z}$       | Logarithm of peak angular accelerations around z-axis measured at ATDs’ head |
| $P_{CSDM} - P_{BrIC}$ | Difference between $P_{CSDM}$ and $P_{BrIC}$                                 |

2.2. Visualization of data with SOMs

In a previous study, principal component analysis (PCA) was used to examine the relationship between head kinematic variables and traumatic brain injury (8). Since crash test data have a high degree of nonlinearity, linear mapping based PCA may not be suitable.

In this study, SOMs were used to visualize data by mapping data on a two-dimensional layer where the location of the input data was determined based on the Euclidian distance. The mapping and visualizing algorithm of the data is explained in reference to the example shown below. The ATD’s data in each test have a set of nine variables such $P_{CSDM}$ described in the previous section. As shown in Fig. 2, the output layer is composed of lattices called units, which have a vector with the same nine dimensions as the input data. All the weighted Euclidean distances $d_i$ ($i = 1, 2, \cdots, n$, where $n$ is the number of units) between each ATD’s data and units on the output layer are calculated, and the input data are mapped to the unit that is the closest to the input vector. The weighted value of $P_{CSDM} - P_{BrIC}$ was zero to prevent highly correlated parameters from affecting the SOM results. The other weighted values were set to one.

![Fig. 2 Mapping ATDs’ data on an output layer](image)

After mapping all the test data on the output layer, the vectors of the units are updated so as to make them more like the input data. The closer the units are to the ones that are mapped by the test data, the more the vectors of the units are updated. After several iterations, the output layer converges as it represents the proximity between all the dummy data. The relationships between variables can be identified by comparing the output layer of each variable that showed the contours of the variable.

2.3. Hierarchical clustering of SOMs

All the ATDs’ data were classified by applying hierarchical clustering to the units of the output layer where the data were mapped using the algorithm explained above. Sets of $P_{CSDM}$ and its corresponding head kinematic parameters that were similar were gathered closer together on the output layer, while other sets that were dissimilar were separated on the layer.

Comparing the clustered data can identify global or local relationships between the $P_{CSDM}$ and ATDs’ head kinematic parameters. Common variable relationships within the clusters...
improve the overall prediction accuracy of the predictor, while the relationships between variables that are specific to each cluster contribute to improving its local prediction accuracy.

2.4. Characterization of each cluster

A partial correlation is a correlation between two variables after removing the effects of other variables and was calculated to examine the effect of ATDs’ head kinematic parameters on $P_{\text{CSDM}}$ quantitatively. A partial correlation between $x_i$ and $x_j$ is given by

$$r_{ij,rest} = \frac{r_{ij}}{\sqrt{r_{ii} \times r_{jj}}}$$

where $r_{ij}$ is a component of an inverse matrix of the correlation coefficient matrix (9). The partial correlations of each cluster were visualized in a graph in which variables were represented by points and connected by a line when their partial correlation was high. A comparison of the graphs of each individual cluster revealed which kinematic parameters have a global or a local effect on $P_{\text{CSDM}}$.

3. Results

3.1. Comparison of brain injury risk based on CSDM and BrIC

Figure 3 shows a comparison of brain injury risk predicted by CSDM (vertical axis) and that of BrIC (horizontal axis). The test results inside the dotted ellipse marked “A” indicate that $P_{\text{CSDM}}$ values were higher than those of $P_{\text{BrIC}}$. Therefore, BrIC underestimated the levels of brain injury risk compared with CSDM in these tests. In contrast, for the test results in the dotted ellipse marked “B”, $P_{\text{CSDM}}$ values were lower than those of $P_{\text{BrIC}}$. In these tests, BrIC overestimated the levels of brain injury risk compared with CSDM. Hence, these results indicated that including other kinematic parameters in the angular-velocity-based predictor would improve its accuracy.

3.2. Classification of data by SOMs and hierarchical clustering

After the 360 ATDs’ data were mapped on the output layer using the SOM algorithm, all the units constituting the output layer were classified into seven clusters among which two of them had relatively higher “$P_{\text{CSDM}} - P_{\text{BrIC}}$” values. The locations and cluster numbers are shown in Fig. 4.

Figure 5 shows the output layers for each variable such as $P_{\text{CSDM}}, P_{\text{BrIC}}$, etc. Black dots in each map represent ATDs’ data in all tests and are located in the same positions in all maps. The units having no test results were used to smooth the contours of the variables. The values of the variables in each region increase as the color of the regions becomes warmer.

An examination of the output layer of “$P_{\text{CSDM}}$” and “$P_{\text{BrIC}}$” revealed that relatively higher levels of brain injury risk of the ATDs’ data were clustered on the left side of these two maps (marked as (1)).

The output layer of the variable “$P_{\text{CSDM}} - P_{\text{BrIC}}$” shows that clusters 1 and 6 had relatively higher values of this variable than the other clusters, indicating that BrIC was less accurate in predicting the brain injury risk based on CSDM in these clusters (marked as (2)). In cluster 1 in which $P_{\text{CSDM}}$ values were higher than those of $P_{\text{BrIC}}$ in the tests, the levels of brain injury risk based on CSDM were underestimated and located in part A of Fig. 3. By contrast, cluster 6 in which $P_{\text{CSDM}}$ values were lower than those of $P_{\text{BrIC}}$ showed that the levels of brain injury risk based on CSDM were overestimated and located in part B of Fig. 3.
3.3. Identification of the parameter affecting $P_{\text{CSDM}}$

Partial correlations between $P_{\text{CSDM}}$ and the other 7 variables in each cluster were calculated and are shown in Fig. 6. The legend indicates that the values of the partial correlations increase with increasing thickness of the lines. Red lines indicate positive partial correlation coefficients and blue lines negative ones. The partial correlation of cluster 1 could not be calculated because the number of tests was too few to calculate the inverse of the correlation coefficient matrix.

The partial correlation between $P_{\text{CSDM}}$ and log $\text{Ang}_z$ in clusters 2, 3, 5, 6 and 7, which contained 327 ATD’s data out of 360 (91%), was at the same level as the partial correlation between $P_{\text{CSDM}}$ and $P_{\text{BrIC}}$. Moreover, these partial correlations were at a relatively higher level than the others. Therefore, adding log $\text{Ang}_z$ to the predictor would improve its global accuracy.

The test data of the 26 ATDs (7%) classified into cluster 4, in which $P_{\text{CSDM}}$ values were relatively higher than in the other clusters, had two relatively strong partial correlations: one was between $P_{\text{CSDM}}$ and $P_{\text{BrIC}}$ and the other was between $P_{\text{CSDM}}$ and log $\text{Ang}_x$. Based on this result, factoring log $\text{Ang}_x$ in the formulation of the predictor would improve accuracy under severe loadings conditions.

Moreover, the graph for cluster 6, in which BrIC overestimated the brain injury risk based on CSDM, showed that the partial correlation between $P_{\text{CSDM}}$ and log $\text{Ang}_y$, was as high as that of $P_{\text{CSDM}}$ and log $\text{Ang}_z$. This suggests that including log $\text{Ang}_y$ in the predictor would correct the overestimation of brain injury risk based on CSDM.

Finally, in cluster 1, the cause of the underestimation of the risk by BrIC was analyzed by comparing the output layer of the SOMs because the partial correlation coefficient could not be calculated. The map of cluster 1 in Fig. 5 shows that the data had higher peak values of linear accelerations log $\text{Acc}_x$ and log $\text{Acc}_y$ and the angular acceleration log $\text{Ang}_x$ than those of the other clusters. Accordingly, BrIC, which is calculated using only the peak angular velocity around each axis, was not able to predict the increase in CSDM caused by linear accelerations, thus resulting in the underestimation of brain injury risk based on CSDM.

To verify this hypothesis concerning the limitation of BrIC, the difference in CSDM was examined using input loadings with (case 1) and without linear accelerations (case 2) of the same test classified in cluster 1. In Fig. 7, the upper graph shows the results for case 1 and the lower graph those for case 2 calculated by SIMon. A comparison of the results indicates that the CSDM value at the end of the calculations (200 ms) in case 2 decreased from 0.42 to 0.30 (shown by dotted circles). The translational accelerations affected the increase in CSDM in eight test results in cluster 1.

4. Discussion

4.1. Kinematic parameters for predicting risk based on CSDM

The kinematic parameters having relatively higher partial correlations as described in section 3.3 probably improve the global and local prediction accuracy of brain injury risk based on CSDM simultaneously.
Firstly, including $\log An_g_z$ in the predictor in addition to angular velocities around three axes improved its global accuracy because the partial correlations between “$P_{\text{CSDM}}$ and $\log An_g_z$” and between “$P_{\text{CSDM}}$ and $P_{\text{BrIC}}$” were relatively higher in clusters 2, 3, 5, 6, and 7 in common.

Secondly, considering $\log An_g_z$ improves the accuracy of the predictor in severe loading situations such as in cluster 4 because the partial correlation between $P_{\text{CSDM}}$ and $\log An_g_z$ was relatively higher. The accuracy of the predictor in such severe loadings will be very important when a vehicle is rated as having high brain injury risk in a vehicle safety performance test.

Finally, the overestimation of brain injury risk based on CSDM, such as in the tests in cluster 6, can be corrected when $\log An_g_z$ is included in the predictor because its partial correlation with $P_{\text{CSDM}}$ was as strong as that seen for $\log An_g_z$.

### 4.2. Updating brain injury predictor based on CSDM

Based on the findings described so far, improving the accuracy of the brain injury predictor will require incorporating the peak values of angular accelerations in each axis in addition to the peak values of angular velocities. Although the actual formulation of a brain injury predictor will be the subject of future studies, this hypothesis was verified by multi-variable regression analysis.

The proposed predictor was formulated by taking CSDM as the objective variable and the peak values of angular velocities and the logarithms of the peak values of angular accelerations around each axis as explanatory variables.

$$CSDM = \left(\omega / \omega_{x,cr}\right) + \left(\omega / \omega_{y,cr}\right) + \left(\omega / \omega_{z,cr}\right) + \left(\log a_x / a_{x,cr}\right) + \left(\log a_y / a_{y,cr}\right) + \left(\log a_z / a_{z,cr}\right)$$

(2)

Table 3 Critical max angular velocities and angular acceleration in each direction based on CSDM

|       | $\omega$ | $\log a$ |
|-------|----------|----------|
| X     | 302.1    | 11.9     |
| Y     | 214.7    | 11.8     |
| Z     | 249.8    | 3.0      |

The results are shown in equation (2), Table 3 and Fig. 8. A comparison with the correlation between CSDM and BrIC in the upper graph of Fig. 8 shows that the accuracy of the proposed predictor was significantly improved as indicated in the lower graph in the figure.

Fig. 8 Comparison of predictors’ accuracy of CSDM

### 5. Conclusion

Vehicle crash test data for 360 ATDs obtained from NHTSA and IIHS were analyzed using SOMs and hierarchical cluster analysis to investigate head kinematic parameters for predicting AIS3+ brain injury risk based on CSDM. Findings are summarized below.

1. Adding the logarithm of the peak angular acceleration around the z-axis, $\log An_g_z$, to the predictor improved its global accuracy for estimating the level of brain injury risk because its partial correlation with $P_{\text{CSDM}}$ was strong in 327 tests out of 360 (91%).

2. 26 tests (7%) had relatively high $P_{\text{CSDM}}$ values which showed strong partial correlations between “$P_{\text{CSDM}}$ and $P_{\text{BrIC}}$” and between “$P_{\text{CSDM}}$ and $\log An_g_z$”. Therefore, factoring $\log An_g_z$ into the predictor can improve its accuracy when a vehicle is rated as having high brain injury risk in a vehicle safety performance test.

3. When the $\log An_g_z$ term was incorporated in the predictor, accuracy was improved in 25 tests (7%) in which BrIC overestimated the brain injury risk. Furthermore, including the peak values of linear accelerations corrected the underestimation of brain injury risk based on CSDM in 8 tests (2%).

4. Multi-variable regression analysis confirmed the hypothesis that including the peak values of angular accelerations around each axis would improve the accuracy of the predictor. The results confirmed that the proposed predictor which included the peak values of angular accelerations around each axis in its formulation demonstrated a significant improvement in accuracy.

In conclusion, incorporating the peak values of angular accelerations in CSDM is necessary to improve the predictor’s accuracy. This paper is written based on a proceeding presented at 2016 JSAE Annual Congress (Spring).

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