Relating scatter in occupant injury time histories to instability in airbag behaviour

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Abstract

Dealing with natural variation in input parameters and environmental conditions presents the automotive industry with significant challenges. Lack of consideration of variability in results can lead to unpleasant surprises during testing, with a consequent risk of unplanned cost and delay. In a purely virtual product development world, analysis techniques must lead to designs that are robust with respect to external noise sources, in order to minimise test-to-test and test-to-prediction variation.

This paper discusses some of the issues faced in dealing with variability in an occupant restraint system, and presents an analysis approach that is helping to provide insight into causes of scatter, leading to potential design improvements to help reduce it. Conventionally the CAE process has used nominal values for input parameters, and has been satisfied with single, deterministic solutions. In many cases this approach is based on unreasonable assumptions, and a structured consideration of variability is vital.

In this context we describe an example where Principal Components Analysis has been used to study scatter in an airbag model. Building on previous experience with the application of this technology to deformed geometries, the technique has been extended to allow a consideration of scatter in curves, as exemplified by the set of chest acceleration time-histories shown in figure 1.

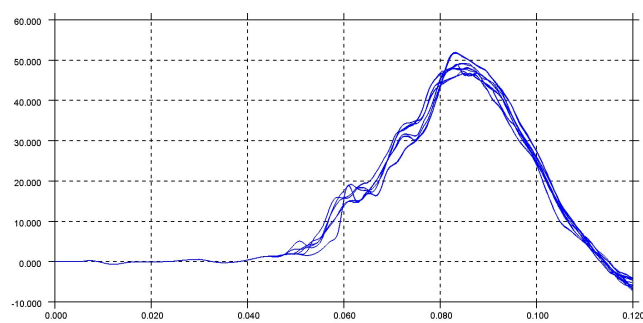

Figure 1.Scatter in chest acceleration time histories

The mathematical background to the PCA method, as implemented in Diffcrash, is presented, and its extension to curves is explained. It will be shown how scatter in two crash dummy channels can be related to each other and to airbag deformation behaviours, as an aid to developing design improvements.

Virtual techniques have much to offer in understanding and managing scatter in physical systems, and the consideration of variability in the CAE process is slowly becoming more common-place. The PCA approach presented here is a useful addition to the toolset available, giving valuable insight into physical phenomena.

Background

Vehicle functional performance targets are becoming ever more stringent. The demands on engineers to create optimized but robust design solutions, which simultaneously satisfy a multitude of requirements, mean that a detailed understanding of the response of the design to variation in input parameters is essential. However, variability is a feature of all physical systems and operating environments, and this can lead to test-to-test variation, with uncertainty in CAE predictions. In an automotive context the list of potential sources of variation is huge and diverse, including such parameters as tolerances on component parameters like panel gauges, uncertainty in crash dummy stiffness, chaotic behaviour of casting fracture, and imprecision in the specification of crash boundary conditions. Given the potential for variation, a successful performance confirmation test on one vehicle will not necessarily be repeated on a second vehicle test, possibly leading to an unwelcome surprise and the need for late remedial design changes, which are generally expensive and inefficient. This is of particular concern in a zero-prototype development process, where, for many load cases, there is provision for only one vehicle confirmation test.

For the reasons above, a consideration of variability is an essential part of any CAE-based product development process. The aim of such consideration is to quantify and minimize the expected test-to-test variation through a structured approach to robust design, and the development of systems that behave in a predictable way. In the CAE environment, new techniques and thought processes are required. In particular, the conventional expectation of a single, deterministic solution to a CAE analysis is bound to lead to a surprise when the product is tested, as a result of the effects already discussed:

- Test to test variability
- Unwarranted assumptions as to input parameter values
- Non-robust CAE models

Before attempting a design optimization, the system must be sufficiently robust that it is not unreasonably sensitive to small changes in input parameters. This requires a systematic analysis of, and improvement in, design stability. Fortunately, CAE techniques can produce useful insight into the nature of variation, as multiple versions of a design can be created and evaluated, and statistical tools can be used to understand and manage the data produced. An early application of this type of analysis in the vehicle development process allows mass and cost-efficient solutions to be created, which reduce the risk of late surprises at test.

The adoption by the industry of a structured approach to managing variability and robustness, using CAE techniques, has so far been the exception, and is only now starting to become more commonplace. New techniques are needed to extend this type of analysis, and one such technique, based on Principal Components Analysis will be described.

Analysis of Robustness using Diffcrash

The Diffcrash software package allows a more in-depth analysis of sources of numerical variability. This software allows the user to identify distinct modes of behaviour from a variability study, and to track these modes to their time and point of origin. This provides information that can help to locate the cause of the variability, as an aid to improving the model. One of the mathematical analysis tools used by DIFFCRASH is Principle Component Analysis (PCA).

PCA Analysis for Crash Simulation Results

According to [1] Principle Component Analysis (PCA) was introduced by Pearson in the context of biological phenomena, and by Karhunen in the context of stochastic processes [2]. In [3] PCA was applied to full crash simulation results. Let
$X_i(p,t)$
be the displacement of simulation run *i* out of *n* simulation runs at node *p* and time *t*. If $\overline{(X)(p,t)}$ is the mean of all simulation runs, the covariance matrix *C* can be defined as
$C := [c_{i,j}]_{1\le i,j\le n}$ and $c_{i,j} := < X_i - \bar{X}, X_j - \bar{X} >_2$

The eigenvectors v_i of *C* form a new basis (principle components) and the $\lambda_1 i$ (square roots of the eigenvalues of *C*) provide a measure for the importance of each component.
If this method is applied to crash simulation results, n^2 scalar products between the simulations runs of length $3 * \#P * \#T$ have to be computed ($\#P$ number of points, $\#T$ number of time steps.)

From $$\hat{X}(a) := \sum_{i=1}^{n} a_i X_i ,$$

it follows that $$\lambda_i = \left\|\hat{X}(v)\right\|_2 .$$

The $\hat{X}(v_i)$ show the major trends of the differences between the simulation results.

Difference PCA

Instead of considering the whole simulation results, correlation matrices can also be defined for the simulation results at parts of the model and for specific time steps. If *P* is a part of the model and T subset of the time steps, then $C_{P,T}$ can be defined as follows:
$C_{P,T} := \left[c_{i,j}^{P,T}\right]_{1\le i,j\le n}$ and

$$c_{i,j}^{P,T} := \frac{1}{N_{P,T}} \sum_{p\in P, t\in T} \left(X_i(p,t) - \bar{X}(p,t)\right) * \left(X_j(p,t) - \bar{X}(p,t)\right) .$$

($N_{P,T}$ denotes the size of P times the size of T .)
The intrinsic dimension of the set of simulation results can be defined as the number of major components in its differences (for more formal definitions see [4, Chapter 3]). Buckling or any other local instability in the model or numerical procedures increases the intrinsic dimension of simulation results at parts which are affected, compared to those that are not affected. Therefore, in the context of stability of crash simulation, those parts and time steps for which the intrinsic dimension increases are of particular interest.
Numerically this can be evaluated by determining eigenvectors and eigenvalues of

$C_{P_1,T_1} - \tau\, C_{P_2,T_2}$
for the covariance matrices of the simulation results at two different parts P_1 and P_2 and two different sets of time steps T_1 and T_2. If there are positive eigenvalues for a certain choice of τ (which separates noise from real signals), the simulation results at (P_1, T_1) show additional effects compared to those at (P_2, T_2). If v_{P_1,T_1} is the corresponding eigenvector, $\widehat{X}(v_{P_1,T_1})$ shows the effect on (P_1, T_1) and also the impact on the other parts of the model. Similar methods can be used to remove those effects from this result, which do not affect (P_1, T_1) directly.
This approach has been filed for application of a Patent at the German Patent office (DPMA number 10 2009 057 295.3) by Fraunhofer Gesellschaft, Munich.

CURVES

Instead of variation of node positions a major interest of the design engineer may the analysis of scatter of curves (c.f. [5]). The analysis of curves can be included into the analysis by defining a matrix $C_{CV,T}$ for each curve *CV* and each time step *T* as follows:
Let
$CV_i(k,t)$
the scalar value of the kth curve at time step t in simulation run *i*, then $C_{CV(k,T)}$ is defined as:
$C_{CV(k,T)} := \left[c_{i,j}^{CV(k,T)}\right]_{1\le i,j\le n}$ and

$$c_{i,j}^{CV(k,T)} := \left(CV_i(k,t) - \overline{CV}(k,t)\right) * \left(CV_j(k,t) - \overline{CV}(k,t)\right).$$

$C_{CV(k,T)}$ may now be used in the analysis in the same way as $C_{P,T}$ before.

Crash Analysis

Consumer crash rating programmes, such as the European 'EuroNCAP', and the American equivalent, 'NCAP', are significant drivers for vehicle design. Crash dummy injury values play a significant role in generating these consumer crash ratings, as well as being the basis for certifying compliance to crash legislation. Dummy injury is controlled by the occupant restraint system, including airbags and seat belt systems. At JLR DYNA models of these components are used in a vehicle system environment to simulate the behaviour of the dummies in response to changes in restraint system input parameters. In a zero-prototype development environment, tooling is released on the basis of this analysis, with a physical test carried out only to confirm compliance to targets. In this context a fundamental characteristic of the system must be a repeatable behaviour, providing confidence that the expected ratings will be achieved. Variation in model behaviour resulting from small changes to input parameters can indicate design instability, or poor modeling quality, and it is essential to isolate the cause of the variation, establish which of these types of sources is responsible, and either improve the design, or rectify the modeling technique.

Variation background

Analysis of sources of variability must start with a characterisation of the nature and size of the variation. In terms of crash analysis, this is often discovered as a spread in peak values such as chest acceleration. These are extracted from time-history curves and are related to scatter in deformed geometry. In both these domains, analysis of a number of overlaid datasets can be confusing, and characterization in terms of distinct behaviors is not straightforward, making identification of a source difficult. PCA analysis allows the spread in behaviours to be decomposed into a small set of distinct significant modes that can be studied individually in terms of their characteristics and sources. The relative strength of each mode can be quantified and a mode with a high relative significance characterises a large proportion of the variation in results. Modifications designed to influence this mode can be expected to have a correspondingly significant effect on the overall behaviour and level of variation. Previous work by the authors [6] has applied this methodology to an analysis of variation in coordinate positions of corresponding nodes in a model. The identification of modes during this analysis has allowed the source of variation in geometric behavior to be studied, and improvements made to the model. The toolset has now been extended to the study of time histories, where a similar approach can be applied to generate characteristic modes in the time-history domain. This allows the influence of the geometrical modes on the observed time-histories to be determined. In this way, development effort can be targeted at the geometrical modes of particular relevance to the time-histories used within the crash rating system, legal compliance standard, or other engineering target system.

Airbag Example

An example of a vehicle crash model has previously been described [6], in which relatively large differences in the dummy injury values were observed, due to small changes to input parameters. The model also showed significant variation in the kinematic behaviour of the airbag and dummy upper body. The source and development of the scatter in the deformed geometry of the dummy and airbag was investigated using the PCA-based tool set implemented in Diffcrash, which led to a modeling improvement that reduced the dispersion in deformed geometry.

Since dummy injury values, which are used for certification of vehicles with respect to crash behaviour, are extracted from time-history curves, it is important to know how scatter in these curves relates to variation in the kinematic behaviours of individual components. As described in the previous section, the PCA technique implemented within Diffcrash was further developed to address this need. In the airbag example, chest acceleration time-histories from 30 runs were compared, the runs differing from each other in small changes to the input parameters, and a significant spread in the chest acceleration time histories may be seen in figure 2. The level of variation at 85ms is too large to allow a confident prediction of crash rating.

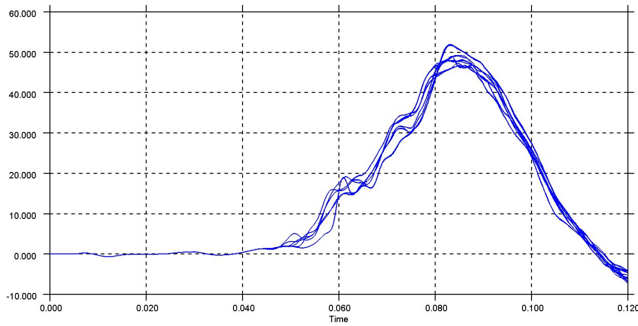

Figure 2. Scatter in chest acceleration time-histories

Using curve PCA, these time-histories can be characterised as a set of curve modes. Typically only the first few curve modes are sufficient to closely approximate the overall data structure, and this allows the engineer to focus on these individual characteristics of the data, rather than attempting to interpret the complete data for all the curves all at once. Curve modes can be visualised as a pair of artificial curves that indicate the bounds of the mode; all of the original curves can be considered to be comprised of varying proportions of the different modes, the first mode being the one that makes the largest contribution to variation in the curves. The most significant chest acceleration curve mode is shown in figure 3. This mode accounts for 44% of the overall scatter in the time-histories, and a reduction in the magnitude of this mode is expected to lead to a significant reduction in overall spread in the original time-histories.

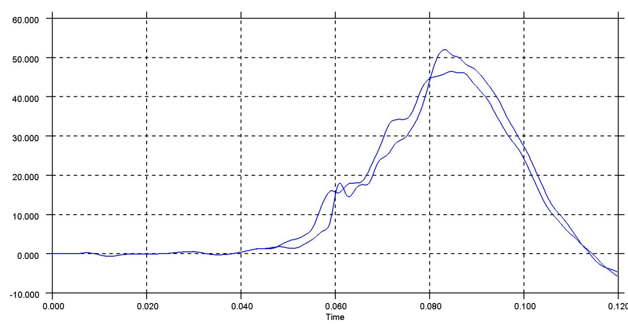

Figure 3. First chest acceleration mode

This analysis forms the basis of further investigation into the source of the variation, with the aim of developing potential design solutions to reduce it. Firstly, it is useful to consider how scatter in the chest acceleration time-history is related to scatter in other dummy injury values. An understanding of this relationship indicates whether a single issue is responsible for scatter in the two channels; a high correlation implies a single issue; a low correlation indicates independent issues that must be addressed separately. A second approach is to study the relationship between curve modes and geometrical deformation modes, as this offers the opportunity of targeting design modifications to address the variation in time-histories.

Curve-curve relationships

Passenger neck moment time-histories for the same 30 runs are plotted in figure 4, and a significant level of scatter can also be seen in this channel.

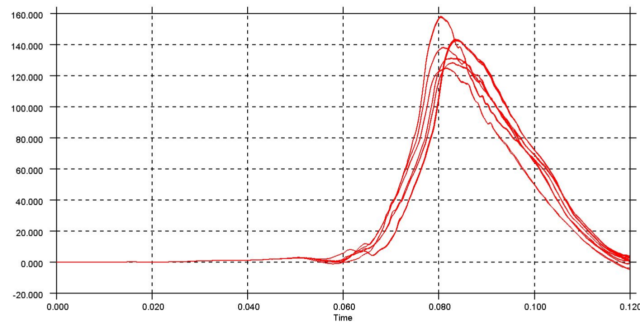

Figure 4. Scatter in neck moment time-histories

The corresponding first neck moment curve mode is shown in figure 5.

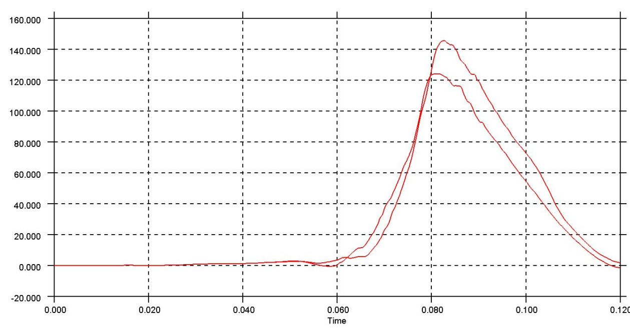

Figure 5. First neck moment mode

Difference-PCA was used to study the relationship between the chest acceleration and neck moment time-histories. DCPA involves the identification of a mode from one set of curves, and the elimination of the effect of this mode from a second set of curves. The reduction in the scatter in the second curve set indicates how closely this is related to variation in the first curve set. In the airbag example, subtraction of the first chest acceleration mode from the neck moment scatter results in a reduction of 30%, indicating a significant, but not dominant, relationship. Measures to reduce scatter in the first chest acceleration mode are expected to reduce scatter in neck moment, but not to eliminate it.

This mode subtraction is further illustrated in figure 6, where the neck moment first mode is plotted, before and after subtraction of the first chest acceleration mode. The reduced separation of mode boundaries, particularly after 80ms, indicates the nature of the reduction in neck moment scatter if the first chest acceleration mode can be eliminated, and shows a significant improvement at the curve maximum.

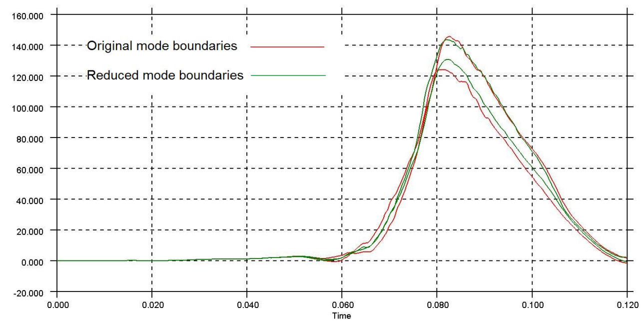

Figure 6. Reduced neck moment curve mode boundaries following chest acceleration mode elimination

Curve-deformed shape relationships

Two techniques can be applied to the study of curve–deformed shape relationships: part-curve correlation and DPCA.

Part-curve correlation involves a value being assigned to each part in the model to indicate its correlation to scatter in a time-history, and this can be visualised as a contour plot. The sequence of plots in figure 7 shows the part-curve correlation contour for chest acceleration, and clearly indicates a link between chest acceleration scatter and airbag behaviour, highlighting it as an area for improvement in design or modeling technique

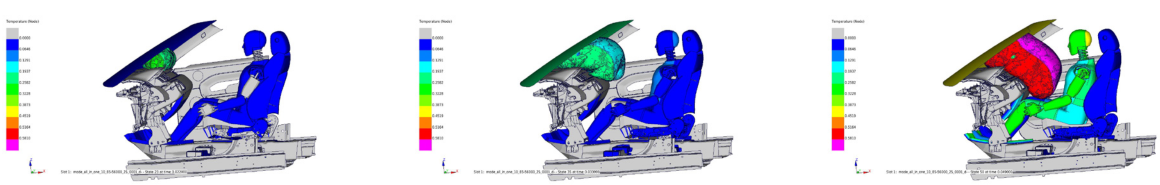

Figure 7. Part-curve correlation plots at 23ms, 35ms and 50ms

To further quantify the strength of this relationship, DPCA allows subtraction of airbag deformed shape modes from scatter in the time-histories, and, in this case, the effect of subtraction of the first two airbag modes is to reduce the scatter in both chest acceleration and neck moment by 20%. This reduction is illustrated by the curve mode boundaries shown in figures 8 and 9 respectively. In particular, the separation of mode boundaries for the neck moment can be significantly reduced after 85ms, which indicates that a meaningful reduction in neck moment scatter can be achieved by improving airbag stability.

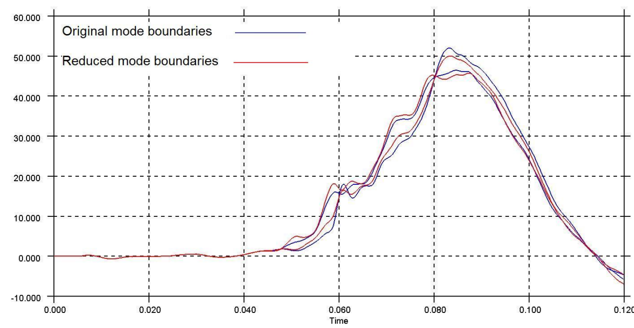

Figure 8.Subtraction of first two airbag deformation mode from chest acceleration mode

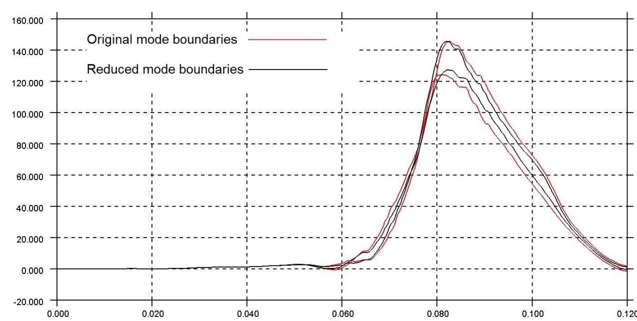

Figure 9. Subtraction of first two airbag deformation mode from neck moment mode

Summary

Creating robust designs in the face of natural variation represents a challenge for a CAE-based development process. However, the CAE process offers new approaches to the study of variation, and techniques based on PCA have been presented, with an example of their application to an occupant restraint system model. In this present work the technique was extended to the treatment of curves, allowing dummy injury time-histories to be analysed. It has been shown that this allows scatter in time-histories for two different channels, to be related to each other. Further, scatter in time-histories can be related to modes of deformation, providing a useful basis for the development of designs that minimise sensitivity to noise in input parameters, and so reduce the risk of disruption to the vehicle development programme.

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