

Advanced Mode Analysis for Crash Simulation Results

Clemens-August Thole

Schloß Birlinghoven, Sankt Augustin, Germany
Clemens-August.Thole@scai.fraunhofer.de

Abstract

Potential scatter of simulation results caused for example by buckling, is still a challenging issue for the predictability. Principle component analysis (PCA) is a well-known mathematical method for data analysis. In order to characterize scatter PCA analysis was applied to the simulation results from a number of runs using all node positions at all time steps. For industrials relevant problems the size of the data base is larger than 100 GBytes (even, if compressed by FEMzip¹[7]). As a result the major components dominating the differences between the simulation results are available.

Since PCA is a mathematically based method, the selected modes do not separate different physical effects like buckling at different parts of the model. PCA rather tries to maximize the variations by combining several physical effects into one mode.

Difference PCA (DPCA) applies PCA analysis to the results for each part and time step. By analysis of the related covariance matrices, the local dimension of the scatter subspace can be identified and correlation between the scatter at different places can be analyzed. Using DPCA, different origins of scatter can be identified and physically meaningful components can be determined. The paper introduces the approach and shows results for an industrial model.

Introduction

In [8] and [4] scatter of the Chrysler Neon model and a model of BMW were analyzed in detail. Buckling and contact heuristics were identified as major sources for scatter. For the design and optimization of car models it is very helpful to deal with a simulation model, which generates similar results even if slight changes of the model are performed. In order to investigate reasons for scatter several optimization tools like LS-OPT[®] [6] support the generation of variants as well as the analysis of scatter of key results (like intrusion). In addition LS-OPT also supports correlation analysis between changes model parameters and field results (like displacements at various nodal points) and various functions to visualize correlations and scatter of simulation results. In [4] a new methods using correlation between displacements of nodes were introduced, which allow to find the origin of scatter in crash simulation. All these methods work, if there is a single dominating source of scatter but fail to separate the impact of several sources.

PCA Analysis for Crash Simulation Results

According to [3] Principle Component Analysis (PCA) was introduced by Pearson in the context of biological phenomena [5] and by Karhunen in the context of stochastic processes [2].

¹ FEMzip is a registered trademark of Fraunhofer Gesellschaft, Munich

In [1] 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 $\bar{X}(p, t)$ is the mean of all simulation runs, the covariance matrix C can be defined as

$$C := [c_{ij}]_{1 \leq i, j \leq n} \quad \text{and} \quad c_{ij} := \langle X_i - \bar{X}, X_j - \bar{X} \rangle_2$$

The eigenvectors v_i of C form a new basis (principle components) and the λ_i (squareroots 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

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

follows that

$$\lambda_i = \|\hat{X}(v_i)\|_2.$$

The $\hat{X}(v_i)$ show the major trends of the differences between the simulation results. The coefficients of the eigenvectors v_i correspond to the contribution of $\hat{X}(v_i)$ to $X_i - \bar{X}$ and can be used for cluster analysis and correlation with input parameters. If input parameters have been changed between the different simulation runs, the correlation analysis will indicate how certain trends can be avoided or increased by changing these inputs (e.g. thicknesses of parts) (c.f.[3], Chapter 2.4] for the properties of PCA analysis in general).

Principle Component Analysis is a mathematical method which determines mathematical trends in contrast to physical trends. To be more specific: λ , the square of the maximal eigenvalue of C , can be determined by

$$\lambda = \left(\max_v \|\hat{X}(v)\| \mid \|v\| = 1 \right)$$

and therefore will be in general a mixture out of several physical effects, like buckling.

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:

$$C_{P,T} := [c_{ij}^{P,T}]_{1 \leq i, j \leq n} \quad \text{and} \quad c_{ij}^{P,T} := \frac{1}{N_{P,T}} \sum_{p \in P, t \in T} (X_i(p, t) - \bar{X}(p, t)) * (X_j(p, t) - \bar{X}(p, t)).$$

($N_{P,T}$ 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 [3], Chapter 3). Buckling or any other local instability in the model or numerical procedures increase the intrinsic dimension of simulation results at parts which are affected compared to those, which 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

$$C_{P_2, T_2} - \tau C_{P_1, T_1}$$

for the covariances 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, $X(v_{P_1, T_1})$ 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..

Example

The new method was tested on the publically available Ford Taurus test case (version with 854692 elements) as provided by the NCAC at the following web-page: <http://www.ncac.gwu.edu/vml/models.html>. Simulations were performed by LS-DYNA[®]. The thicknesses of all parts were changed by +20%. A DOE was applied using a latin hypercube sampling with 100 simulation runs. The thicknesses of the first 99 parts were changed individually while the remaining parts were treated as one group.

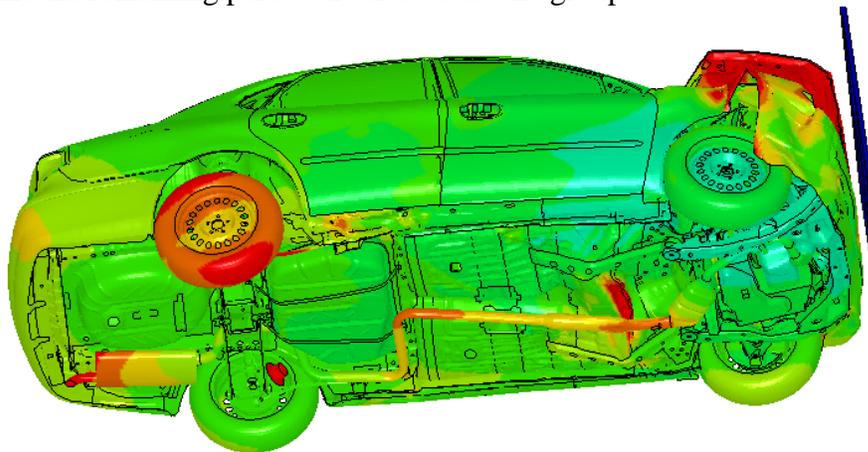


Figure 1: Maximal local difference between simulation results as color coding computed by DIFF-CRASH [4] (range 0-100 mm)

Figure 1 shows the maximal between the simulation results computed by DIFF-CRASH², a tool for the statistical analysis of crash-simulation results. It shows substantial scatter for example in the floor section.

² DIFF-CRASH is a registered trademark of Fraunhofer Gesellschaft, Munich

Results with global PCA

Figure 2 shows the results of the principle component analysis. The outliers of $\log\left(\frac{\lambda_i}{\lambda_{i-1}}\right)$ show, that there are a few dominating components starting at component 80. Most interesting are the two last components, which clearly separate from the rest.

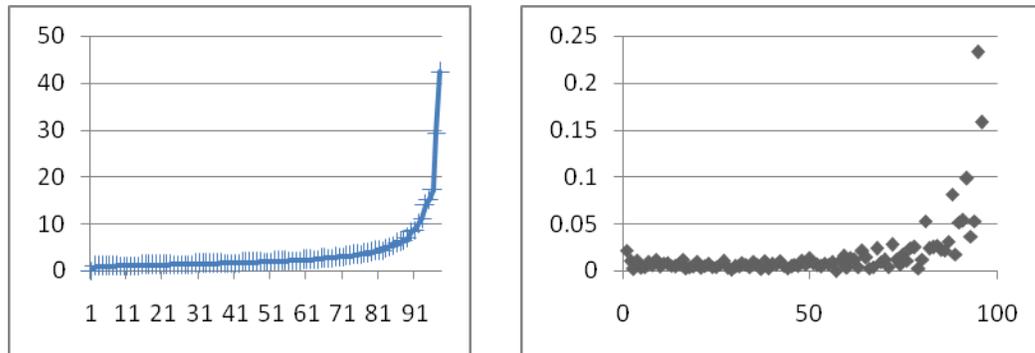


Figure 2: λ_i (Importance measures) for the principle components and $\log\left(\frac{\lambda_i}{\lambda_{i-1}}\right)$

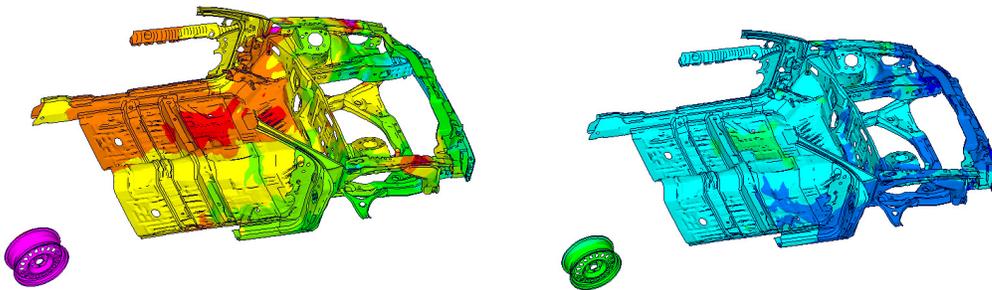


Figure 3: Fringe plots of the two most important components from global PCA on a selected number of parts

The fringe plots on Figure 3 show the two most important components at the final state. Both cover almost the whole car. The contributions of each simulation run to the most important component are directly correlated with the thicknesses of the group of remaining parts, which have been changed simultaneously. The coefficients of the second component are not correlated (even if non-linear basis functions are used) with any of the thickness variation.

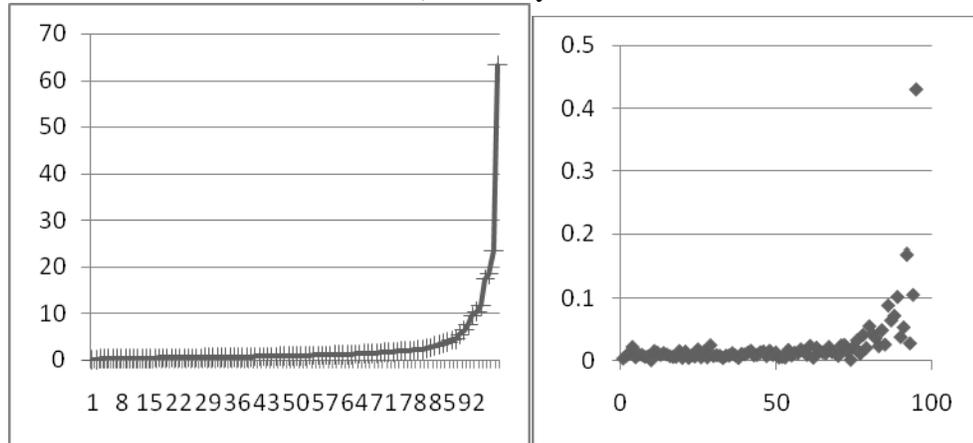


Figure 4: λ_i for the principle components of local analysis of Part 2000085 and $\log\left(\frac{\lambda_i}{\lambda_{i-1}}\right)$

Results with local PCA for spitwall (Part 2000085)

In a second step the PCA analysis has been applied only to the spitwall at time step 150 ms. The intrusion of the spitwall is one of the design criteria for the safety of the car and therefore of special interest for the design engineer.

Figure 4 shows that 4 components are dominating the differences of the simulation runs at the spitwall. Figure 5 shows the most important two components as fringe plots for their displacement on the geometry of the car. The most important component is very similar to that of the global analysis. The second component shows buckling at the floor section which seems to influence the spit wall at the 150 ms.

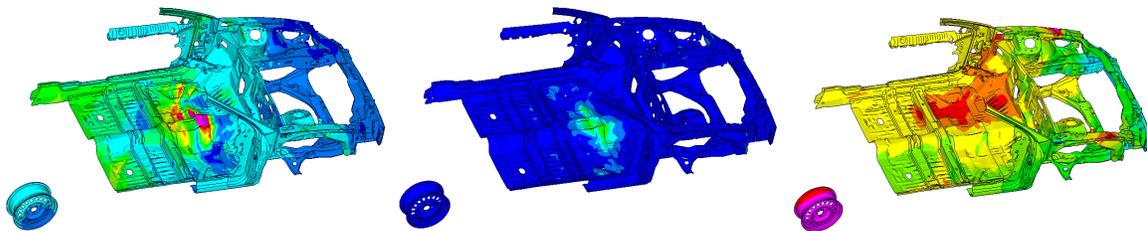


Figure 5: Fringe plot of the displacements of the two most important components from the local PCA analysis of the spitwall (Part 2000085) at 150 ms and for the second component also at 40 ms (Range 0-30mm)

Results with DPCA for spitwall (Part 2000085)

In a final step, DPCA was applied to the spitwall and the floor section. Using this analysis it turned out, that the buckling at the floor section has almost no impact on the scatter at the spitwall (see Figure 6).

Performing a DPCA analysis of the spitwall with all other Parts and time steps buckling of the Part 2000014 (longitudinal rail) between time step 6 and 7 is very important for the behavior of the spitwall. Figure 7 shows the dominating component at 30 ms and 150 ms. At 30 ms it is an almost isolated effect at the longitudinal rail which affects later almost all parts.

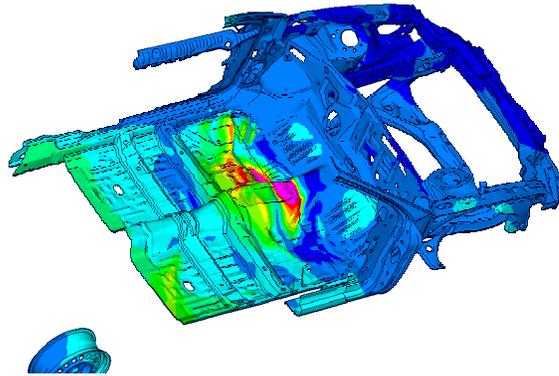


Figure 6: Fringe plot of the most important component of the DPCA analysis of the floor section and the spitwall.

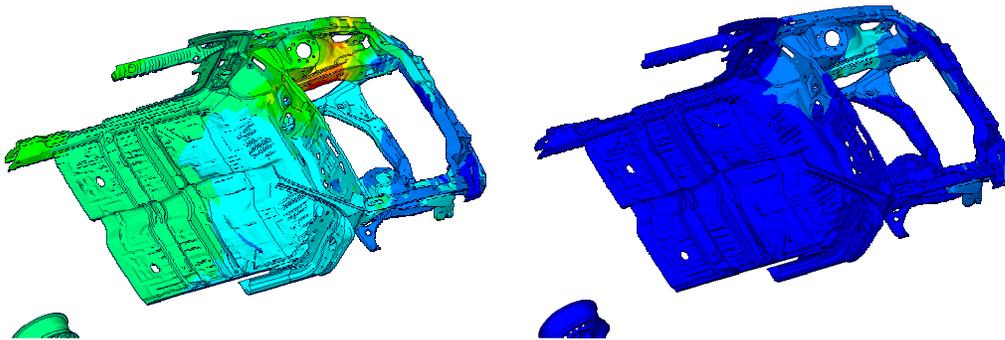


Figure 7: Fringe plot of the most important component of the DPCA analysis of spitwall and longitudinal rail after a clean-up with other scatter candidates.

Summary

Local principle component analysis and DPCA were introduced to the analysis of optimization and stability of crash simulation results. For the most important component a clear correlation with the simultaneous change of the thickness of a group of parts could be identified. DPCA turned out to be useful for the identification of the most important buckling component influencing the spitwall as a secondary effect. Future work will show results of this approach also for non-linear data analysis methods.

Acknowledgments

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