Machine Learning Approaches for Data from Car Crashes and Numerical Car Crash Simulations

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Abstract

During the product development process of cars, numerical simulations are used to, for example, study the influence of variations in the material properties, the geometry of parts, or changes in connecting components. Engineers analyze and compare the different simulations using their own engineering knowledge and employ post-processing tools, which are typically limited to the simultaneous analysis of only a few simulations at a time. The complex structure of the data and its sheer size, the required 3D visualization of the geometry and the needed inspection of the associated design variables of each configuration prohibits a detailed comparative analysis of more than a few simulations by hand.

Motivated by this, we present new machine learning approaches to analyze bundles of numerical simulations. Furthermore, we introduce an analysis method that allows the studying of the correspondence between numerical simulations and highly resolved, in time and space, three dimensional measurement data from real car crash experiments. On the one hand, we use methods for so-called nonlinear dimensionality reduction. These methods are able to compute a lower dimensional representation of the data, along which an intuitive and comparative characterization of a simulation bundle can be achieved. In particular, this analysis approach allows an easy identification of different deformation behavior in the numerical simulation bundle. On the other hand, a fundamentally new approach allows the representation of each simulation in a new compact representation as a sum of elementary components, which can be understood as analogous to the Fourier transform, but for geometries and shapes. The analysis of several simulations then takes place in the obtained space of so-called spectral coefficients. We present applications of this new data analysis procedure for the study of many simulations with changes in the input parameters and for the comparison between time dependent simulations and a real crash experiment.

Overall, we demonstrate how machine learning approaches enable a fast evaluation of not only simple post processing quantities but the complete 3D deformations of many finite element design variants simultaneously. This considerably improves the usefulness of simulation data management systems supporting a faster, simplified and improved post processing of many simulation results.

1. Challenges in the Virtual Development Process

In the automotive sector, numerical simulations of different design configurations mark the virtual product development process. Here, material properties, shapes, and interconnection of parts and connecting components are varied. In addition, different load cases are investigated. Efficient software for the assessment of several simulation results exists only as long as well-chosen quantities of interest, e.g. curves, intrusion or acceleration, are studied. For the interactive and detailed analysis of numerical simulations specialized 3D visualization software is used.

An effective, data-driven handling of bundles of numerical simulations for the comparison of different results, not only based on some key quantities, but on the whole results itself, is so far only possible to a limited extent. Approaches from machine learning, which are based on nonlinear dimensionality reduction, were successfully used to represent simulation results in a lower-dimensional space, which is computed from the data. See Bohn et. al., 2013, Garcke & Iza-Teran, 2014, Garcke & Iza-Teran, 2015, Iza-Teran, 2014, Iza-Teran & Garcke, 2014, and Schöne et. al, 2013 for further information. Through the dimensionality reduction, an intuitive visual organization of many simulations is possible. The arrangement of the simulations in three dimensions takes different changes in their geometry, i.e. different deformations during the collision, into account by employing suitable mathematical principles.

Furthermore, in recent years new optical measurement methods were developed, which can deliver hundreds of detailed 3D point cloud measurements per second (Heist et. al., 2014). Due to the high resolution in space and time, detailed measurement data are obtained from a real crash experiment. A direct alignment, however, between 3D simulations and 3D data is not yet possible. The present article addresses these limitations. The presented approaches allow an alignment of simulation and measured data in an entirely new way. It delivers a substantial improvement during the different phases of the product development process, especially for the automotive industry.

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2. Approaches for the Evaluation of Many Simulations

Due to the large size of the underlying data, the evaluation of numerous simulations require methods for data reduction. Two of those are presented, where the first one is based on manifold learning, an area of machine learning. The results in Bohn et. al, 2013, Garcke & Iza-Teran, 2015, Garcke & Iza-Teran, 2014, Iza-Teran, 2014, Iza-Teran & Garcke, 2014, and Schöne et. al., 2013 have already proven its applicability for simulation data. The second one is a new analysis method introduced in Iza-Teran, 2016 and Iza-Teran & Garcke, 2016. We will present the underlying major ideas of those two approaches in the following.

2.1. Diffusion Maps

Methods for dimensionality reduction are based on the assumption that for high-dimensional data sets, the dimension in this context is *number of nodes * number of time-steps*, one can find a much lower intrinsic dimension. A short example may illustrate this phenomenon: Consider a component that rotates around an axis. The rotation angle is the only parameter and for every angle one can find a component that belongs to it. Using a discrete mesh the component is discretized and so they can be seen as a collection of points and elements on the mesh. Hence, the representation of this component is a high-dimensional vector and its dimension belongs to the number of nodes forming the component. However, the intrinsic dimension is still one and belongs to the rotation angle.

In this context the diffusion maps approach creates a similarity matrix out of the current data, i.e. the part under different angles, using a proper distance-measure. One can proof, that the eigenvectors of this matrix approximate the intrinsic coordinates, assuming enough data is used. The different positions of the part, i.e. the different meshes, may be sorted by their spectral coordinates in the eigenvector basis. In our illustrative example, the result is an ordering according to the rotation angle, which is represented by the first eigenvector.

2.2. Spectral transformation of surface-discretization

The main principle of our new approach consists in finding a suitable basis, which represents the information from the discretization. This can be understood as an analogy to the Fourier-transform in time series analysis. A compact representation of a periodic signal is achieved by applying the Fourier transform and, after that, by using only its frequencies in the Fourier-space. A closer look on that yields, that under the transformation, a different basis containing sine- and cosine-functions, is used to span the periodic signal. According to this new basis, periodic signals can now be represented very compactly and therefore the analysis of many of those periodic signals, with different frequencies, can be done easily in the frequency-space because now every signal can be organized by its frequency.

We will now outline two possibilities to compute such a basis for a finite element discretization. For more details, see Iza-Teran, 2016 and Iza-Teran & Garcke, 2016.

Geometric approach

As said above, using the Fourier-transform a periodic signal can be written as a sum of symmetric components because it may be represented on a circle using sine and cosine, i.e. the Fourier-basis. Therefore, the Fourier-basis leads to a very compact representation of those signals. To carry over this property to a finite element mesh, one should think about symmetries analogously. For example, in the case of a rotation it is possible to use functions on a sphere, so-called spherical harmonics. Using this basis, rotations may be, as in the case of periodic signals, represented very compactly. The compactness of this basis lays in its rotational invariance, so specific rotations can be written as Fourier-coefficients in that basis.

This principle can for example be generalized to deformations which they do not tear the structure apart. During a crash, the distances on the surface are preserved, at least approximately, as long as no fractures arise. Such distance preserving deformations are called isometries. Our new approach now consists in obtaining a new basis, which is invariant to isometries. With a geometry-based ansatz, using the discrete Laplace-Beltrami operator on the discretization mesh of the parts, a spectral decomposition of the deformations results in a kind of elementary deformations. This is in correspondence to the Fourier-transform and the described example.

Stochastic approach

The new approach employing symmetries can be enhanced with a stochastic setting. Suppose that some simulations already have been computed with small changes in the input parameters. We will now consider these changes as stochastic. Furthermore, we assume that the deformations, due to the different parameters, are small in comparison to a reference configuration in a short interval of the simulation. Hence, to every point of the mesh a “point cloud” can be assigned, namely the set of movements for the chosen point at a fixed time step, as observed in all the different simulations. Based on Singer & Coifman, 2008 and Kushnir et. al. 2012, one can assemble a covariance matrix for the “stochastic” movements from the individual point clouds. Further, using the covariance matrix, the Jacobian for the transformation between the reference simulation and every other simulation can be approximated, which then allows a suitable distance measure between pairs of simulations. As a result of this approximation and the resulting distance measure, a new basis can be computed which is invariant to these kind of transformations, see Iza-Teran & Garcke, 2016 for the mathematical details.

3. Comparative Analysis

After a suitable basis is computed, every simulation can be written as a sum of elements of that basis and as a result, a comparative analysis can be performed efficiently. The comparison of the simulations is now based on the obtained spectral coefficients. An interesting property of this new representation is that said elements can be seen as different scales and that they are independent from each other. Recall the example with the rotating component: The parts of the structure, where a rotation and a translation happens, are built out of these two independent components. The first spectral component represents the translation, the second the rotation. This property and its generalization to other isometries enables interesting and important applications, some of which we will introduce in the following.

4. Applications

We will now present two use cases. The first one deals with the comparative analysis of many simulation results, the second one with the comparison of experiment and simulation.

4.1. Comparison of Many Simulations

We study a FE-model of a Chevrolet C2500 Pick-Up Truck, from the National Crash Analysis Center (NCAC), containing approximately 60000 nodes and elements (Bohn et. al., 2013). A head-on collision is studied, where we vary the plate thickness of nine different parts between the 116 different numerical simulations we performed. From every simulation result the deformation of the beams was extracted and a geometrical basis was computed, under the assumption that the distances inside of a part are preserved in every time step. Using the new basis the resulting deformation for each plate thickness parameter setup can be written as a sum of elementary components.

We are now focusing on the beam and the x, y, z coordinates of the translation in the new basis. The obtained spectral coordinates for a deformed and moved part now represent the contribution of the corresponding elementary component. For illustration, we now take the first component in x, y, z direction. Hence, we obtain three coefficients per simulation and per time step. We look at about 100 time steps per simulation, which we now can visualize simultaneously in a single diagram. In other words, for hundreds of time steps and simulation results, it is now possible to depict the temporal development of the crash behavior, see figure 1. In the figure, every point represents a result of a simulation at one time step, we show in this way a position for each simulation at each time step. In this case, the bifurcation of the simulation results is clearly visible using the elementary components. It is easy to see how all simulations start with the same geometry and then form two different modes over time. In particular, the specific time step of the bifurcation is approximately identified.

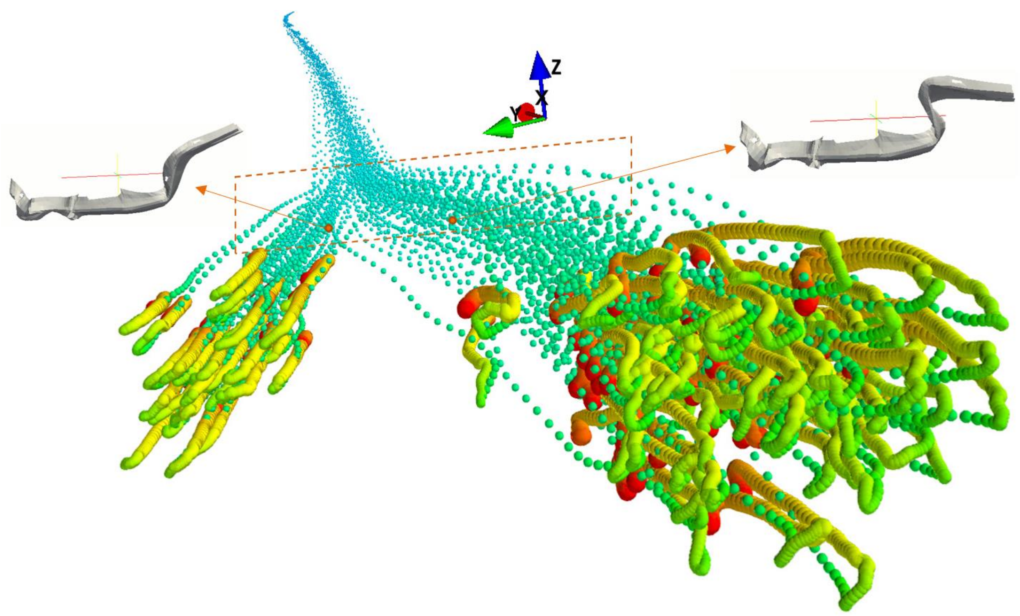

Figure 1: Comparative analysis of about 100 time-dependent simulations. Every point represents a simulation at a specific time step. A bifurcation is obvious; two modes of the deformations are clearly visible. The specific time step of the bifurcation is also approximately identifiable.

4.2. Comparison with Experimental Collisions

4.2.1. Deformation

The decomposition based on the described stochastic approach delivers not only a decomposition in translations and rotations. Global deformations of a structure as well as local deformations are obtained as elementary components. Based on said basis, we implemented a matching process between a simulation and high resolution 3D measurements coming from real crash experiment. As a result, an innovative comparison between real and simulated deformations is now possible.

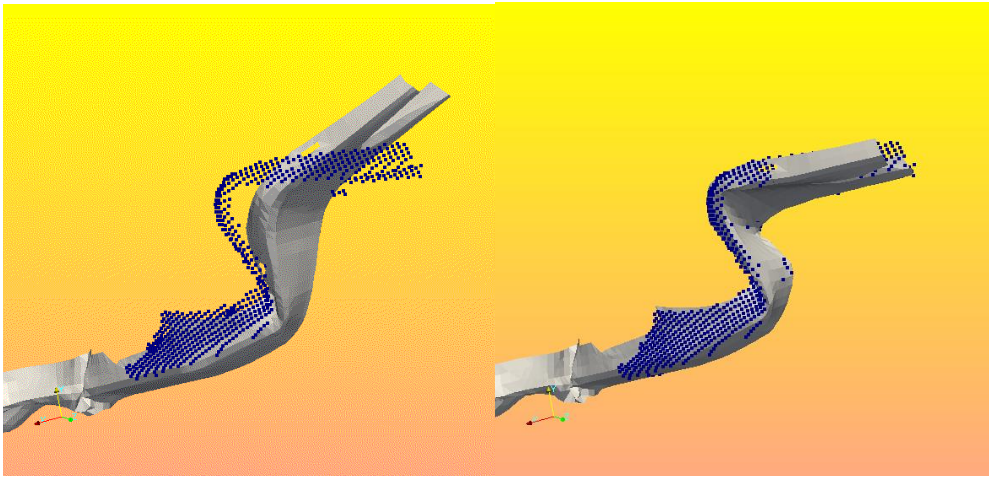

Figure 2: The decomposition of the geometry into elementary components enables an easily computable morphing of the simulation mesh. Using that, a matching of a mesh with a measured point cloud obtained from the experiment is possible.

In figure 2, a beam and a synthetic 3D measurement, both with different deformations, are shown on the left hand-side. The elementary components are made of different local deformations and one of those is essentially corresponding to the bending of the front part. In an optimization step the spectral coefficients corresponding to the components are modified until the discrete simulation data approximates the real deformation of the structure. The obtained result is shown on the right hand-side of figure 2.

4.2.2. Alignment

We will now present results from a real test-structure studied in the internal Fraunhofer project "Hochgeschwindigkeits-3D-Messdatenerfassung zur Validierung von Experiment und Simulation in der Crashbewertung", together with Fraunhofer EMI and IOF. In the experimental setup, the structure gets under load by an accelerated mass. In the course of the project, several real experiments were performed, but we will focus on one to illustrate our approach for comparing simulation and experiment. A FE-model, which describes the test structure, was designed at Fraunhofer EMI, see figure 3.

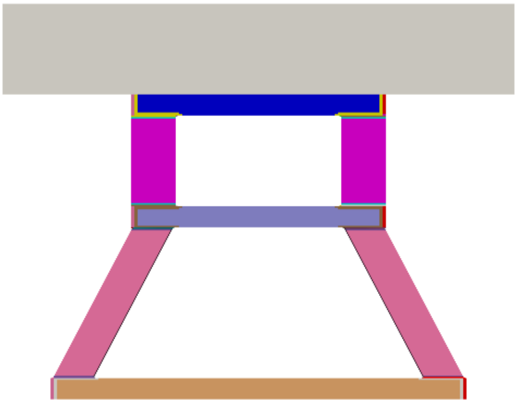

Figure 3: Finite-element model of the test-structure.

The position of the camera allows the measurement of a 3D point cloud covering parts of the upper beam, see figure 4 (left). About 45 numerical crash simulations were performed, with a spot weld thickness randomly chosen between [1.8, 2.19], see figure 4 (right) for an illustration of the setup.

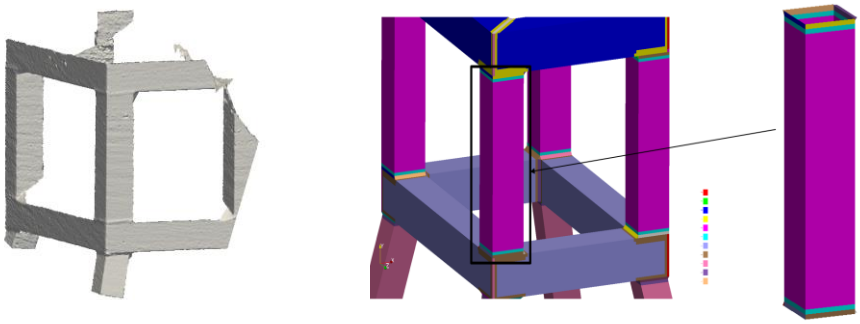

Figure 4: The test structure that was used for the experiments. The point cloud from the real experiment (left), a finite-element model of the test-structure and the extracted beam for the analysis (right).

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For the alignment and data analysis the following steps were done:

1. Computation of the stochastic basis from the simulations and the spectral coefficients in this basis for the simulation results.
2. Calculation of the spectral coefficients for the experimental data.
3. Identification of the simulation that is the closest to the experiment by comparing the spectral coefficients. A joint visualization of an experiment together with a matching simulation is shown in figure 5.
4. Dimensionality reduction using diffusion maps.

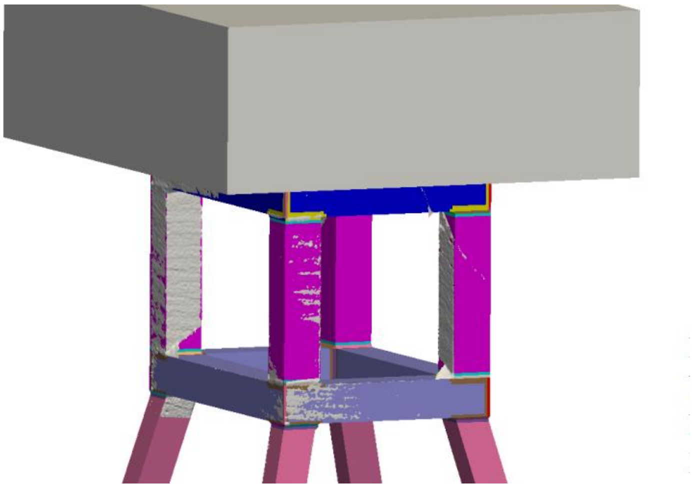

Figure 5: Superposition of data from an experiment and a simulation, as a result of the introduced alignment procedure.

Here, the dimensionality reduction enables an overview of all 46 simulations in terms of spot weld thickness. See figure 6 for a lower-dimensional embedding of the time-dependent simulations, where the input data for diffusion maps are the Euclidean distances of the spectral coefficients computed by the introduced procedure.

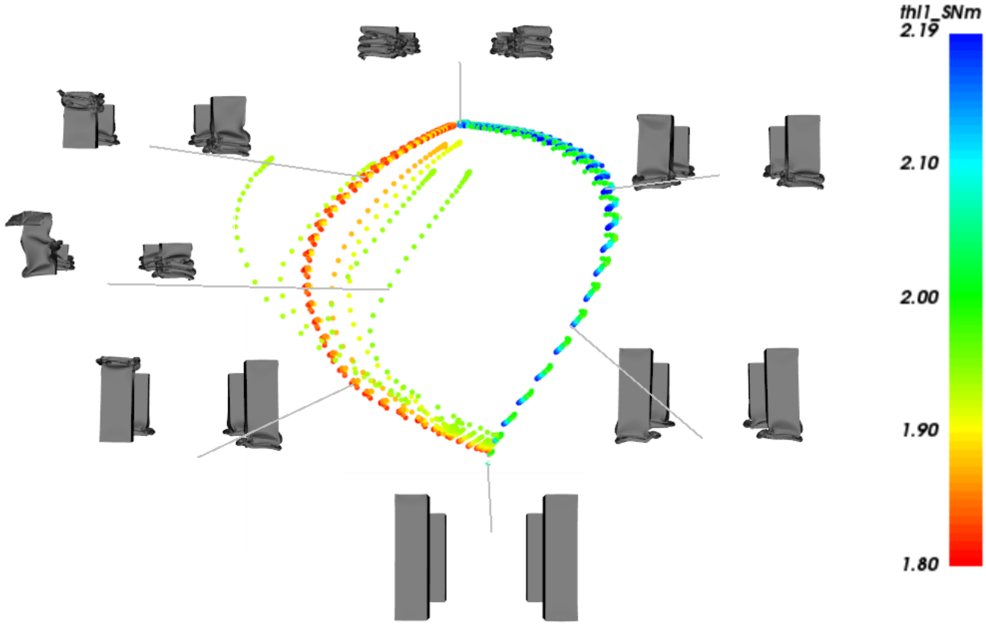

Figure 6: Embedding of 46 simulations and 61 time steps using diffusion maps. The color of each point indicates the value of the spot weld for the corresponding simulation.

We clearly observe the different modes, see the grey images in figure 6 to compare the bending-behavior. The left side of the three-dimensional embedding corresponds to the deformations starting in the upper area; the right side corresponds to those starting in the lower area. Outliers are also included; these unstable deformations are different to both modes. In addition, figure 6 clearly shows that the spot weld thickness has a strong influence on the obtained deformation behavior.

In a further analysis, we now locate the coordinates of the experimental data in the embedding. This allows an evaluation of both, simulation and experimental data, regarding the choice of parameters, see figure 7.

We showed here an exemplary comparison between numerical simulations and physical experiments using our new approach. The investigation of a real car component under load will be part of our ongoing further research.

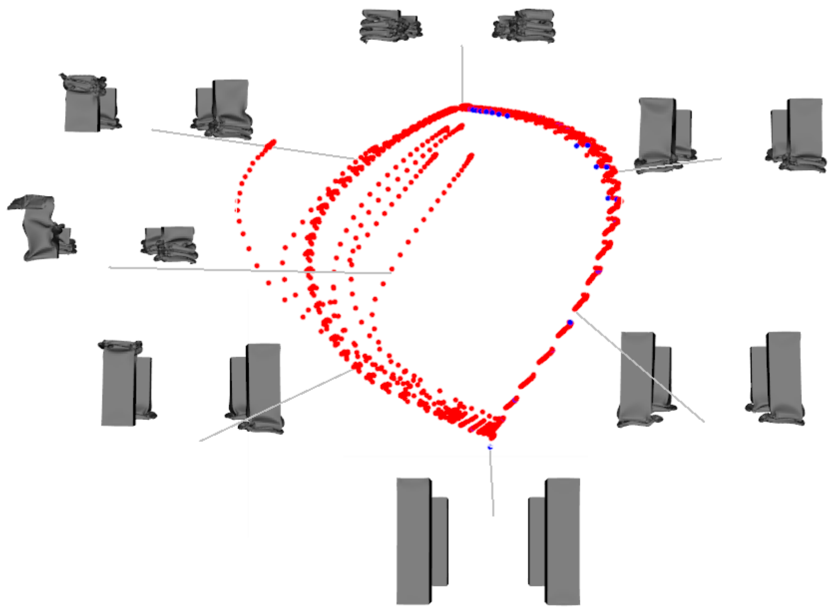

Figure 7: Embedding of experimental and simulation data using diffusion maps. The blue points represent the experimental data as it is aligned with the simulation results in the course of time.

4.2.3. Alignment with the von Mises Stress

In a real crash scenario, the focus of the development process lays not necessarily on the upper beams, but on the beams at the bottom, which are connected to the firewall of the car. The used test structure is, however, so robust, that the beams at the bottom have not been significantly deformed in the experiments, so that their deformation behavior is already very robust.

Nevertheless, it is important to examine the influence of the beams from the upper part on those at the bottom, especially in view of the changes in the spot welds. To study this behavior we will now take from the numerical simulation results the von Mises stress of the parts at the bottom as an input data for the data analysis, see figure 8.

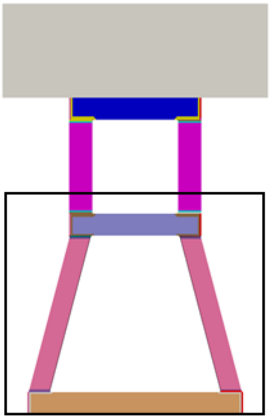

Figure 8: Image of the test structure. The frame marks the area from which the von Mises stress data stems.

For the analysis of the deformations, we use the diffusion maps approach. Here the von Mises stress from the bottom of the structure was taken; the corresponding embedding can be seen in figure 9. Interestingly, one can get information on the deformation of the upper structure from this embedding obtained from the von Mises stress. As in the analysis before, three characteristic modes were found: a) the deformation begins at the top of the part and b) the deformation begins on the bottom and c) outliers. Since we are able to align the experimental result with the numerical simulations, we know the approximate position of the experiment also in this embedding by taking the simulation with the closest deformation. Thereby, we can indirectly determine to which mode of the von Mises stress the experimental result belongs.

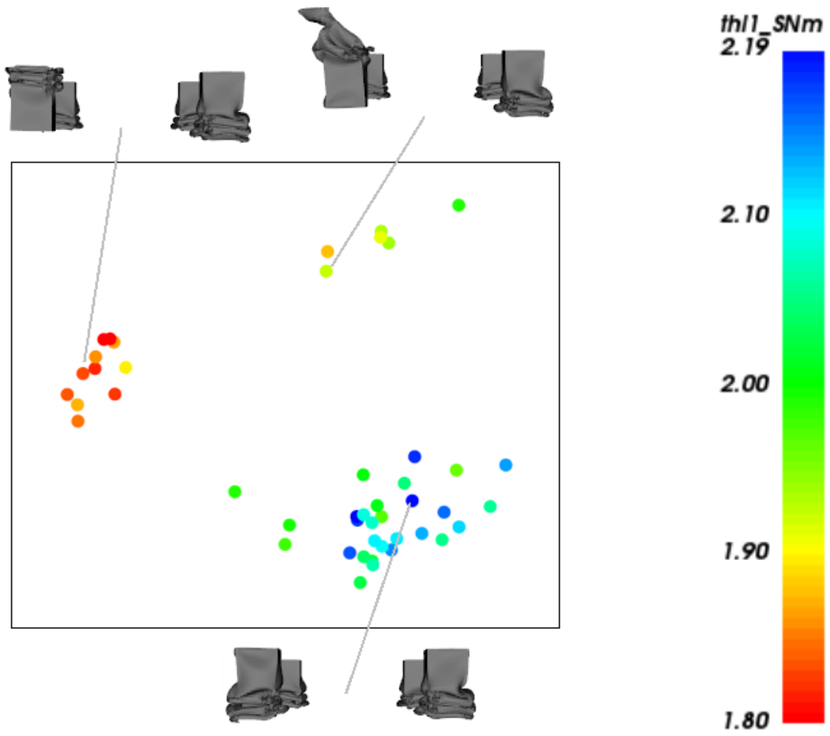

Figure 9: Embedding according to the von Mises stress at time step 20. Here the color of each simulation corresponds to the thickness of the spot weld. Characteristic deformations for every group are shown as well. The real experiment is located in the group at the bottom right.

5. Conclusion

We proposed new approaches for the evaluation of several simulation results that allow an intuitive visual overview for the parameter depending behavior during the collision. Additionally, we introduced new approaches for the combined analysis of simulation and experimental data. Furthermore, we presented an indirect analysis, in which information about the observed experimental bending behavior of the upper beams was aligned with the stress behavior of the lower beams.

These methods offer new opportunities for the analysis of many simulation results and allow integrating experimental data into such a data analysis. A usage of said methods on current industrial cases promises very interesting results for the engineering practice.

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