Super-Ensembler: Interactive Visual Analysis of Data Surface Sets

Lena Cibulski[a,b], Borislav Klarin[c], Martin Sopouch[d], Bernhard Preim[b], Holger Theisel[b], Krešimir Matković[a]

[a] *VRVis Research Center, Vienna, Austria*
[b] *Otto-von-Guericke University, Magdeburg, Germany*
[c] *AVL AST, Zagreb, Croatia*
[d] *AVL List, Graz, Austria*

Abstract

Multiple-run simulations are widely used for investigation of dynamic systems, where they combine varied input parameters and different kinds of outputs. In this work, we focus on a simulation type that outputs an ensemble of surfaces for each simulation run. Multiple simulation runs, in this case, result in a set of surface ensembles – a super-ensemble. We propose an advanced data model, abstract analysis tasks, and introduce an analysis workflow for the exploration of super-ensembles. To address the challenging exploration and analysis tasks, we present Super-Ensembler, a visual analytics system for analysis of data-surface collections as super-ensembles. We introduce novel aggregation methods and corresponding visualizations. The aggregation techniques reduce data complexity by either yielding a super-ensemble of a simplified data type or a conventional surface ensemble. Novel visual representations include an overview visualization for super-ensembles, 3D multi-resolution box plots, and intersection contours. Together with standard views, such as scatter plots, parallel coordinates, or histograms, they are integrated into a coordinated multiple views framework. The newly proposed methodology is developed in a close collaboration with experts from the automotive domain. We evaluate our approach by means of a case study in the context of gear transmission design. Positive feedback and reported speed-up of the analysis indicate the usefulness of the presented approach.

1. Introduction

Simulation is a powerful tool to understand the behavior of dynamic systems in nature, science, and technology. Depending on the subject, various types of simulation can be used, which produce different kinds of output – from simple scalar values to complex data types. In this work, we focus on a simulation that generates multiple, related data surfaces as output for a single simulation run. Several techniques for an analysis of such surface ensembles have been proposed [1, 2, 3].

Multiple simulation runs can be executed to gain an understanding of how simulated processes evolve depending on varying input parameters, thus delivering insights into the sensitivity of simulation models. Existing analysis techniques can be applied to each of the surface ensembles resulting from individual runs. However, such an approach does not address relations between individual ensembles. Some analysis tasks might not be possible to solve when regarding the output of multiple-run simulation as a set of independent ensembles. In contrast to that, we consider the simulation results as a complex, coherent structure, which we call *super-ensemble*.

As a consequence, novel analysis techniques are needed. Tam et al. identify the potential of ”soft knowledge”, which is only available in human-centric approaches [4]. It includes the ability to consider consequences of a decision or to infer associations from common sense. For analyzing the relations between the simulation parameter space and the corresponding super-ensemble, we therefore pursue a visual analytics approach.

We present Super-Ensembler, a visual analytics system that supports the exploration of super-ensembles emerging from multiple-run simulation. Surface-specific and standard visual representations are brought together using coordinated multiple views. On-the-fly aggregation can be performed on a structural level, i.e. from super-ensemble to representative ensemble, or on the data type, i.e. from surfaces to curves or scalars. We evaluate the proposed system in an inter-disciplinary collaboration with experts from the automotive domain. A case study demonstrates how common analysis tasks can be solved and indicates the usefulness of the presented approach.

The proposed analysis approach addresses the ambitious task of visualizing and exploring super-ensembles. The main contributions can be summarized as follows: (1) An advanced data model called super-ensemble and novel aggregation techniques. (2) Identification and abstraction of analysis tasks in collaboration with domain experts. (3) A novel analysis methodology for super-ensembles and derived ensembles. (4) Super-Ensembler, a visual analytics framework, which addresses the analysis tasks and integrates newly proposed visualization and interaction techniques.

2. Approach Overview

2.1. Data Model

The simulation considered in this work outputs m related data surfaces in a single run. A *data surface* is a 2D scalar field, which can be pictured as a height surface over its domain. In our case, the data surfaces represent simulated forces on the tooth flanks of a gear wheel (Figure 1). A *data surface ensemble* refers to a set of surfaces, e.g. all data surfaces generated within

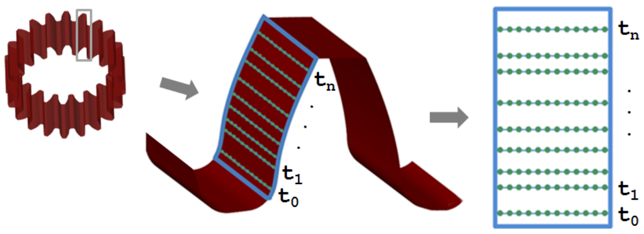

Figure 1: Surfaces are constructed from discretized contact lines, which move along the tooth flank over time (left). All contact lines at discrete time points t_i form a rectilinear surface grid (right).

one run. Common multi-field data sets originate from different quantities, e.g. pressure, temperature, and precipitation in meteorology. Our scalar fields represent the same quantity, making them directly comparable. Consequently, height surfaces are a suitable representation, as differences are directly visible and features like intersections have a clear meaning.

Executing n simulation runs results in n data surface ensembles of size m. Thus, we investigate an ensemble of data surface ensembles, which we call a *super-ensemble*. A super-ensemble can be represented as a $n \times m$-matrix of data surfaces. Traditional approaches cannot be applied to this type of ensemble. Therefore, novel visualization and interaction methods are needed for exploration and analysis of super-ensembles.

2.2. Aggregation

Due to the data complexity, we provide aggregation at different levels. On a structural level, single surface ensembles can be extracted from the super-ensemble. At some point of the analysis, users might be interested in the surfaces resulting from one specific simulation run. In this case, users can interactively select the desired simulation run for further analysis, which we call *run-centric* approach. The corresponding surface ensemble is called *focus ensemble*. For another task, however, users might need to analyze one specific attribute. As an example, they want to see how the forces on one single tooth flank behave depending on different gear designs (i.e. simulation runs). Again, they can manually select the desired focus ensemble, which belongs to one tooth flank in this case. We call this approach *domain-centric*.

A *representative ensemble* results from each row (i.e. simulation run) or column (i.e. attribute) being summarized by one single surface. This aggregation is achieved using projection, where the respective row or column is mapped to one single representative surface. An example projection type is the minimum (maximum, median, average) projection: for each point of the 2D function domain, the minimum (maximum, median, average) of the entire ensemble is stored in the representative surface.

During the analysis process, certain simulation runs or attributes (and their corresponding surface ensembles) can be excluded from the analysis. It results in a *refined super-ensemble*, which can be treated like any other super-ensemble.

On a data-specific level, super-ensembles with simplified data types can be derived. The original super-ensemble's individual members can be aggregated using projections along the axes, resulting in a *curve super-ensemble*, i.e. each data surface being represented by a curve. Data surfaces can also be represented by scalar values, for example the overall maximum, resulting in a *scalar super-ensemble*. This could be used to efficiently determine if simulated forces exceed a certain maximum tolerance on any tooth flank for any gear design.

The concrete aggregation type depends on the analysis circumstances and task to be solved. Also, not all needed aggregates can be determined in advance, as they dynamically result from analysis. For these reasons, we enable on-the-fly computation of aggregates.

2.3. System Overview

We developed the proposed methodology in collaboration with experts from the automotive industry, where data surfaces represent the simulated forces on the tooth flanks.

When visualizing a large number of data surfaces it is challenging to gain a spatial understanding and to identify similarities and differences among the shape of the surfaces. When we talk about large data sets, we mean super-ensembles containing tens of thousands of data surfaces. For visually exploring sets of data surfaces, we propose Super-Ensembler, a visual analytics system. It makes use of coordinated multiple views, where surface-specific views are combined with standard views, such as histogram, scatter plot, or parallel coordinates. Such a combination supports constant switching between detail and scalability, offering a powerful opportunity for drill-down.

Figure 2 shows an example configuration for exploring the results of a gear simulation. Input parameters (usually scalar values) can be assessed via standard views (Figure 2a). Simulation outputs are displayed in the right column of the system (Figure 2c). Together with the input parameters, they serve as a supportive environment for data surface analysis. The main canvas (Figure 2b) is primarily used for surface-specific views, which are described in Section 4.

Super-Ensembler supports the analysis of complex relations in large data sets by integrating visual representations using linking and brushing as well as focus and context techniques.

3. Related Work

Coordinated multiple views (CMV) support the analysis of complex relations in large and high-dimensional data sets [5, 6]. A survey on CMV is provided by Roberts [7].

The exploration of simulation input and corresponding output also relates to the field of parameter studies. A recent survey on visual parameter space exploration is provided by Sedlmaier et al. [8]. Bergner et al. [9] presented ParaGlide, a visualization system that allows for exploration and partitioning of parameter spaces. Beham et al. [10] presented an approach for exploring relations between parameters of a shape generator and the resulting geometries. Pretorius et al. [11] analyze the relationships between parameter settings for image analysis algorithms and the corresponding output.

Ensemble data do not originate from simulations only, but occur in various forms. Ensembles can consist of scalar or vector fields [12], weather forecasts [13], contours [14, 15, 16],

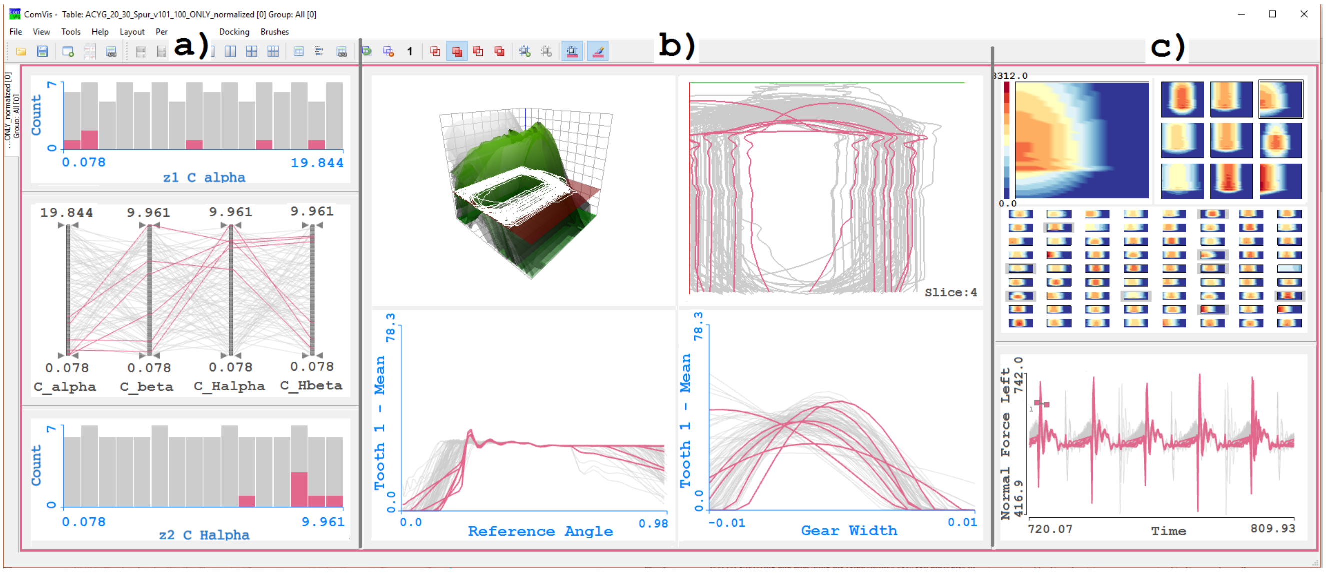

Figure 2: An example configuration of the proposed interactive visual analysis system. Simulation input (a), the current main visualization (b), and additional complex simulation output (c) are displayed in a single window. All views are linked and automatically updated according to brushes, thus supporting an exploration of relations between control parameters (a) and simulation output (b, c).

3D isosurfaces [17], image segmentations [18], or even volume data [19]. They are well-known from meteorology, where repeated simulations characterize the uncertainty of weather predictions. Wang et al. [20] proposed nested parallel coordinates to analyze relations between the high-dimensional parameter space and resulting climate ensembles. While their approach is based on a single time-dependent quantity, we consider multiple quantities as output per execution, which are combined into a super-ensemble.

Several methods have been proposed for visual analysis of ensemble data. Wilson and Potter [21] provide an overview of ensemble data characteristics and consequences for visual analysis. Common approaches dealing with such data are based on complex ensemble members, but they mainly address ensembles of a moderate size (around 50 members) [19, 17, 12]. In contrast, we analyze super-ensembles with tens of thousands of data surfaces as members.

An intuitive approach to visual exploration of ensemble data is to reduce the complexity by summarizing characteristics via statistical measures [22]. Potter et al. [3] presented Ensemble-Vis, which provides statistical aggregation of weather ensembles. For displaying multiple measures, they combine different visual representations, e.g. via overlay. We display five measures using one visualization, which can also be applied to subdivisions of the member domain. We also allow for on-the-fly derivation of aggregates other than descriptive statistics. In addition to ensembles of climate model outputs, Genton et al. [23] analyzed samples of brain images using descriptive statistics. After ranking the sample images, they define and visualize components similar to a common functional boxplot: a representative (median) surface/image as well as an inner and outer envelope.

Simulation results from different application domains can be modeled as surface ensembles. Piringer et al. [1] arrange data surfaces, which result from a bearing simulation, as rectangular icons in a scatterplot-like way. We advance this approach by providing an arrangement of heat maps that offers better scalability. Matković et al. [2] proposed a multiple-level approach closely related to our work. It considers scalar values and surface profiles for aggregation, which is realized per ensemble member. Their data model directly integrates data surfaces as atomic unit. We extend the model to super-ensembles and provide aggregation techniques and corresponding visualizations.

Visualization of surface super-ensembles involves the challenge of simultaneously displaying multiple intersecting surfaces. Intuitively, occlusion can be overcome by rendering interior surfaces opaque surrounded by (textured) surfaces rendered translucent [24]. Bair and House [25] studied different grid textures for visualization of two nested surfaces to improve the perception of the surface shape. Busking et al. [26] propose the use of image-based rendering to visualize two intersecting surfaces, which can even be deformed interactively. Ambiguity regarding surface intersections is addressed by contours. Alabi et al. [27] also support the identification of differences among shapes of surfaces. They derive one composite image from multiple surfaces by alternatingly chaining slices of the surfaces. In this way, differences between adjacent surfaces become visible. However, the mentioned approaches focus on visualizing only a few intersecting surfaces, while we face the challenge of visualizing a large number of surface ensemble members.

4. Interactive Visual Analysis of Surface Super-Ensembles

Visual analysis of super-ensembles delivers insights into large, high-dimensional data sets. It offers the potential for gaining a thorough understanding of the underlying simulation model. Remember, that the simulation might consist of hundreds of runs with hundreds of outputs each, yielding tens of thousands of ensemble members. Various challenges emerge due to the complex composition of the data.

4.1. Analysis Tasks and Workflow

Based on a collaboration with experts from the automotive domain, we identify common analysis tasks, which they face when dealing with simulation ensemble data. There are two leading questions: (1) How do outputs change by modifying the values of control parameters? (2) For which control parameter settings does the simulation produce a desired output?
We identify specific tasks for the analysis of super-ensembles:

T1: Multi-resolution overview – familiarize with the data. Develop an initial idea of a suitable analysis workflow.

T2: Characterization – identify characteristics of surface value distribution, e.g. detect regions exhibiting high values.

T3: Sensitivity analysis – what significance do individual control parameters have for simulation outputs? How do specific input parameter values affect the simulation output?

T4: Regions of interest – identify control parameter settings that result in a desired surface shape. When dealing with stresses, identify set-ups leading to a uniform distribution.

T5: Side-by-side comparison – compare one ensemble member to another one.

T6: Detailed investigation – investigate single ensemble members in detail while preserving the ensemble context.

T7: Flexibility – constantly change the perspective, e.g. between detail and overview.

Following Shneiderman's information-seeking mantra "Overview first, zoom and filter, then details-on-demand" [28], we introduce an analysis workflow that enhances the exploration of super-ensembles and derived aggregates (Figure 3). The global exploration loop addresses the analyst's need to constantly switch between views and aggregations at different levels of detail (**T7**). The analysis starts with a multi-resolution overview of the super-ensemble. It is in turn enclosed in a loop, which enables the analyst to change the resolution and to refine the super-ensemble via filtering (Figure 3, left). After having gained a first impression of the data set, the underlying data can be narrowed for a more focused investigation (Figure 3, center). The loop at this stage addresses the characterization task (**T2**) and enables the analyst to steer the analysis process by selecting representative ensembles for visualization. This also involves the computation of aggregates in the form of curve or scalar ensembles, where needed. From there, the analyst can also re-enter the overview loop to get a feeling for the analysis context. To gain a precise understanding of individual instances or to validate findings, detailed information can be requested, e.g. the actual data record (Figure 3, right). Such information might also be a starting point for another iteration of the global exploration loop.

4.2. Overview Visualization for Super-Ensembles

At an early stage of the exploration loop, analysts are interested in exploring overall patterns and correlations that can be observed throughout the super-ensemble. For this purpose, they need to gain an overview of the values' distribution across the entire surface domain (**T1**). Therefore, it is essential to efficiently summarize important distribution characteristics (**T2**). In the following, we describe visualization and interaction techniques that support these tasks.

3D Box Plots Descriptive statistics quantitatively describe the main features of data [29]. Box plots are a common method for visually representing such statistics [30]. We construct 3D box plots across all members to provide guidance for further analysis (Figure 4a). They serve the user's spatial imagination and allow for building up a mental connection between a box plot and the represented surfaces. When viewing 3D box plots, only the statistical measures have to be interpreted, without the need to transfer the features' positions to 3D space, which would be required with 2D box plots. A polyhedron, which corresponds to the interquartile rectangle in 2D box plots, serves as a simplified histogram within the interquartile range. This representation is inspired by the histplot [31].

Analysts might need to assess how the surface distribution behaves in parts of the surface domain. To convey local characteristics, a multi-resolution overview is supported by providing 3D box plots at a number of *cells* (Figure 4c), which can be arbitrarily chosen. Orbiting around the scene as well as zooming towards individual 3D box plots hold the potential to solve arising occlusion issues up to a certain degree. However, when strongly increasing the spatial resolution, the interpretation of box plots is disturbed.

For a more focused overview within a region of interest, the user can select a particular cell of the surface domain. This triggers statistics at a higher resolution (**T4**), realized by further subdividing the cell. The corresponding 2D box plots for each new subdivisions are then presented in a separate view. The 2D box plots also support the multi-resolution approach, allowing the analyst to flexibly switch between different levels of detail.

2D Box Plots 2D box plots are arranged in a matrix, which reflects the positions of the corresponding subdivisions within the 3D box plot view. To provide a spatial orientation, these subdivisions are highlighted (Figure 4d, left). This helps to perform a side-by-side comparison between the 2D box plots of a certain cell and the 3D box plots across the entire domain. 2D box plots allow for occlusion-free investigation and therefore form a beneficial complement to 3D box plots.

For optimal usage of the screen space, all 2D box plots are of the same size. As we want to emphasize both low values and high values – one of them as desired, the other one as undesired, depending on the objective – we choose a cold-to-warm color scheme to encode the statistical values (Figure 4d, right). It provides similar visual emphasis for both categories [32] and makes use of an intuitive interpretation, while being colorblind-safe. As 2D box plots are not arranged within a global scale, assessing their ranges takes cognitive effort. To simplify their interpretation, we provide an indicator for the covered range next to each box plot (Figure 4e, left).

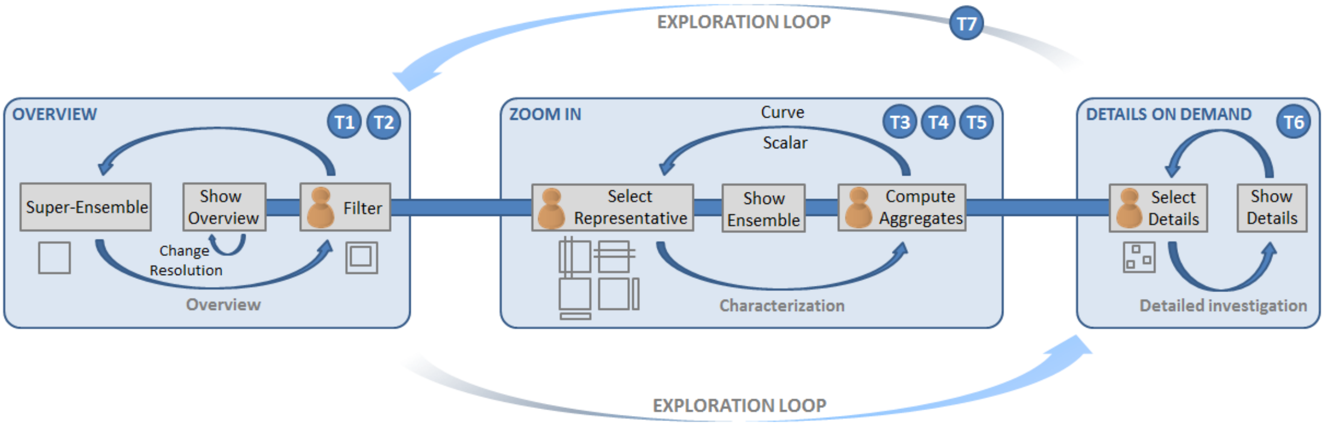

Figure 3: The proposed workflow for analysis of surface super-ensembles. Three different stages are integrated into an overall exploration loop. The analysis starts with a multi-resolution overview (left). Afterwards, the analyst can steer the process in a certain direction (center). Regions of interest can then be analyzed in detail (right). For exploration, the analyst constantly switches between the stages. The encircled numbers refer to the analysis tasks that are primarily solved in each stage.

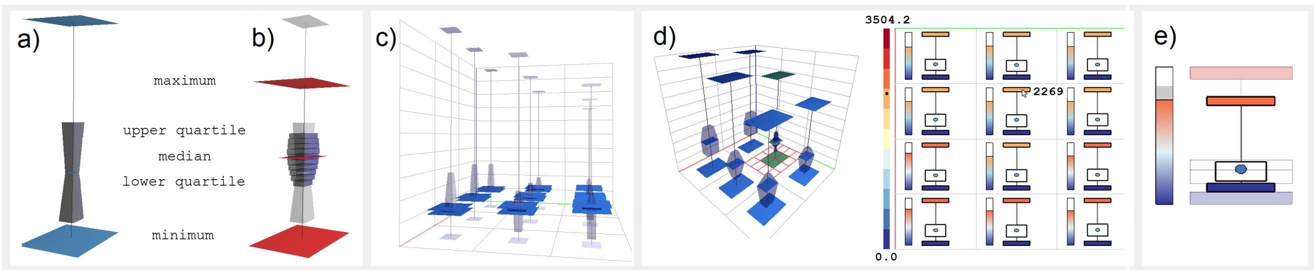

Figure 4: Statistical aggregation across members. a) An exemplary 3D box plot. b) The same box plot updated to a brush and hovered. c) Box plots depicted at a number of cells. The brush results in a uniform distribution. d) The same data set with a different resolution. Details for a selected 3D box plot (left) are displayed via 2D box plots (right). Corresponding subdivisions are marked (left). e) An exemplary 2D box plot depicting a brush. The colored bar displays the covered range.

From considering the overview visualizations, the analyst might have detected simulation runs or attributes that she does not want to be included in the following analysis process. For this purpose, she can refine the super-ensemble by filtering and either proceed with a more focused analysis or consider the overview visualizations again to assess the changes.

Intersection Contours Assessing the data surfaces' original shape is helpful for a thorough understanding of the investigated system. Despite occlusion issues, the domain experts insisted on being provided with data surfaces displayed in a 3D coordinate system. We provide intersection contours as an overview step prior to a detailed analysis of surface shapes.

These contours are computed per surface as intersections with a horizontal cutting plane and open up an additional perspective on the data. They are simultaneously displayed in two different ways: (1) the contours are drawn onto the cutting plane in a 3D surface display (Figure 5, left), and (2) they are presented in a separate 2D display (Figure 5, right). In this way, the spatial context information is preserved in the surface display, while the analyst performs a more precise investigation of the contours in a separate display (**T5**). By scrolling through the slices, the analyst can get insights into the distribution of surfaces in an ensemble, in particular when parts of surfaces are not well distinguishable. Remember that a target ensemble might contain thousands or even tens of thousands of data surfaces. Using intersection contours, a large number of members can be depicted simultaneously without limiting visual analysis.

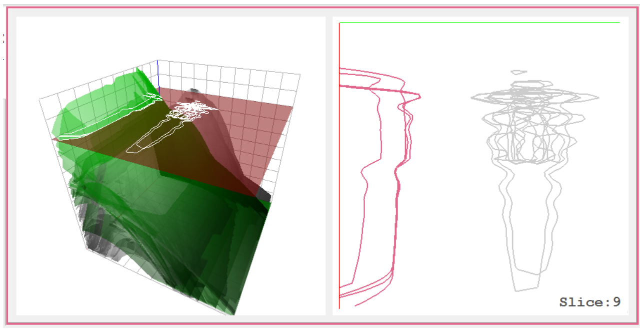

Figure 5: Intersection contours drawn onto the cutting plane in the 3D surface display (left) and displayed in a separate view (right). Brushed contours are colored, while context is depicted in gray.

Aggregated Surface Profiles Intersection contours alone open up a rather limited perspective for a highly scalable overview. In addition, individual ensemble members can be aggregated along one independent variable, resulting in one curve profile per data surface as described by Matković and colleagues [2] (Figure 2b, bottom). In the gear design context, surface profiles were extensively used to evaluate whether the tooth flanks tended to exhibit a phenomenon called edge-loading, which might cause gear failure or damage (**T6**). From there, the analyst can also intuitively drill down to a subset of surfaces with desired or undesired distributions for further analysis: either in more detail by entering the characterization loop (Figure 3, center) or by re-entering the overview loop (Figure 3, left).

4.3. *Visualization of Data in Focus*

To narrow the search space to a region of interest, the analyst can select a focus ensemble, compute an appropriate representative ensemble, or simply use brushing to define a set of data surfaces for further investigation. Brushing is in particular useful when the significance of certain control parameters for simulation output is to be analyzed (**T3**).

According to the focus and context principle [33], the selection of a data subset results in an update of all current views. Intersection contours and surface profiles update by highlighting the corresponding contours and profiles. For 3D box plots, the statistical measures are re-computed based on the brush (Figure 4b). Context box plots help to establish a relation between the brushed data in focus and the entire data set. 2D box plots also update their appearance according to the brushed data subset. Box plots representing the brush are displayed less widely to not occlude the context 2D box plots in the background. To enable a direct comparison between brushed data and context data, the statistical measures corresponding to the selection are depicted relative to the context box plot's range (Figure 4e).

In the following, we will describe additional visualizations that are particularly suited for an analysis of data subsets as well as details on-demand.

Heat Maps At this stage of the exploration loop, the analyst is ready to analyze and compare instances of surfaces themselves. This implies that corresponding visual representations are of a certain size to be able to identify regions of interest. Therefore, we suggest to use such visualizations at an advanced stage of the analysis, where data records have already been drilled-down to a reasonable number. At this stage, we integrate heat maps into the system, because they do not suffer from occlusion and, depending on the color encoding, provide fast perception of regions of interest. Analysts can choose a heat map for in-depth analysis of a single surface or compare multiple data surfaces using side-by-side heat maps.

4.4. *Visualizing Details On-Demand*

To round off the analysis and to verify the findings, one might request details on individual surfaces (**T6**). For example, the exact values for statistical measures in 2D box plots are displayed when hovering over the corresponding rectangle. Such details are in particular important, when multiple similar surfaces should be compared to identify the best-suited one (**T5**).

3D Surface View At an advanced stage of the analysis, the analyst needs to get an idea of the actual shape of surfaces. For this purpose, a 3D surface view is provided. This was important for our domain experts, as it helped to build up a mental image of the surfaces' shapes and their positions. Occlusion issues are addressed by rendering surfaces with a transparency that depends on the distance to the viewer (Figure 5, left). It enables the analyst to view the interior of a surface ensemble (**T2**). Perceiving and comparing shapes of tens or hundreds of potentially intersecting or nested surfaces might still be challenging. Therefore, the 3D surface view will only offer benefits when used with a limited set of data surfaces.

Data surfaces exceeding a certain threshold, e.g. a tolerance, can be brushed using the cutting plane in the 3D surface display (**T4**). All surfaces that intersect with the plane are selected. To exclude surfaces, another cutting plane can be used, such that only surfaces having a peak in between both planes remain. Both planes can be hidden to not disturb the analysis.

Data View Visual representations emerge from a mapping of the underlying data [34] and do not provide access to the raw data. To draw conclusions on which values to choose for simulation input parameters, analysts need to derive exact values as an analysis result (**T6**). We therefore provide a data view, which shows the full data table records for a brushed set of surfaces.

5. Case Study — Loaded Tooth Contact Analysis

Gears are of central importance for a wide range of mechanical devices. Their design affects key functions like durability, efficiency, noise and vibration emission. To ensure a valuable performance, gears have to be highly accurate and reliable. In the case of fatigue or failure, they may cause great damage to the enclosing machine. Designing gears such that low and uniformly distributed stresses arise at the tooth flanks highly contributes to the prevention of failure. To establish a beneficial gear design, it is essential to gain an understanding of dependencies between gear designs and the resulting stresses. Interactive visual analysis helps to fulfill this task.

5.1. *Simulation and Resulting Data Set*

Various parameters define the way in which gear operation is performed. We utilize multiple-run simulation for investigation of different gear designs. These forces are simulated using the AVL Power Unit [35], which is used by the domain experts in their daily routine. The simulation model consists of two spur gears, which are mounted on parallel shafts.

The data set resulting from simulation consists of scalar input parameters (representing gear design and operating conditions) and the corresponding contact stresses for the entire gear wheel. For each simulation run, we process the output of the simulation solver, such that we yield gear stresses per tooth flank represented by one data surface each. The simulation solver computes gear stress values at a discretely sampled contact line that moves along the tooth flank during operation. These reference points build up a rectilinear grid (Figure 1), which forms the 2D surface domain. The simulated values at each of the grid points form the actual data surface. The data surfaces resulting from multiple simulation runs make up the super-ensemble, with 'gear design' along the rows and 'tooth flank' along the columns.

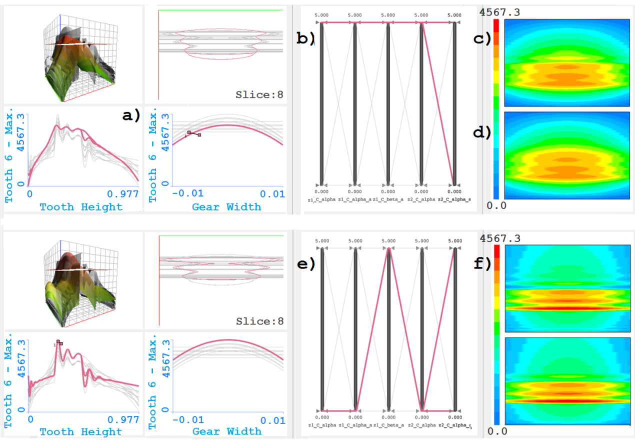

Figure 6: Brushing low forces (a) results in control parameter settings (b) exhibiting a desired force distribution (c, d). Inappropriate parameter settings (e) lead to large and sharp contact forces (f).

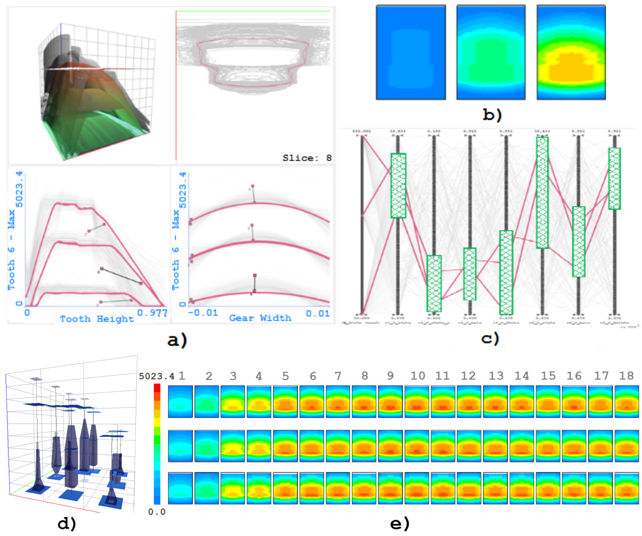

Figure 7: : Interactive exploration of the design space. Selecting desired patterns (a to c). Reverse check, selecting identified ranges and viewing intermediate results as 3D box plots (d). Final results of three desired profile corrections are shown using heat maps (e).

5.2. *Interactive Visual Analysis of Teeth Contact*

Profile modifications are applied to a gear design to improve the gear mesh behavior in terms of the contact load at the mating flanks. Irregularities, such as misalignments and operational clearance, are compensated to avoid high local edge and tip loading. The analysis follows two steps to evaluate how interactive visualization contributes to a deeper understanding of gearing systems and helps to validate design improvements.

Familiarization – Standard Gear Design Process As a first step, the experts analyze a well-known case and familiarize with the visual analysis techniques by reproducing findings from their practical experience. Five standard gear profile modifications with states *applied* and *not applied* are combined to 32 different gear designs. The corresponding data set contains 672 data surfaces, which are arranged as 21 or 32 ensembles, depending on the chosen approach. To evaluate a gear design, engineers need to assess its quality and, if it is not sufficient, identify profile modifications that should or should not be applied to achieve the target requirements (Figure 6).

Maximum surface profiles (Figure 6a) are used to gain an overview of the distribution of forces (**T1**). They also convey an overall impression of whether edge loading, e.g. high force values at the left or right border of the gear width, occurs. As gear stresses are to be minimized, the profiles exhibiting low contact forces are brushed (**T4**). The corresponding control parameters are depicted using parallel coordinates (Figure 6b). The shown design variants have four profile modifications in common and differ only with respect to the tip relief applied to the gear (**T3**). Occlusion-free and intuitive side-by-side comparison (**T5**) of the two designs is provided using heat maps (Figure 6c and d). One of the heat maps depicts a desirably smoother tooth contact (Figure 6d). The color scheme was chosen to meet the experts' standard color scale, to which they are used. In an analogue way, gear designs can be identified, which might lead to gear failure. Applying crowning to the pinion without applying the other profile modifications (Figure 6e) leads to large contact forces (Figure 6f), which may cause flank surface damage (**T3**).

These results agree to the practical experience and confirm the usefulness of an interactive visual analysis of the tooth contact.

Advanced Gear Design Process In a second step, the mating of gears under more realistic conditions is analyzed. The simulation consists of $n = 900$ runs, which are characterized by three different speed and load conditions and seven varied profile modifications (for the meaning of n and m see Section 2.1). We analyze the arising forces on all tooth flanks of one entire gear wheel, leaving us with a data surface ensemble of size $m = 21$ for each simulation run. Consequently, the entire data set is composed of 18900 data surfaces. Surface profiles are used to brush the desired range of forces, in which edge loading is reduced (Figure 7a, bottom left). The selected variants still exhibit increased contact forces in the middle section of the gear width (**T2**). Such undesired design variants are excluded by using a subtract brush (Figure 7a, bottom right). In the end, three design variants with desired characteristics are selected. They can be investigated in detail (**T5**) to verify the resulting force distributions (Figure 7b). The corresponding reduced design space is depicted in the parallel coordinates plot (Figure 7c). The green rectangles indicate the preferable ranges of profile corrections that lead to a desired tooth contact behavior.

To validate the results described above, a reverse check is performed, by brushing the identified preferable profile corrections in the parallel coordinates plot. This results in 27 gear designs, which are depicted by 3D box plots for statistical overview (Figure 7d). As there are differences in the maximum forces for different parts of the tooth flank, one can conclude that some of the gear designs still seem to exhibit undesired behavior (**T2**). In the previous analysis, those were not considered, because the corresponding surface profiles were subtracted from the brush. By repeatedly refining the brush in the parallel coordinates and considering overview visualizations like the 3D box plots (**T7**), the design space can be narrowed to the most preferable combination of profile corrections. The result is validated by viewing the force distributions on all pinion teeth for the identified gear design under the three different speed conditions (Figure 7e).

6. Discussion

The analyst is constantly faced with a trade-off between detail and scalability. The domain experts stated that traditional tools hold difficulties when investigating details, while keeping an eye on the development of contact patterns within the entire system. We provide views that support tasks at different levels of detail. No view alone is sufficient, but a simultaneous investigation of different views holds the potential for a thorough exploration of super-ensembles.

The 3D box plots were primarily used for investigating the gear stresses in a specific region of the tooth flank. This is important when engineers want to influence specific areas of the contact pattern, e.g. the edges of the tooth flank to reduce edge loading. Although 2D box plots would suffice for providing the statistical measures, 3D box plots better blend in with the 3D context. In spite of occlusion, the domain experts appreciate the more meaningful impression that 3D box plots convey.

For building up a mental model of the distribution of ensemble members, the 3D surface display is of crucial importance. It was extensively used at different stages of the analysis. The domain experts stated that, in the long term, the 3D display will be an essential support for the assessment of gear contact results. Aggregated surface profiles also significantly contributed to the analysis; they were primarily viewed to gain an initial impression of the distribution's characteristics, e.g. whether undesired edge loading occurs. The domain experts also used the surface profiles to exclude surfaces exhibiting such phenomena from further analysis. In contrast to that, the intersection contours were not extensively used by the experts.

Although we carefully chose the color-coding scheme for the heat maps, the domain experts insisted on using their standard color scale. The benefit of lowering obstacles by providing common techniques might exceed the benefit of novel techniques with a steep learning curve. Heat maps were mainly used to compare data surfaces and therefore to identify the most suited gear design from a number of candidates. Although we propose a CMV system that might not be intuitive for domain experts, they were relatively quickly familiar with it. Parallel coordinates were extensively used for accessing control parameters, which is rarely reported.

To summarize, the domain experts highly appreciate the novel methodology. Conventional tools used in the automotive domain do well in side-by-side comparison of selected design variants, but fail to support an overview of a large number of variants to identify the most important control parameters. Traditional analytical methods follow a rather sequential process. They strongly rely on the experts' working experience regarding the implications of certain parameter variations. Depending on trends and patterns that are identified in simulation output, the experts vary individual design parameters to steer the results in the desired direction. Design parameters like the type of gearing, the number of teeth, or the modulus can be relatively easily derived from the requirements of the target gear application (e.g. axis distance or transmission ratio). However, there are parameters, for example different profile modifications like bending of the tooth flank, whose implications on the arising stresses are more subtle and exhibit quite complex cross-relations. Using intuition and their working experience, domain experts might be able to narrow the value range of such parameters, but determining precise values might be difficult. Our approach provides an efficient way to perform such fine-tuning by smoothly supporting an explorative sensitivity analysis. When a suitable design has been identified, the corresponding exact values for all involved parameters can be accessed to be used for the actual manufacturing process. According to both experts, the described visualization methods significantly add value to state-of-the-art methods for gear contact analysis. They reported that the newly proposed techniques simplify and at the same time deepen the understanding of correlations between gear design and gear stresses. Besides the domain of gearing, the presented methodology is widely applicable to other domains like meteorology, engineering, or lighting design, where data sets can be represented as super-ensembles.

7. Conclusion

Due to data complexity, the analysis of an ensemble of surface ensembles is challenging. In this paper, we introduce Super-Ensembler, a visual analytics framework to support the analysis of super-ensembles. An advanced data model adequately represents the underlying data. To support the identified analysis tasks and workflow for exploration, novel aggregation techniques and corresponding visualizations are integrated. The methodology has been developed in collaboration with experts from the domain of gearing systems. For evaluation, we performed a case study, where gear contact stress during operation was simulated. It revealed not only an analysis speed-up, but the experts were also enabled to solve tasks that go beyond the possibilities of conventional tools, in particular related to overviewing a large number of design variants.

In the future, we will integrate the frequency domain as an additional feature for noise and vibration analysis. The analysis of gear contact phenomena would also benefit from integrating several physical quantities, e.g. normal force, sliding velocity, and deformation, to be investigated simultaneously. Finally, to qualitatively assess the Super-Ensembler's potential for the gearing domain, a more formal user study with several domain experts has to be carried out. This is complicated as the experts are sparsely settled and have a tight schedule.

[1] Piringer H, Pajer S, Berger W, Teichmann H. Comparative Visual Analysis of 2D Function Ensembles. Computer Graphics Forum 2012;31(3):1195–204.

[2] Matković K, Gračanin D, Klarin B, Hauser H. Interactive Visual Analysis of Complex Scientific Data as Families of Data Surfaces. IEEE Transactions on Visualization and Computer Graphics 2009;15(6):1351–8.

[3] Potter K, Wilson A, Bremer PT, Williams D, Doutriaux C, Pascucci V, et al. Ensemble-Vis: A Framework for the Statistical Visualization of Ensemble Data. In: IEEE International Conference on Data Mining Workshops (ICDMW). 2009, p. 233–40.

[4] Tam GKL, Kothari V, Chen M. An Analysis of Machine-and Human-Analytics in Classification. IEEE Transactions on Visualization and Computer Graphics 2016;.
[5] Gresh DL, Rogowitz BE, Winslow RL, Scollan DF, Yung CK. WEAVE: A System for Visually Linking 3-D and Statistical Visualizations, Applied to Cardiac Simulation and Measurement Data. In: Proc. of IEEE Visualization. 2000, p. 489–92.
[6] North C, Shneiderman B. Snap-Together Visualization: A User Interface for Coordinating Visualizations via Relational Schemata. In: Proc. of Advanced Visual Interfaces. ACM; 2000, p. 128–35.
[7] Roberts JC. State of the Art: Coordinated & Multiple Views in Explanatory Visualization. In: Proc. of the International Conference on Coordinated and Multiple Views in Explanatory Visualization (CMV). IEEE; 2007, p. 61–71.
[8] Sedlmair M, Heinzl C, Bruckner S, Piringer H, Moeller T. Visual Parameter Space Analysis: A Conceptual Framework. IEEE Transactions on Visualization and Computer Graphics 2014;20(12):2161–70.
[9] Bergner S, Sedlmair M, Möller T, Abdolyousefi SN, Saad A. ParaGlide: Interactive Parameter Space Partitioning for Computer Simulations. IEEE Transactions on Visualization and Computer Graphics 2013;19(9):1499–512.
[10] Beham M, Herzner W, Gröller ME, Kehrer J. Cupid: Cluster-Based Exploration of Geometry Generators with Parallel Coordinates and Radial Trees. IEEE Transactions on Visualization and Computer Graphics 2014;20(12):1693–702.
[11] Pretorius AJ, Bray MAP, Carpenter AE, Ruddle RA. Visualization of Parameter Space for Image Analysis. IEEE Transactions on Visualization and Computer Graphics 2011;17(12):2402–11.
[12] Ferstl F, Bürger K, Westermann R. Streamline Variability Plots for Characterizing the Uncertainty in Vector Field Ensembles. IEEE Transactions on Visualization and Computer Graphics 2016;22(1):767–76.
[13] Sanyal J, Zhang S, Dyer J, Mercer A, Amburn P, Moorhead RJ. Noodles: A Tool for Visualization of Numerical Weather Model Ensemble Uncertainty. IEEE Transactions on Visualization and Computer Graphics 2010;16(6):1421–30.
[14] Fofonov A, Molchanov V, Linsen L. Visual Analysis of Multi-Run Spatio-Temporal Simulations Using Isocontour Similarity for Projected Views. IEEE Transactions on Visualization and Computer Graphics 2016;22(8):2037–50.
[15] Whitaker RT, Mirzargar M, Kirby RM. Contour Boxplots: A Method for Characterizing Uncertainty in Feature Sets from Simulation Ensembles. IEEE Transactions on Visualization and Computer Graphics 2013;19(12):2713–22.
[16] Pfaffelmoser T, Westermann R. Visualizing Contour Distributions in 2D Ensemble Data. In: EuroVis-Short Papers. The Eurographics Association; 2013, p. 55–9.
[17] Demir I, Kehrer J, Westermann R. Screen-space silhouettes for visualizing ensembles of 3d isosurfaces. In: Proc. of IEEE PacificVis Visualization Notes. 2016,.
[18] Fröhler B, Möller T, Heinzl C. GEMSe: Visualization-Guided Exploration of Multi-Channel Segmentation Algorithms. In: Computer Graphics Forum; vol. 35. Wiley Online Library; 2016, p. 191–200.
[19] Demir I, Dick C, Westermann R. Multi-Charts for Comparative 3D Ensemble Visualization. IEEE Transactions on Visualization and Computer Graphics 2014;20(12).
[20] Wang J, Liu X, Shen HW, Lin G. Multi-Resolution Climate Ensemble Parameter Analysis with Nested Parallel Coordinates Plots. IEEE Transactions on Visualization and Computer Graphics 2017;(1):81–90.
[21] Wilson AT, Potter KC. Toward visual analysis of ensemble data sets. In: Proc. of the Workshop on Ultrascale Visualization. 2009, p. 48–53.
[22] Kao D, Dungan JL, Pang A. Visualizing 2D Probability Distributions from EOS Satellite Image-Derived Data Sets: A Case Study. In: Proc. of IEEE Visualization. 2001, p. 457–589.
[23] Genton MG, Johnson C, Potter K, Stenchikov G, Sun Y. Surface Boxplots. Stat 2014;3(1):1–11.
[24] Diepstraten J, Weiskopf D, Ertl T. Transparency in Interactive Technical Illustrations. In: Computer Graphics Forum; vol. 21. Wiley Online Library; 2002, p. 317–25.
[25] Bair A, House D. Grid With a View: Optimal Texturing for Perception of Layered Surface Shape. IEEE Transactions on Visualization and Computer Graphics 2007;13(6):1656–63.
[26] Busking S, Botha CP, Ferrarini L, Milles J, Post FH. Image-Based Rendering of Intersecting Surfaces for Dynamic Comparative Visualization. The Visual Computer 2011;27(5):347–63.
[27] Alabi OS, Wu X, Harter JM, Phadke M, Pinto L, Petersen H, et al. Comparative Visualization of Ensembles Using Ensemble Surface Slicing. In: Proc. of Visualization and Data Analytics (VDA). 2012, p. 1–12.
[28] Shneiderman B. The Eyes Have It: A Task By Data Type Taxonomy for Information Visualizations. In: Proc. of the IEEE Symposium on Visual Languages. IEEE; 1996, p. 336–43.
[29] Mann PS. Introductory Statistics. Wiley; 2013.
[30] Potter K. Methods for Presenting Statistical Information: The Box Plot. In: Hagen H, Kerren A, Dannenmann P, editors. Visualization of Large and Unstructured Data Sets. GI-Edition Lecture Notes in Informatics (LNI) S-4; 2006, p. 97–106.
[31] Benjamini Y. Opening the Box of a Boxplot. The American Statistician 1988;42(4):257–62.
[32] Harrower M, Brewer CA. ColorBrewer.org: an Online Tool for Selecting Colour Schemes for Maps. The Cartographic Journal 2003;40(1):27–37.
[33] Hauser H. Generalizing focus+context visualization. In: Scientific Visualization: The Visual Extraction of Knowledge from Data; chap. Generalizing Focus+Context Visualization. Springer; 2006, p. 305–27.
[34] Card SK, Mackinlay JD, Shneiderman B. Readings in Information Visualization: Using Vision to Think. Morgan Kaufmann; 1999.
[35] AVL LIST GmbH . AVL EXCITE Power Unit. `https://www.avl.com/excite/-/asset_publisher/gYjUpY19vEA8/content/avl-excite-power-unit`; 2017. Accessed: 2017-04-09.