

Engineering Data Analytics

innexation through science

B. Sendhoff and L. Gräning Honda Research Institute Europe



Engineering Data Analytics

From engineering design process ...

... to the (holistic) design of complex systems





- focus on one CAE discipline
- data analytics restricted to one discipline
- data analytics frequently restricted to one team and/or design step

- optimal spatio-temporal problem decomposition
- multi-disciplinary design process
- multi team and multi tool integration
- cross-disciplinary data analytics
- knowledge extraction



- size of engineering CAE data scales with the demand for precision
- with the replacement of experiments by simulations data size increases dramatically
 - unsteady compressible LES simulations of mutiple engine cycles generated data in the **peta byte range**
 - high fidelity crash simulation ~100GB per analysis
 tera byte range

- test processes, e.g. for advanced driver assistant systems
 - sensory information can generate 5TB per hour
 - 10.000km estimated as 125 hours resulting in data in the peta byte range



- Compact feature based representation
 - store only data along traced particle
 - select & calculate features related to the design targets
 - preserve only streamlines with high information content (entropy based)



1/5 of the streamlines preserve 50% of information

Design objective (e.g. correlation to engine efficiency) based data compression



- reduction of uncorrelated flow data
- feature similarity estimated based on feature distributions along individual streamlines
- correlation between design changes and stream line features has been derived using mutual information



CAE Design Process – Three Spaces





Constraints



Objective Values



- different model qualities (LES/RANS), different mesh sizes and mesh geometries due to different objectives and different stages in the design process requiring different local precision
- different classes of design representations and design evaluation (CAE tools)



variations of design representations in one class due to different design focus,
e.g. by different design teams or different stages of development





Unified Representation and Shape Mining



- unstructured polygonal surface mesh (simple and high-dimensional) $\mathcal{M}:(\mathcal{V},\mathcal{K})$
 - list of vertices $\mathcal{V} = (\vec{v}_1, \dots, \vec{v}_n)$
 - p simplices $\{i_1, i_2, i_3, ..., i_{\mu}\}$, with $i_l, l \in [1 ..., n]$
 - enclosing a polygonal face made up of μ segments
 - the surface patches define a locally linear approximation of the surface

vertex displacement – measuring differences to a chosen reference mesh

$$\Delta_i^r \triangleq \delta_{i,j}^{r,m} = \delta(\vec{\nu}_i^r, \vec{\nu}_j^m) = (\vec{\nu}_j^m - \vec{\nu}_i^r) \circ \vec{n}_i^r, \delta \in (-\infty, +\infty)$$



Shape Mining for Design Processes



Shape Mining: Modeling Surface Interrelations



Geodesic distance



Concept Learning





- Interaction analysis provides an algorithmic basis to support and revise the decomposition of complex problems
- Interaction calculation & visualization
 - Interaction values are normalized by the entropy of the design quality
 - Line thickness codes strength of the three-way interactions





- b) rear lift force
- A. Redundancy among all parameters
- B. Interaction between parameters at roof and side
- C. Redundancies and Synergies cancel each other out







Local Interaction – Flow Field Interaction

Iocal interaction analysis





Interaction map visualizing local interaction between A1 and A4

interaction analysis based on the flow field





Concept Learning

Estimating the relevance of the design concepts





Utility:

$$\operatorname{util}(A \to C, \boldsymbol{D}) = \operatorname{vol}(O, \boldsymbol{D}) \cdot \operatorname{IS}(A \to C, \boldsymbol{D})$$

Hypervolume of nondominated solution set co

Interestingness measure: correlation between A and C

$$IS(A \to C, \boldsymbol{D}) = \sqrt{conf(A \to C, \boldsymbol{D}) \times conf(C \to A, \boldsymbol{D})}$$

 $\operatorname{conf}(A \to C, \mathbf{D}) = \frac{\operatorname{supp}(A \to C, \mathbf{D})}{\operatorname{cov}(A \to C, \mathbf{D})}$

- hyper volume measures the quality of the concept in an multi-objective sense
- coverage measures how many designs in my data relate to the design concept
- support measures how many of the designs that belong to my concept relate to the similar objectives

Flow Field based Analysis with Compressed Data

- Flow field analysis based on the quantification of streamline similarities
 - Visualization & analysis of flow field similarities



entropy based compression



· Flow field retrieval

λ	LQ	Best matches id	Time fraction	Correct matches
1.0	2450	77,73,95	100.0%	100.0%
0.9	423	77,73,95	≈22.0%	90.0%
0.7	264	77,73,95	≈ 17.8%	90.0%
0.5	161	77,95,73	≈12.5%	50.0%
0.2	46	95,77,73	≈2.5%	10.0%

same best matches for reduction to ~10% of stream lines, with only 18% of the computation time compared to the raw stream line set





- Engineering Data Analytics (EDA) targets the analysis of data from different design processes, dfferent disciplines and representations
- challenges are the data size and the heterogeneity of the data
- intelligent data compression and a good choice of a unified representation are prerequisites for a successful data analysis process that augments engineering knowledge
- interacton analysis and concept learning can provide new design insight and measure higher order correlations between design variations
- flow field analysis provide important and more comprehensive information on the design process
- Interaction and utility can equally be used for combining different domains
- EDA is not restricted to the design process, it also includes e.g. test scenarios with variations to the sensor set-up, environmental variations, different drivers, scenarios



DAMIOSO – Data Mining on High Volume Simulation Output

- Algorithms for managing, mining, learning and optimizing based on massive data generated by computational simulations
- Combining optimization and simulation technologies under the scope of massive data and long simulation time





DAMIOSO





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