



Data driven Computational Mechanics at EXascale



DCoMEX

Data driven Computational Mechanics at EXascale

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Specification of the UQ aware image segmentation software

DELIVERABLE D5.2

Version No 1



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Description

Deliverable 5.2 describes the final additions to the UQ aware image processing model and software tool. The model makes algorithms for 3D geometry reconstruction from 3D images available. As an extension to D5.1, this report contains the specifications of Task 5.2, and describes the image-based estimation of geometric uncertainties that has now been added to the image segmentation software tool.

In this, the DCOMEX image processing tool continues to follow the modular design (detailed on in D5.1), and plugins offer well-defined interfaces to established open sources image processing software. The plugins offer critical functionality for 2D and 3D image processing, as well as means for export of the generated meshes to MSolve data formats. Additional export options for representing uncertainties have now been identified for considering geometric uncertainties as being relevant to the modeling and have been implemented. To this end, in addition to the functionality detailed on in D5.1, the image segmentation software tool now offers means for exporting representations that consider uncertainties in different ways detailed on in the following.

Being the final report on the DCOMEX image processing tool, the present report expands on the description of the software module from Deliverable 5.1. It details on the recent additions for considering uncertainties that result from uncertain image segmentations

1. Generating probabilistic segmentations

Segmentation methods are organized as plugins in the DCOMEX image segmentation tool. Both the generic tools – such as Ilastik [Berg], or SNAP-ITK [Yushkevich] – and the segmentation tools of the DCOMEX tumor usecase [Kofler] are capable of generating probabilistic output.

They all return 2D or 3D volumetric volumes for each class of interest, with class probabilities assigned to each pixel/ voxel. By passing them through the pipeline to the export function, they can be reformatted to match import data formats of MSolve.

2. Output: Meshes with node probabilities

The first export format enables a use of the probabilities as continuous labels indicating absence or presence of a structure / label by identifying class probabilities with class ‘concentrations’. To this end, local class probabilities are assigned to the nodes of a mesh. This mesh is generated from one selected structure serving as the modeling domain. As an example, for the brain tumor modeling use case, the selected structures is the “brain” class that is exported as a mesh. The probabilities assigned to the nodes of the “brain” mesh are then tissue subclasses, or tumor structures. In this case, the modeling domain is well

defined, class probabilities may be used in the MSolve model to enter stochastic decisions, e.g., on whether state transitions or a propagation of mixture components is taking place.

The modeling domain can be chosen to be a mesh, or a regular grid. In the latter case the exported model may align with the image grid, and the export is a multidimensional array with class probabilities and a domain mask – the current output for our baseline tumor growth models.

2. Output: Ensembles of meshes

Traditional Image-Based Simulation Workflow



Efficient Quantification of Uncertainty in Image-based Physics Simulation Workflow (EQUIPS)

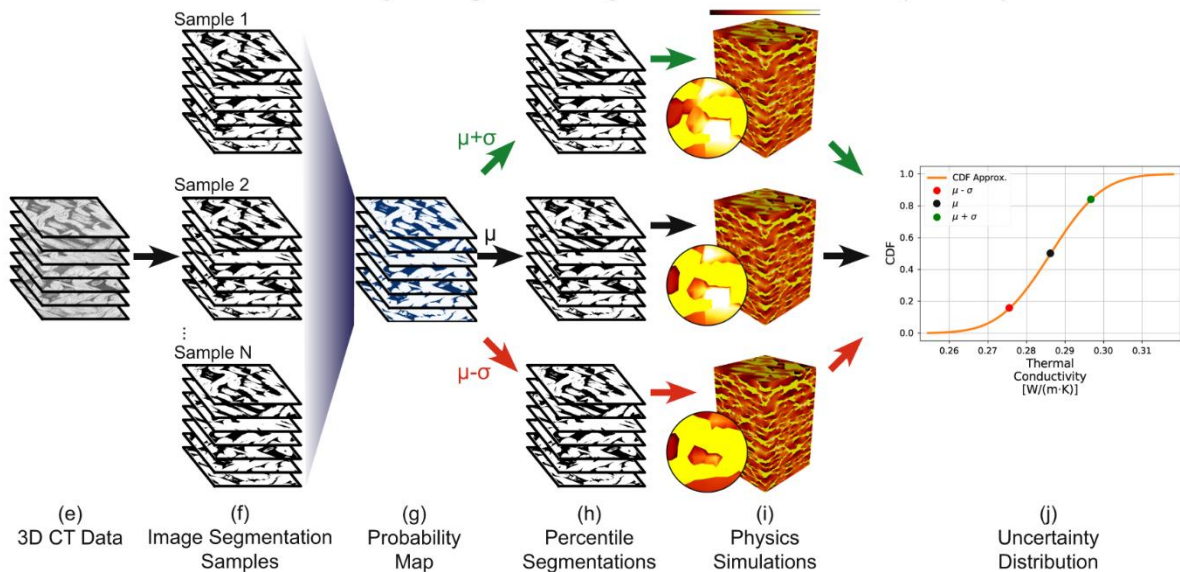


Figure 1: Illustration and concept from [Krygier] that is also implemented in the DCOMEX segmentation tool. The top figure illustrates the traditional image-based simulation workflow with single simulation domain derived from the most likely segmentation of the image. The bottom figure illustrates the idea of using the most likely segmentation of the image as a modeling domain, together with additional domains that represent more extreme cases of possible image segmentation. This results in a distribution of likely results from the simulator (here: a simulation of thermal conductivity), indicating the dependency of the simulation output on the simulation domain.



The second export format deals with the problem that identifying a single class with the modeling domain may not always be as straightforward – or desirable – as in the brain example. In addition, identifying class probabilities with class concentrations may not always be a valid choice, and MSolve simulation models may not be built to consider stochastic components.

In this case, the full stochasticity of the uncertain domain can be integrated in the preparation of the spatial domain(s), as illustrated in Figure 1: The probability maps are transformed into an **ensemble** of simulation domains, that sample and represent highly likely domains, as well as extreme cases. In this, we follow the approach of [Krygier] who demonstrated the benefit of not only using a single modeling domains that represents the one most likely segmentation of the probability map - for example, obtained by threshold the at 50% - but also of using and simulating on additional domains that align with the isolines of other quantiles, e.g., thresholding the probability maps at 10% or 90%. By doing so, the dependency on and sensitivity to – some – extreme modifications of the modeling domain can be considered.

Different from [Krygier] we may deal not only with one simulation domain and class, but with multiple classes. As such, we implement the idea of discretizing domains at extreme isolines of the spatial probability map by reweighting function, together with a subsequent re-normalization of the probabilities. E.g., we apply weights [0.1, 1, 10] of a class to sample isolines to obtain isolines at (about) the 10% and 90% level. Each probability map can be reweighted individually, the total number of exported discretized meshes can represent either the full combinatorial set of isoline and class combinations, or a subset.

Again, the final output can be chosen to be a mesh with discrete mesh labels indicated class membership, or a regular grid with disjunct class labels.

References

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