Uncertainty quantification for fragmentation prediction of reentering space object

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The "Loi relative aux Oprations Spatiales" (LOS, Law of Space Operation) legally obliges space companies like ArianeGroup to deorbit end-of-life objects and to ensure that the reentry in the Earth atmosphere of these objects presents no risk for human assets.
To assess the risk associated with a reentry event, ArianeGroup needs to predict the trajectory of the object but also the fragmentation time. At ArianeGroup, it is done by coupling a trajectory solver coupled with an aerodynamic solver and a fragmentation model. These physical models involve many unknown parameters and dedicated uncertainty quantification methods are needed to assess the reliability of the simulation-based predictions. Formally, this set of solvers used to predict the object trajectory is called a System of Solvers (SoS) and to propagate the uncertainties through this SoS standard uncertainty propagation methods are too costly and alternative dedicated methods have to be derived. For instance, surrogate-based methods aiming at approximating the SoS as a whole may be extremely demanding, while exploiting the structure of the system can drastically reduce the computational effort [2].
In this work, we propose an original method for constructing a system of Gaussian Processes (SoGP) to form a surrogate model of a system of solvers and apply it to the fragmentation prediction tool developed by ArianeGroup. The SoGP is composed of a set of Gaussian Processes (GP) that reproduces the structure of the SoS under study. Each solver of the SoS is associated with a GP in the SoGP which is trained to approximate its corresponding solver. The advantages of the SoGP, compared to constructing a single GP for the whole system at once, are the following. First, the SoGP has a richer structure and offers more flexibility. Second, training the SoGP requires learning multiple but usually simpler individual solvers, possibly adapting the training efforts. On the contrary, a global GP model needs to learn the (generally) more complex mapping between the SoS inputs and its outputs and requires the simulation of the whole system.
The important contribution of this work is the derivation of adaptive training strategies for SoGP. Adaptive learning is widely used to train single GP. To reduce the SoGP prediction error more effectively, one wants to select new training samples for each GP, and possibly to train only a selected subset of GP. To do so, we derive a predictive variance decomposition of the SoGP into contributions from individual GP. For practical use, unbiased estimators of these contributions are derived along with lower computational cost (but biased) approximations. The decomposition of the predictive variance is the backbone of training algorithms proposed subsequently, that identify the GP and its input point having the highest contribution to SoGP variance. The SoGP approach and the proposed training algorithms are tested on analytical problems and for the quantifying the uncertainties in the fragmentation predictor.

Références

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