PhD Position: Machine learning for real-time drift prediction in thermography-controlled thermomechanical manufacturing processes

Context

Quality control of welding or additive manufacturing operations is crucial in the aeronautical, nuclear and naval sectors. In this field, digital twinning is set to play an increasingly important role, on several levels. Firstly, a faithful simulator of thermomechanical manufacturing operations can reduce the calibration time of welding operations, through virtual optimization. Secondly, the digital twin can be used to monitor the progress of a welding operation, and its potential drifts, by comparing simulations with realtime measurements. In this way, the digital twin is continuously calibrated to monitor the operation in progress, making it possible to predict potential drifts and their consequences in terms of the quality of the manufactured part.
For more than 10 years, work carried out at the Mechanics Department of École des Mines has reduced the computation times associated with faithful, finite element, welding and additive manufacturing simulations through the use of meta-modeling and machine learning techniques, in order to provide lightweight simulators for optimizing the choice of forming operation parameters. More recently [1], numerical matching approaches have demonstrated the feasibility of predicting stresses in a material during welding, based on thermographic images acquired in real time. The approach developed is relatively generic, but it comes up against technical limitations that we propose to address, by stepping back from the application to focus on the AI algorithms on which this approach is based. The current limitations are threefold. Firstly, the algorithm cannot predict large deviations from nominal, and cannot represent multimodal distributions of quantities of interest. This can artificially decrease the accuracy of the digital twin. More modern neural network architectures need to be deployed to overcome this limitation. Secondly, the temporal dimension of the problem is not really addressed, as the methodology is seen as a sequence of Independent calibration problems. Finally, the machine learning algorithms used are based on structured data, which limits the genericity of the approach.

Scientific and technical program

We propose 4 Woking Package for this PhD.

WP1. First, we propose to deploy nonlinear generative models (variational autoencoders, diffusion networks) to replace PCA on welding data obtained in previous work. Additional data can be generated if necessary. We will start, in the case of the variational autoencoder [2,6], by developing a conditioning method based on the on-line optimization of Gaussian distributions for the autoencoder latent variables.

WP2. Secondly, we propose to explore AI architectures based on convolutions on point clouds [3,4], in order to improve the genericity of the approach compared with the methods currently used (fully connected networks and convolutions on structured data such as 2D images).

WP3. Thirdly, we will address the temporal dimension of the problem. The analysis of series of thermographic images could enable us to progressively improve the calibration of uncertain parameters in the forming process. To this end, we will turn to recurrent architectures and/or

transformers [5] to exploit the measurement history. Given the volume and dynamics of the data (3D arrays), their processing will have to be optimized to guarantee real-time operation.
WP4. Once these fundamental artificial intelligence tools are in place, we aim to develop an automated data acquisition approach. This will rely on the generative aspect of AI to guide data generation in an optimal way, thus limiting the amount of finite element calculations needed to train generative AI.

Deliverables: A tool library deployed as open source and implemented in the PyTorch AI Python library. Finite element simulations, if necessary in addition to the data banks already available on our hard disks, will be carried out in the in-house codes available at CMAT and CEMEF at Mines Paris PSL.

The PhD provides a unique multidisciplinary environment to carry out new challenging research machine learning in engineering, as well as an outstanding opportunity to work on real-world manufacturing applications.

Applicants

The duration of the **PhD is 3 years, to start to start in the fall of 2024**.
Applicants will have (or be in the process of obtaining) a master's degree in applied mathematics, or mechanics of materials, with an outstanding academic record (at or near the top of their class) at master's level. Preferred candidates will possess demonstrable experience in the numerical modelling and finite element simulations, numerical programming ability using python, professional command of English, good presentation skills, and the ability and willingness to work collaboratively within a multi-disciplinary team.
Prior experience in collaborative projects using git would be appreciated.
Annual gross salary: about 29k€.

Contact
Formal applications should include a detailed cv, letter of motivation, list of publications (in case of joint authorship, please clearly indicate your own contribution), official transcript of grades for the qualifying degree, and the names, affiliations, and email addresses of two academic referees who can provide details about your academic profile in relation to this position (please do not include any reference letters in your application).

Applicants must also provide samples of research papers or sections of dissertation demonstrating their ability to engage in doctoral level academic writing.

Enquiries and **applications should be directed to:**
David.ryckelynck@minesparis.psl.eu

References

[1] Pablo Pereira Álvarez, Pierre Kerfriden, David Ryckelynck, Vincent Robin, Real-Time Data Assimilation in Welding Operations Using Thermal Imaging and Accelerated High-Fidelity Digital Twinning, Mathematics, 2021

[2] Christopher M. Bishop, Pattern Recognition and Machine Learning, 2006

[3] Yue Wang, Yongbin Sun, Ziwei Liu, Sanjay E. Sarma, Michael M. Bronstein, Justin M. Solomon, Dynamic Graph CNN for Learning on Point Clouds, ACM Transactions on Graphics (TOG), 2019

[4] V Krokos, SPA Bordas, P Kerfriden, A graph-based probabilistic geometric deep learning framework with online enforcement of physical constraints to predict the criticality of defects in porous materials, International Journal of Solids and Structures, 2022

[5] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In International Conference on Learning Representations, 2020.

[6] Hugo Launay, David Ryckelynck, Laurent Lacourt, Jacques Besson, Arnaud Mondon, Francois Willot, Deep multimodal autoencoder for crack criticality assessment, IJNME, 2021