From big data to key data

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Abstract — The tremendous inflation in the amount of data to be processed in mechanical tests calls for more efficient extraction of the sought final mechanical information, be it a constitutive law or a specific property. This efficiency may be tailored to not only reduce the computation load for the identification, following model reduction techniques, but also deflate the volume of acquired data, or "data pruning", and hence the acquisition time. A route to fast 4D experiment will naturally emerge.
Keywords — Image-based identification, Model reduction, Fast 4D identification

Introduction Today, tomography based mechanical tests offer the ultimate access to a full 4D characterization. This dream becoming reality alas comes with a huge cost, that of the acquisition of a large number of 3D-volume data as the sample is loaded. A large number of tomographies, each composed of a large number of radiographies, each with an ever increasing definition, not only come with a long acquisition time, but also with very severe constraints and challenges both for the specimen for which no relaxation or creep is tolerated, and for the experimental set-up that should remain free of drift for days. Even when considering 2D tests, it becomes customary to process thousands of high definition images, leading to huge data processing (computation) costs.

This observation prompts for a proper methodology to handle those experiments, and new ways to benefit from these remarkable new opportunities but at mastered costs.

Spatio-temporal framework One first observation is that time being sampled at a fast rate, displacement fields as sought using DIC or DVC have often a temporal evolution that is smooth, thus it is advantageous to introduce a time evolution that is parameterized coarsely in time. Namely, the displacement field may be written as

$$\boldsymbol{u}(\boldsymbol{x},t) = \sum_{i,j} u_{ij} \phi_i(\boldsymbol{x}) \varphi_j(t) \tag{1}$$

where the time functions $\varphi_j(t)$ span numerous time frames. The fact that the reference image does not evolve in time provides an efficient formulation, whereby the computation of the kinematic unknowns scales linearly in the number of temporal unknown. This route was explored in Ref. [1]. Note however that at this stage, this feature reduces the number of unknowns, but not the amount of data to be handled.

Pyramidal description The regularity of the displacement field is also a motivation for using a pyramidal approach where a rough determination of the displacement is first sought based on a coarse image stack. The latter corresponds to a space and time convolution of the image stack by a mollifying kernel, followed by a suited subsampling. Such a processing can conveniently be iterated, eventually with different reduction factors in space and time, leading to a pyramidal construction [2]. When the space-time displacement has been obtained at a specific level of the pyramid (starting from its top), it may be used as an accurate pre-determination of the next finer level. Most of the computation time is naturally spent at the bottom level, and a suited pre-determination reduces the number of needed iterations at this stage.

PGD approach More than often, the chosen kinematic basis has a dimensionality that is much larger — not to be limiting — than the effective number of degrees of freedom that are needed to describe the studied case. In order to exploit this "simplicity", the Proper Generalized Decomposition (PGD) is an elegant method that has been introduced in the domain of *model reduction*. It consists of adding "modes" progressively, one at a time, and as long as the residual level necessitates. Such an approach for DIC and

DVC (in the space dimensions) has been pioneered by Passieux *et al.* [3, 4]. In our case, a mode is the product of a temporal $a_j\varphi_j(t)$ function and a spatial $b_i\phi_i(\boldsymbol{x})$ field. The PGD approach naturally leads to a sparse representation of the displacement field [5]. Here again, a net gain results from the reduction in the number of degrees of freedom that are introduced.

Data pruning In all the previous items, the entire set of data is used. However, because of a large redundancy, not all data are equally important, or useful. Hence, one can be dispensed with some data, either in the processing to speed up the exploitation of an experiment, or better, in the acquisition, to perform much faster experiments, an appealing route for tomography-based mechanical tests, whereby only few radiographies may be used to compute a displacement field, once the full microstructure is known) using a Projection-based DVC [6].

Gathering all the above ingredients offer the opportunity to perform few-minute 4D in-situ experiment and analyze them successfully [7, 8].

References

[1] G. Besnard, S. Guérard, S. Roux & F. Hild. A space-time approach in digital image correlation: Movie-DIC. *Optics and Laser Engineering* **49**:71–81, 2010.

[2] F. Hild, B. Raka, M. Baudequin, S. Roux & F. Cantelaube. Multi-scale displacement field measurements of compressed mineral wool samples by digital image correlation. *Applied Optics* **41**:6815–6828, 2002.

[3] J.C. Passieux, & J.N. Périé, High resolution digital image correlation using proper generalized decomposition: PGD-DIC. *International Journal for Numerical Methods in Engineering* **92**:531–550, 2012.

[4] L.A. Gomes Perini, J.C. Passieux, & J.N. Périé, A Multigrid PGD-based Algorithm for Volumetric Displacement Fields Measurements. *Strain* **50**:355–367, 2014.

[5] J. Neggers, O. Allix, F. Hild & S. Roux. 'Big Data' in experimental mechanics and model order reduction: Today's challenges and tomorrow's opportunities. *Archives of Computational Methods in Engineering*, 2017. https://doi.org/10.1007/s11831-017-9234-3

[6] T. Taillandier-Thomas, S. Roux & F. Hild. A soft route toward 4D tomography. *Physical Review Letters*, **117**:025501, 2016.

[7] C. Jailin, A. Bouterf, M. Poncelet & S. Roux. In situ µ-CT-scan mechanical tests: Fast 4D mechanical identification. *Experimental Mechanics*, 2017.

[8] C. Jailin *et al.* ???? *Photomechanics Conference*, 2018.