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► **To cite this version:**

Arturo Mendoza, Clément Jailin. Automatic crack detection based on machine learning and DVC. iDICs 2020 - International Digital Image Correlation Society, Oct 2020, Virtual Conference, France. hal-03016000

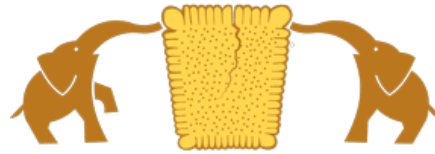
HAL Id: hal-03016000

<https://hal.science/hal-03016000>

Submitted on 20 Nov 2020

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Automatic crack detection based on machine learning and DVC

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Abstract — A voxel-based crack detection method is proposed from DVC results and a simple machine learning algorithm. The method, that requires almost no input and manual fine tuning, exploits observable characteristic of brittle cracks and independent of the material and the experimental procedure. Two applications are performed on two different materials whose cracks were imaged on a tomograph and highlight the efficiency and simplicity of the proposed method.

Keywords — DVC, Machine Learning, Crack detection

Introduction Images play an important role in the mechanical characterization of materials (*e.g.*, DIC). In particular, the matter of identifying the presence of a crack and its subsequent extraction has been widely explored and is usually based on a *ad hoc* sequence of classical segmentation methods (*e.g.*, simple threshold, Otsu’s method, etc) followed by morphological operations (*i.e.*, erosion and dilation) so as to “clean” the segmentation. Two main inconveniences arise with such procedure. First, the custom nature of such procedures means that they need to be performed for each use case. And second, the inherent subjectivity present in the choice of the required parameters (*e.g.*, thresholds, size of erosion kernel, etc.). The challenges imposed by this latter were addressed in references [1, 2] with the use of observables based on features of the material (and its behavior). This approach allows removing the subjectivity in the choice of a threshold value, since it is chosen so as to better approach the known observable [1]; as well as allowing to judge the uncertainty that its related to the procedure, by observing the variability of various micro-mechanical simulations guided by the segmentation procedure [2]. The goal of this research is to provide a methodology that simultaneously addresses both issues previously highlighted.

Methods and materials The proposed voxel-based crack detection method aims to be a general one for brittle materials without any further fine tuning nor manual intervention. Clearly, such conditions imply that any analysis based on the gray level images of the observed samples are to be discarded, since these can vary widely from one to another. The measurement is obtained via FE-based DVC: from the computed principal strains (at the voxel scale) and the resulting residuals. Indeed, these four *features* not only describe the behavior that is sought, but also “remove” the material observed from the analysis (when correlation is successful the material micro structure vanishes). As such, any given state of a sample is represented by four images: the residual image highlights any discontinuities (not captured by the continuous displacement field representation), and the principal strains images highlight the crack opening and crack plane. Next, in order to account for changes in the scale, a multi scale strategy is applied with the convolution of the four previous channels with an isotropic Gaussian kernel of size 1, 3 and 5. Because a discontinuity is searched, fast variations are enhanced with the magnitude of all generated image gradients. This last feature is similar to the Canny or Deriche edge detector (without the *non-maxima* suppression). *In fine*, 32 channels are employed for describing any voxel state of a sample. The present study will profit from two tensile traction tests observed by high-resolution X-ray computed tomography. The first test consists of seven scans at increasingly loading stages of a pre-cracked sample made of spheroidal graphite cast iron. No crack is present in the first three scans, the sample yields in the following four scans. The second test consists of eleven scans at increasingly loading stages of a notched

sample made of glass fiber reinforced epoxy resin composites. Some micro-cracks start appearing at the sixth scan, but close on the seventh; only to re-appear during scans eight and nine, and close on the tenth; finally, the crack propagates in the last scan. Therefore, a simple supervised machine learning algorithm called Decision Tree is trained for discriminating between “crack” and “not crack” voxels. For such, *only* the last scan of the cast iron test is taken for training, with a ground truth constructed from the residual with a threshold of 25% of the initial dynamic range of the image.

Results A Decision Tree of 14 levels with 59 nodes is obtained with the procedure described previously. 22 nodes are driven by the features derived from the residual image, 10-17 and 10 by respectively the first, second and third strain component. Also, the decision seems equally weighted by the different scales: 18-14-14-13 nodes for a Gaussian kernel of respectively 0-1-3-5 voxels. 23 nodes are driven by the “edge” derived features and 36 of the remaining ones. Then, the model is applied on the cast iron test leading to a clearly detected crack. Finally, the same Decision Tree, trained on only the last scan of the cast iron test, is applied on the eleven scans of the glass fiber composite test. The results are extremely gratifying, not only the last crack is easily detected, but also all the micro-cracks are easily extracted with almost to none false positives.

Discussion and Conclusion A general method for crack identification based on measurements extracted from DVC and employing machine learning techniques was proposed. Its simplicity of use (requires almost no user input), makes it attractive for applications dealing with large volumes of data. Moreover, given that the method consists in characterising the crack events via material/mechanical signatures, the approach is independent of the studied material. This is proven with the method being learnt on only one image of a cast iron sample and being tested on a never seen glass fiber composite sample. Finally, the chosen Decision Tree algorithm allows itself for analysing and understanding the segmentation process (by inspecting its decision rules).

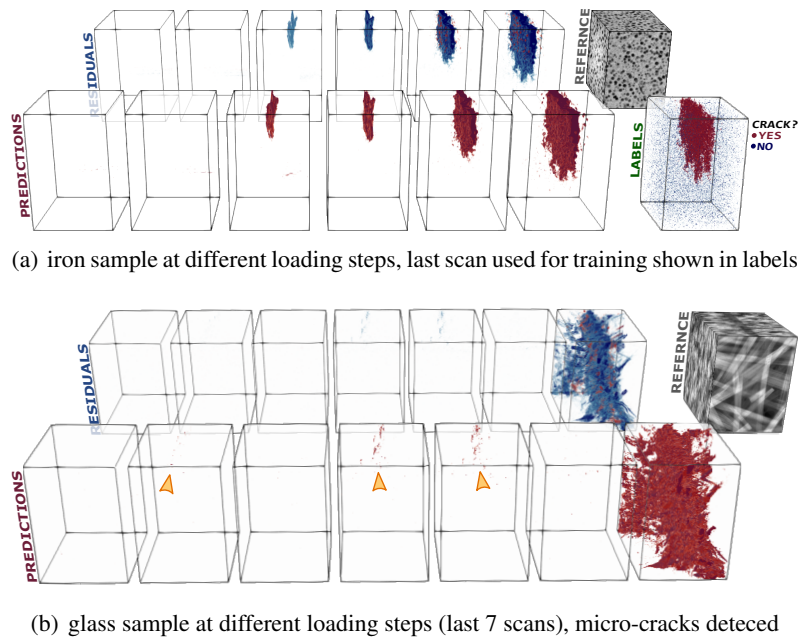


Figure 1: Results of the crack detection method (blue) using the residual images as input features (red)

References

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