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Use of diffuse approximation on DIC for early damage detection in 3D carbon/epoxy composites

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ABSTRACT

This work is part of a global experimental approach aiming at studying the damage and rupture of 3D carbon/epoxy composites and based on multiinstrumented experiments. It focuses on the use of digital image correlation (DIC) in order to detect the development of local non-linearities corresponding to damage (with no other non-linearities) and is limited to small deformation. To that purpose, the strain field is required, hence derived from the measured displacement field, through a diffuse approximation algorithm. This approach is detailed and studied in terms of filtering and some criteria are proposed to choose the filtering parameters. A pragmatic approach based on the evolution of the linear approximation of the strain is proposed in order to detect local non-linearities leading to a local damage indicator. The effect of the filtering on the damage detection is then discussed.

1. Introduction

The 3D composite reinforcements grow up as a new generation of composite materials and complement the traditional 2D reinforcements. The main advantage of these new architectures consists in overcoming a major drawback of composite laminates: delamination [1,2]. Various studies have shown the contribution of this type of reinforcements in terms of improvements concerning the interlaminar and off plan properties [3–7]. With these improved properties come modified in plan properties as well as new damage processes. The control of the damage process in these materials is therefore a key issue in order to develop engineer structures. This implies the identification, monitoring and understanding of the phenomena of damage, in particular to nurture any further development of model, aiming at being predictive, reliable and robust.

The present study lies in a global research work, concerning the characterization of the damage and energy dissipation in such composites, in order to understand how the damage tolerance can be significantly increased. The global approach aims at highlighting the scenarios of failure of these materials under different types of loading (static, fatigue, impact, etc.). As performed on standard composites in the past [8–10], it is based on a rich multi-instrumentation to detect and track damage. This multi-instrumentation correlates measurements from conventional techniques such as extensometer gauges, post-mortem microscopic observations to newer techniques such as acoustic emission, infrared thermography, RX, videomicroscopy in situ observations and digital image correlation (DIC). The latter takes an important place in modern instrumentation [11,12]. It allows, when used with care, to detect local strain gradient in relation to the microstructure of the material [13,14].

Within this framework, the present paper focuses on the use of digital image correlation (DIC) for the detection and localization of the first sites of damage at very low strain levels ($\sim 10^{-3}$). Due to its strong heterogeneity, the microstructure actually affects the location of the sites of damage. A keypoint to any further work is to fully understand the time and place for the advent of damage accurately. Hence the proposed approach, as detailed in Section 4, yields a local damage indicator from the DIC measurements, dedicated to small deformation and damage, as it is the case with 3D carbon/epoxy composites. As an evolution of the idea from [15], the proposed approach is based on the qualitative evolution of the local strain to loading ratio. Since DIC yields the displacement field, the strain field is to be derived from it. Such an operation is very sensitive to experimental noise, especially for low strain level [16] and we have to pay special attention to the control of noise when differentiating the measured displacement. Actually, at such strain levels, DIC usually suffers from low signal to noise ratio (SNR) and some specific approach is proposed in the following to deal with this issue. Other approaches such as the grid method [17,18] or the meshfree random grid method (MRG) [19,20], based on the tracking of well-defined patterns on the specimen, allow to improve the SNR at these strain levels. Nonetheless, it is chosen

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here to use DIC because of its versatility and availability within the current work.

The dealing of the noise can be introduced at the DIC level, for example by using some *a priori* mechanical information when seeking the displacement fields from the images [21], but this usually means a mechanical model of the experiments exists, even though some recent developments have shown the ability of mechanical regularisation at the DIC level with less reliable models [22]. Nonetheless, when using some standard DIC tools, the problem of differentiating noisy data remains and the displacement field is to be considered on a regular data grid. The most basic approach to derive the strain from the displacement field is to use finite difference where it is possible to choose the space step or the degree of approximation to control the filtering and the accuracy [23], but the effect on the filtering is often limited. It is also very common to apply approaches coming from signal and image processing such as kernel smoothing methods [24], where one difficulty is to reconstruct the data up to the edges of the measurement area. Alternatively, it appears to be very fruitful to choose reconstruction strategies based on approximation methods, because they lie on a theoretical framework. They can offer a way to introduce some mechanical information and guarantee the reconstruction to be optimal to a given criterion [25]; hence they can be seen as a way to construct optimal smoothing kernels. In approximation methods, the measurements are projected, usually through a least-squares formulation, on a function basis, which will be differentiated afterward, the two steps can be performed with two different basis [26]. In such approaches, the two keypoints in order to control the filtering of the noise are (i) the choice of the function basis [27–29] and (ii) the choice of local [30] or global [31] least-squares. In a previous study [32], it has been shown that good results could be reached when either the function basis (e.g. finite element functions) or the least-squares (e.g. diffuse approximation) were based on local spans. The method based on diffuse approximation developed in [32] appeared to be effective and will be used in the following. A keypoint of the use of the strain reconstruction methods is the choice of the filtering parameters in order to filter the noise while keeping the mechanical information.

In the present paper, the filtering method is applied to a tensile test on a 3D composite in order to detect and localize early damage and a specific damage indicator is proposed. First the diffuse approximation (DA) is recalled and its theoretical behavior detailed. Then, the choice of the filtering parameters of the DA is discussed on real test data and a pragmatic criterion is proposed. Finally, the damage indicator is introduced and applied to the above mentioned example of a tensile test and the effect of the filtering on the results is discussed.

2. Strain reconstruction: Use of the diffuse approximation

2.1. Framework and notations

In order to help describing the scenario of rupture from the DIC data, we aim at deducing the strain field from the displacement field. Before detailing the proposed method, its framework is first exposed. The input of the method is a set of displacement data on a regular grid of data points $\underline{x}_i$, on a zone denoted Ω. The displacements are expressed through their components $(\tilde{u}, \tilde{v})$ in the $(\underline{e}_X, \underline{e}_Y)$ basis associated with the directions of the CCD captor. Let the measurements be written as follows:

$$\underline{\tilde{u}}(\underline{x}_i) = \tilde{u}(\underline{x}_i)\underline{e}_X + \tilde{v}(\underline{x}_i)\underline{e}_Y = \underline{u}_{ex}(\underline{x}_i) + \delta\underline{u}(\underline{x}_i), \quad \forall i \in [1, N] \tag{1}$$

where $\delta\underline{u}$ represents the perturbation on the measurements and $\underline{u}_{ex}$ is the exact mechanical field. $\delta\underline{u}$ is assumed to be a random error and the measurement systematic error will be considered included in $\underline{u}_{ex}$. The filtering of the systematic error implies some mechanical *a priori* knowledge, as proposed in [21]. Here the filtering is not based on any mechanical considerations but will yield satisfactory results since the systematic error remains small on the studied cases.

The output of the method is a reconstructed displacement and a reconstructed strain. The chosen strain is the infinitesimal strain tensor $\underline{\varepsilon}$, considering applications for carbon/epoxy composites with small deformation hypothesis. Furthermore, the tensorial strain components in the $(\underline{e}_X, \underline{e}_Y)$ basis are represented in a vectorial format, using the classical convention [33]:

$$\underline{\varepsilon} = \begin{bmatrix} \varepsilon_{XX} \\ \varepsilon_{YY} \\ \varepsilon_{XY} \end{bmatrix} = \begin{bmatrix} \frac{\partial u}{\partial x} \\ \frac{\partial v}{\partial y} \\ \frac{1}{2}\left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x}\right) \end{bmatrix} \tag{2}$$

The aim of the reconstruction is to yield a strain field as close as possible to the one associated with $\underline{u}_{ex}$. The reconstruction operator being linear (see Section 2.2), we can split the reconstruction of $\underline{\tilde{u}}$ as the sum of the reconstruction of the exact field $\underline{u}_{ex}$ and the one of the perturbation alone. The reconstructed field $\underline{u}_{ap}(\underline{x})$, at any $\underline{x}$, can therefore be written as:

$$\underline{u}_{ap}(\underline{x}) = \underline{u}_{ex}(\underline{x}) + \delta\underline{u}_k(\underline{x}) + \delta\underline{u}_b(\underline{x}) \tag{3}$$

where $\delta\underline{u}_k(\underline{x})$ is the approximation error due to the filtering of the exact field and $\delta\underline{u}_b(\underline{x})$ is the random error due to the noise. The same splitting can be applied to the reconstructed strain field $\underline{\varepsilon}_{ap}$.

2.2. Formulation

The proposed approach is based on the use of local weighted least-squares [30]. Here, the local regression tool is the diffuse approximation (DA) [34]. The diffuse approximation was first proposed as an alternative to the finite element method for the solving of partial differential equations and has since been applied to various fields, such as optimization [35], mesh generation [36] or field transfer [37]. The parameter controlling the filtering is the span of the influence zone of each data point. One keypoint of the method is that it yields both a continuous displacement field and its derivatives (in a diffuse manner) at once, as explained in the following. For each component of the displacement field, for example $\tilde{u}$, the reconstructed field is sought at any point $\underline{x}$ (x,y) of Ω, as the solution of the following minimization problem:

$$\min_{a(\underline{x})} J_{\underline{x}}(a(\underline{x})), \quad \text{with}$$
$$J_{\underline{x}}(a(\underline{x})) = \frac{1}{2} \sum_{\underline{x}_i \in V(\underline{x})} w(\underline{x}, \underline{x}_i)\left(p(\underline{x}_i - \underline{x})\{a(\underline{x})\} - \tilde{u}(\underline{x}_i)\right)^2 \tag{4}$$

where

- $\underline{x}$ is constant with respect to the minimization;
- the unknown $\{a\}$ is a vector of coefficients and, afterwards, is defined at any $\underline{x}$ by (4), as: $a^* = \mathrm{Argmin} J_{\underline{x}}(a)$;
- $p(\underline{x})$ is the line vector of the monomials of the approximation basis, which is not necessarily polynomial. Here, a polynomial basis of degree 2 is chosen, since it appeared in [38] it was a good compromise between filtering and approximation errors;
- $V(\underline{x})$ represents the bounded neighborhood of $\underline{x}$ collecting the data points $\underline{x}_i$ taken into account in the reconstruction at point $\underline{x}$, ensuring the locality of the reconstruction;
- $w(\underline{x}, \underline{x}_i)$ is a weighting function that equals zero outside $V(\underline{x})$ and can be any positive function defined on $V(\underline{x})$. Based on the fact the data grid is rectangular and periodic, the weighting function is chosen as: