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Strain field denoising for digital image correlation using a regularized cost-function

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ABSTRACT

In digital image correlation (DIC), the widely used forward-additive Newton–Raphson (FA-NR) algorithm and the recently introduced equivalent but more efficient inverse-compositional Gauss–Newton (IC-GN) algorithm are capable of providing both displacements and displacement gradients (strains) for each calculation point. However, the obtained displacement gradients are seriously corrupted by various noises, and for this reason these directly computed strains are usually considered as useless information and therefore discarded. To extract strain distributions more accurately, much research efforts have been dedicated to how to smooth and differentiate the noisy displacement fields using appropriate numerical approaches. In this contribution, contrary to these existing strain estimation approaches, a novel and alternative strain estimation approach, based on denoising the noisy strain fields obtained by FA-NR or IC-GN algorithm using a regularized cost-function, is proposed. The effectiveness and practicality of the proposed strain estimation technique is carefully examined using both computer-simulated images with imposed homogeneous and inhomogeneous deformation, and experimentally obtained images. Experimental results reveal that the strains obtained by the proposed method are comparable to those determined by post-processing of the displacement fields using conventional pointwise least squares strain estimation approach.

1. Introduction

Digital image correlation (DIC) techniques [1–3] have been extensively investigated and routinely used for displacement, strain and shape measurement in various research and engineering fields due to its prominent advantages of simplicity, robustness and versatility. By comparing the digital images recorded in different configurations by almost any imaging device, DIC is capable of extracting the full-field displacements and strains encoded in these recorded images of the test sample surface. It should be noted first that in mechanical testing and structural stress analysis, the strain distributions are generally more valuable, because they are closely related to many important mechanical parameters and material properties (such as stress state, elastic modulus, Poisson's ratio, and coefficient of thermal expansion) of the test sample.

As a full-field optical technique based on digital image capture and digital image processing, the DIC technique relies on a nonlinear optimization algorithm to retrieve displacements and displacement gradients (strains) of each measurement point. At present, iterative spatial domain cross-correlation algorithms (e.g., the classic and widely used forward-additive Newton–Raphson (FA-NR or NR) algorithm [4–8] and the equivalent but more efficient inverse-compositional Gauss–Newton (IC-GN) algorithm [9,10]), combined with a robust matching criterion (e.g., a zero-mean normalized cross-correlation criterion [11,12]) and a high-accuracy sub-pixel interpolation algorithm (e.g., quintic B-spline interpolation scheme [13–15]) have been considered as a defacto standard for accurate sub-pixel displacement detection.

Although it is convincingly demonstrated [16] that the NR algorithm provides highest sub-pixel registration accuracy and widest applicability by considering the relative deformation and rotation of the target subset, the displacements and displacement gradients of the calculation point outputted by these algorithms are generally very noisy. Fig. 1 shows an example of DIC measurement of a perforate specimen subjected to uniaxial tension along vertical direction. The y-directional displacements and strains directly computed using NR algorithm with a subset of 33×33 pixels are shown in Fig. 1(a) and (b), respectively. Though the contours of displacement filed contain small saw-toothed fluctuations, which reflect the influence of random noise, the overall regularity and symmetry of the detected displacement

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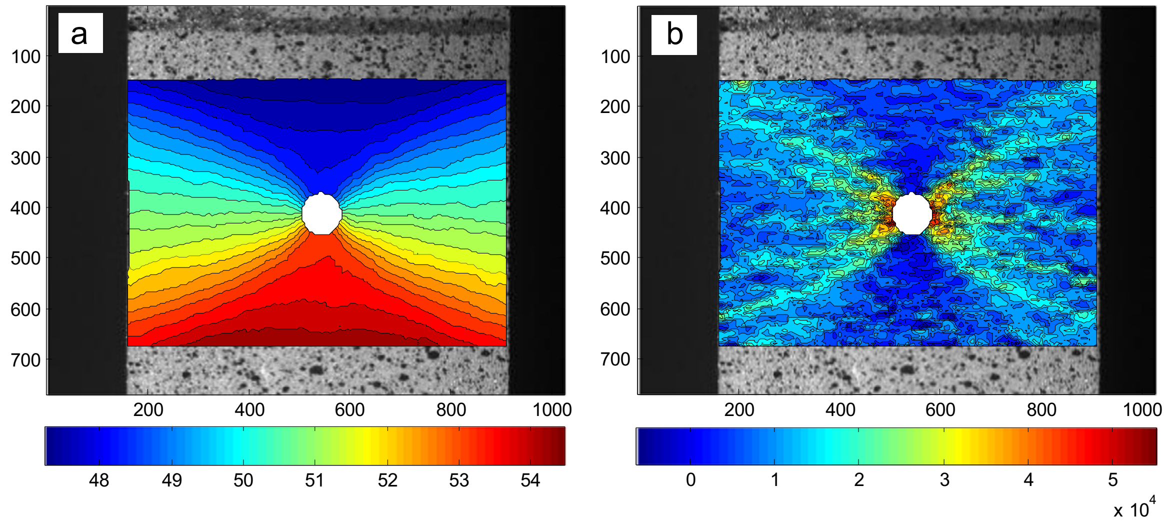

Fig. 1. Contour plots of the y-directional (a) displacement map, and (b) strain map computed by NR algorithm.

distributions can be clearly viewed. In contrast, the strain field shown in Fig. 1(b) is much worse. The large variations in measured strains almost hide the underlying deformation regularity. It is therefore difficult for us to draw any valuable information from Fig. 1(b).

In the classic paper [4] regarding NR algorithm written by Bruck et al., it is concluded that "Thus, use of the gradient terms obtained by the Newton–Raphson method to estimate local strains with reasonable accuracy is limited to strains greater than approximately 0.010". Possibly due to this reason, it is widely believed that post-processing of the displacement field may provide more accurate strain estimation. Following this idea, some researchers smoothed the noisy displacement fields first using various approaches, such as a finite element method (FEM) [17–20], a thin plate spline smoothing method combined with generalized cross-validation [21], and a penalized least square regression method [22]. Afterwards, a simple numerical differentiation is applied to the smoothed displacement fields to extract strain fields. These techniques have two shortcomings. First, the implementation of FEM smoothing or TPSS is rather complicated and time-consuming. Second, the small fluctuations in the smoothed displacement fields can also be amplified by the numerical differentiation. Aside from the above-mentioned approaches, an easy-to-implement yet effective pointwise least squares (PLS) algorithm [23–25] has also been proposed to extract strains from noisy displacements. The basic idea of PLS algorithm is to fit local displacements within a predefined strain calculation window using polynomials, typically, a bilinear plane. Since noise can be largely removed during local fitting, the PLS algorithm provides better strain distributions than the simple finite differences in terms of smoothness. However, while using the PLS algorithm, a proper strain calculation window must be selected with care to get a balance between smoothing and accuracy. It is concluded that for homogeneous deformation, a large strain calculation window is preferred. However, it still lacks explicit guidelines for the users to choose a proper strain calculation window for inhomogeneous deformation. In this case, large window leads to over-smoothed results, while small strain calculation window is not able to suppress the noise in the displacements. For this reason, high-fidelity strain estimation remains to be an unsolved problem in DIC, especially when larger strain gradients and material heterogeneities are presented.

Unlike these existing strain estimation approaches, which are all based on the post-processing of the displacement fields, we will focus on the noisy strain fields offered by NR algorithm in this work. We consider that noisy strain fields directly provided by NR algorithm, although noisy, also contain valuable information and are thus worth further exploration. Based on this consideration, a novel and alternative regularization denoising approach for extracting high-credibility strain fields directly from the noisy strains computed by NR algorithm is developed. It should be noted first that although mean filter and median filter are simple examples in digital image process, they generally do not give satisfactory results. The main idea of the proposed regularization denoising method is to reconstruct the noisy (or corrupted) strain map by introducing *prior* information or assumptions about underlying strain distribution. Note that similar regularization methods have been successfully used for fringe pattern and phase pattern denoising [26–28]. However, to the best of our knowledge, we are the first to introduce the regularization method into DIC for strain estimation.

In the following sections, the basic principle of the classic NR algorithm will be briefly reviewed first. Then, the regularized cost-function for noisy strain field denoising is described in detail. After that, computer simulated speckle images with homogeneous and inhomogeneous deformation are processed to verify the effectiveness of the proposed method. Finally, images of real experiment are used to demonstrate the practicality of the proposed method.

2. Digital image correlation using Newton–Raphson algorithm

DIC deals with surface images of a test sample recorded before and after loading. The basic principle of the standard subset-based DIC is schematically illustrated in Fig. 1. First, a region of interest (ROI) is specified in the reference image, within which the regularly spaced pixel points are defined as points of interest. Then, to accurately determine the location of each measurement point of the ROI, a square reference subset of $(2M+1)\times(2M+1)$ pixels centered at the interrogated point $P(x, y)$, rather than a single pixel point, is tracked in the target image to find its most similar counterpart. Once the location and shape of the target subset with maximum similarity are found, the displacements and displacement gradients of the reference subset center can be determined. The same tracking procedure is repeated on the other points of interest to obtain full-field deformation of the ROI.

Though various correlation criteria have been defined for quantitatively evaluating the similarity between the two subsets,