The impact of penalties over mechanical cracks

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Abstract.
In this work we study the “classical brightness” methods and their regularization parameters presented in “Secrets of optical flow estimation and their principles” [1] in order to assess those that can improve the accuracy of the strain field estimation which is one important field of interest in mechanics.

Introduction

The accuracy of strain measurement is essential for the analysis of different engineering structures. In the last years, Digital Image Correlation(DIC) techniques have become widely used due to their ability to generate an efficient full-field measurement. Most of DIC software [2,3,4] are based on a the approximation of the displacement field on a grid, in a way similar to the finite element method, and they use a classical quadratic norm in order to quantify the difference in the sequence of images. On the other side the optical flow technique proposes robust models able to predict the displacement fields at each pixel in the presence of outliers through the use of a combination of different penalties able to preserve the discontinuities with a Tikhonov regularization [5] which is considerably widespread in DIC software able to add a regularization weight when the size of the element is small.
This work aims not only to analyze the impact of Tikhonov parameter, but also to compare the Charbonnier and the Lorentzian norms with the traditional least squares on the detection of cracks.

Method description

Let u and v be respectively the horizontal and the vertical displacement fields, ρ a given penalty. We denote by λ the Tikhonov parameter.

$$\mathrm{E(du,dv)}=\int_\Omega \rho\Big((I_2(p+w+dw)-I_1(p))^2\Big)+\lambda\Big(\rho\big((\nabla_x(u+du)^2\big) \\ +\rho\big((\nabla_y(u+du))^2\big)+\rho\big((\nabla_x(v+dv))^2\big)+\rho\big((\nabla_y(v+dv))^2\big)\Big)dp, w=(du,dv) \quad (1)$$

Where I_1 represents the reference and I_2 is the deformed image and p=(x,y) are the spatial coordinates of a given pixel and dw=(du,dv) are the best increments to estimate at each step.

The optical flow field is obtained by minimizing the Eq. (1) and the optimization achieved by solving the associated Euler-Lagrange equations. We study beside the classical L^2 norm, the Charbonnier norm which is a variant of the L^1 norm defined by $\rho(x^2)=\sqrt{x^2+\varepsilon^2}, \varepsilon:=0,001$ and the Lorentzian norm $\rho(x^2)=\log(1+\frac{x^2}{2\sigma^2}), \sigma>0$

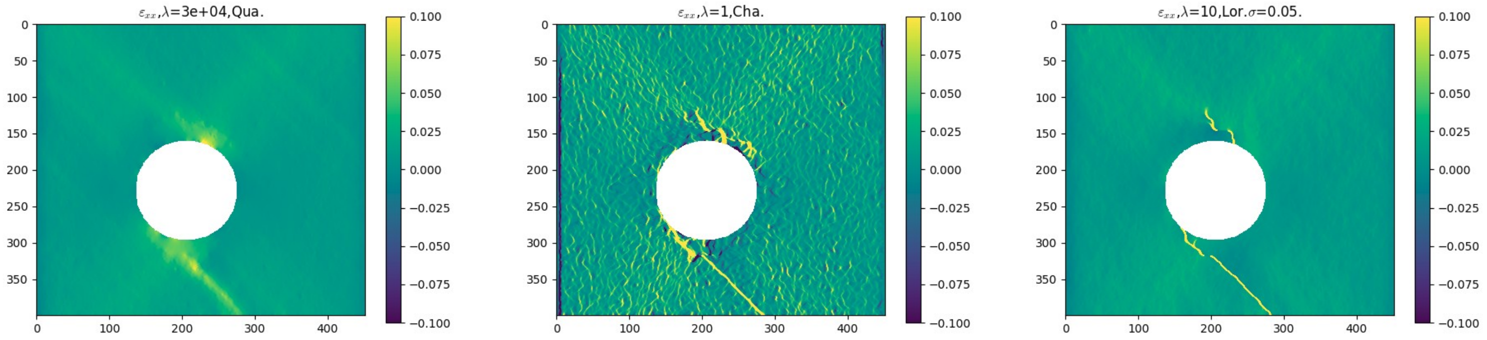
Finally, a median filter is applied at each iteration of the process in order to remove the noise. These methods have shown their efficiency of predicting accurate displacement fields on Middlebury dataset [6] image sequences but they were not tested on mechanical images.

Results

To investigate the effects of the algorithms parameters we choose an image sequence of a holed tensile test specimen made of +/- 45 Carbon/Epoxy composite material [7]. This specific type of materials has the property of creating a distinct through discontinuity, which serves as an ideal test scenario for analyzing the impact of the method on the shape of the break, as assessed by the resulting strain. The uniaxial strain fields ε_{xx} obtained with different penalties are shown in the Fig. 1.

Conclusion

The results prove that the value of the parameter of regularization as well as the choice of the penalty can highly impact the structure of the strains. In the presence of noise, the Charbonnier norm preserves the physical discontinuities while it tends to create spurious strain. The least square norm widely used in most of the DIC codes is able to reduce the noise, but it diffuses the strain. Finally, using a Lorentizan norm with a correct value of σ can lead to less noisy results while conserving the discontinuity.



(A) (B) (C)

Fig. 1: Uniaxial strain field ε_{xx} for different norms, (A) Charbonnier, (B) Quadratic (C) Lorentzian norm

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