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Improved initial guess with semi-subpixel level accuracy in digital image correlation by feature-based method

Yunlu Zhang*, Lei Yan, Frank Liou

Department of Mechanical Engineering, Missouri University of Science and Technology, Rolla, MO 65401, USA

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ABSTRACT

The quality initial guess of deformation parameters in digital image correlation (DIC) has a serious impact on convergence, robustness, and efficiency of the following subpixel level searching stage. In this work, an improved feature-based initial guess (FB-IG) scheme is presented to provide initial guess for points of interest (POIs) inside a large region. Oriented FAST and Rotated BRIEF (ORB) features are semi-uniformly extracted from the region of interest (ROI) and matched to provide initial deformation information. False matched pairs are eliminated by the novel feature guided Gaussian mixture model (FG-GMM) point set registration algorithm, and nonuniform deformation parameters of the versatile reproducing kernel Hilbert space (RKHS) function are calculated simultaneously. Validations on simulated images and real-world mini tensile test verify that this scheme can robustly and accurately compute initial guesses with semi-subpixel level accuracy in cases with small or large translation, deformation, or rotation.

1. Introduction

Digital image correlation (DIC) is an optical deformation measurement method. Primary advantages of DIC include simple implementation, low environment requirements, and non-contact full-field measurement [1]. Therefore, DIC has been applied in the room temperature tensile test [2], high temperature tensile test [3], nondestructive evaluation [4], fracture test [5,6], bending test [7], measurement of the coefficient of thermal expansion [8,9], and many other areas since the invention in 1980s [10]. Besides applications, much effort has also been devoted to enhancing accuracy, robustness, and efficiency of DIC algorithms.

DIC algorithm usually consists the initial pixel level and subpixel level searching stage. The subpixel level searching stage commonly falls into two categories: subset-based (local) DIC and fullfield-based (global) DIC. The fundamental difference between these two categories is that the calculation of a point of interest (POI) is independent from other POIs in local DIC or should follow displacement continuity constraint in global DIC. Forward additive Newton–Raphson algorithm (FA-NR) [11] and more computational efficient inverse compositional Gauss-Newton algorithm (IC-GN) [12] are most widely used subpixel level searching algorithms. These algorithms are great at finding local optimal deformation parameters accurately. However, an initial guess close to the global optimum need to be provided to these algorithms first. Otherwise, they may fall into local optimum due to sensitivity of the initial value. Besides, an initial guess for full-field DIC [13–15] is also essential and is beneficial for convergence if it is close to the global optimum.

While subpixel level searching methods receive much research attention, there are only a few studies regarding the improvement of the initial guess. Integer-pixel searching (IPS) algorithm is typically employed to get initial pixel level displacement. This algorithm calculates cross correlation coefficient of a subset at candidate positions locate around POI. The integer displacement to the location with highest similarity will be the initial guess. Nevertheless, it is considered to be computation intensive. Tsai and Lin [16] utilized the precomputed sum-table to increase computational efficiency. Conducting the calculation in the spectral domain could largely increase the speed via fast Fourier transformation (FFT) [17]. Zhao et al. [18] and Wu et al. [19] utilized population-based method algorithms to accelerate calculation. Besides the computational burden, one limitation of the IPS method is that it assumes the dominant rigid body translation. In the case of large nonuniform deformation or rotation, the assumption would not hold true. Another drawback is that it may generate a few outliers have evident incompatible displacements with other POIs and are hard to be removed conveniently. Because the pixel level searching is conducted individually for each POI and no continues deformation constrain is applied. To overcome this weakness, the reliability-guided method [20,21] was proposed to eliminate the need for pixel level searching except the seed point.

* Corresponding author.
E-mail address: yunlu.vincent.zhang@gmail.com (Y. Zhang).

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Finding correct correspondence between two images is a fundamental problem in computer vision and it is an essential precondition in many applications including object tracking, pose estimation, and 3D reconstruction. The correspondence is usually formed via unique points, namely feature points, in images. Information from a local region around the feature point could be extracted by the feature descriptor. Thus the correspondence of feature points could be detected from similarity between feature descriptors. Resemblance between feature matching and estimating initial guess in DIC makes it is possible to take advantage of well-developed techniques by computer vision community. Zhou et al. [22] obtained initial deformation parameters for the seed point by matching scale-invariant feature transform (SIFT) features. To eliminate possible false matched pairs, preliminary matches were filtered out by random sampling consensus (RANSAC) algorithm to fit into an affine transformation. Then after subpixel level searching, refined deformation parameters of the seed point is transferred to one of its neighbors through reliability-guided procedure. A similar approach was applied by Wang et al. [23] with improved random sampling consensus (iRANSAC) to cope the case with large deformation and rotation or images have periodic patterns. Zhou and Chen [24] expanded this approach into 3D-DIC and extracted correct matches by selecting feature points that persevere the number of neighbor features. Nevertheless, these investigations have been focused on getting the initial deformation parameter of a seed point by fitting an affine transformation into the feature points around the seed point. One limitation of the seed point and reliability-guided method is that it is a serial approach and hard to be parallelized. Moreover, the affine transformation assumes the uniform deformation condition that will be only approximately valid in a small region and in the small deformation case.

In the present research, we propose a novel feature-based initial guess (FG-IG) scheme to robustly estimate initial guesses for POIs in a large region even in the case of large nonuniform deformation or rotation. The feature matching part of the scheme is based on newly developed feature guided Gaussian mixture model (FG-GMM) [25]. The proposed method is capable of calculating all six deformation parameters with semi-subpixel level accuracy directly from reproducing kernel Hilbert space (RKHS) coefficients. The rest of the paper is organized as follow. The feature-based scheme is detailed in Section 2. The FB-IG and IPS method are validated against simulated images and real world tensile tests in Section 3. Finally, conclusions are given in Section 4.

2. Initial guess of deformation parameters by feature-based method

2.1. Basic principal of digital image correlation

The goal of the DIC algorithm is to obtain displacements and strain field within the region of interest (ROI) from the video or images of the specimen in different states. For subset-based DIC, it is archived by tracking POIs, e.g. centers of subsets. Positions of POIs are known in the reference image and needed to find out deformed positions in the current image. The reference and current image usually are the undeformed and deformed image respectively. The reference image can also be the deformed image that positions of POIs have been determined previously in the incremental scheme [26].

A subset is typically a small square image patch around POI. The deformation field inside this subset is commonly approximated by the first order shape function. Coordinates of any point in the deformed subset in the current image are

$$\begin{aligned} x^* &= x + u + u_x(x - x_0) + u_y(y - y_0) \\ y^* &= y + v + v_x(x - x_0) + v_y(y - y_0) \end{aligned} \tag{1}$$

where (x, y) is coordinates of corresponding point in the undeformed subset, (x_0, y_0) is coordinates of POI in the reference image. u and v are the displacements in x and y directions, u_x, u_y, v_x, v_y are first order gradients. The combination of $[u, v, u_x, u_y, v_x, v_y]$ is called the deformation parameter $\boldsymbol{p}$.

The objective of subset based DIC is to find the best deformation parameter $\boldsymbol{p}$ that maximizes similarity of subsets matrices in both images. There are various criteria available to quantify similarity of matrices and Pan et al. [27] proved that most of them are equivalent. Zero-mean normalized cross correlation (ZNCC) criterion is adopted here for its invariance to linear illumination change.

The ZNCC coefficient of two subsets in the reference and current image is

$$C_{ZNCC}(\boldsymbol{p}) = \frac{\sum_\Omega (F(x,y) - \bar{F})(G(x^*, y^*) - \bar{G})}{\sqrt{\sum_\Omega (F(x,y) - \bar{F})^2}\sqrt{\sum_\Omega (G(x^*, y^*) - \bar{G})^2}} \tag{2}$$

where $F(x, y)$ and $G(x^*, y^*)$ are intensity values in the reference and current images, $\bar{F}$ and $\bar{G}$ are mean intensity values of the subsets, Ω is the set of points in the subset. The possible range of C_{ZNCC} is $[-1, 1]$. The higher the value of C_{ZNCC} represents higher similarity between two matrices. C_{ZNCC} represents the exact match. For deformed positions (x^*, y^*) not on integer pixels, e.g. subpixel positions, an interpolation scheme should be employed. Bi-cubic b-spline interpolation is used in this research.

As mentioned previously, FA-NR and IC-GN are effective algorithms to solve the nonlinear multi-variable optimization problem. The more computational efficient IC-GN algorithm is adopted in this research. However, these gradient-based methods only converge to the global optimum when a close initial guess is provided. The IPS method is commonly selected as the pixel level searching algorithm. The idea of this algorithm is simply compare C_{ZNCC} of subsets centers around POI in the current image. The location with highest C_{ZNCC} is considered the initial position for subpixel level searching.

2.2. Feature extractor and promoting uniformly distributed features

Features are interest and unique locations in images that can be easily compared and tracked. By extracting feature in the reference and current image and correctly matching corresponding pairs, the deformation field on these specific locations is obtained. This is the fundamental idea of estimation the initial guess by the feature-based method.

SIFT [28] and speeded up robust features (SURF) [29] are two widely used feature extractors in computer vision. However, these gradient-based descriptors impose a computational burden in the application. Oriented FAST and Rotated BRIEF (ORB) [30] were proposed to enhance the speed while without loss robustness. Main contributions include an oriented FAST (features from accelerated segment test) feature detector [31] and an oriented BRIEF (binary robust independent elementary features) feature descriptor [32]. Therefore, ORB descriptor is adopted in this research.

One problem associated with ORB and most feature detectors is the lack of consideration of the spatial distribution of detected features. The only criterion to select a candidate feature point is its cornerness response. This nonuniform character degrades the matching quality when only a few features are extracted in a part of the interested region while unnecessary dense features in certain regions may waste computation power.

An effort [33] was made to modify the standard SIFT detector to generate more uniformly distributed features. In principle, the same approach could be utilized in the FAST detector. However, a simpler yet effective clustering method is proposed that no alteration of the feature detector algorithm itself is required.

POIs are shown in Fig. 1(a) that cover the surface of the specimen in the bottom. Features inside a patch of the image that encompass all POIs with additional padding length are detected to limit detected features inside ROI or close to its boundary and save computation time as shown in Fig. 1(c). With the clustering approach, all POIs are clustered into groups of points in the reference image by the k-means clustering method as shown in Fig. 1(b). A small patch of the image encompasses each cluster with additional padding length is detected for features separately. All