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Digital Image Correlation with Dynamic Subset Selection

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ABSTRACT

The quality of the surface pattern and selection of subset size play a critical role in achieving high accuracy in Digital Image Correlation (DIC). The subset size in DIC is normally selected by testing different subset sizes across the entire image, which is a laborious procedure. This also leads to the problem that the worst region of the surface pattern influences the performance of DIC across the entire image. In order to avoid these limitations, a *Dynamic Subset Selection* (DSS) algorithm is proposed in this paper to optimize the subset size for each point in an image before optimizing the correlation parameters. The proposed DSS algorithm uses the local pattern around the point of interest to calculate a parameter called the *Intensity Variation Ratio* (Λ), which is used to optimize the subset size. The performance of the DSS algorithm is analyzed using numerically generated images and is compared with the results of traditional DIC. Images obtained from laboratory experiments are also used to demonstrate the utility of the DSS algorithm. Results illustrate that the DSS algorithm provides a better alternative to subset size "guessing" and finds an appropriate subset size for each point of interest according to the local pattern.

1. Introduction

Digital Image Correlation (DIC) is a photogrammetric technique proposed by Peters and Ranson [1]. It measures deformation remotely using images of the specimen taken before and after deformation. It involves segmenting the image into small *subsets* and correlating each subset of the reference image with a subset of the deformed image. The specimen requires a random pattern to uniquely identify each point of the specimen with the help of its neighboring points. The optimization process in this technique was improved in later studies [2–5].

Deformation measurement requires the reconstruction of displacement as well as strain fields. Recent studies suggest that different imaging techniques such as image matching or image registration or pattern matching techniques can be used as alternative to DIC [6–10]. However, the major limitation of these techniques for deformation measurement in deformable solids is the subpixel accuracy which is usually required around 1/100th of a pixel (strain accuracy is down to 10^{-3}). On the other hand, DIC demonstrated success to achieve required high accuracy for deformation measurement and is regularly used for the reconstruction of displacement and strain fields in deformable solids.

The accuracy of DIC is dependent on many different parameters, and the pattern on the surface of the specimen plays a pivotal role. In most cases, instead of using a natural pattern on the specimen, a speckle pattern is applied to the specimen to improve the accuracy of DIC.

To optimize the performance of DIC, the user needs to select a subset size which is large enough to have good intensity variations in a subset. On the other hand, the subset size needs to be small enough to follow the first-order displacement function approximation employed by DIC, which effectively assumes that a straight line taken in a subset will remain straight after deformation. Thus, different subset sizes are normally tested to find the optimal subset size for the DIC procedure, which is a time consuming and inefficient process.

There are a few studies in which different speckle patterns, their properties and their relationship with different subset sizes are analyzed. None of the literature, however, was able to provide a relation between subset size and speckle pattern.

Haddadi and Belhabib [11] recommended the use of small speckles (in terms of pixels) which will consequently require a small subset size. Their experiments reported that performance of DIC for random small speckles is better than for large ones. Later, Barranger et al. [12] studied the difference between deformable and non-deformable speckles and proposed that for small speckle sizes, the difference in performance of DIC has low influence on measuring the strain, which is calculated by differentiating the displacement recovered by DIC. Recently, Crammond et al. [13]

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proposed that there is dependence between size and density of speckles within the pattern which influences the accuracy of deformation measurement using DIC.

Lecompte et al. [14] studied the quality of the speckle pattern in a multiple parameter space including speckle size, speckle spacing, image resolution and their relationship with the subset sizes. The study suggests that small speckles with small subset size and large speckles with large subset size are optimal for DIC and emphasizes the importance of finding a relationship between subset size and speckle pattern. Hua et al. [15] studied the effect of speckle size and their density on DIC and proposed to use high density speckle patterns with the speckle size between 3 and 5 pixels to obtain reliable results. The study also proposed a parameter called mean subset fluctuation which represents the gradient trend of the intensity in the subset. The study raised the importance of finding the relationship between subset size and speckle size by showing that mean bias error of measured displacement is linearly related to the mean subset fluctuation.

Yaofeng and Pang [16] studied entropy of the image and found that entropy of the subset can be used to represent the quality of the subset image for DIC. The study suggested using patterns with uniform entropy to obtain high accuracy. In their experiments, the entropy was kept uniform and a large subset size was used. The study proposed that a large subset size performed better when the actual deformation follows the first order displacement approximation used in the DIC technique. The study also mentioned that accuracy deteriorates significantly for large subset sizes when the actual deformation does not match the assumed displacement function in DIC.

Pan et al. [17] proposed the *Sum of Square of Subset Intensity Gradient* (SSSIG) technique to find the optimal subset size for the given image. Later Pan et al. [18] proposed the *Mean Intensity Gradient* (MIG) followed by improvements suggested by Yu et al. [19]. All three techniques used intensity gradients in the sum of squared difference correlation procedure and propose a relationship between correlation procedure and pattern of an image. The technique involves optimizing threshold values of SSSIG in the optimization process of DIC and considers the global pattern of the image.

Huang et al. [20] proposed DIC with self-adaptive Gaussian window to reduce the influence of subset size from the DIC technique. This technique was extended by Yuan et al. [21]. The results show that accuracy of displacement reconstruction is similar to the standard DIC, while the accuracy of the strain reconstruction was close to the accuracy obtained by the standard DIC based on the Newton–Raphson technique.

It is seen that most of the proposed techniques consider the global pattern of the image instead of a local pattern around the point of interest for subset size selection or assessing quality of a pattern in a subset. It is difficult to optimize the subset size using the global pattern of the image because the speckle pattern is usually different at different areas of the image due to the randomness of the pattern. Thus, it is imperative for the subset size to vary over the image at different points to maintain high accuracy in measurement. A few techniques considered the local pattern of the image but their performance was limited with constraints of specific speckle size and density of speckles. However, in real world scenarios, it is not possible or very cumbersome to paint a random pattern on a specimen with constraints of speckles size, spacing and density requirements.

In this study, a new Dynamic Subset Selection (DSS) algorithm is proposed which can optimize the subset size by considering the local pattern around the point of interest in the subset. The results show that the DSS algorithm performs well on different speckle patterns. The performance of the DSS algorithm is verified by testing it with images that are produced numerically. This examines the intrinsic accuracy of the algorithm by avoiding camera errors [22,23]. The images are generated using the DISTRESS Simulator proposed by Hassan et al. [24]. Laboratory experiments are also conducted to show the performance and applicability of the proposed DSS algorithm.

This paper is organized as follows. The DIC technique, which is a fundamental to understanding the necessity of the proposed DSS algorithm, is discussed in Section 2. The proposed technique is presented in Section 3 and experimentally evaluated in Section 4. The paper is concluded at the end.

2. Digital Image Correlation

Digital Image Correlation (DIC) is a remote contactless computer vision technique to correlate two images. These images are usually called the reference image and deformed image capturing the projections of the specimen's surface before and after deformation respectively. DIC can be used to analyze two dimensional or three dimensional deformations. The focus in this study is a two dimensional DIC. It requires simple setup, which requires camera, light source, computer and specimen, as shown in Fig. 1.

DIC works on the presumption of displacement continuity which means that after deformation the neighboring pixels in the images will always remain the same. Each pixel in the reference image is found in the deformed image to calculate the displacements of each pixel on the surface of specimen in both horizontal and vertical directions as shown in Fig. 2. The point of interest is always kept in the center of the reference subset.

The correlation can be found either as Zero-Normalized Cross-Correlation criteria C_{ZNCC} or Zero-normalized Sum of Squared Difference criteria C_{ZNSSD}. These criteria are interchangeable and are preferred because of their insensitivity to the light fluctuations [25,26]. They are presented mathematically as:

$$C_{ZNCC} = \sum_{i=-M}^{M} \sum_{j=-M}^{M} \left[\frac{\{f(x_i, y_j) - f_m\}\{g(x_i', y_j') - g_m\}}{\Delta f \Delta g} \right]$$

$$C_{ZNSSD} = \sum_{i=-M}^{M} \sum_{j=-M}^{M} \left[\frac{f(x_i, y_j) - f_m}{\Delta f} - \frac{g(x_i', y_j') - g_m}{\Delta g} \right]^2 \quad (1)$$

where $f()$ and g() represents the gray intensity of a pixel in the reference and deformed images respectively, and

$$f_m = \frac{1}{(2M+1)^2} \sum_{i=-M}^{M} \sum_{j=-M}^{M} f(x_i, y_j)$$

$$g_m = \frac{1}{(2M+1)^2} \sum_{i=-M}^{M} \sum_{j=-M}^{M} g(x_i', y_j')$$

$$\Delta f = \sqrt{\sum_{i=-M}^{M} \sum_{j=-M}^{M} [f(x_i, y_j) - f_m]^2}$$

$$\Delta g = \sqrt{\sum_{i=-M}^{M} \sum_{j=-M}^{M} [g(x_i', y_j') - g_m]^2}$$

The size of the subset in Eq. (1) is $(2M+1) \times (2M+1)$ pixels. It is required to estimate values for six variables to calculate C_{ZNCC} or C_{ZNCC} [27]. These parameters are $u(P)$, $v(P)$, $\frac{\partial u(P)}{\partial x}$, $\frac{\partial u(P)}{\partial y}$, $\frac{\partial v(P)}{\partial x}$ and $\frac{\partial v(P)}{\partial y}$. The values of parameters are optimized to find maximum correlation of the subsets. Many studies have been done to optimize the process of finding optimal values for the parameters [28–33]. In this study, the commonly used optimization method of Newton–Raphson iterations is employed which is known for its high accuracy [25].