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Increasing accuracy and precision of digital image correlation through pattern optimization

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ABSTRACT

The accuracy and precision of digital image correlation (DIC) is based on three primary components: image acquisition, image analysis, and the subject of the image. Focus on the third component, the image subject, has been relatively limited and primarily concerned with comparing pseudo-random surface patterns. In the current work, a strategy is proposed for the creation of optimal DIC patterns. In this strategy, a pattern quality metric is developed as a combination of quality metrics from the literature rather than optimization based on any single one of them. In this way, optimization produces a pattern which balances the benefits of multiple quality metrics. Specifically, sum of square of subset intensity gradients (SSSIG) was found to be the metric most strongly correlated to DIC accuracy and thus is the main component of the newly proposed pattern quality metric. A term related to the secondary auto-correlation peak height is also part of the proposed quality metric which effectively acts as a constraint upon SSSIG ensuring that a regular (e.g., checkerboard-type) pattern is not achieved. The combined pattern quality metric is used to generate a pattern that was on average 11.6% more accurate than a randomly generated pattern in a suite of numerical experiments. Furthermore, physical experiments were performed which confirm that there is indeed improvement of a similar magnitude in DIC measurements for the optimized pattern compared to a random pattern.

1. Introduction

The accuracy and precision of digital image correlation (DIC) is based on three primary components: image acquisition, image analysis, and the subject of the image. Development of the first two (i.e., image acquisition techniques and image correlation algorithms) has led to widespread use of DIC [1–11]; however, fewer developments have been focused on the third component. Typically, subjects of DIC images are mechanical specimens with either a natural surface pattern or a pattern applied to the surface. Research in the area of DIC patterns has primarily been aimed at identifying which surface patterns are best suited for DIC, by comparing multiple patterns [12,13,11,14–17]. Because the easiest and most widespread methods of applying patterns have a high degree of randomness associated with them (e.g., airbrush, spray paint, particle decoration, etc.), less effort has been spent on exact construction of ideal patterns. With the development of patterning techniques such as microstamping and lithography, patterns can be applied to a specimen pixel by pixel from a patterned image [18,19]. In these cases, especially because the patterns are reused many times, an optimal pattern is sought such that error introduced into DIC from the pattern is minimized.

DIC consists of tracking the relative motion of an array of nodes from a reference image to a deformed image. Every pixel in the images has an associated grayscale (intensity) value, which for the purpose of the current work is assumed to be between 0 (black) and 1 (white), with discretization depending on the bit depth of the image. Because individual pixel matching by grayscale value yields a non-unique scale-dependent problem, subsets of (2 M+1) by (2 M+1) pixels around each node are used for identification, where M is the number of whole pixels from the center to edge of the subset. A correlation criterion is used to find the best match of a particular subset of a reference image within a deformed image. The reader is referred to [8,10,7] for enumerations of typical correlation criteria. A common choice which will be used herein, is the zero-normalized cross-correlation (ZNCC) coefficient:

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$$C = \sum_{i=-M}^{M} \sum_{j=-M}^{M} \left[\frac{(f(x_i, y_j) - \overline{f}^{(M)})(g(x'_i, y'_j) - \overline{g}^{(M)})}{\Delta f \Delta g} \right] \quad (1)$$

with

$$\overline{f}^{(M)} = \frac{1}{(2M+1)^2} \sum_{i=-M}^{M} \sum_{j=-M}^{M} f(x_i, y_j)$$
$$\overline{g}^{(M)} = \frac{1}{(2M+1)^2} \sum_{i=-M}^{M} \sum_{j=-M}^{M} g(x'_i, y'_j)$$
$$\Delta f = \sqrt{\sum_{i=-M}^{M} \sum_{j=-M}^{M} (f(x_i, y_j) - \overline{f})}$$
$$\Delta g = \sqrt{\sum_{i=-M}^{M} \sum_{j=-M}^{M} (g(x'_i, y'_j) - \overline{g})} \quad (2)$$

where $f(x_i, y_j)$ is the grayscale value of a pixel at location (x_i, y_j) in the reference image and $g(x'_i, y'_j)$ is the grayscale value at location (x'_i, y'_j) in the deformed image. Mapping functions from (x_i, y_j) to (x'_i, y'_j), which are commonly referred to as subset shape functions, account for the displacement and distortion of the subset. As illustrated by Schreier and Sutton [5] and Lu and Cary [6] systematic errors can be introduced by representing the underlying deformation with under-matched shape functions. An important implication, as discussed by Sutton et al. [7], is that in the presence of highly localized deformations (e.g., crack fronts) error can be reduced by minimizing the subset size. In other words, smaller subsets allow more accurate resolution of localized deformations. Contrarily, the choice of optimal subset size has been widely studied [20–22,13,23,12] and a general consensus is that larger subsets with more information content are more robust to random error. Specifically, this has been shown for the case of over-matched shape functions in which larger subsets sizes must be used to offset increased amounts of random error [24]. Thus, an optimal subset size balances the systematic error from under-matched deformations with random error from measurement noise and over-matched deformations [13].

The alternative approach pursued in the current paper is to choose a small subset size and optimize the information content therein (i.e., optimizing an applied DIC pattern), rather than finding an optimal subset size. Recently, the auto-correlation function has been used as a means of identifying favorable properties of a pattern [20,16,17,25]. The auto-correlation function A is a correlation of a reference image with itself, or more precisely: $A(u, v) = C$ where $g(x'_i, y'_j) = f(x_i + u, y_j + v)$. Bossuyt [25] even goes as far as to create DIC patterns based on the supposition of the optimal frequency content of A.

If a quantitative metric for a pattern's suitability for accurate and precise DIC measurements is identified, this pattern quality metric can be utilized in an optimization procedure that produces ideal patterns. Though many DIC pattern quality metrics have been proposed in the literature, they have unfavorable properties, such as non-optimal patterns which maximize the metrics, which make them ill-suited for use in pattern optimization. In the current work, a new metric for pattern quality is introduced that is better suited for optimization. Specifically, the new metric derives from multiple metrics in the literature, such that the unfavorable properties of each are avoided.

The remainder of the current paper is structured as follows. In Section 2, common pattern quality metrics from the literature are reviewed. Section 3 discusses the reasons why each metric, alone, is not suitable for optimization. Section 4 introduces a multi-metric optimization strategy and discusses a pattern created using the strategy, including a performance comparison to a purely randomly generated pattern when subjected to numerical deformations. In Section 5, physical experiments are performed which both validate the previously used numerical assessment and confirm the improved performance of the optimized pattern.

2. DIC pattern quality metrics

The ultimate goal of any DIC pattern assessment is to determine which aspects of a pattern are responsible for introducing error into the DIC measurements. The most straight forward way to approach this is simply to perform DIC tests with a known deformation and multiple patterns, where the relative errors introduced by each pattern can be calculated from the DIC measurements. An example of this methodology is seen in the work of Haddadi and Belhabib [11] where rigid body displacements and several patterns were used to estimate the effect of a pattern on DIC accuracy. Especially in the case of experimentally-based pattern assessments like the above, a large effort is required to make a single assessment of a pattern. The development of pattern quality metrics has been aimed at more efficiently assessing a pattern's suitability for DIC based on a single image of the pattern. Many unique pattern quality metrics have been proposed in the literature, several of which will be described herein.

Before introducing the pattern quality metrics considered in the current work, it is important to make a subtle but important distinction between a pattern and the image captured by the image acquisition system. Aside from environmental and optical noise added by the imaging system, patterns and images will also differ in scale. In other words, a single pixel in a pattern may correspond to multiple image pixels, depending on the level of magnification. It is assumed that the pattern quality metrics discussed herein, when applied to a pattern, are representative of the DIC performance using images taken of the pattern at any increased magnification.

2.1. Sum of square of subset intensity gradients

During image acquisition, experimental noise is inevitably added to the images. An ideal pattern is robust to the noise. In one dimension, assuming zero-mean Gaussian noise with standard deviation, σ, is added to each of the images, error in displacement measurements have variance of approximately:

$$VAR(\epsilon) \approx \frac{2\sigma^2}{\sqrt{\sum_{i=-M}^{M} \sum_{j=-M}^{M} [f_x(x_i, y_j)]^2}} \quad (3)$$

where ϵ is the difference between the true displacement and the measured displacement [26,22,7,27]. The subscript x denotes partial differentiation with respect to x. It should be noted that, when interpolation is used in the reconstruction of $f(x, y)$ or $g(x', y')$ at non integer (pixel) displacements, a bias error is also present [7] where:

$$E(\epsilon) \propto \frac{1}{\sqrt{\sum_{i=-M}^{M} \sum_{j=-M}^{M} [f_x(x_i, y_j)]^2}} \quad (4)$$

From the above equations, it can be seen that an increase in the term under the square roots in Eqs. (3) and (4), which is known as the sum of square of the subset intensity gradient (SSSIG), has the effect of decreasing the variance of errors and reducing bias error; this has also been shown by the numerical experiments of Pan et al. [28]. Additionally, SSSIG was used as a local quality metric by Pan et al. [22] in order to determine an adequate subset size given a pattern.

The derivations of the expectation and covariance of displacement errors has also been extended to two-dimensions showing similar functional forms [27]. Importantly, the two-dimensional formulations also indicated that the variances in each direction are not independent. In the current work, the following two dimensional definition of SSSIG (denoted S) is used:

$$S = \sum_{i=-M}^{M} \sum_{j=-M}^{M} |\nabla f(x_i, y_j)|^2 \quad (5)$$

where $|\nabla f(x_i, y_j)| = \sqrt{f_x(x_i, y_j)^2 + f_y(x_i, y_j)^2}$. Note that the definition is an extension of the original one dimensional SSSIG definition to two-dimensions in a manner similar to Pan et al. [28]. Implementation of S throughout the current work utilizes finite difference estimates of the