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Automatic detection and classification of damage zone(s) for incorporating in digital image correlation technique

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ABSTRACT

Digital image correlation (DIC) is a technique developed for monitoring surface deformation/displacement of an object under loading conditions. This method is further refined to make it capable of handling discontinuities on the surface of the sample. A damage zone is referred to a surface area fractured and opened in due course of loading. In this study, an algorithm is presented to automatically detect multiple damage zones in deformed image. The algorithm identifies the pixels located inside these zones and eliminate them from FEM-DIC processes. The proposed algorithm is successfully implemented on several damaged samples to estimate displacement fields of an object under loading conditions. This study shows that displacement fields represent the damage conditions reasonably well as compared to regular FEM-DIC technique without considering the damage zones.

1. Introduction

Digital image correlation (DIC) is an emerging technique for monitoring object deformation/strain in non-contact manner. Over the years, many research works have been carried on diversified applications. In 2001, Zhou and Goodson have developed an iterative, spatial-gradient based DIC algorithm for subpixel deformation gradient measurement [1]. The ability of DIC technique to capture the heterogeneous deformation fields appearing during compression of ultra-light open-cell foams is presented by Wang and Cuitiño [2]. They have validated their results with theoretical model and found to be in good agreement. In 2003, Hung and Voloshin have developed a fast and simple (FAS) detection algorithm based on DIC for measurement of the surface deformation of planar objects [3]. The concept of finite element method (FEM) has been applied by Sun et al. to determine directly the complete, two-dimensional displacement field during the image correlation process on digital images [4]. They have used both numerical studies and a real experiment to verify the proposed formulation and shown that the image correlation with the finite element formulation is computationally efficient, accurate, and robust. In 2006, Besnard et al. have introduced the concept of multi-scale approach on top of FEM based DIC method to generate meaningful solution for a fine texture and large initial displacement measurement [5]. FEM based DIC method is unable to produce precise deformation information of an object having discontinuities. For that reason the concept of extended finite element method (X-FEM) is introduced by Réthoré et al. for the measurement of displacements through DIC [6]. They have also presented a crack shape optimization algorithm based on a two-scale multi-field minimization of the correlation residual. This method has further refined by Chen et al. by inventing two-step extended digital image correlation (X-DIC) [7]. They have applied their proposed method to measure the cross-crack displacement field in the uniaxial tensile test and the three-point bending test and shown that it has potential to measure and analyze the deformation field in discontinuous region.

The methods described above measure deformation/strain by considering a single joint at a known position. But in practical application it is required to know the joints information automatically. In 2011, Nguyen et al. have developed a new automated method of fracture identification and quantification based on standard DIC approach [8]. The work on automatic crack monitoring is further carried out by Valença et al. [9]. They have used direct shear tests (DSTs) for calibration and validation of their proposed algorithm.

In this research work, an algorithm is presented for automatic detection and classification of multiple damage zones on surface of an object. Then the proposed algorithm is incorporated in the DIC algorithm to calculate displacement fields. The paper describes the proposed algorithm in detail for identifying damage zones enclosing an area using convex hull method. Then the potential of the proposed algorithm is quantified by applying it on experimental samples. Comparative studies are also conducted to show the advantages of proposed

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algorithm for measurement of displacement fields with regular FEM-DIC method without considering damage zones.

2. Automatic damage zone(s) detection and classification method

Fig. 1 shows a flowchart of the proposed algorithm for automatic detection of damage zone(s).

The algorithm begins with filtering noises such as speckle pattern from the deformed image. Speckles are generated using random gaussian patterns throughout the image and is essential for DIC process. It is now required to de-speckle the image for detecting the areas having fractures/damages. For this purpose, Gaussian smoothing algorithm is found to be sufficient to remove the effect of speckles in the image. After the removal of speckles, edge detection technique is introduced to identify the points having fractures. The performance of Canny's edge detection algorithm has found to be better for preserving edges while removing speckle noises [10]. For that reason, it has been used in this research work.

Classical Hough transform is the most commonly used algorithm for detection of lines in polar coordinates (r,θ). In Hough transformation, a threshold value is required to be set for the number of collinear points in order to consider for a valid edge. In this study, it is fixed as 25 based on all possible cases and observations. Hough transformation generates a set of (r,θ) points as shown schematically in Fig. 2. Now it is required to group them into clusters such that a few points belong to the same fracture and so on. It may be noted that there is no prior information regarding the number of groups. For this reason an automatic clustering technique needs to be applied so that like points are clustered in the same group.

In the following, hierarchial clustering based algorithm is explained in details and also given in Fig. 3. Let us assume there are N data points. Compute Euclidean distance between points i and j as:

$$d_{ij} = \| \tilde{x}_i - \tilde{x}_j \| \tag{1}$$

If d_{ij} satisfies the minimum distance criterion, points i and j will be clustered in one group. The number of data points will be reduced to $N-1$ and similar process continues. Note that in this process several like points will be clustered into the same group and there may be several such groups. The advantage of this algorithm is that it is simple to implement and number of groups is not a priori. Fig. 3 lists the implementation procedure using a computer program.

To better understand the proposed procedure, let us manually examine some of the calculation steps. Suppose for an example, there are 10 points generated after the Hough transformation as given in Table 1.

Here $N=10$. Now initialize CurMin$=0$, PreMin$=0$, th1$=12$ and th2$=3$. The Euclidean distance matrix between data points is given in Table 2.

From Table 2, it can be seen that Euclidean distance between data 1 and 4 is 3.61, which is the minimum among all possible combinations. Since abs(CurMin-PreMin)$=3.61 < $th1, data 1 and 4 are merged into one cluster. Number of sample becomes $N=10-1=9$ and the value of CurMin is set to 3.61. With updated values, it is now required to form a new distance matrix by considering single linkage decision rule. According to this rule, Euclidean distances $d(i,1)$ and $d(i,4)$, where $i=1,2,\ldots,10$ and $i\neq 1$ and $i\neq 4$ are compared. If $d(i,1)<d(i,4)$, then $d(i,1)$ will be set in $\{i,[1,4]\}$ position as shown in Table 3 and vice versa. All other components of distance matrix given in Table 2 are kept the same.

Now for the next iteration, PreMin$=3.61$ and the minimum Euclidean distance is found to be 10 between data point 3 and 9 and CurMin is set to 10. Again abs(CurMin-PreMin)$=6.39 <$ th1, therefore 3 and 9 are merged to form a single cluster. Number of sample becomes $N=9-1=8$ and similar single linkage rule mentioned above is applied to form a new matrix. In this way, the process continues to find data points in the same cluster or to form a new cluster as in this case of data 7 and 8.

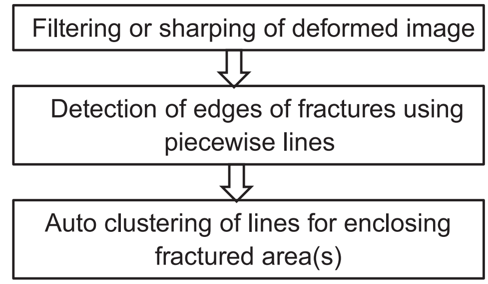

Fig. 1. Flowchart for automatic damage zones detection, classification and damage contour generation technique.

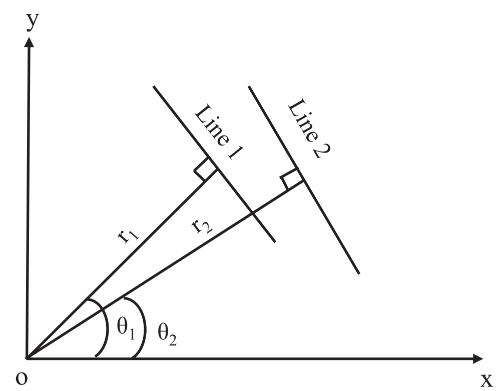

Fig. 2. Lines in Hough space.

```
Input:   N numbers of data points
Output: Classified data
Initialization:
'th1' is the maximum allowable difference between current minimum distance
and previous minimum distance;
'th2' is the minimum number of data points required to represent a
group/cluster
'PreMin' is the minimum distance of previous iteration = 0;
'CurMin' is the minimum distance of current iteration = 0;
'count' is used to check the loop condition = 0;
Main Program:
While (count != 1) do
        PreMin=CurMin;
        Find the closest (most similar) pair of clusters and assign that
        minimum distance value to 'CurMin';
        If (abs(CurMin - PreMin) < th1) then
                Merge them into a single cluster;
                Compute distances (similarities) between the new cluster
                and each of the data points or members of other clusters;
                N=N-1;
        else
                count = 1;
        end
end
Finally generate the group/cluster details if the number of group members > th2
```

Fig. 3. Auto clustering algorithm.

Table 1
r and θ points after Hough transformation.

	1	2	3	4	5	6	7	8	9	10
r	293	300	294	291	294	312	326	312	300	329
θ	8	70	42	11	29	118	279	252	50	87