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ANALYSIS OF SOME DIGITAL IMAGE CORRELATION TECHNIQUES

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Abstract

Digital Image Correlation (DIC) is a basic tool [1,2] used in numerous applications including stereometry [3-5], video image compression [6-13], recognition of moving objects [14,15], the study of displacements in solid mechanics [16-24], fluid velocity field measurement [25], etc. Hence a large number of algorithms has been proposed which differ essentially as to computation times, accuracy and reliability of the results in the presence of noise. First some applications using DIC are briefly illustrated, then some of the more interesting algorithms are described. The most significant results obtained using DIC for studying in-plane deformation of a specimen are then examined.

1) INTRODUCTION

Digital correlation is a numerical method for comparing two images that may represent generated or natural scenes and which can be acquired in rapid succession or at different times.

a) Shape Recognition

Suppose we have a library of generated images representing objects or graphic symbols (e.g. letters of the alphabet). With a DIC programme it is possible to find their positions inside a digital image (e.g. recognise a printed text). Similarly the position of known objects can be identified on satellite imagery. This type of application is complicated by the fact that during acquisition the objects to be distinguished may have undergone complex transformations of rotation and scale; for this reason alternative techniques are currently preferred that act on the objects contours. Another possible use of DIC is for identifying persons entering reserved areas (banks, cars, etc.) checking fingerprints or the eye fundus.

b) PIV (Particle Image Velocimetry)

The PIV technique can be used to study the flow field of fluids. This technique consists in inseminating the fluid with minute particles (that will not alter the flow field), in illuminating a section thereof with a plane of light and in acquiring two images in quick succession. A DIC programme can then be used to measure the displacement of the particles with time and establish their velocity in the plane. The algorithms generally used calculate the correlation coefficient resorting to the FFT proprieties [25]. Automatic systems for PIV applications are now available on the market [26].

c) Video image compression [6-13]

DIC is an essential component of video image compressors (e.g. H.263, MPEG 2: Motion Picture Expert Group) that reduces the temporal redundancies between successive frames. Suppose we have already acquired, compressed and transmitted an image at time t-1. The image acquired at time t usually differs very little from the previous one. This suggests subtracting the two images before compression, so as to reduce storage space. To further reduce the number of bits to be transmitted, it is possible to establish, with a DIC algorithm, the deformation undergone by the image between time t-1 and t. The image is then subtracted from the previous once the latter has been suitably deformed to compensate motion, and the signal deriving therefrom is coded and trasmitted. The majority of DIC techniques developed so far are of the Block Matching type (BM). Using BM techniques the image is divided up into rectangular non-overlapping blocks of the same size (usually 16 x 16 pixels) which are subjected to rigid displacement. The displacements are then estimated by searching in a part of the second image for the block that provides the best correlation.

d) Stereometry

Some programs for stereo image analysis and the virtual reconstruction of 3D objects use DIC for matching subsets of pixels belonging to the right and left images [3,5].

e) Super resolution

To enhance the resolution of images acquired with infrared CCD containing few large pixels, several images of the same object can be acquired shifting the CCD slightly, in horizontal and vertical direction between frames. The information is then integrated, thus enhancing resolution. This requires knowing exactly how much the CCD has been shifted between frames, which can be done a posteriori using a DIC program [27].

f) Solid mechanics

Thin specimens loaded in-plane are often used in solid mechanics. By acquiring two images of the surface, before and after loading, their displacement can be analysed [16-24]. In latter years, employing several CCD's, this technique has been extended to the analysis of more complex deformation states [20,21].

2) DIC ALGORITHMS

Many algorithms have been developed for the broad range of DIC applications and these have been optimised in relation to the kind of image to be processed, computation time and desired accuracy. For example, in video image compression, the images often contain several objects in relative motion, some of which can partially mask others or can appear or disappear with time. Thus the motion field is not continous, but may be nil in some zones and vary abruptly in others. The algorithms should yield results in real time and required accuracy is in the order of the pixel. International standards (such as MPEG) resort to block-matching (BM) algorithms [6-13] whereby for each block of the current frame the best matching block within the search window in the previous frame is determined on the basis of a matching criterion. The relative position of the best matched block is taken as motion vector of the reference block. The accuracy of BM algorithms depends on three factors: size of the search window, search technique and block matching criterion. Denoting with NxN the size of the blocks, the search area is usually limited to (2N+1) x (2N+1) pixels, centred around the position of the reference block. The *full search* algorithm provides the optimal solution by an exhaustive search, within the search window, for the best-matched block. However, because this procedure is highly computational intensive results cannot be obtained in real time. Several techniques have been proposed for reducing computational complexity, such as the *three step search* [6] and the *2D logarithmic search* [7] which reduce the number of search positions within the search window, assuming that matching error increases as the searched point moves away from the exact point. In actual fact, this assumption does not always hold and can lead to errors. Several block matching criteria have been proposed, some adapted to hardware implementations [11]. The most popular criteria are the Mean Absolute Difference (MAD), the Sum of Squared Differences (SSD) and the Correlation Coefficient (CC). If we denote with f(i,j,t) and f(i,j,t-1) the brightness in the pixel (i,j) at time t and at time t-1 respectively, and with (u,v) the relative position of the two blocks being compared, the three criteria can be written as follows:

$$MAD(u,v)=\sum_{i=1}^{N}\sum_{j=1}^{N}\left|f(i,j,t)-f(i+u,j+v,t-1)\right| \tag{1a}$$

$$SSD(u,v)=\sum_{i=1}^{N}\sum_{j=1}^{N}\left(f(i,j,t)-f(i+u,j+v,t-1)\right)^2 \tag{1b}$$

$$CC(u,v)=1-\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left(f(i,j,t)*f(i+u,j+v,t-1)\right)}{\left[\sum_{i=1}^{N}\sum_{j=1}^{N}f^2(i,j,t)\right]^{1/2}\left[\sum_{i=1}^{N}\sum_{j=1}^{N}f^2(i+u,j+v,t-1)\right]^{1/2}} \tag{1c}$$

The advantage of the CC matching criterion is that it yields unit normalised values, but requires an large number of multiplications. For this reason the MAD criterion is usually preferred. The displacement vector (u,v) of the block is the one that minimises the selected matching function. One technique for reducing the computational complexity of BM algorithms is to reduce the search area using the displacements of spatially neighbouring blocks. Because the motion field is usually non homogeneous it may happen that one block overlaps two zones that in reality have very different displacement and this generates errors. To overcome this drawback, blocks of variable size, depending on motion content, can be used [12]. The stationary background can be divided into macro blocks, while the edges of the moving objects are divided into smaller blocks.

In solid mechanics applications (except for the edge of the objects where the displacement vector undergoes abrupt variations with respect to the stationary background), the motion field is homogeneous, and this can be exploited for algorithms optimisation and result interpolation. Computation time is not important but accuracy should be as great as possible and commensurate with the quality of the optical acquisition system. Alternatively several workers [19,23,25] use algorithms based on the correlation function and FFT properties. This technique generates the so-called Young fringes in digital form similarly to what happens in experimental speckle photography [28]. In this case, from each block of the undistorted image, one adds the corresponding block of the distorted image. Then the spectrum is calculated by means of FFT and a fringe pattern is obtained whose orientation and step indicate respectively the direction and value of the displacement between the first and second frame. This displacement, expressed in pixel, is obtained directly by calculating the Fourier transform of the fringe system. If the predicted displacement is less than N pixel, then the image is divided into blocks (overlapping where necessary) of at least 2Nx2N pixels. To enhance accuracy several interpolating techniques in the frequency domain have been proposed. If the displacement is very small (less than 5 pixels) then it cannot be estimated: in [23] a very interesting solution to this problem has been proposed. The FFT technique is very fast but because each block is treated separately from its neighbours, the information acquired during computation cannot be used to accelerate its execution. Consequently greater attention has been focused on BM algorithms insomuch as they leave greater room for improvement.

3) APPLICATION OF DIC TO SOLID MECHANICS

We have used DIC on images having random distribution grey levels, as happens when recording the intensity distribution reflected by an optically rough surface illuminated by coherent light, obtaining a laser speckle effect [28]. Speckle methods in white light, for which digital correlation usually provides the best results, are used when the natural appearance of the surface is used for calculating displacements and in-plane deformations. The speckle effect can also be obtained artificially, for example by spraying white paint on a reflecting black surface. Some workers have suggested marking the surface of specimens with signs of known shape and position to monitor their displacement under load [29]. Though numerical processing of the images (preceded by a delicate calibration process) is relatively simple and fast, the technique is not always applicable insomuch as the surface of the object might be damaged or be so small as to render marking impossible.

Consider two recorded images of the undeformed and deformed object. The basic assumption underlying digital correlation techniques is that the temporal variations in grey intensity distribution are in a one to one correspondence with the displacements. Thus the brightness variations should not be generated by other sources, such as, for example, a change either in direction or in intensity of light.

Only 2D displacement fields are considered here. Thus the optical axis of the CCD camera must necessarily be perfectly perpendicular to the specimen surface such that it is only subjected to in-plane displacements. Any displacements parallel to the optical axis would be misinterpreted by the DIC programme.

Suppose that, after loading, the points of each subset are displaced by:

$$x_2 = x_1 + u + \frac{\partial u}{\partial x}\Delta x + \frac{\partial u}{\partial y}\Delta y \qquad y_2 = y_1 + v + \frac{\partial v}{\partial x}\Delta x + \frac{\partial v}{\partial y}\Delta y \tag{2}$$

where (x_1,y_1) and (x_2,y_2) are the coordinates of the point before and after loading, u and v denote displacements in the x and y directions with respect to the central point $P_0(x_c,y_c)$ of the subset, $\partial u/\partial x$, $\partial u/\partial y$, $\partial v/\partial x$, $\partial v/\partial y$ are the deformations of the subset, and Δx e Δy the distance of point $P(x_1,y_1)$ from point $P_0(x_c,y_c)$. The assumed deformation process is shown in Fig. 1.

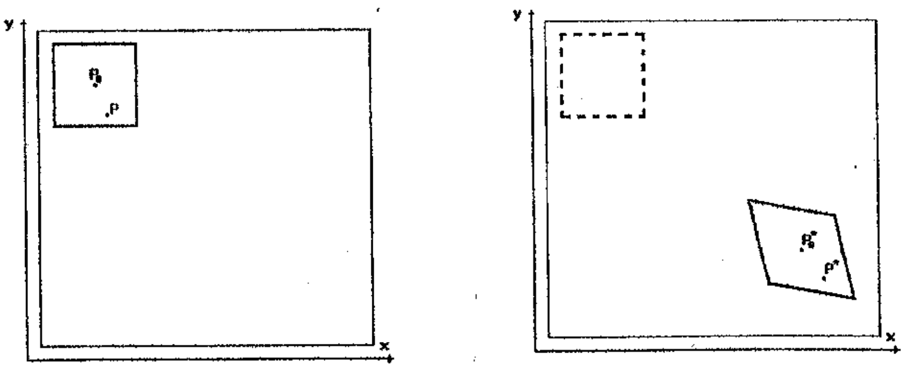

Fig. 1.Block configuration before and after loading.

Image correlation consists in finding the values of u, v, $\partial u/\partial x$, $\partial u/\partial y$, $\partial v/\partial x$, $\partial v/\partial y$ that minimise one of the matching criteria shown in (1). Then these values are suitably modified, as shown in the following example for the MAD criterion.

$$MAD\left(u, v, \frac{\partial u}{\partial x}, \frac{\partial u}{\partial y}, \frac{\partial v}{\partial x}, \frac{\partial v}{\partial y}\right) = \sum_{x_1}^{N}\sum_{y_1}^{N}\left| f(x_1, y_1, t) - f(x_1 + u + \frac{\partial u}{\partial x}\Delta x + \frac{\partial u}{\partial y}\Delta y, y_1 + v + \frac{\partial v}{\partial x}\Delta x + \frac{\partial v}{\partial y}\Delta y, t-1)\right| \tag{3}$$

The search for the minimum of the function (3) is rather complicated, as the solution lies in a continuous six dimensional space. Thus simplified techniques have to be used. Furthermore, the calculation of one of the matching criteria, presupposes the estimation of intensity in points of the deformed image, which do not necessarily coincide with the pixels. Consequently, interpolating functions such as bilinear and bicubic spline functions are used.

The code we implemented is divided into two parts. First of all the whole displacement is rapidly estimated using the BM technique. Then the solution is optimised using *Newton-Raphson* minimisation [18] or the *Optical Flow* algorithm proposed in [30]. The results are then filtered using a polynomial interpolation and the displacements are accepted only if the correlation coefficient improves. In any case, the operator must input the search window size of the rigid displacements $(u,v)_{min}$ and $(u,v)_{max}$ and the size N of the subsets. We are still investigating the automatic choice of these two parameters. The *full-search*, *coarse-fine* [1] and FFT correlation algorithms can be used to get a first tentative estimate. The last one will not be discussed below for reasons of conciseness

a) *Full-search algorithm*

Because of the computation requirements of this technique we have used a variety of strategies to reduce its complexity. As a first displacement estimate we used the (u_0,v_0) value found for the neighbouring blocks that had already been calculated. Using this value the MAD (u_0,v_0) is calculated which, reasonably speaking, should be close to the optimum value. Then we proceed to calculate all the MAD for each pair of values (u,v) within the search window. As the calculation consists in accumulating, pixel-by-pixel, the difference between two blocks, when this difference is greater than the MAD (u_0,v_0), calculation can be interrupted. Conversely, we get a new minimum of the MAD and hence a new displacement vector. Experience has shown that on average the computation time can be cut by half. To speed up the execution time even further, instead of using all the N by N pixels in the block to calculate the MAD, especially for large blocks it is possible to use one every two or three pixel, thereby reducing computation by a factor of four and nine respectively.

b) C*oarse-fine* algorithm

This technique which is used for large search windows, consists in finding the displacement vector by using images of increasing resolution. The starting images are compressed, reducing their resolution by means of a Gaussian filter. The level of compression, proportional to 2^n, is chosen such that the search window is limited to a few integer (u,v) (generally 3x3). Once the first estimate (u_0,v_0) of the displacement vector has been obtained by means of a BM algorithm, we move to a lower level of compression, equal to half the previous one. In this case the search window, centred on $(2u_0,2v_0)$, consists of 3x3 pairs of values. The procedure continues until the initial resolution has been obtained.

4) APPLICATION AND ANALYSIS OF RESULTS

To assess the accuracy and reliability of the method we examined the effect of noise. A commercial 8 bit CCD camera with 640x480 pixels was used. A specimen speckled with paint was placed on a vibration isolated bench and 100 theoretically identical 300x300 pixel images were acquired. These data were used to calculate the average image and the standard deviation (SD) of each pixel. The worst and average SD were found to be equal to 19.6 and 3.1 grey levels, corresponding to 7.7% and 1.2% of the peak signal.

We then calculated the mean of the first 50 images acquired, considering it the "exact" reference signal. From a second set of 50 frames we extracted first 1, then 4, 9, 16, 25, 36, 49 frames obtaining 7 means for comparison with the reference signal. Based on these data we calculated the signal-to-noise ratio (SNR) using the following formula:

$$SNR = \frac{1}{N * N} \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{signal(i,j)}{\left| image(i,j) - signal(i,j) \right|} \tag{4}$$

where *signal(i,j)* denotes the pixel intensity (i,j) of the reference frame and *image(i,j)* is the intensity of the corresponding pixel in one of the 7 means. As digital correlation acts on pairs of pixel blocks, we observed how SNR changes as block size varies. Figure 2 shows the trend of the worst SNR with regard to the block size and the number of acquisitions used to generate the means.

SNR increases with the number of averaged images, but for more than 16 frames no improvement is observed. As block size increases so too does the SNR, but the benefits derived for blocks larger than 49x49 are limited.

Then we analysed the effect of noise on the displacements values calculated by a DIC programme. The frames to be compared were obtained by averaging two sets of 50 frames. The largest displacement observed was 0.008 pixel, while the mean displacement was 0.004 pixel.

The third test consisted in numerically applying known displacements to a specimen image with increasing levels of noise. For generating numerical images, bilinear interpolation was used. The image was divided into 121 blocks of 49x49 pixels. Fig. 3 shows the smallest, mean and greatest error in calculated displacements with respect to the applied values for the different algorithms used. In this case the frames compared were free of noise. Interestingly, error displays a sinusoidal trend versus displacement, a feature observed by other workers [17,30,31].

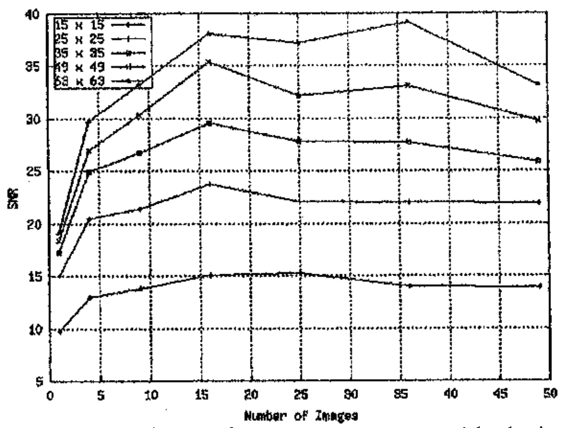

Fig. 2. Variation of the worst SNR versus block size and number of averaged frames

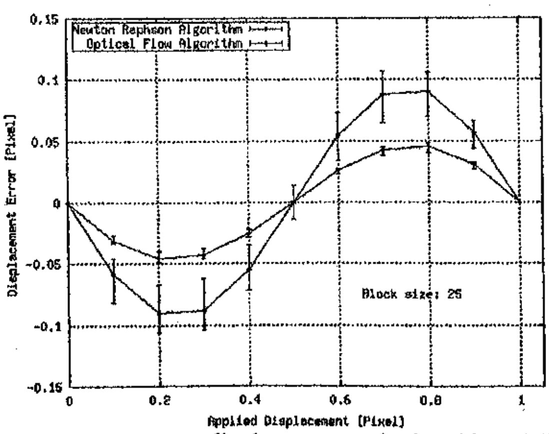

Fig. 3. Error on displacement calculated by a DIC programme versus applied displacements.

Figures 4 and 5 show the variations in the lowest, mean and highest displacement values versus block dimension and noise level, calculated using the algorithms proposed in [18] and [30] respectively. As can be observed, as the number of acquisitions per image and block size increase, the results become more stable. For a noise level comparable with that produced by the CCD used here, using blocks of 49x49 pixels, the greatest error generated by the algorithm [18] was less than 0.05 pixel, and less than 0,01 pixel for the algorithm [30].

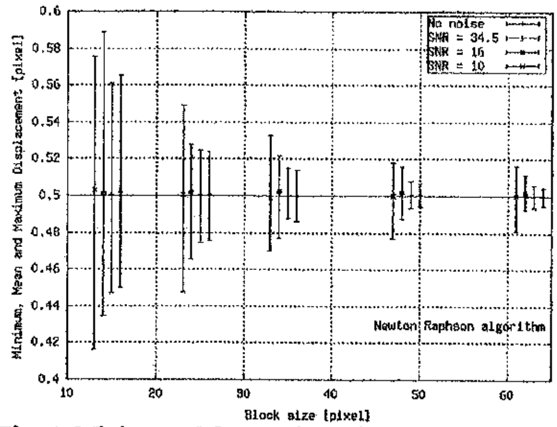

Fig. 4. Minimum, Mean and Maximum Displacement calculated by Newton Raphson algorithm versus Block Dimension and Signal to Noise Ratio

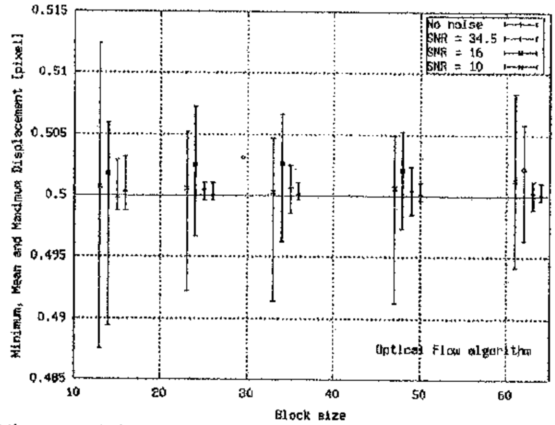

Fig. 5. Minimum, Mean and Maximum Displacement calculated by the Optical Flow algorithm versus Block Dimension and Signal to Noise Ratio.

The fourth test consisted in measuring the rigid displacements applied to a specimen by means of a micrometer. The images were divided into 110 blocks of 49x49 pixels and the bilinear function was used in the DIC algorithms. The results, shown in Fig. 6, substantially confirm the above observations. In particular, the sinusoidal systematic error can be reduced [31] to obtain an error of about 0,01 pixel.

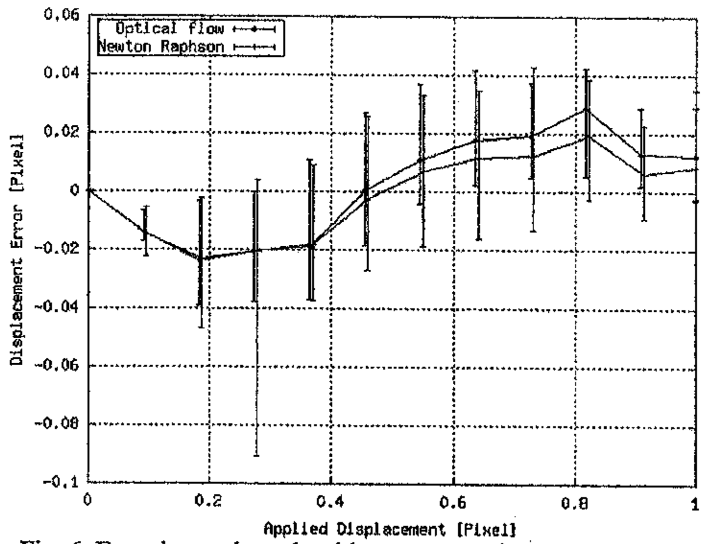

Fig. 6. Experimental result without systematic error correction.

If the accuracy in calculating the displacements is equal to δ then two N pixels apart points will, after loading, be displaced by $u_1 \pm \delta$, $u_2 \pm \delta$. Thus the mean deformation will be:

$$\varepsilon_{calculated} = [(u_2 \pm \delta) - (u_1 \pm \delta)]/N = (u_2 - u_1)/N \pm 2\delta/N = \varepsilon_{exact} \pm error$$

For example, if $\delta = 0.01$ pixel and N = 50 pixels, the error is 0.04%. For this reason some workers recommend using large subsets, but this prevents rapid changes in displacements being monitored.

5) CONCLUSIONS

In this paper different DIC techniques have been presented. In particular, we focused our attention on the correlation function and the different algorithm to find the most accurate solution. In all the tests conducted here, the optical flow algorithm proved to be the most accurate and reliable and much faster than the Newton-Raphson minimisation. Furthermore, its response is not as sensitive to block size and noise and consequently smaller blocks can be chosen.

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