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Digital image correlation search method based on particle swarm algorithm

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Abstract. Digital image correlation method is an important optical technique for surface displacement and strain measurement. An approach based on Particle Swarm Optimization algorithm for sub-pixel correlation search is described in this paper. The new Algorithm does not involve reasonable guess of displacement and deformation gradient and the calculation of second-order derivatives of the digital images. Benefiting from the abilities of global optimum and parallelism searching, and compared with genetic algorithm, the new approach can complete the sub-pixel correlation search with high accuracy and less computational consumption. Computer-simulated images are then used to verify this method. The experimental results show that the new approach is a practicable sub-pixel searching method.

Introduction

Digital image correlation method (DICM), which is also named digital speckle correlation method (DSCM), has become one of the important methods in modern optical measurement techniques in recent years. The method introduced by Peters and Ranson[1], as an automatic, non-contact, whole-field measurable one, is a powerful and popular tool which can be applied to many research and engineering applications[2-4]. Because digital image correlation method directly processes the digitized images, correlation search only locates integer pixel level. To further improve measurement accuracy, various sub-pixel translation algorithms have been developed by many researchers in the past decades. Compared with search in integer pixel level, the sub-pixel search method is time-consuming. So far, these common sub-pixel algorithms include intensity interpolation[5], correlation coefficient curve-fitting[6], Newton-Rapson[7], gradient-based method[8], genetic algorithms[9-12], and artificial neural network methods[13-14] and so on. However, these algorithms often require reasonable initial guess of displacement and deformation gradient. Iterative algorithms also require the calculation of second-order spatial derivatives of the digital images, which increase the computation complexity. Some optimization methods in math have already been applied to DICM in recent years, thus some satisfactory results have been obtained. These researches and applications greatly extend the theory of DICM.

Particle swarm optimization (PSO) is a brand-new algorithm based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. PSO is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles move around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the whole swarm's best known position. After updated positions being discovered, these will then come to guide the movements of the entire swarm. The process repeat, and, by doing so it is hoped, that a satisfactory solution will eventually be found. In the past decades, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. This paper introduces PSO to sub-pixel correlation search of DICM, and achieves accurate and fast search.

The principle of DICM

The basic principle of DISC is to match two speckle patterns before and after deformation. Typically, a subset of $(2M+1)^2$ pixels from the reference image is chosen to find its location in the deformed image. Once the location of the subset in the deformed image is found, the displacements of the subset center can be determined. A correlation coefficient is defined to express the similarity of the two image subsets, whose correlation coefficient is on the peak of the distribution of the correlation coefficients, is determined as the optimum matched image subset. Due to the characteristic of single-peaked, correlation coefficient is often adopted as follows, and the distribution of correlation coefficients is shown in Fig.1.

$$C=\frac{\sum_{y=-M}^{y=M}\sum_{x=-M}^{x=M}\left[f(x,y)-f_m\right]\left[g(x^*,y^*)-g_m\right]}{\sqrt{\sum_{y=-M}^{y=M}\sum_{x=-M}^{x=M}\left[f(x,y)-f_m\right]^2}\cdot\sqrt{\sum_{y=-M}^{y=M}\sum_{x=-M}^{x=M}\left[g(x^*,y^*)-g_m\right]^2}} \tag{1}$$

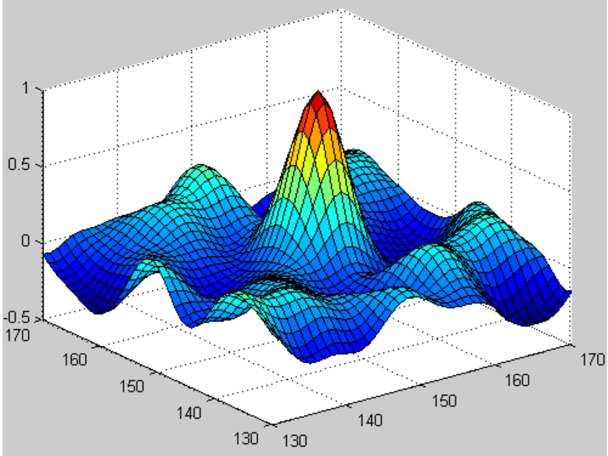


Fig. 1 The distribution map of correlation coefficients

Where $f(x,y)$ and $g(x^*,y^*)$ presents the reference and the deformed subset intensity value, respectively. It assumes that each of these subset points (*x, y*) in the reference image is mapped to (x^*,y^*) in the deformed image using the following equations:

$$\left.\begin{aligned} x^* &= x_0+u+\frac{du}{dx}\Delta x+\frac{du}{dy}\Delta y \\ y^* &= y_0+v+\frac{dv}{dx}\Delta x+\frac{dv}{dy}\Delta y \end{aligned}\right\} \tag{2}$$

Where u and v are the displacements for the image subset centre in the x and y directions respectively. The terms Δx and Δy are the distances from the subset center (x_0, y_0) to the point (x,y). The principle of DICM could be simply shown as Fig.2 (take the displacement measurement of a point P as an example). The gradient terms in Eq.2 signifies that the $(2M+1)^2$ rectangular subset surrounding a point P can be stretched or compressed.

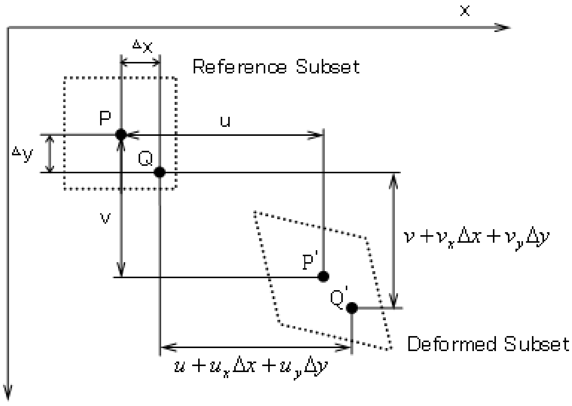


Fig. 2 Reference subset and deformed subset

The value of $u, v, \partial u/\partial x, \partial u/\partial y, \partial v/\partial x, \partial v/\partial y$ which maximize C are the local deformation gradients for the selected subset. The main objective of the image correlation search is to find these six values for the subset under investigation, and then repeat it for all subsets in a given region so as to find the whole-field deformation profile.

The implementation of PSO Algorithm

The procedure of PSO is as follows:

a. Initialize the populations. Allocate position to every particle with an uniformly distributed random decimal: $x_i \sim U(-1,1)$, $i=1,2$,denote displacements. $x_i \sim U(-0.5,0.5)$, $i=3,4,5,6$ denote displacement gradient.

b. use the Eq.1 to evaluate the fitness for every particle.

c. for all i, if $fitness_i > pBest_i$, and then $PBest_i = fitness_i$, $X_i^{PBest} = X_i$, if $fitness_i > gBest$, and then $X_i^{GBest} = X_i$;

d. Update every particle's velocity. $v_i(k+1) = \omega v_i(k) + c_1 r_1 [x_{pBest} - x_i] + c_2 r_2 [x_{gBest} - x_i]$ (3)

e. Update every particle's position. $x_i(k+1) = x_i(k) + v_i(k+1)$ (4)

f. Until a termination criterion is met (e.g. number of iterations performed, or adequate fitness reached), or go (2).

Because of the characteristics of digital image, the gray information obtained is discrete in nature. This means that no gray level information is available between pixels. To obtain higher accuracy, an approximation of gray level values between pixels is needed. It was found that higher accuracy could be obtained by using bicubic spline interpolation[7].

Verification by numerical experiment

To evaluate the measurement accuracy and performance of the sub-pixel translation algorithms described above, computer-simulated images[7] are generated in this study. Numerical simulation experiments are used for analyzing in controlled conditions. The detailed features of the simulated speckle image are listed as follows: the size of images is 300×300 pixels; the size of speckle is 3 pixels; and the number of speckles is 1500. The left image is reference image, the middle one is the histogram of the left image, and the right one a deformed image with u=0.65 and v=0.35.

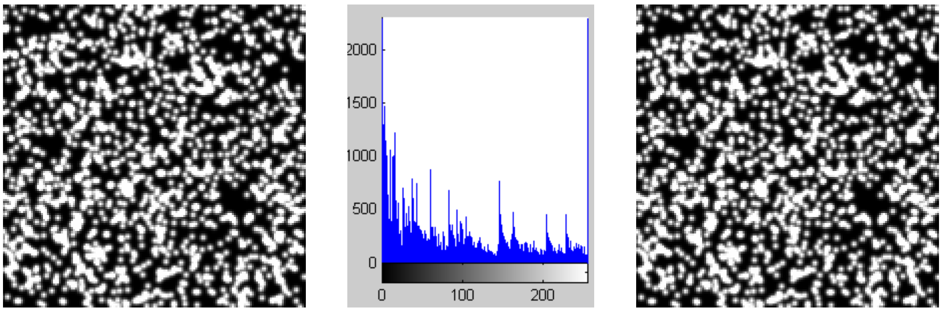


Fig.3 Reference image and its histogram and deformed image

For every image pair, the total number of calculated points with fixed positions in original image is 1681 (41*41 pixels). The discrete root mean square error is calculated. The discrete error is defined by errors associated with sub-pixel translation algorithms which can be decomposed into two components: systematic error and standard deviation (SD) error. Given the actual pre-imposed displacement d_{imp} and the measured displacement d_i, the systematic error can then be defined as:

$$E_{sys} = d_{mean} - d_{imp} \tag{5}$$

Where $d_{mean} = \frac{1}{N}\sum_{i=1}^{N} d_i$ represents the mean of the N estimated displacements. The SD error is defined as:

$$SD = \sqrt{\frac{1}{N-1}(d_{mean} - d_{imp})^2} \tag{6}$$

This can reflect the deviation of the measured displacement corresponding to the mean value, and has a certain relationship with the random error.

A series of simulated speckle images was investigated first, with sub-pixel displacements ranging from 0 to 1pixel, corresponding to a shift of 0.05 pixels between two continuous images.

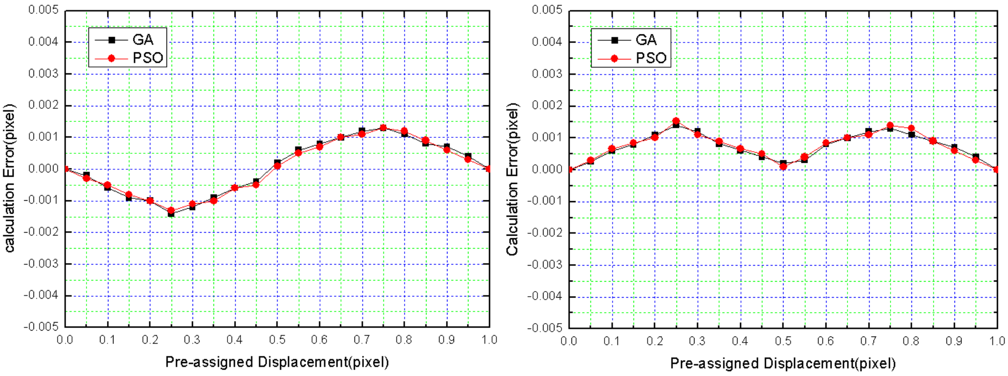
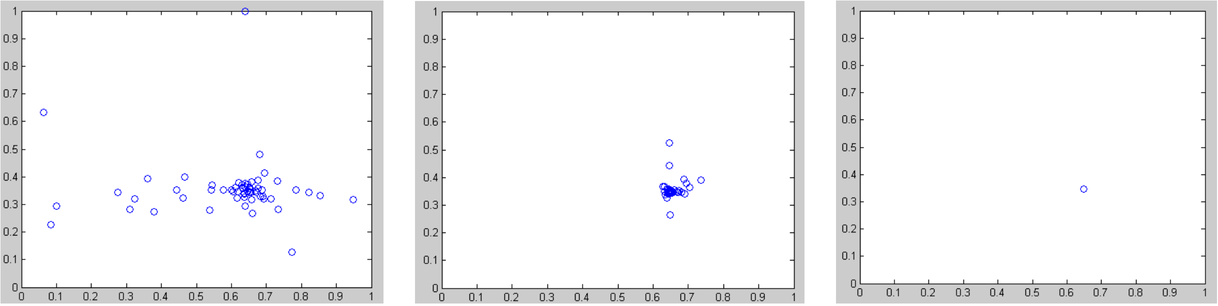


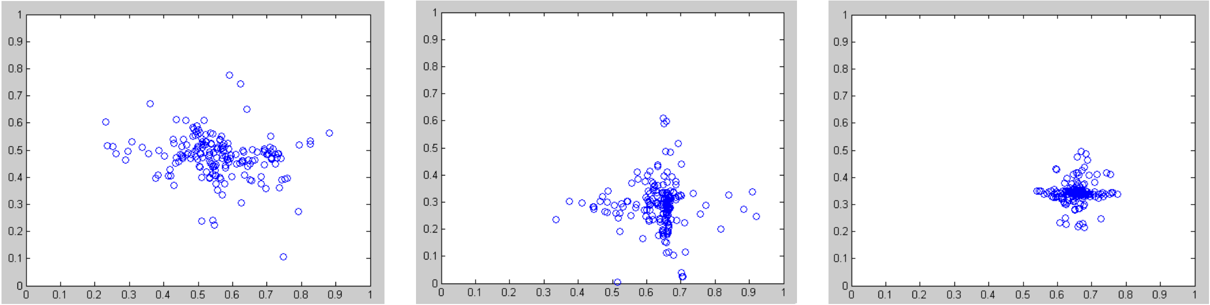
Fig. 4 Systematic errors and SD error of GA and PSO With 41*41 pixels subsets

The number of Particle in PSO is 60, and the expected number of iteration is 200. Momentum factor ω is 0.7. Learning factor c_1 and c_2 is 2. The number of population in GA is 200, and expected number of evolution generation is 500. Fig.5 and Fig.6 give the characteristics of convergence for solutions based on PSO and GA respectively. Fig.7 shows convergence of fitness based on PSO and GA.



Gen=50 Gen=100 Gen=200

Fig.5 The convergence of solutions based on PSO



Gen=100 Gen=300 Gen=500

Fig.6 The convergence of solutions based on GA

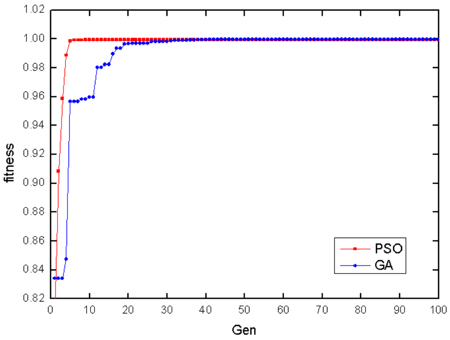


Fig.7 The convergence of fitness

Particles can change their positions using random velocity in the solution space. Considering the evolution generation of particles, PSO algorithm shows the strong random character, so it possesses low complexity than GA algorithm. From the above experimental results, we can conclude PSO algorithm is good than GA algorithm in search efficiency of solution.

Conclusions

A sub-pixel search algorithm based on PSO for DICM is presented, and the paper introduces the basic principle of DICM. This paper discusses about application of PSO in DICM and detailed implementation process in correlation search. Compared with genetic algorithm, the accuracy of PSO algorithm is not further improved, but the speed is fast than GA algorithm. The experimental result shows that PSO algorithm is a kind of practical sub-pixel search method.

Reference

[1] W.H. Peters, W.F. Ranson. Digital imaging techniques in experimental stress analysis.Opt. Eng, 1982, 21(3): 427-431.

[2] G. Zhan , P. Jaydev, Desai. Estimating zero-strain states of very soft tissue under gravity loading using digital image correlation. Medical Image Analysis, 2010, 14: 126-137.

[3] F.M. Sánchez-Arévalo, G. Pulos. Use of digital image correlation to determine the mechanical behavior of materials. 2008, 59: 1572-1579.

[4] Y.H. Huang, L. Liu, T.W. Yeung, Y.Y. Hung. Real-time monitoring of clamping force of a bolted joint by use of automatic digital image correlation. Optics & Laser Technology 2009, 41: 408-414.

[5] Q. Yu, et al. Image Based Precise Measurement and motion measurement (Beijing: Science Press) , 2002. (in Chinese)

[6] P.C. HUNG, A.S. Voloshin. In-plane strain measurement by digital image correlation. Journal of the Brzailian society of Mechanical Sciences and Engineering, 2003, 25(3): 215-221.

[7] H.A. Bruck, S.R. McNeill, M.A. Sutton, et al. Digital image correlation using Newton-Raphson method of partial differential correction. Experimental Mechanics,1989, 29:261-267.

[8] P. Zhou, K. E. Goodson. Subpixel displacement and deformation gradient measurement using digital image/speckle correlation. Optical Engineering, 2001, 40(8): 1613 -1620.

[9] C. Tang, M. Liu, H.Q. Yan, et al. The improved genetic algorithm for digital image correlation method. Chinese Optics Letters, 2004, 2(10): 574-577.

[10] L. Pilch, A. Mahajan, T. Chu. Measurement of whole-field surface displacements and strain using a genetic algorithm based intelligent image correlation method. Journal of Dynamic Systems, Measurement, and Control, 2004, 9(126): 479-488.

[11] S.P. Ma, G.C. Jin. Digital speckle correlation method improved by genetic algorithm. Acta Mechanica solida Sinica, 2003, 16(4): 266~273.

[12] H.Q. Jin, H.A. Bruck. Pointwise digital image correlation using the genetic algorithm optimization method. 2004,14(5):234~243.

[13] C.P. Mark, W.S. Chung, G.S. Michael. Subpixel microscopic deformation analysis using correlation and artificial neutral networks.Optics Express, 2001, 8(6): 322-327.

[14] C.P. Mark, W.S. Chung, G.S. Michael. Fast subpixel digital image correlation using artificial neutral networks. Image Proceeding, 2001, 2: 901-904.

[15] J. Kennedy, R. Eberhart. Particle swarm optimization. in: Proceedings of the 4th IEEE International Conference on Neural Networks[C], Piscataway: IEEE Service Center, 1995, pp.1942-1948.

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DOI References

[8] P. Zhou, K. E. Goodson. Subpixel displacement and deformation gradient measurement using digital image/speckle correlation. Optical Engineering, 2001, 40(8): 1613 -1620.
http://dx.doi.org/10.1117/1.1387992
[10] L. Pilch, A. Mahajan, T. Chu. Measurement of whole-field surface displacements and strain using a genetic algorithm based intelligent image correlation method. Journal of Dynamic Systems, Measurement, and Control, 2004, 9(126): 479-488.
http://dx.doi.org/10.1115/1.1789968
[13] C.P. Mark, W.S. Chung, G.S. Michael. Subpixel microscopic deformation analysis using correlation and artificial neutral networks. Optics Express, 2001, 8(6): 322-327.
http://dx.doi.org/10.1364/OE.8.000322