ABSTRACT

Digital image correlation (DIC) is a whole-field and non-contact strain measuring method. It could provide deformation information of a specimen by processing two digital images captured before and after the deformation. To search the deformed images, a hybrid genetic algorithm, in which a simulated annealing mutation process and adaptive mechanisms are combined with a real-parameter genetic algorithm, is adopted in this work. This method is used to measure the strain during the micro tensile testing of nickel thin film. In addition to the conventional single region, double region is proposed to calculate the strain by DIC. The results indicate that while the strains obtained by single region are reasonable, those obtained by double region are accurate. Also the mechanical properties of nickel thin film could be accurately obtained.

Introduction

In 1982 Peters and Ranson [1] first employed digital image correlation for displacement and strain measurement under the assumption that there is a one-to-one correspondence on the intensity pattern of surface images before and after deformation. They have proved this assumption, and two displacements and four displacement gradients were searched for in-plane deformation. Sutton et al. [2] defined the intensity difference of two digital images as a correlation coefficient and deduced the two-dimensional displacements of the centerline of a cantilever beam subjected to an end load. Chu et al. [3] utilized a cross-correlation coefficient as an objective function and measured the rigid body translation, rigid body rotation, and uniaxial uniform strain. Their results also indicated that a bilinear interpolation may be better than a higher order polynomial interpolation for the reconstruction of digitally recorded intensity pattern. Among these papers, the searching method was a coarse-fine iterative technique, in which the searching range was progressively reduced until the stop criterion was satisfied. Newton-Raphson method was later applied to search the six deformation components [4-5], and it was 20 times faster than the coarse-fine iterative technique. To achieve better accuracy on the deformation components, Sutton [6] discussed the effects of some key parameters and recommended that it was necessary to use nonlinear interpolation, 12-bit quantization, and high frequency sampling. Plastic incompressibility and thin-sheet assumptions was used by Wattringe et al. [7] to derive the third displacement component, and Lu and Cary [8] refined the digital image correlation by implementing a second-order approximation of the displacement gradients. Luo et al. [9] utilized a pin-hole camera model to express the transformation relating three-dimensional world coordinates to two-dimensional computer-image coordinates by the use of camera extrinsic and intrinsic parameters. In addition, digital image correlation has been applied to the measurement of surface profile [10], the heterogeneous deformation of polymeric foams [11], and high strain gradient measurements [12].

Among the above literature, Newton-Raphson method was commonly used to search the deformation components because it was fast. However, one drawback of this method is that it may find a local minimum not the true minimum. To avoid this drawback, the searching ranges of the deformation components must be reduced to be small enough before starting this method, and a coarse method was always applied with Newton-Raphson method. Since to search the most suitable deformation components between two subsets in two images could be considered as an optimization problem, it is very
interesting to use genetic algorithm (GA) to replace the two-step Newton-Raphson searching method. Genetic algorithm is different from most conventional calculus-based searching algorithms in the following characteristics. First, genetic algorithm makes no limitation on the search space of optimization problems. For example, the continuity and differentiability of functions are not required such that it can be easily applied to versatile fields. Secondly, genetic algorithm searches for the optimum solutions through parallel computation of a population of solutions, not just a single solution. Thirdly, genetic algorithm is based on natural selection criteria not deterministic rules, and the gene operators play important roles. Finally, genetic algorithm uses the information of fitness value directly, and other mathematical knowledge is not needed. However, to strengthen the performance of genetic algorithm, one possibility is to combine it with simulated annealing and adaptive mechanisms to create a hybrid algorithm.

Instead of Newton-Raphson method, a hybrid genetic algorithm [13] is used in digital image correlation in this work to release the limitation on the range of the searched parameters. To increase the accuracy and reliability of this algorithm, some key parameters such as population number, generation number, subset size, iteration number, and searching strategy are suggested. In addition to the conventional single region for strain searching, a double region is proposed to calculate the strain parameters such as population number, generation number, subset size, iteration number, and searching strategy are obtained.

Digital image correlation

On using the discrete pixels of a digital image and their grey level values for intensity, these data are recorded as a two-dimensional array. Under the assumption that there is a one-to-one correspondence on the intensity pattern of two images taken before and after a deformation increment, one could deduce the deformation information from the intensity pattern. To remain within the limit of linear approximation of the deformation, a region of pixels called subset should be small enough. If a subset is arbitrary chosen from the image taken before a deformation increment and a reference point \((x_0, y_0)\) as well as a nearby point \((x, y)\) is selected from this subset, the position \((x', y')\) of the nearby point after the deformation increment could be described as

\[
x' = x + \frac{\partial u}{\partial x} dx + \frac{\partial u}{\partial y} dy \\
y' = y + \frac{\partial v}{\partial x} dx + \frac{\partial v}{\partial y} dy
\]

(1)

where \((u, v)\) are the displacements of the reference point, and \((dx, dy)\) are the position differences of the reference point and the nearby point before deformation. The components of the first-order displacement gradient are denoted as \(\frac{\partial u}{\partial x}\), \(\frac{\partial u}{\partial y}\), \(\frac{\partial v}{\partial x}\), and \(\frac{\partial v}{\partial y}\). Since only a two-dimensional deformation is considered in the above equations, one needs two displacement components and four displacement gradient components to describe the position of a nearby point.

Generally, the positions of the reference point and the nearby point after deformation are not located at pixel points of the digital image taken after deformation, and there are no grey level values for these points. Hence, interpolation is necessary to retrieve their grey level values such that the intensity pattern of the subset could be obtained. In this work, a bilinear interpolation is used. Under the assumption and limit described above, one could find a subset in the deformed image that is correspondent to the undeformed subset by considering the displacements and displacement gradients. To represent the correlation of these two subsets, a least squares correlation coefficient is commonly used. In addition, to include the effect of offset of a grey level value that could result from the difference in the brightness of the images, an offset value \(w\) is added as

\[
\Phi = \sum_{i,j=Cz/2}^{Cz/2} \left[ I_1(x_i, y_j) - I_2(x'_i, y'_j) + w \right]^2
\]

(3)

where \(I_1(x_i, y_j)\) and \(I_2(x'_i, y'_j)\) denote the intensities of the points in the subsets from the undeformed image and the deformed image, respectively. The size of the subset is represented as \(Cz \times Cz\). If the dimension of subset is small, the offset value could approximate the out-of-plane displacement. Now it could be considered as an optimization problem in which the correlation coefficient is to be minimized and the design variables are the two displacements and the four displacement gradients as described in Eqs.(1-2).

Hybrid Genetic Algorithm

A novel hybrid algorithm based on a real-parameter GA (RGA) [13] is introduced in this section. This novel hybrid algorithm maintains the merit of GA by using its crossover and mutation processes and includes simulated annealing as another mutation process. Also adaptive mechanisms are added to adjust the probabilities of the crossover and mutation operators for
improving the hill-climbing ability of optimum solutions. As most GA-based optimization methods, the elite strategy is also adopted to insure the quality of the searched solution.

To create the true initial population, two populations of solutions are randomly generated. By defining a normalized fitness, the fitness of the two solutions that are randomly picked from each population is evaluated. The solution that has a higher fitness value becomes a solution of the true initial population. This process is called tournament criterion. In the reproduction process, the Darwinian principle of “survival of the fittest” is utilized, and the well-known roulette selection criterion is used to produce the next population. The solution with higher normalized fitness has a higher survival probability into the next population.

In the crossover process, a novel crossover operator is utilized here to improve the performance of RGA. If a random number \( r_{\text{random}} \) doesn’t exceed the crossover probability \( P_c \), a random crossover point is generated and the crossover operator is applied from this selected point to either the end point \( n \) or the start point \( 1 \) of the solution, which is randomly selected. For example, suppose that the parents could be described as \( y_1 = \{a_1, a_2, \ldots, a_n\} \) and \( y_2 = \{b_1, b_2, \ldots, b_n\} \), where the parameters \( a \) and \( b \) are real numbers and \( n \) is a positive integer representing the total number of the parameters to be searched. If the randomly generated number is \( i \) and the end point \( n \) is chosen, the new solutions are

\[
y_1' = \{b_1, b_2, \ldots, a_i, a_{i+1}, \ldots, a_n\} \\
y_2' = \{a_1, a_2, \ldots, b_i, b_{i+1}, \ldots, b_n\}
\]

The expressions for the pairs of \((a_j, b_j)\), where \( j = i \sim n \), are

\[
a_{i} = a_i a_i + (1-a_i) b_i \\
b_{i} = a_i b_i + (1-a_i) a_i
\]

where \( a_i \) is a random number and \( 0 \leq a_i \leq 1 \).

As for the RGA mutation process, the uniform mutation operator is adopted. Each parameter of a solution is to be mutated or not according to its random number \( r_{\text{random}} \) whose value is between 0 and 1. If \( r_{\text{random}} \) doesn’t exceed the mutation probability \( P_m \), then the mutation process is executed. For example, the parents are represented as \( y_{\text{re}} \) and \( y_{\text{SA}} \), which may be obtained after the reproduction process and the SA mutation process, respectively. When the \( i \)th parameter \( y_{\text{rei}} \) of the parent \( y_{\text{re}} \) are selected to be mutated, the new parameter value \( y'_{\text{rei}} \) after RGA mutation is

\[
y'_{\text{rei}} = a_i y_{\text{rei}} + (1-a_i) y_{\text{SA}i}
\]

where \( a_i \) is a random number and \( 0 \leq a_i \leq 1 \). The \( i \)th parameter of \( y_{\text{SA}} \) is denoted as \( y_{\text{SA}i} \).

The simulated annealing mutation process operates as follows. Generate randomly a new solution from the neighborhood of the original solution that may be obtained from the crossover process. If the value \( E_j \) of the new objective function is less than the value \( E_s \) of the original objective function, that is \( E_j - E_s < 0 \), the new solution is better than the old one and it is accepted. On the other hand, if \( E_j - E_s \geq 0 \), the new one is accepted only when its acceptance probability \( \text{Pro}(i) \) defined below is greater than a random value between zero and one. The acceptance probability is represented as

\[
\text{Pro}(i) = 1 - e^{-\frac{(E_j - E_s)}{T_l}}
\]

where \( l \) denotes an integer time step, \( T_0 \) is an initial constant temperature, \( T_l \) is a temperature sequence.

When the best solution keeps the same for some consecutive generations, the executed algorithm may be stuck at a local minimum, and some changes should be done on the searching strategy of the algorithm to prevent premature convergence. Adaptive mechanisms are proposed to do the change. When the best solution is the same for the lasted consecutive \( N \)
generations and $N > N_{\text{frozen}}$, the crossover probability and mutation probability are changed according to the following two equations

$$P_c = P_{c0} + \frac{N - N_{\text{frozen}}}{N}(\alpha - P_{c0})$$

(11)

$$P_m = P_{m0} + \frac{N - N_{\text{frozen}}}{N}(\beta - P_{m0})$$

(12)

where $N_{\text{frozen}}$ is a given positive integer constant called frozen number, and $P_{c0}$ and $P_{m0}$ are the initial crossover probability and the initial mutation probability, respectively. Besides, $\alpha$ and $\beta$ are real constants. If $N \leq N_{\text{frozen}}$ or the fittest solution changes such that $N$ is reset to zero, the crossover probability and mutation probability are equal to their initial values. In addition, the elitist strategy, by which the best solution of each generation is copied to the next generation, is adopted here to insure the solution quality.

As investigated by He et al. [14], when the above hybrid genetic algorithm is applied to DIC, the population size is recommended to be 100 and the generation number is 60. The subset size is chosen to be 30x30 because larger size will take more searching time and smaller size will result in worse results. As for the searching strategy, it is recommended to use the separated searching in which the three displacement components, two normal strains, and two shear strains are searched separately and consecutively. If one iteration is denoted as that one of the three groups of design variables is updated in the separated searching, the iteration number is better to be 60. The other parameters of the hybrid genetic algorithm are suggested in [13].

![Figure 1. Schematic of nickel thin film specimen (unit:mm).](image)

**Manufacturing processes**

The dimension of the specimen is shown in Figure 1. The gauge section of the nickel specimen is 1 mm long and 0.5 mm wide. To connect with the grip, two circular holes with 2 mm diameter are designed in the end section of the specimen. Besides, there are two supporting sections around the gauge section to protect it from breaking during the transportation and handling before test. It is noted that only the gauge section and part of the supporting sections of the nickel specimen does not bond with the silicon wafer, and the other parts of the nickel structure are bonded with silicon wafer to strengthen them.

The fabrication processes of the nickel specimen are described as follows. To clean the wafer, it was consecutively immersed into piranha ($H_2SO_4 : H_2O_2=3:1$) with $100^\circ C$ for ten minutes, DI water for 5 minutes, buffered oxide etchant (BOE) for 20 seconds, and DI water for 5 minutes. Then it was dehydrated at $120^\circ C$ for 5 minutes. After cleaning the wafer, it was put into an oxidation furnace with $1000^\circ C$ to grow 1μm silicon dioxide on both sides. After that, the wafer was consecutively cleaned by DI water, acetone, and isopropyl alcohol (IPA) as well as dehydrated by nitrogen. Then, a thin layer of S1818 photoresist with 1-2 μm thickness was spin-coated on the front side of the wafer. After baking the photoresist at 90$^\circ C$ for 3 minutes, the first mask used to pattern the photoresist was aligned with the wafer, and the photoresist was exposed by the ultraviolet (UV) photolithography with near 365 nm wave length and developed by Shipley Microposit MF-319 developer. A thin layer of S1818 photoresist was spin-coated on the back side of the wafer to protect the silicon dioxide layer. BOE was used to etch out the silicon dioxide layer and IPA was used to clean the photoresist. Now S1818 photoresist was spin-coated on the back side of the wafer again to have about 1-2 μm thickness, and it was baked at 90$^\circ C$ for 3 minutes. Then the second mask used to transfer the pattern of the specimen was aligned, and exposure and post exposure baking were performed. The nickel thin film was grown by electric plating with gold as the conducting layer. Acetone was used to clean S1818 photoresist. Before the final
step of etching, the specimen was put into a teflon mode to protect the nickel structure from the attack of etchant. After that, tetramethyl ammonium hydroxide (TMAH) was heated to 90°C and used as an anisotropic wet etchant to etch out the silicon base from the backside.

**Experiment procedure**

The tensile testing was conducted at a MTS Tytron 250 microforce testing system under displacement control. A pin-hole grip to hold the specimen was fabricated, and a nut with a soft spring and a washer was used to fix the specimen. The load range of this system is from 0.001 N to 250 N and its displacement resolution is 0.1 μm. The crosshead rate of loading the specimen was 1 μm/sec or 0.5 μm/sec. To connect the grip with the testing system, the alignment and the horizontal need to be carefully adjusted. After putting the specimen on the grip, the supporting part of the specimen was cut away so that the entire load was applied to the gauge section of the specimen. In addition to the grip displacement recorded by the testing system, the strain of the specimen was measured by digital image correlation.

![Load-displacement curve obtained by MTS with 1μm/sec loading rate.](image)

**Results and Discussions**

Three nickel specimens with the thickness of 12 μm, 9 μm, and 9 μm were tested. The first specimen with 12μm thickness was tested under 1 μm/sec crosshead rate, and the others were under 0.5 μm/sec. For the first specimen, the load-grip displacement curve is shown in Figure 2. To measure the strain by digital image correlation, digital images were taken in every ten seconds during the testing. As shown in Figure 3, two subsets were selected and denoted as y(320)x[200] and y(280)x[200] that represent the y and x coordinates of the reference point of each subset and will be called single region later. The y-
directional strains measured by both the grip displacement and digital image correlation with respect to the y-directional stresses are compared in Figure 4. It is very surprising that the strains obtained by the grip displacement of MTS are significantly larger than those obtained by digital image correlation. If one examines the two curves obtained by digital image correlation, there is some variation such that they are not so straight as the one obtained by MTS. Even though these two curves are quite close, there is still some difference between them. To judge the correctness of these two curves, two subsets that are denoted as double region in Figure 3 are selected on the top and bottom of the gauge section of the specimen. Instead of calculating the strains from each subset, the distance between these two subsets are calculated before and after the deformation by digital image correlation. Then, the y-directional strains are calculated from the change of the distance. The results are denoted as double region in Figure 4. It is evident that the initial part of the curve obtained by double region is straighter. Moreover, this curve is about the average of the two curves obtained from single region. From these results, one could say that the large strains obtained by MTS are not correct. The possible reason might be that in addition to the gauge section, the end sections of the specimen may be also extended without the protection from the silicon wafer because they may be separated under extension. Therefore, the grip displacement of MTS cannot represent the displacement of the gauge section of the specimen. As for the variation of the strains obtained by digital image correlation with single region, this may result from the variation of the method because the strains are the derivatives of the displacement and they are not as sensitive as the displacements during the searching process. In addition to the variation of digital image correlation, the variation between the two curves obtained from single region may be caused by the nonuniform deformation at different regions.

Figure 4. Stress-strain curves of the specimen with 12 μm thickness under 1 μm/sec loading rate.

Figure 5. Stress-strain curves of the specimen with 9 μm thickness under 0.5 μm/sec loading rate.

If the crosshead rate of loading the specimen is 0.5 μm/sec, the load-grip displacement curve is similar to that in Figure 2. The strains obtained by one single region, the double region, and MTS with respect to stresses are shown in Figure 5. Similarly, the strains obtained by the grip displacement of MTS are larger and incorrect. The strains obtained by single region and double region are very close, and the results of double region have little variation. Hence, one could say that the strains obtained from double region are better than those obtained from single region or MTS. As compared to the laser-based interferometric strain/displacement gage [15], in which two reflective gage markers needs to be deposited on a specimen surface for displacement measurement, digital image correlation with double region is nature and simple.
Figure 6 shows the stress-strain curves of the three specimens under two loading rates obtained by digital image correlation with double region. The number 1 denotes the specimen with 1 μm/sec loading rate and 12 μm thickness, and numbers 2-3 represent those with 0.5 μm/sec loading rate and 9 μm thickness. From this figure, it may imply that the loading rate considered has no evident effect on the stress-strain curve. Also, the nickel specimens have nonlinear stress-strain curve before fracture. The Young’s moduli of these specimens are 110 GPa, 118 GPa, and 105 GPa, and their average is about 111 GPa. Their Maximum strength is 601 MPa, 597 MPa, and 676 MPa. The high variation on maximum strength may be due to the quality variation from the electric plating process.

Figure 6. Stress-strain curves of two loading rates by digital image correlation with double region.

Conclusions

A deformation measurement method of digital image correlation combined with a hybrid genetic algorithm is proposed. The results indicate that this method is effective and stable if some key parameters are appropriately chosen. This method is applied to measure the strain during the tensile testing of nickel micro specimens. The results show that the grip displacement of the MTS micro force testing system should not be used to calculate the strain because of the possible extension of the end sections. The strains obtained by digital image correlation with single region are reasonable, but there are some variations from the method itself and from the different points selected on the specimen. These problems could be smeared out if double region is used in digital image correlation, and the strains obtained are accurate. Hence, it should be recommended. Also, the measured Young’s modulus of nickel thin film is about 111 GPa, and its maximum strength is about from 600 MPa to 680 MPa.

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References