Statistical Analysis of Estimated Displacement Measurements using Digital Image Correlation

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***Abstract*:** This paper presents details of the statistical analysis of the estimated displacements on a sample of pearlitic steel. It is mostly used in construction, automobiles, and industries. The displacement measurement of deformation is computed in the horizontal and vertical direction with pixel accuracy. Digital Image Correlation (DIC) is a non-contact technique to estimate u and v displacement. The deformation of the sample is computed using NCORR software. Detailed statistical analysis has shown that the displacements have a strong correlation between them.

***Keywords*:** **Digital Image Correlation, Displacement Measurement, Open source DIC software Ncorr.**

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I. INTRODUCTION

For structural assessment, studies on material deformation have gained importance in recent times. In most of these studies, materials are deformed under various conditions and the accumulation of strain is analyzed in terms of stress or strain rates. This approach, though provides a gross assessment about the deformation of a material, it does not give any clue about the variation in the strain distribution within a material. Such assessments many a time overestimate the strength of the material. To overcome this shortcoming finite element-based simulations have been implemented. A combination of simulation and experimental analysis solves the distribution-related issues but it is not able to take into account the structural variation within the material. To incorporate the materials-related variations, microstructures of the materials are investigated, and post-failure analysis is used to assess the material after deformation.

In the present research work, a better approach has been adopted where with the help of a scan electron microscope high-resolution images of material are captured before and after deformation. Subsequently with the help of digital image correlation a particular point or region within the material is traced on deformed microstructure to access the movement of a pixel in x-direction and y-direction. The horizontal movement of a pixel in the x-direction is called u-displacement and the vertical movement of a pixel in the y-direction is called v-displacement. To measure u-displacement and v-displacement, it is necessary to mark a region of interest in the reference image. Under this region of interest, a subset of an image can be chosen in the reference image and tracking of a subset in the deformed image can be done using appropriate DIC algorithms. The approach used in the present study provides information about the accumulation of strain in local regions which can be used to identify the regions of failure in very early stages, whereas most of the present techniques are not sensitive to such early response of the materials.

The first step towards deformation analysis is displacement measurement. With the help of displacement measurement, strain analysis can be completed. Displacement measurement and strain analysis help to test the strength of material by finding the breaking point or failure point of the material. This type of analysis helps to modify the manufacturing process of materials. There are various existing methods to measure strength e.g. scratch strain gauge, electric resistance strain gauge. The problem with these existing methods is that a strain-measuring instrument has to be attached to the sample. Such physical contact sometimes may induce additional stress, which is unwanted. In this experiment, a non-contact technique is implemented. The advantage of such a technique is that I do not induce instrument related stress to the sample

Swift advancements in the field of digital image processing in the past few years have drawn considerable attention and owing to these advancements, many analyzers have developed various DIC techniques for the measurement of the entire strain field [1,2]. The Digital Image Correlation technique can be applied with high accuracy just by comparing the two images of the same region; one before and the second after the deformation [2]. One of the main superiorities of the DIC technique is that it is a non-contact technique that provides full field and considerately high accuracy for the calculations of full-field displacement.

In the present paper, to estimate full-field displacement in a metallic sample a 2-D DIC system, which uses open-source software Ncorr, has been employed. To study deformation, pearlitic steel was selected as a material. The typical microstructure of pearlitic steel is composed of fine lamellar arrangements of two phases, namely, ferrite and cementite (shown in figure 1). Fine distribution of lamellae (~ 2μm) helps in capturing small details in displacement during deformation, as arrangements of lamellae change significantly, which can easily be recognized and can be used to accurately determine in estimating the displacement precisely [3,4].

2. MATERIALS AND METHODS

DIC uses recorded images of a material as it is being deformed as inputs and calculates displacements (shown in figure 2). The reference image is broken into subsets, and image-processing techniques are used to track the position of subsets from one image to the next. DIC is a technique that uses images of a material as it undergoes deformation to calculate displacement and strain fields over the surface of the material. It is a powerful technique in that it uses image tracking techniques that are agnostic to scale, and thus allows non-contact strain measurement at various scales. DIC takes subsequent images as input, starting with the reference, image. Within the reference image, a region of interest is identified and broken into various subsets. The unique pattern of grayscale values in a given subset is then used to identify its location in later images of the material, and thus the subset undergoes some deformation. The transformation used to map the reference subset to its current deformed state provides the information necessary to generate displacement and strain data. Surface patterning is essential to DIC's ability to track a subset location from one image to another. Subsets are identified by the unique pattern of grayscale values within the subset, and the reliability and resolution of DIC are dependent on the uniqueness of these subsets. In one extreme, a speckle pattern with very fine patterning would allow for extremely high spatial resolution, but would not provide the uniqueness of subsets needed for accurate deformation tracking. In the opposite extreme, very coarse patterning may provide a unique subset, but the spatial resolution would be restricted by the large size of the speckling. The ideal patterning will choose the subset size and speckle size to strike a balance between spatial resolution and image tracking accuracy. Some applications rely on the pattern of grayscale values naturally present in the images being analyzed, but most applications take advantage of an applied speckle pattern. Either way, the goal is that each subset will have a unique pattern that can be recognized in deformed images [5].

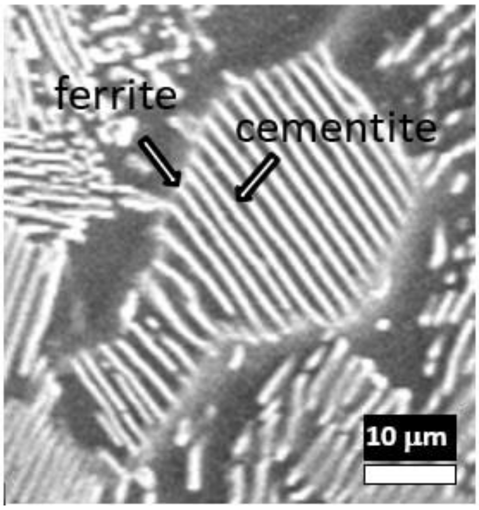


Fig.1 Microstructure of the pearlitic steel.

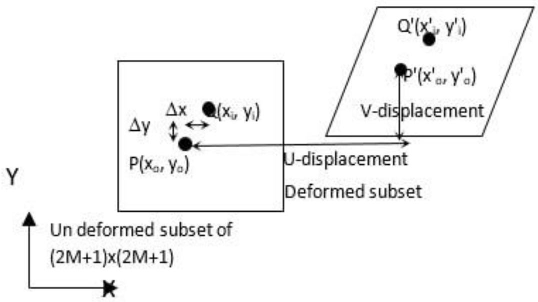


Fig.2 Representation of fundamental principle of DIC method [1, 2]

As schematically shown in Fig. 2, the deformation of the specimen can be tracked. Different points of the sample image are tracked in the deformed sample and movement of pixels in the horizontal and vertical direction is defined as follows:

$$x_i' = x_i + \alpha(x_i, y_i) \quad (1)$$
$$y_i' = y_i + \beta(x_i, y_i) \quad (2)$$

Pixels undergo deformation in the form of translation and rotation. This can be represented by the following equation

$$\alpha(x_i y_j) = u + u_x\Delta x + u_y\Delta y \quad (3)$$
$$\beta(x_{i,} y_j) = v + v_x\Delta x + v_y\Delta y \quad (4)$$

As seen in Fig.2 Δx can be computed by subtracting x_o from x_i and Δy can be computed by subtracting y_0 from y_i u and v denotes horizontal and vertical displacement respectively.

With the help of equation 5 normalized correlation between the sample and deformedsubset

$$C_{NCC} = \sum_{i=-M}^{M}\sum_{j=-M}^{M}\left[\frac{f(x_i, y_j)g(x_i', y_i')}{\bar{f}\bar{g}}\}\right] \quad (5)$$

Here at location (x_i, y_i), f(x_i,y_i) : grayscale intensity functions of the reference sample. g(x_i',y_i') : grayscale intensity functions of the deformed sample [6,7,8]:

$$\bar{f} = \sqrt{\sum_{i=-M}^{M}\sum_{j=-M}^{M}\left[f(x_i, y_j)\right]^2} \quad (6)$$

$$\bar{g} = \sqrt{\sum_{i=-M}^{M}\sum_{j=-M}^{M}\left[g(x_i', y_j')\right]^2} \quad (7)$$

2.1 Statistical Analysis

To investigate the relationship between u-displacement and v-displacement, the correlation between the two can be calculated using the Pearson correlation coefficient 'r'.

$$r = \frac{1}{n-1}\sum\frac{(x_i-\bar{X})(y_i-\bar{Y})}{s_x s_y} \quad (8)$$

In addition, by defining another variable as z, equation 8 can be rewritten as

$$r = \frac{1}{n-1}\sum z_x z_y \quad (9)$$

Where $z_x = \frac{(x_i-\bar{X})}{s_x}$ and $z_y = \frac{(y_i-\bar{Y})}{s_y}$

The non-zero value of r represents the relationship between the two variables. In case r is zero; it means the two variables are not related to each other. When the distribution is not completely known, Pearson's coefficient does not provide a proper relationship between the variables, in such cases, the Spearman rank correlation coefficient test can be performed to crosscheck the validity of the correlation between the two variables. The Spearman rank correlation coefficient is defined by

$$r_s = 1 - 6\sum\frac{d^2}{N(N^2-1)} \quad (10)$$

In this computation, samples of u-displacement and v-displacement are arranged as per their rank. Also, the difference in their corresponding ranks is used for this test. The computational complexity of this method is less as compared to other statistical methods.

2.2 Material

In the present study, pearlitic steel, the composition given in Table 1, is used. Samples of the steel were heated up to 800℃ and cooled inside the furnace under controlled cooling rates so that the high-temperature γ--austenite phase (fcc crystal structure) could eutectoidally decompose into α-ferrite and Fe_3C cementite phases. Under the controlled cooling rates, well-defined alternate

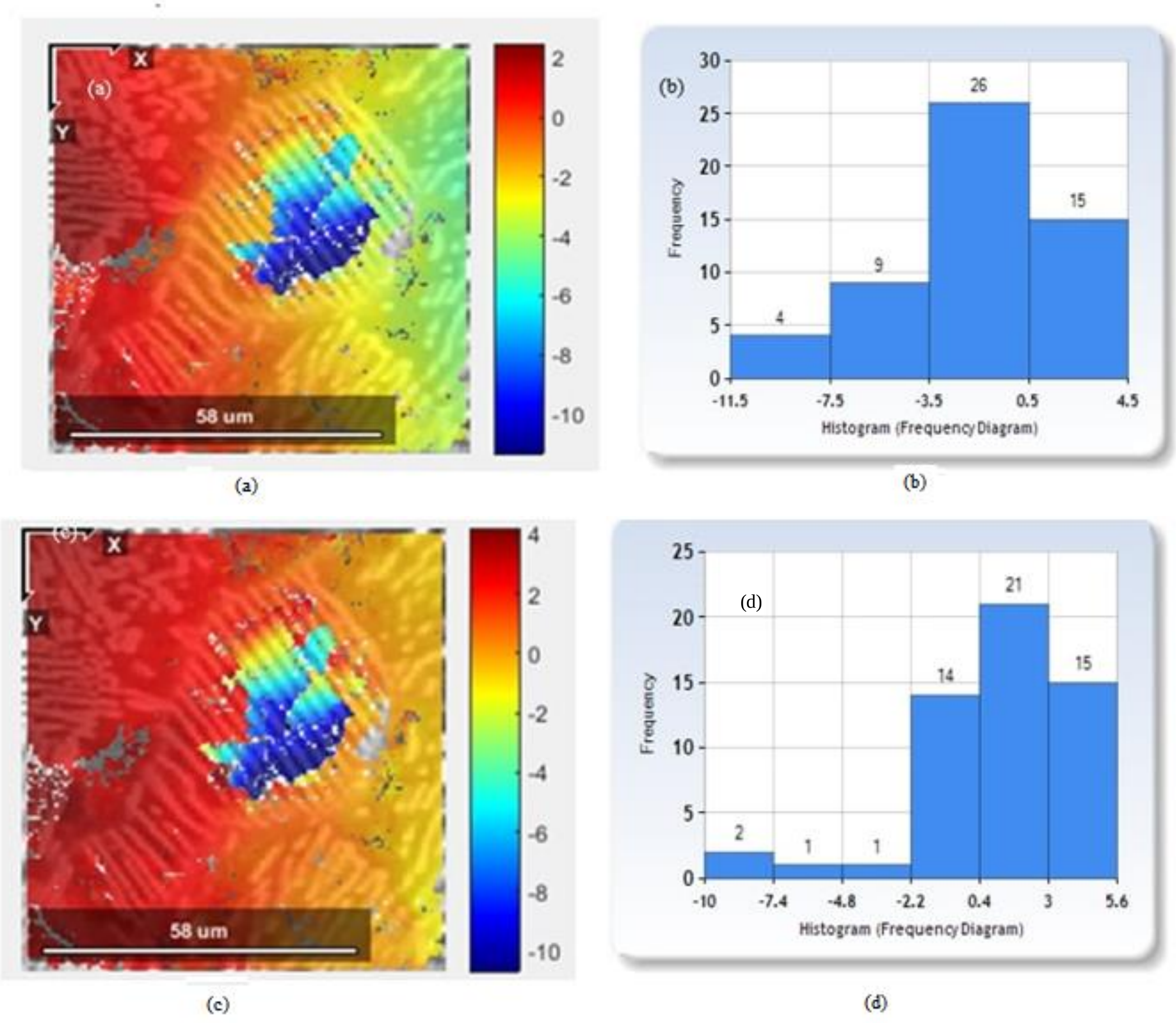


Figure 3 (a) u-displacement, (b) histogram of the u-displacement. (c) v-displacement, (d) histogram of the v-displacement

lamellae of ferrite and cementite phases formed in the microstructurethe samples were subsequently polished and examined under a scanning electron microscope (SEM). Figure 1 is showing a typical microstructure of the samples. Suitable regions were identified in the samples and to identify the region after deformation indentation marks were made on the surface of the sample. Predetermined deformation was given and subsequent to deformation, sample wad carefully polished by colloidal silica and deformed microstructure was re-examined under SEM, and images were digitally recorded [10,11].

Table1 Chemical composition of pearlitic steel

	Fe	C	Si	Mn	P	S
wt%	98.072	0.76	0.24	0.91	0.013	0.005

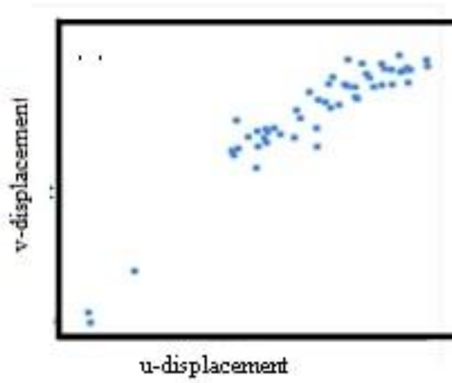
4. RESULTS AND DISCUSSION

In the present research work, the DIC technique is used for the measurement of u-displacement and v-displacement, which provides the displacement measurement of each point in the horizontal and vertical direction. The mean of u-displacement and v-displacement are computed as -1.64 micrometres and 1.1 micrometres respectively, while the standard deviation of u-displacement and v-displacement is calculated as 3.1 and 2.85 [11,12].

Fig 3(a) and 3(c) represent the u-displacement and v-displacement at different points on the sample surface. Fig 3(b) and 3(d) represent the histogram of u-displacement, and v-displacement respectively. From the Table, it can be seen that the minimum value of u and v displacement are almost equal, while the maximum value of v-displacement is almost double the maximum value of u-displacement. This can be concluded that there is a more vertical movement of pixels as compared to horizontal movement. Examining figures 3(a) and (c) it can be observed that variation in the displacement after deformation was successfully captured in these figures. By comparing figures 3(b) and 3(d), it can be observed that maxima of the u-displacements lie in the negative region whereas v-displacements lie in the positive region of the displacement [13,14].

By comparing figures 3(a) and (c), it may be noticed that the pattern of displacement is nearly the same in both images[15]. This indicates that both the displacements maintain a correlation that was further investigated with help of the Pearson correlation coefficient between the u-displacement and v-displacement. The computed value of the Pearson Correlation coefficient, a methodology of which has already been explained in the previous section, was estimated to be 0.9427. Figure. 4(a) shows the scattered plot of Pearson correlation between u and v-displacements. As the arrangement and orientation of the points in the graphs shown in Figure 4(a) show a positive, it indicates a positive correlation between the two displacements. In order to verify the value of the Correlation coefficient, the Spearman rank correlation coefficient was also computed which was estimated to be 0.9146. Figure.4 (b) shows the scattered plot of the Spearman coefficient. As both the coefficients are almost equal to each other, it may be concluded that the u-displacement and v-displacement, have strong correlations.

Since the values of both the coefficients are positive and close to 1, it indicates a strong positive correlation between the two. It suggests that during deformation a positive displacement in u induced a positive displacement in v and vice versa [16, 17].



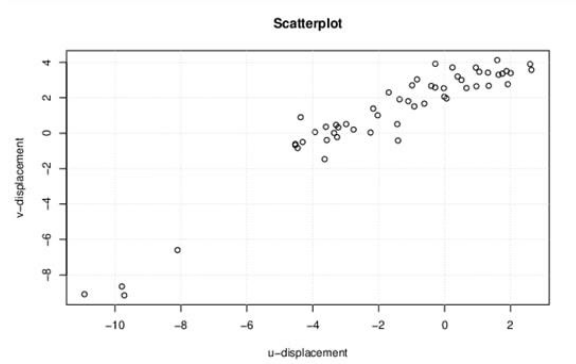
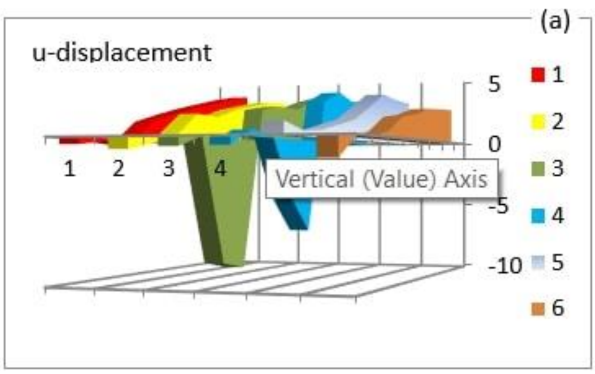


Fig. 4(a) Pearson correlation plot

Fig. 4 (b) Spearman correlation between u-displacement and v-displacement.



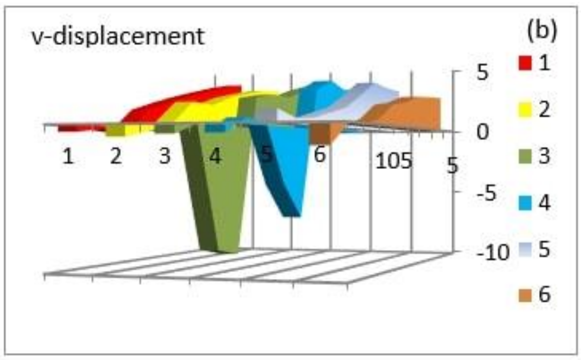


Fig- 5. (a) u displacements along 6 rows equidistant distributed in the image. The similarity between the displacement clearly shows a strong relationship between the two displacements.

Fig- 5(b) showing v displacement along 6 rows equidistant distributed in the image.

Table 2 Statistical parameters of u and v displacements

	Min (mm)	Median (mm)	Max (mm)	Max (mm)	Standard Deviation	Standard Error (%)
u	-13.75	-1.01	2.98	-1.64	3.1	0.422
v	-14.09	1.8	4.6	1.1	2.85	0.388

In order to under the correlation between the displacements further, displacements along few equidistant rows are plotted in figure 5(a) and (b). These rows are given numbers 1 to 6. By comparing these figures, it could be visualized that negative u-displacements of row 4 also show negative v-displacements. Similarly, positive displacements of rows 1 and 6 are similar for both u and v displacements. It can, therefore, be inferred that the correlation not only exists on a global basis but also exist point-wise point.

4. CONCLUSION

In the present work, pearlitic steel was used to determine the modifications imparted by deformation. The displacements, u and v are determined using first-order shape functions. These displacements have shown a strong correlation between the two. Detailed Pearson correlation analysis showed a strong positive correlation between u and v displacements. This was further verified using the Spearman correlation coefficient. Nearly similar values of both the correlation coefficients confirmed a strong positive correlation. Detailed row-wise analysis along with the histogram plots has shown that a strong correlation also exists row-wise [18, 19].

This experiment has clearly demonstrated the interrelationship between the two u and v displacements. This study can be extended to estimate the different strains, which would help in identifying regions of strain concentrations, which, in turn, will help in identifying the potential regions of crack initiation.

Conflict of Interest: There is no conflict of interest in the present work.

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