

# Digital Volume Correlation Analysis for a Cross-Ply Laminated Composite Structure using a Fully 3D-based Correlation Algorithm

Sooyoung Lee<sup>1</sup>, Eonyeon Jo<sup>2</sup> and Wooseok Ji<sup>3\*</sup>

<sup>1,2,3</sup> Department of Mechanical Engineering, Ulsan National Institute of Science and Technology,  
Ulsan, 44919, Korea

(\* E-mail: wsji@unist.ac.kr)

**Keywords:** Digital volume correlation, X-ray tomography, in situ testing

## ABSTRACT

Digital volume correlation (DVC) technique is applied to map a three-dimensional (3D) displacement field on the volume of interest in a unidirectionally continuous fiber-reinforced laminated composite imaged through a high-resolution X-ray microscope. A new fully three-dimensional correlation algorithm is developed to overcome the deficiencies of the typical DVC technique that is based on the two-dimensional (2D) digital image correlation (DIC) algorithm. The accuracy of the present DVC algorithm is demonstrated using tomographic images of a composite specimen subjected to a tensile load. Subsurface 3D displacement field of the loaded composite specimen is computed using both the present DVC method and the conventional process. It is shown that the present correlation algorithm produces far more reliable results over the typical DVC process.

## 1 INTRODUCTION

Fiber reinforced plastic (FRP) composite materials are now widely used in commercial and military aerospace applications owing to the superior specific weight properties that monolithic materials cannot have. However, when the composite materials are loaded, damage and failure at the fiber length scale are prone to occur mainly because of the significant stiffness mismatch between a fiber and polymer matrix. Furthermore, the progression of the damage and failure is very complicated due to the morphology of its microstructure such as internal heterogeneity and multi-layered composition. These characteristics of composites requires conscientious studies in the quantitative characterization of various failure mechanisms occurring inside the material. Quantitative deformation data of the subsurface material is the key to examine failure mechanism of the composite materials. However, this requires a technique that is capable of mapping full-field strain data in the whole volume of a specimen, which is unavailable from traditional strain measurement methods. The image-based reconstructed model is one potential approach owing to its sub-micron resolution of X-ray micro-computed tomography ( $\mu$ CT). The association of X-ray micro CT acquisitions and the digital volume correlation (DVC) technique allows the measurement of displacements and strains in the whole volume of specimen [1]. In the presentation, fully 3D-based DVC algorithm is developed and applied to compute a deformation data of a laminated composite specimen under a tensile load. The validation of the present algorithm is demonstrated using tomography images of the specimen subjected to tensile loading. The present DVC algorithm is compared with the conventional DVC method.

## 2 CORRELATION PROCESS BETWEEN IMAGES

### 2.1 Principles of the correlation process – Digital image correlation technique

DVC technique can be considered as a straightforward extension of the well-established digital image correlation (DIC) technique and shares its simplicity in principles and effectiveness in applications [2]. DIC technique computes deformation data of a specimen by tracking small motions of randomly distributed points on the specimen surface from a series of photography images taken while the specimen is being deformed. DIC process starts from defining points of interest (POI) in the region of interest (ROI) as shown in Figure 1. POIs are located on the same global coordinates in both

images for the reference (un-deformed) and deformed states. Then, a “facet”, a set of several pixels, with its center conforming to a POI is constructed in the reference image as shown in Figure 1. A searching area larger than the reference facet is assigned at the corresponding POI in the image of the deformed state. DIC algorithm then searches for a new position of the target facet in the search area using a mathematical correlation method such as a normalized cross correlation (NCC) method expressed as

$$C_{NCC}(P) = \frac{\sum_{x=-M}^M \sum_{y=-M}^M (f(x,y) - f_m)(g(x-u, y-v) - g_m)}{\sqrt{\sum_{x=-M}^M \sum_{y=-M}^M (f(x,y) - f_m)^2} \sqrt{\sum_{x=-M}^M \sum_{y=-M}^M (g(x-u, y-v) - g_m)^2}} \quad (1)$$

Here,  $P$  is a vector defined between the two center points of the reference and the target facets,  $M$  is the half-width of the square facet,  $f(x, y)$  is a grayscale intensity at coordinates of  $(x, y)$  in the reference facet,  $g(x-u, y-v)$  is the intensity value at  $(x-u, y-v)$  in the target facet, and  $f_m$  and  $g_m$  are the mean intensity values of every pixel inside of the facets in the reference and deformed states, respectively.  $C_{NCC}$  is a correlation coefficient, which has a range of 0 to 1 where 1 means two facets in the reference and deformed states are perfectly correlated. Physical meaning of Eq. (1) can be explained by considering two comparing images (facets) as two vectors. The NCC equation is then regarded as the inner product of two vectors divided by the norms of each vector, which is equivalent to the cosine of the angle between the two vectors. Therefore, two vectors representing the reference and the target facets are the same when the angle is zero, resulting in the correlation coefficient value of one.

The position of the target facet in Figure 1 is determined where the maximum  $C_{NCC}$  value (not necessarily one) is found inside the search area. The position with the maximum coefficient value is considered as the moved position of the reference facet due to the deformation of the specimen. Thus, the displacement data can be calculated from the coordinates of the two center points of each facet. Full displacement data in the region of interest can be obtained after the same procedure is applied to all the other POIs in Figure 1. Note that the resolution of the computed displacement field is dependent on the number of POIs in the ROI.

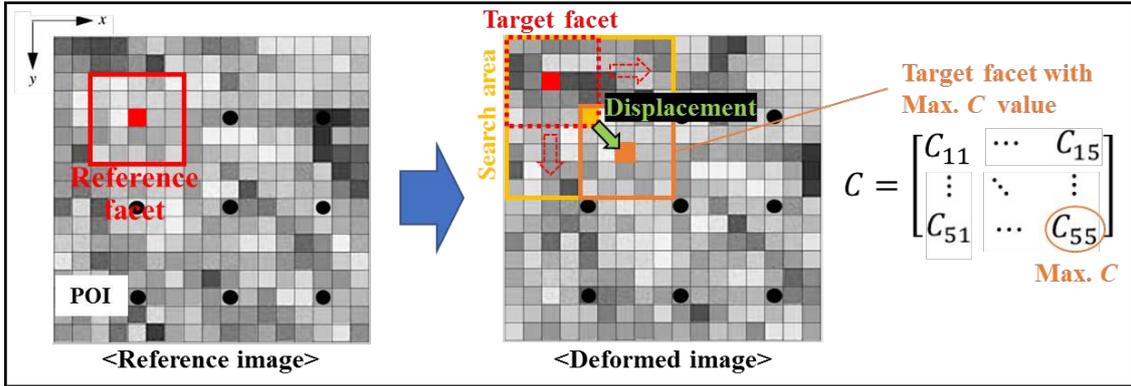


Figure 1: Schematic illustration of the DIC technique principle

## 2.2 Digital volume correlation technique

As mentioned in the prior section, DVC technique shares its core principles with the DIC techniques in many ways. DVC technique uses 3D volume of a specimen typically imaged by X-ray micro-computed tomography ( $\mu$ CT) and discretizes the volume with cubical subvolumes that correspond to facets of the DIC technique. While the DIC technique utilizes an artificial speckle pattern sprayed on a specimen surface, DVC typically uses a natural microstructural pattern inside a material for the intensity value of a subvolume. Fundamental unit is a voxel, which is a cubic-shaped 3D pixel. Generally, its concept in tomography is the expansion of a pixel in a tomogram through the thickness direction.

Numerous slice-images (tomograms) acquired by X-ray  $\mu$ CT are stacked up along the rotation axis of a sample to construct the 3D volume as described in Figure 2. Each pixel in the  $xy$ -plane of a slice-image has one greyscale value that is associated with density at the physical location in the specimen. As shown in Figure 2, each 2D slice-image has an artificial thickness of one pixel.

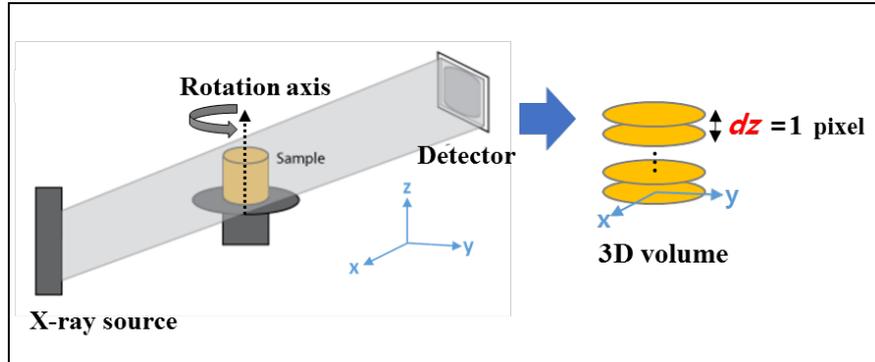


Figure 2: Schematic illustration of  $\mu$ CT

Figure 3 shows several stacks of 2D tomograms in a reference state and a deformed state. Conventional DVC algorithm [3] defines a cubical subvolume using the top and bottom faces as shown in Figure 3. This subvolume is identified by the center point,  $P(x_0, y_0, z_0)$ , between the two faces. The center points of the subvolumes conform to POIs seeded in the tomograms both in the reference state and the deformed state at the same global coordinates, following the general working principle of the DIC technique (see Figure 1). The center point of the target subvolume,  $P(x'_0, y'_0, z'_0)$ , in the deformed state is then found by applying the DIC search process based on Eq. (1) to both the top and bottom faces as illustrated in Figure 3. After the locations of the top and bottom faces in the deformed state are determined, the center point of the target subvolume can be calculated and finally the 3D displacement vector is obtained using the coordinates of the two center points of the reference and target subvolumes.

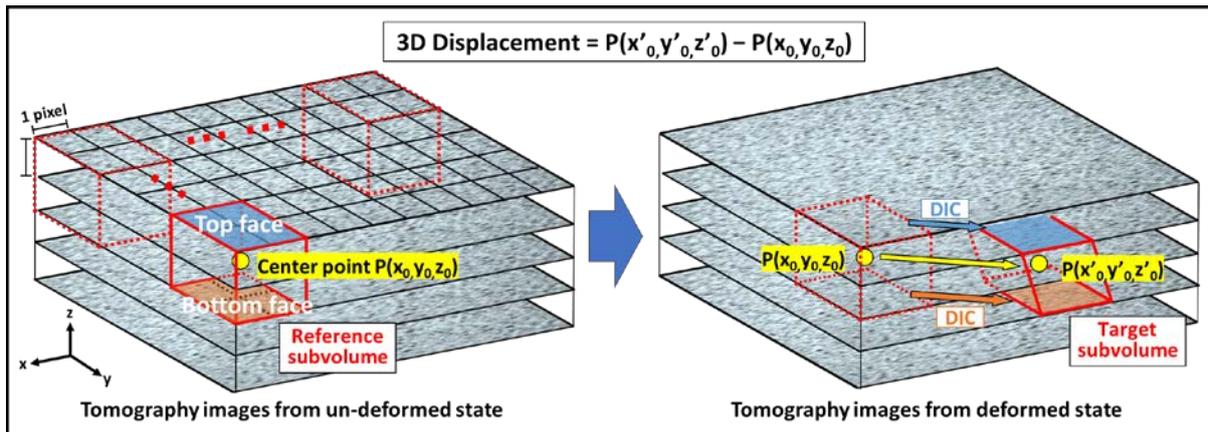


Figure 3: Correlation process of the conventional DVC algorithm [3]

In the presentation, a new DVC approach with a fully 3D-based correlation method is proposed. Eq. (1) for computing a correlation coefficient in 2D space is extended to 3D space in the present DVC algorithm by including all the voxels inside a subvolume, not only the pixels in the top and bottom faces. Eq. (1) is then modified as

$$C_{NCC}(P) = \frac{\sum_{x=-M}^M \sum_{y=-M}^M \sum_{z=-M}^M (f(x,y,z) - f_m)(g(x-u, y-v, z-w) - g_m)}{\sqrt{\sum_{x=-M}^M \sum_{y=-M}^M \sum_{z=-M}^M (f(x,y,z) - f_m)^2} \sqrt{\sum_{x=-M}^M \sum_{y=-M}^M \sum_{z=-M}^M (g(x-u, y-v, z-w) - g_m)^2}} \quad (2)$$

where  $C_{NCC}$  is, again, a correlation coefficient,  $P$  is a vector defined between the two center points of

the reference and the target subvolumes as shown in Figure 4,  $M$  is the half-width of the cubical subvolume,  $f(x, y, z)$  is a grayscale intensity at coordinates of  $(x, y, z)$  in the reference subvolume, and  $g(x-u, y-v, z-w)$  is the intensity value at  $(x-u, y-v, z-w)$  in the target subvolume. The major difference between Eq. (1) and Eq. (2) is the definition of  $f_m$  and  $g_m$ . In Eq. (2), they are the mean intensity values of every voxel inside the subvolume in the reference and deformed states. Instead of correlating top and bottom faces using the DIC-based correlation method, the present DVC algorithm searches for the target subvolume in the deformed state using the greyscale value averaged over the subvolume.

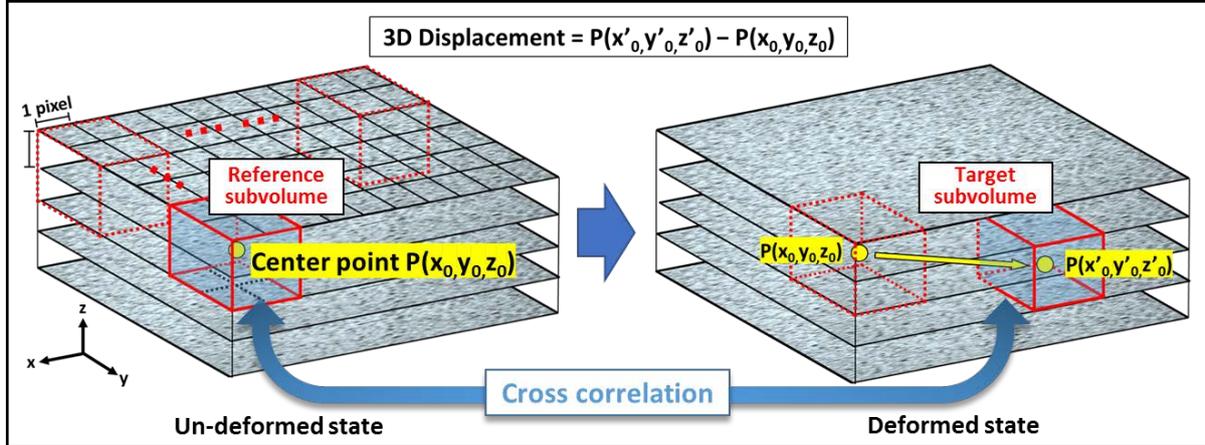


Figure 4: Subvolumes and the correlation process of the present DVC algorithm

### 3 RESULTS AND DISCUSSION

#### 3.1 Demonstration of the present DVC algorithm

The accuracy of the correlation method implemented into the present DVC algorithm is evaluated using a simple example of a rigid body translation. A volume with the size of  $400 \times 200 \times 80$  voxels as shown in Figure 5 is subjected to the rigid body translation by 8 voxels along each of the  $x$  and  $y$  directions and 6 voxels along the  $z$  directions. The translation can easily be exercised by shifting all the components in the 3D matrix that represents the image of the volume. Figure 5 displays the volumes in the initial state and in the translated state altogether. Displacement field computed using the present DVC algorithm is mapped on the translated volume as shown in Figure 5. As can be seen in Figure 5, the present DVC program produces 12.8 voxels (square root of  $8^2 + 8^2 + 6^2$ ), which is the expected displacement under the prescribed condition.

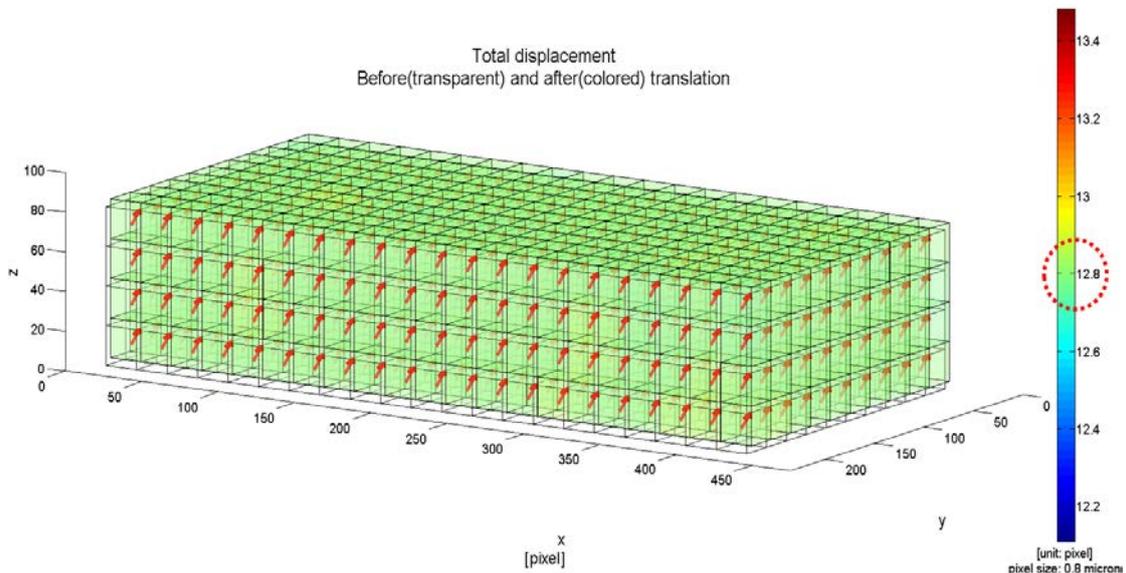


Figure 5: Displacement field calculated by the present DVC algorithm for a rigid body translation

### 3.2 DVC results on experimental data

The present DVC algorithm is applied to the quantitative deformation analysis of a composite material subjected to a tensile load. Carbon fiber/epoxy prepregs material was utilized to manufacture the laminated composite specimen with the layup sequence of  $[90_2/0_2]_s$ . Detailed dimensions of the specimen are shown in Figure 6. The specimen was imaged through a laboratory scale X-ray  $\mu$ CT device (Zeiss Xradia Versa 520) in Korea Institute of Science and Technology (KIST) while the specimen was loaded in the Deben microtest tensile stage. Tomograms were taken at several loading sequences; 250N, 500N, 750N and 1000N. At each loading step, total 980 slice-images were obtained with the resolution of  $986 \times 1006$  pixels per image. The length of one pixel is correspondent to  $4.26 \mu\text{m}$ . A sample slice-image is shown on the right side of Figure 6. For the deformation analysis on the loaded specimen, the tomograms are cropped so that the volume of interest is properly defined inside the material as shown in Figure 6. As a result, the size of the VOI in the  $xy$ -plane where the present DVC algorithm is applied is set to  $400 \times 240$  pixels ( $1.7 \times 1 \text{ mm}$ ) as indicated in Figure 6.

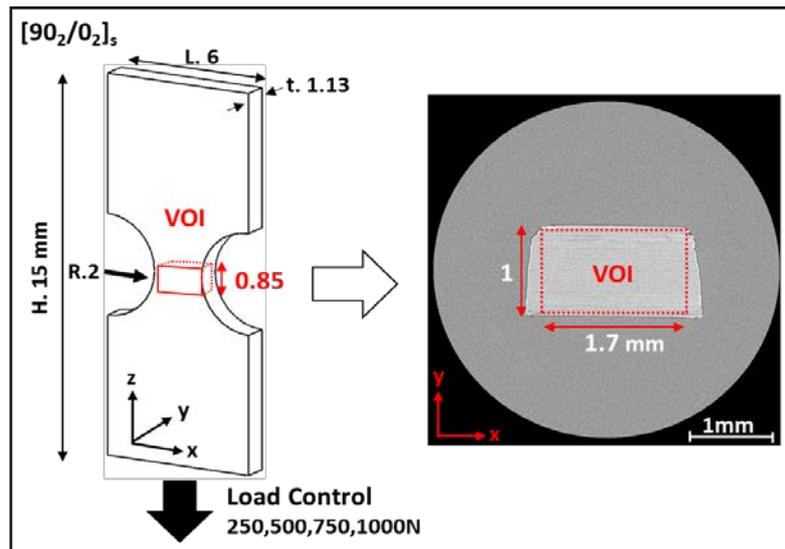


Figure 6: Specimen configuration (left) and a sample tomogram with the volume of interest (right)

Figure 7 shows the 3D-rendered results of tomography images with various failure patterns in different colors. As can be seen in Figure 7, the X-ray  $\mu$ CT is capable of visualizing the progression of failure occurring inside the material. At the load of 500 N, fiber splitting failure in 0-degree layers (blue color) is detected while only transverse cracks in 90-degree layers (red color) are observed at 250 N. Additional transverse cracks (yellow color) are also found as the load is increased from 250 N to 500 N. The present DVC algorithm is applied between the initial transverse crack as indicated in Figure 7, resulting in the length of the VOI being 0.85 mm along the  $z$ -direction.

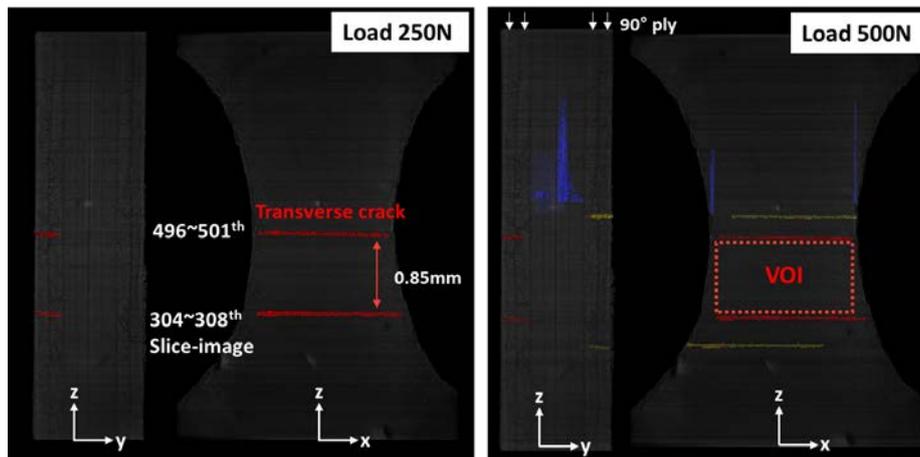
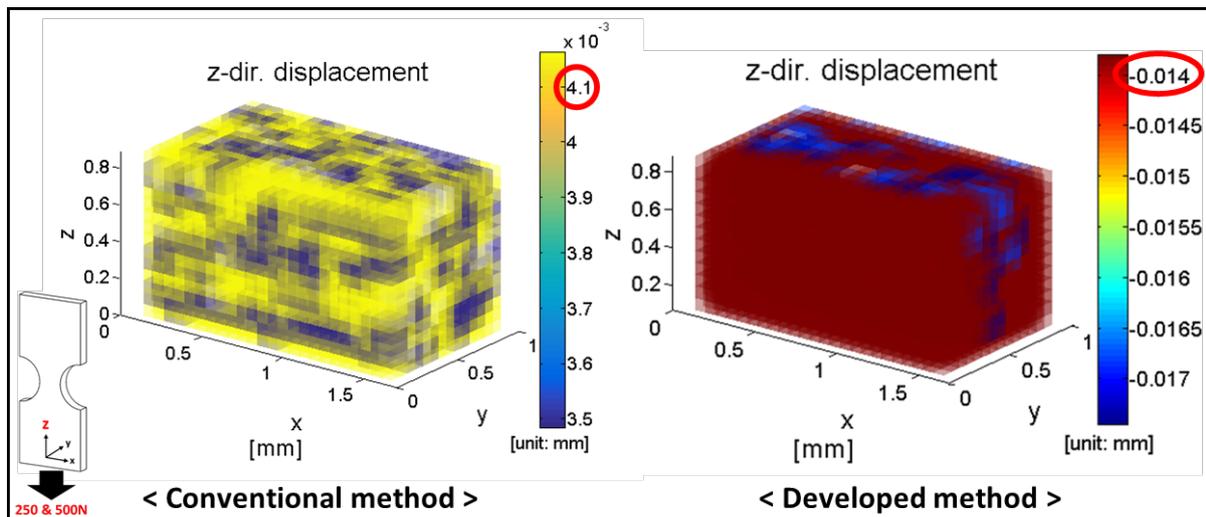


Figure 7: Visualization of cracks in 3D-rendered images at 250 N (left) and 500 N (right)

The VOI region is discretized with total 3588 cubical subvolumes while the size of one subvolume is  $31 \times 31 \times 31$  voxels. The subvolumes are evenly distributed over the region and each subvolume is overlapped with adjacent ones by 15 voxels in the  $x$ ,  $y$  and  $z$  directions. Tomography images at 250 N and 500 N are used for the deformation analysis using both the conventional and the present DVC techniques. Figure 8 compares the displacement field results obtained from the conventional and the present methods. The displacement fields are mapped on the un-deformed configurations for both cases. As can be seen in Figure 8, the displacement field calculated by the conventional DVC method (left side of Figure 8) produces a significantly erroneous result. There exists a significant difference between the stiffnesses of  $0^\circ$  and  $90^\circ$  plies along the loading direction, but the conventional DVC method is unable to distinguish them in the computed displacement field. Furthermore, the direction of overall displacement value is opposite to the loading direction, which should be negative since the loading is applied downwards. These imply that correlations of some subvolumes are unrealistically done. The internal structure of the unidirectionally continuous fiber reinforced composite material considered in the presentation is quite regular and, thus, the greyscale values of the faces in Figure 3 do not greatly vary. This may result in an unrealistic correlation outcome. Since the conventional DVC method performs the search process twice for the top and bottom faces to determine the target subvolume, the error becomes significant even if one of the faces is inappropriately correlated. Therefore, the working principle of the DIC algorithm tracks faces anyhow but the direct application of the algorithm to 3D tomography images is dangerous when the natural microstructural pattern is not as distinct as the speckle pattern for the DIC technique.

The present DVC method performs the correlation process using the mean intensity values of all the voxels in the subvolume (see Eq. (2)). Hence, the subvolume can have a higher singularity individually and the correlation result is likely to be more reliable. As shown in Figure 8, the present DVC method produces a reasonable displacement result. From the present DVC analysis, it is found that the inner section ( $0^\circ$  plies) of the specimen deforms more than outer  $90^\circ$  plies. As shown in Figure 7, since the transverse cracks are already present in the  $90^\circ$  plies at the load of 250 N, the  $0^\circ$  plies in the VOI carries almost all the load as the load increase from 250 N to 500 N. As a result, the deformation of the  $0^\circ$  layers should be a bit larger than that of the  $90^\circ$  layers. As can be seen in Figure 8, the present DVC is capable of capturing this deformation behavior and it can be concluded that all the subvolumes are appropriately correlated without any outliers.



**Figure 8: Displacement fields obtained from the conventional (left) and the present (right) process**

Figure 9 compares correlation coefficients values calculated by the conventional and the present DVC techniques. It is noted that the correlation coefficient values are not high in general for both cases (average value 0.4633 for the conventional method and 0.3522 for the present process), mainly due to the natural microstructural pattern of the composite material. As shown in Figure 9, the correlation performance of the conventional DVC process seems to be better if only the coefficient values are considered. However, it is already demonstrated in Figure 8 that the conventional one

produces an unrealistic deformation result. The correlation coefficient values can be higher, but the higher value does not guarantee a proper correlation for 3D tomography images as previously discussed. This requires the establishment of totally new criterion for judging reliability of a DVC calculation for the successful application of the DVC approach.

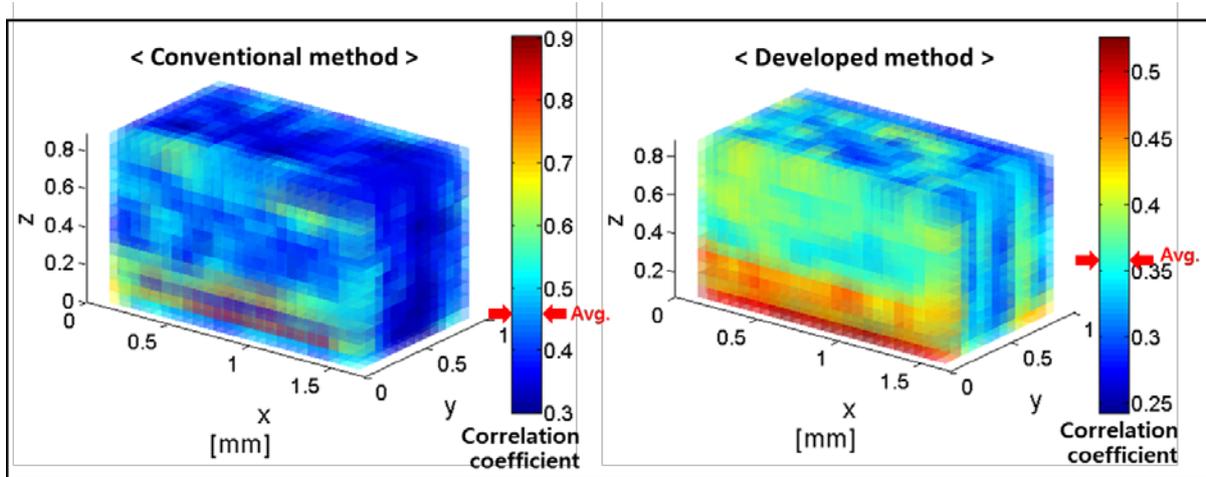


Figure 9: Correlation coefficients obtained from the conventional (left) and the present (right) process

#### 4 CONCLUSIONS

DVC technique combined with the X-ray  $\mu$ CT technology is applied to examine the mechanical behavior inside of a laminated composite material. It is shown that the natural texture of the composite material can be used in the DVC approach and the present DVC algorithm can track realistic motions of each subvolume without any outliers. It is also found that the conventional criterion based on the correlation coefficient only may not be enough for judging the accuracy of DVC results.

#### REFERENCES

- [1] Brault, Romain, et al. "In-situ analysis of laminated composite materials by X-ray micro-computed tomography and digital volume correlation." *Experimental Mechanics* 53.7 (2013): 1143-1151.
- [2] Wang, T., et al. "GPU Accelerated Digital Volume Correlation." *Experimental Mechanics* 56.2 (2016): 297-309.
- [3] Bay, Brian K., et al. "Digital volume correlation: three-dimensional strain mapping using X-ray tomography." *Experimental mechanics* 39.3 (1999): 217-226.
- [4] Bar-Kochba, E., et al. "A fast iterative digital volume correlation algorithm for large deformations." *Experimental Mechanics* 55.1 (2015): 261-274.