Using Digital Image Correlation to Analyze Deformation in Wood-based Liquid Deposition Modelling

Kushagra Gautam[1], Dana Solav[2], Shany Barath[3] and Guy Austern[4]
[1, 3, 4]*Faculty of Architecture and Town Planning, Technion- Israel Institute of Technology.*
[4]*Faculty of Mechanical Engineering, Technion- Israel Institute of Technology.*
[1]*kushagra.g@campus.technion.ac.il, ORCID: 0009-0000-7882-9781*
[2]*danas@technion.ac.il, ORCID: 0000-0003-3215-0401*
[3]*barathshany@technion.ac.il, ORCID: 0000-0003-0776-7389*
[4]*guyaustern@technion.ac.il , ORCID: 0000-0003-3377-4814*

Abstract. Upcycling wood waste is a long-standing challenge in manufacturing, particularly in creating precise and durable products from leftover wood. 3D printing offers a sustainable solution by utilising recycled wood waste, reducing the need for new wood, and lowering environmental impact. However, issues like deformation and shrinkage after printing remain a challenge, affecting result precision. Current methods like 3D scanning provide volumetric data but fail to track the deformation of specific points. This paper introduces a Digital Image Correlation (DIC) based method to overcome these limitations. DIC measures 3D displacements without contact, offering detailed point-to-point insights into shrinkage, which could be used to develop a dataset for a machine learning model that can predict deformation and compensate for it. We used DIC to track the deformations of 3D wood prints over 24 hours and compared the results to 3D scans of the same prints. The findings show that DIC improves deformation tracking, enhancing understanding and supporting sustainable manufacturing with recycled wood.

Keywords. Additive Manufacturing, Digital Image Correlation (DIC), Sustainable Manufacturing, Surface Deformation Tracking, Data collection in 3D printing

1. Introduction

Traditional wood manufacturing methods contribute significantly to environmental degradation, including deforestation and large amounts of waste. Up to 40% of raw wood is often discarded (Adhikari and Ozarska 2018) This has led to a push for sustainable alternatives like recycled wood to reduce waste and conserve resources. Traditional wood recycling methods include the use of harmful binding resins containing formaldehyde. Liquid Deposition Modelling (LDM), a 3D printing technique that extrudes liquid or semi-liquid materials layer by layer to create solid

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objects, offers a sustainable solution by using powdered wood waste with water (Rosenthal et al. 2018). LDM minimizes waste, reduces reliance on virgin wood, and is energy-efficient due to its precise material deposition. This technology helps create a circular economy by repurposing wood by-products into useful items, decreasing both environmental and material footprints.

Controlling deformations such as shrinkage is an important challenge in 3D printing, particularly when using wood-based materials. Shrinkage can impact on the dimensional accuracy and the structural integrity of printed objects. Factors such as the composition of the wood-based paste, print geometry, infill percentage, printing speed, and drying conditions all contribute to this issue (Cohen et al. 2024). Shrinkage often results from the loss of moisture during the drying process, leading to uneven contraction that can distort shapes or weaken structures (Rosenthal et al. 2023). Recent research has employed technologies like laser scanners (Hoo, Dritsas, and Fernandez 2022) and computer vision (Tamke et al. 2023) to document the geometry and improve the precision of 3D-printed wood products. However, these methods have difficulties in tracking point-to-point deformation (Rossi Gabriella et al. 2023), which is necessary for accurately mapping these changes.

This paper describes a novel Digital Image Correlation (DIC) based method for analysing deformation in LDM of wood-based objects. DIC is a non-contact optical technique that utilizes high-resolution images captured from multiple cameras to measure 3D full-field displacements and strains with exceptional precision (Michael A., Orteu, and Schreier 2009). DIC uses stereo calibration and image cross-correlation techniques to track the point-to-point three-dimensional movement of specific points on the object's surface, allowing for detailed monitoring of how the material deforms during and after the drying process. DIC also provides surface strain mapping, which helps visualize the relative changes in the shape or size of a material under different forces, such as tension or compression.

We suggest that the information gathered using DIC can be highly informative for investigating 3D printing in wood-based materials, where shrinkage and cracking can compromise the structural integrity of the final product. The main objective of this research is to develop a method for measuring deformation in wood prints. Such a method can be used to improve our understanding of such deformations and advance the acceptance of sustainable wood-based prints.

2. Background

2.1. LDM PRINTING: MATERIALS AND CHALLENGES

In recent years, 3D printing has become a mainstream technology, enabling the production of intricate, customizable objects with minimal waste. Among the various 3D printing methods, LDM stands out for its ability to use liquid or semi-liquid materials, such as wood-based pastes, to construct complex shapes layer by layer (Rosenthal et al. 2018). In this research, we used a commercial-grade all-natural material composed of wood waste, called Daika wood (https://daikawood.com/). Daika can be mixed with water to create a printable paste (Cohen et al. 2024). However, printing with recycled wood-based material presents unique challenges as wood fibres behave differently than synthetic materials. As the wood dries, it loses moisture and shrinks unevenly, which can distort the shape of the printed object (Rosenthal et al. 2023).

2.2. DIC FOR DEFORMATION MEASUREMENT

Several methods are used to measure shrinkage and deformation in 3D printing, and each has its limitations. Marking objects with trackers, used by Rossi et al. (2023) provides only limited data due to the need to place physical markers on the subject. Laser scanning, used by Dritsas et al. (2023) captures the overall shape extremely well, but it cannot track local material deformation. Point cloud comparison methods have also been proposed (Tamke et al. 2023), but they cannot track point-to-point deformations in wood prints.

In different fields, DIC has emerged as a widely utilized method for measuring displacement and strain with high precision (Yang et al. 2022). DIC is a non-contact method that provides highly accurate deformation estimates across tensile testing and various material characterisation applications. DIC uses high-resolution images of the surface of the object, taken simultaneously from multiple views, to measure 3D deformations. This is done by analysing the cross-correlations between subsets of pixels in different images to identify matching material points and does not require physical trackers like photogrammetry, structured light and laser scanning methods. These points are then mapped to 3D space using pre-determined extrinsic and intrinsic parameters of the cameras. To increase its accuracy, the surface is typically painted with a high-resolution random speckle pattern. The dense time-varying point cloud can then be further analysed to compute displacements and surface strains, which provides detailed data on how the material or structure responds to loads or other processes like temperature change or drying. While it is extensively used in other fields, as far as we know, there has been no previous application of DIC for analysing post-3D printing deformations.

3. Methods

In this study, we aimed to develop a DIC system and measurement protocol to accurately monitor deformations in 3D-printed wood-based materials over time. The preliminary research involved testing multiple setups to optimize the data collection and processing methods. Following the conclusions of these tests, we decided that moving the samples to capture images from different directions interferes with the data collection. To address this, we developed and built a custom low-cost 12-camera DIC setup, arranged to capture high-resolution images of the printed samples from all angles simultaneously. This setup allows the measurement of multiple specimens in series and eliminates potential errors from sample repositioning. In addition, we developed specialised grabbing software to capture the images and manage the data efficiently, incorporating real-time environmental monitoring and image processing. To validate the results of the method, each sample was scanned in 3D, and results from the DIC were compared with 3D scans using a Cloud-to-Cloud Distance analysis in CloudCompare (http://cloudcompare.org/) software.

3.1. DIC SETUP AND EQUIPMENT

We constructed a DIC setup using 12 USB cameras, as shown in Figure 1. The cameras were arranged in a concentric layout with a 30° angle between each two adjacent cameras. All cameras were from ELP USB Webcam, featuring an 8 MP IMX323 sensor, and a varifocal lens (5-50 mm), capturing images at 3264x2448 pixels. Flexible LED strips provided even lighting around the rig. The cameras were connected to a PC with 12 USB 3.0 ports to handle high data transfer without bottlenecks. The 3D prints were dried on a drying rack, where temperature, humidity and wind speed were closely monitored documented in parallel with images using Arduino based grabber extension.

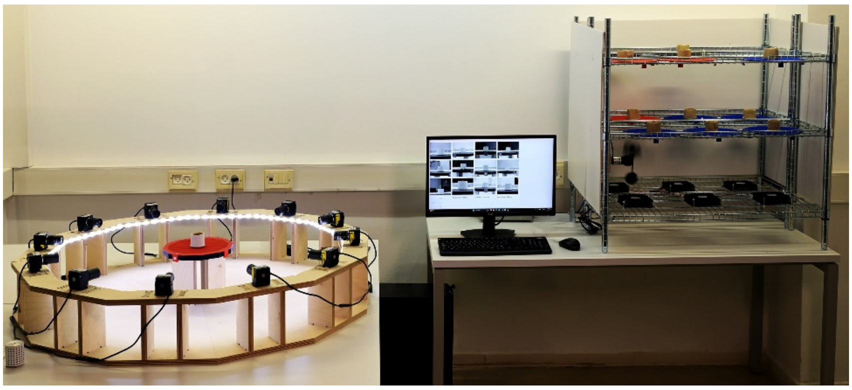

Figure 1. (left to right) DIC setup with 12 cameras, custom 12 USB port PC and drying rack with ventilation and environmental data capturing sensors.

3.2. DATA CAPTURE AND MANAGEMENT SOFTWARE

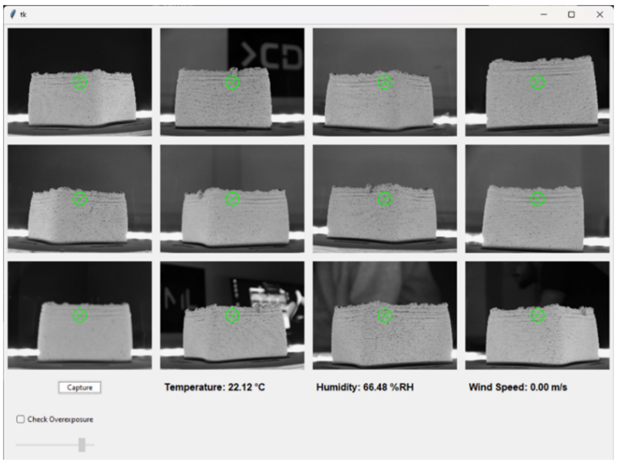

Figure 2. Screenshot from the developed grabber software

A grabber software (Figure 2) was developed to capture, process, and manage images from all cameras, integrating real-time environmental data such as temperature, humidity, and wind speed. The system employs a Python-based graphical user interface (GUI) that organizes camera feeds into a mapped grid format for streamlined management and access. The GUI provides controls for capturing multiple images simultaneously, checking overexposure, and setting environmental thresholds, and allowing users to monitor and adjust camera settings effectively. The open-source code is freely available at https://github.com/cdml-lab/grabber_DIC.git .

The software captures images from each camera, extracts the red channel to highlight long wave detail and converts each image to grayscale. The software then saves the images as TIFF files and automatically organizes them in folders, while the environmental data is logged in a CSV file. This automated data organization makes it easy to document several samples simultaneously. The images are processed using the open-source MATLAB toolbox MultiDIC (Solav et al. 2018). This toolbox processes images from multiple cameras to obtain 3D data, including shapes, displacements, and strains. To enable 3D reconstruction, the cameras were spatially calibrated. This was achieved by taking images of a cylindrical calibration object simultaneously by all the cameras and processing them using MultiDIC to obtain the camera parameters required for 3D reconstruction. The stereo DIC setup was validated by capturing a set of images and evaluating the null-strain values, as demonstrated in (Solav et al. 2018; Solav and Silverstein 2022).

3.3. PRINTING AND DRYING PROCESS

To test the setup, a commercial wood-based material called Daika was used due to its high deformation while printing and local availability. Additionally, exhausted coffee grounds, an organic waste material, were added to the Daika-water mixture to increase the random speckle pattern for the DIC process. This mixture was thoroughly kneaded until it reached a dough-like consistency suitable for extrusion-based printing (Cohen et al. 2024). This preparation ensured a consistent texture and structural stability for the wood-based prints, laying the groundwork for precise testing.

Figure 3. (left to right) WASP 40100 LDM printer, printed samples

The 3D printing was conducted on a WASP 40100 LDM printer (https://www.3dwasp.com/) (Figure 3), fitted with a 6 mm nozzle to allow precise control over material flow and extrusion. The print speed was set at 0.07 m/s, and the extrusion rate was maintained at 0.6 cc per unit volume. These settings were chosen to optimise print quality while minimising potential deformation during the extrusion and layering processes. Three distinct shapes were selected to observe and analyse deformation patterns: a cylinder (50 mm in diameter and 50 mm in height), a hollow cube (50 mm per side, 50 mm in height), and a hollow triangular prism (70 mm side length, 50 mm in height). Each shape was printed with a layer height of 2 mm in a spiralised pattern to maintain structural uniformity. A total of nine prints (Figure 3), three for each shape, were produced to ensure repeatability and provide a broad dataset for future analysis.

After printing, the samples were placed on a drying rack within a controlled environment. The temperature and humidity levels in the room were constantly monitored and maintained between 20–25°C and 50–60% relative humidity to promote uniform drying. Gentle airflow (Beaufort scale) was provided at a rate of 3–5 m/s using fans to minimise differential shrinkage and potential warping, ensuring consistent drying conditions across all samples.

3.4. DATA ACQUISITION WITH 3D SCANNER AND DIC

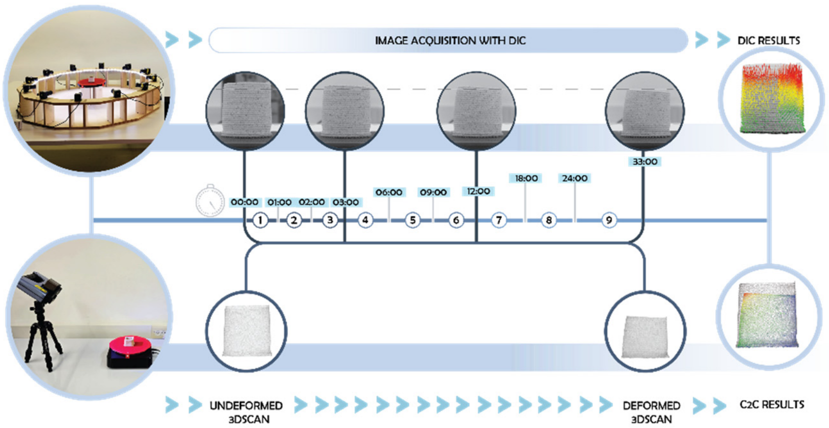

Figure 4. Sequential steps of complete process with timeline.

The samples were scanned using an EinScan Pro 2X V2 scanner (SHINING3D, China) immediately after the printing process and again after full drying (see Figure 4). These scans captured the detailed geometry of the prints, and the resulting files were converted into point clouds and meshed to serve as a reference for tracking changes in shape and dimensions. Data for DIC was captured using the custom-built setup and software (Section 3.2). The DIC measurements began 40 minutes after printing, followed by three sets of images taken at 1-hour intervals, three images at 3-hour intervals, two images at 6-hour intervals, and the last one at a 9-hour interval, totalling 9 sets of images over 33 hours (Figure 4). This schedule allowed for detailed observation of deformation over time, as the shrinkage due to drying slowed down with time.

3.5. DATA PROCESSING USING MULTI DIC

The acquired images were processed using the MultiDIC toolbox using the method from (Solav et al. 2018; Solav and Silverstein 2022). Initially, cross-correlation analysis was performed on pixel subsets across different images to identify corresponding material points. These points were then transformed into a dense 3D point cloud for each step. Subsequently, the points were linked to creating a vector-based tracking system (Figure 5). This process provided precise measurements of displacement magnitude and direction of each tracked point on the object.

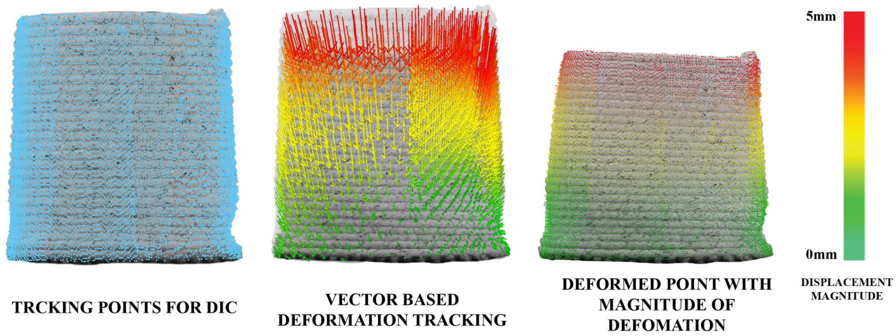

Figure 5. Vector-based tracking system with DIC

3.6. VALIDATION OF DIC DATA

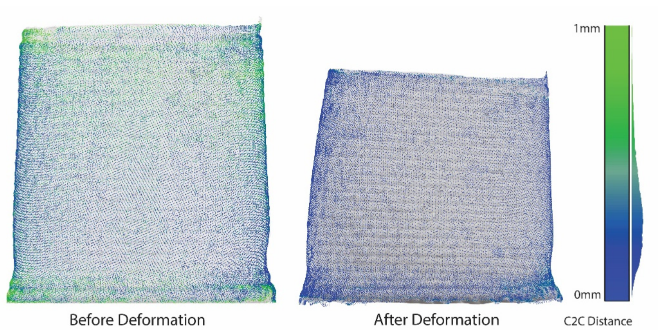

Figure 6. Distance comparison between DIC point cloud and EinScan Pro 2X V2 scans

DIC provided both the original and deformed point clouds, enabling precise tracking of movement over time by directly connecting corresponding points. To validate the results, we compared them to the 3D scan obtained from the EinScan Pro 2X V2, processed using the open-source software CloudCompare (http://cloudcompare.org) to obtain a Cloud-to-Cloud distance analysis. We compared the point clouds generated by the scanner with those from the DIC setup, both before and after the deformation. This analysis demonstrated the reliability of the DIC methodology. Validation revealed a close match between the initial 3D scan and the first cycle of DIC data, with most points aligning within 0.25 mm, and only a few spots showing deviations up to 1 mm (Figure 6). A similar consistency was observed in the final cycle, indicating accuracy across the process. These findings demonstrate the potential of DIC for precise deformation tracking in applications where high spatial accuracy is critical.

4. Results

4.1. COMPARISON BETWEEN DEFORMATION TRACING METHODS

In this section, we observe the shrinkage of the 3D prints, comparing the CloudCompare results, derived from comparing the initial and final scans, and the DIC results, highlighting the strengths and limitations of each method. CloudCompare is a user-friendly tool that utilizes the closest point algorithm to detect deformation and track volumetric changes. However, this approach requires manual alignment of the object within the 3D workspace. In our test, it yielded inaccurate results by identifying incorrect closest points in the point cloud (Figure 7), which may introduce positioning errors and compromise accuracy.

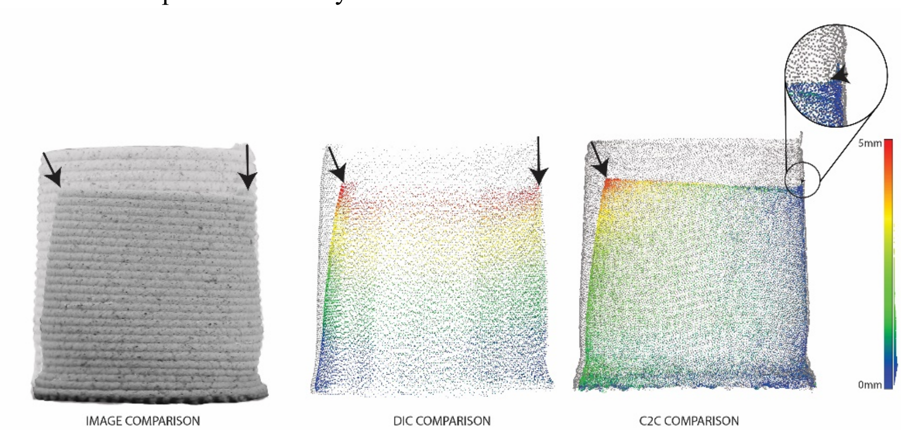

Figure 7. result comparison between DIC and scan for validation using CloudCompare.

Conversely, DIC offers a more detailed analysis by capturing pixel shifts from sequential images to generate high-resolution deformation point clouds (Figure 8) at various timestamps. This provided a comprehensive, precise view of the deformation of each point in the sample over time. However, DIC requires a more complex setup and a surface with a random pattern for precise correlation. While DIC excels in delivering detailed and localized deformation data across all zones, CloudCompare primarily focuses on overall volumetric and shape changes (Figure 8), which may not effectively capture localized trends within specific sections of a printed structure.

4.2. LOCAL DEFORMATION ANALYSIS

The DIC results show that the shrinkage of LDM in recycled wood ranges from 11% to 18% in the XY plane and from 25% to 28% in the Z direction when the prints are dried at 20–25°C temperature, 50–60% relative humidity, and constant airflow of 3–5 m/s. These results indicated that the deformation is not uniformly distributed along the axes and varies across different sections, influenced by geometric properties and height from the base. Using the DIC method, 50,000 data points were obtained from each model, offering detailed insights into deformation across the print surface. It is evident that shrinkage in the Z direction increased with distance from the base support. In contrast, the XY plane showed a central sagging area on the face with a corner, leading to uneven sections, which is not present in calendarial prints showcasing geometry with corners deform unevenly.

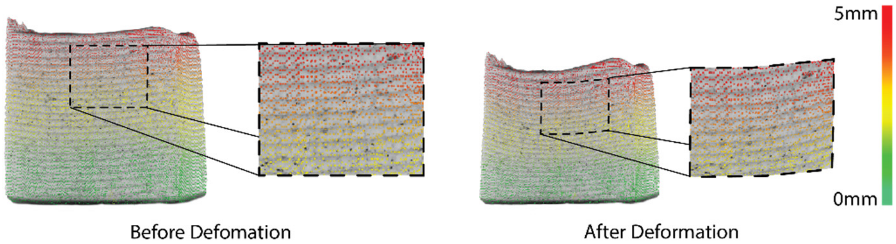

Figure 8. Point-to-point deformation tracking with DIC

5. Discussion and Conclusions

This study highlights the potential of DIC as an advanced method for analyzing deformations in wood-based LDM prints. By providing high-resolution, point-to-point tracking, DIC offers unparalleled insights into how recycled wood materials behave during and after printing. The ability to generate detailed point clouds allowed us to map deformation patterns with exceptional accuracy, identifying critical shrinkage trends and localized structural changes. This capability is particularly valuable for addressing the challenges of uneven drying and dimensional inaccuracies in LDM.

Despite its advantages, DIC has certain challenges that need to be considered. Preparing the object's surface with a high-contrast speckle pattern can be difficult. Ensuring precise calibration of multiple cameras makes the setup process complex and time intensive. Additionally, capturing and processing large volumes of high-quality images require significant computational resources and careful experiment design. These factors may limit its availability but do not diminish its utility for precise deformation tracking.

Future work could focus on analyzing a large set of samples and using the gathered data to train Machine Learning models to predict 3D shrinkage and deformation. The large number of data points obtained from each physical sample indicates that models can be efficiently trained. This puts DIC at a significant advantage over other data acquisition methods, which generate fewer data points with which models can be trained. The trained ML models could optimize LDM printing parameters, predict deformation and amend the printer toolpath for more accurate prints and reduce material waste. By addressing these challenges and building on its strengths, DIC could play a pivotal role in advancing sustainable manufacturing practices in 3D printing with recycled wood materials.

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