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A novel heuristic approach to detect induced forming defects using point cloud scans

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Abstract

The research paper delves into the importance of point cloud data obtained from 3D scanning technology ensuring quality control in industrial settings. It presents a new heuristic approach that utilizes the wavelet algorithm and other techniques to detect and characterize induced forming defects accurately. The proposed approach offers more flexibility, ease of use, and better results based on descriptive and prescriptive analyses from DRM. The results demonstrate that the wavelet algorithm was successful in identifying and characterizing forming defects in point cloud data.

Keywords: point cloud, design methodology, forming defects, evaluation, visualisation

1. Introduction

1.1. Motivation

The validation of composite parts is a critical aspect of the manufacturing process, ensuring that the designed geometries meet standard quality standards and performance criteria. Non-destructive testing techniques are vital in validating composite parts without compromising their integrity. Methods such as ultrasonic testing, X-ray radiography, and thermography are employed to identify induced defects, delaminations, or voids that might be present within the material. This paper presents a comprehensive study on detecting the induced forming defects such as bridges, wrinkles and gaps using point cloud-based (PC) data (Eberly, 1999). The paper proposes a novel heuristic approach that utilizes wavelet analysis to enhance the precision and efficiency of defect identification in PC datasets (Liu *et al.*, 2021). The wavelet approach is preferred over existing methods in terms of versatility, computational efficiency, and performance across different fields such as image analysis, pattern recognition and standard signal processing. This study features relevant literature and proposes an innovative heuristic approach inspired by Zhang and Chen (2022). The study features descriptive and prescriptive components, with a review of relevant literature and the proposal of the innovative heuristic approach (Ying and Chen, 2013). This research has taken a multi-step approach to the analysis, including data preprocessing, wavelet transformation, thresholding, clustering, and visualization. This approach confirm the effectiveness of the wavelet algorithm in detecting defects, with a high level of accuracy and reliability in detecting other types

* This article has been updated since original publication. A notice detailing the change has also been published.

of defects, including scratches, dents, and cracks (Saleh *et al.*, 2020; Stopjakova *et al.*, 2005; Shi *et al.*, 2004). An essential contribution of the research is incorporating a clustering algorithm, which not only aids in defect identification but also plays a crucial role in detecting and analyzing gaps within the scanned PC data (Bártová and Bína, 2019). The clustering algorithm employs a modified DBSCAN algorithm, which is effective in identifying gaps in the point cloud data, leading to a more comprehensive and accurate analysis of the data (Bártová and Bína, 2019). Overall, this innovative approach represents a significant advancement in the field of point cloud analysis, with the potential to have a substantial impact on design methodology and design for manufacturability.

1.2. Background

Composite materials have gained immense popularity and high demand for several decades due to their remarkable versatility, durability, and suitability for various industrial applications (Saeed *et al.*, 2022a; Saeed *et al.*, 2022b; Boisse, 2015). In this research, the double dome geometry is considered due to its intricate curves and complexities during forming. However, during the forming process of these materials, they often encounter unequal stress and pressure, resulting in various types of defects on their surface such as wrinkles, bridges, gaps illustrated schematically in Figure 1 (Boisse *et al.*, 2018). Wrinkles appears on the surface of the formed part when there is insufficient pressure or tension during the forming process. Bridging appears when the geometry has a curved shape and due to additional stress the material is unable to cover the radii of the geometry. Thus, resulting in larger area/void between the material and the geometry. Whereas the gaps appear where the material is not fully consolidated during forming. However, with the latest design and technology advancements, these defects can be mitigated to deliver high-quality, high-performing composite products (Amri *et al.*, 2017; Heslehurst, 2014; Huang, 2013; Hussain *et al.*, 2014). To ensure quality control and prevent costly repairs and downtime, identifying and addressing these defects is crucial (Jovančević *et al.*, 2017). Various data analysis methods can be employed to detect and analyze these defects, depending on the specific approach used for defect detection on the material's surface (Ying and Chen, 2013; Bártová and Bína, 2019). Wavelet analysis is a mathematical tool that can analyze signals and images at different scales and resolutions (Saleh *et al.*, 2020). It is an effective method for detecting and characterizing forming defects in composite materials, providing precise results and improving the efficiency of quality control processes (Yang *et al.*, 2022).

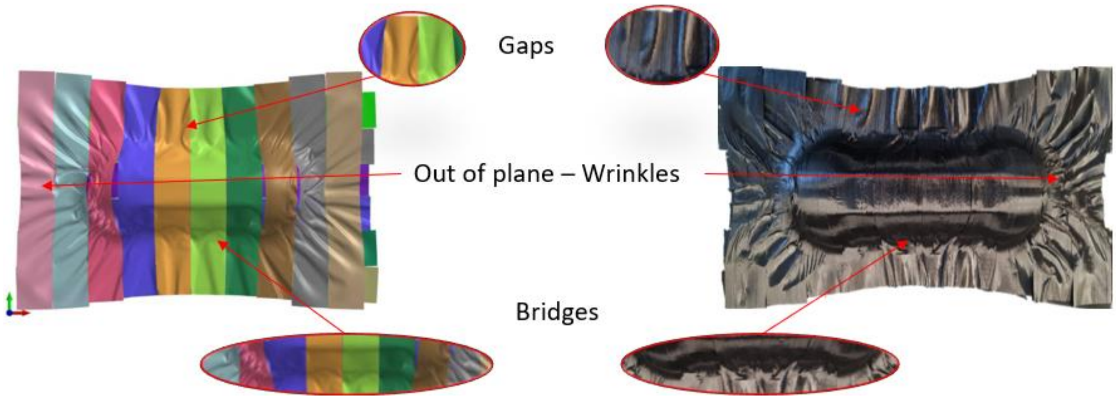

Figure 1. Common types of defects present in the formed part

On the other hand, clustering algorithms group similar data points together to identify patterns and outliers in the data (Bártová and Bína, 2019). This feature enables the identification of areas that require further inspection and enhances the accuracy and efficiency of defect detection and analysis. Overall, it is essential to employ advanced techniques such as wavelet analysis and clustering algorithms to ensure quality control and prevent costly repairs and downtime in industrial settings (Márquez, 2013). These methods can significantly improve the performance and longevity of composite materials, making them more reliable and suitable for various industrial applications (Simon, 2011).

Detecting the induced forming defects poses several challenges due to the nature of the geometry, processes and the material. Forming tools usually have complex geometries which include intricate

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curves, shapes and structure. It is essential to detect minor defects in these geometries using advanced inspection approaches to ensure reliability. Another aspect to reliability is integrating the defect detection framework seamlessly in different manufacturing process to avoid any inefficiencies in the production. These inefficiencies could also include material variability because during composite forming process certain properties such as fiber orientation and alignment and matrix content can affect defect creation. Based on these challenges PC data has become increasingly important in a wide range of fields, including 3D modelling, object detection, and inspection, due to its ability to provide an exact representation of surfaces in the form of a 3-D geometry (Liu *et al.*, 2021; Jovančević *et al.*, 2017). The key research question is In what way can point cloud-based inspection be effectively used to detect induced forming defects. However, the presence of defects or anomalies in point clouds can significantly impact the quality of the data and lead to potential issues in design processes (Ma *et al.*, 2023). In this research paper, we present a comprehensive method for detecting three specific types of defects in point clouds as illustrated in Figure 1, namely "wrinkles," "bridging," and "gaps". This approach combines various techniques, each designed to address specific defect types and strategically employed to complement one another, optimizing the overall detection process. To detect the "wrinkles" defect, this research employs the wavelet algorithm, which offers a robust approach for analyzing the frequency content of signals, making it an ideal approach for identifying defects in scanned PC data. To detect the "bridging" defect, this research compares the scanned PC with an original simulated or CAD data, which allows to identify anomalies that may be present due to deviations from the original design. In addition to this comparison, KD-tree analysis and statistical methods are utilized to identify and extract instances of this defect. One of the most significant challenges in point cloud data processing is the detection of "gaps", which can significantly impact the data quality. To address this, clustering algorithm is considered that groups data points spatially close and structurally similar (Bártová and Bína, 2019). In the context of gap detection, the clustering algorithm helps identify clusters of points with significant spatial discontinuities, indicating the presence of gaps in the PC. By integrating a clustering algorithm for gap detection, the detection enhances the overall effectiveness in identifying and characterizing defects using scanned PC data, providing a comprehensive solution for quality control and manufacturing processes. In summary, the approach mentioned in this research is limited to the composite parts using PC data comprehensively and effective solution that combines various techniques strategically to identify and characterize different types of anomalies.

1.3. Literature review

Defect detection in point cloud data is a subject of extensive research, and numerous techniques have been explored to address this issued (Belnoue *et al.*, 2017). One of the most popular approaches is filtering, which removes unwanted noise and enhances the quality of the data (Zhang *et al.*, 2016). Another common technique is segmentation, which partitions a point cloud into smaller, more manageable subsets (Zhang *et al.*, 2016). Feature extraction is also widely used to extract specific information from the data (Ying and Chen, 2013). Despite these well-established techniques, existing approaches often need to be revised in accuracy, robustness, and computational efficiency. As a result, this research has explored various other methods to tackle this issue as illustrated in Figure 2. Structural approaches such as Auto-correlation, Co-occurrence matrix, and Spectral Approaches like Gabor transform, and wavelet transform have been employed to capture the structural properties of the data (Yang *et al.*, 2022; Ying and Chen, 2013; Zhang *et al.*, 2016). Model-based approaches rely on pre-defined models to detect defects in the data. Learning approaches utilize machine learning algorithms to learn from the data and identify anomalies automatically (Simon, 2011; Stopjakova *et al.*, 2005). Structural approaches combine multiple techniques to create a comprehensive approach for detecting defects. Hybrid approaches combine two or more techniques to achieve more accurate and robust results (Saleh *et al.*, 2020). Finally, motif-based approaches focus on identifying recurring patterns in the data to detect defects. Overall, the field of defect detection in point cloud data is a complex and challenging area of research that requires careful consideration of various factors such as accuracy, robustness, and computational efficiency. While existing techniques have made significant progress in this area, there is still much work to be done to develop more effective and efficient methods for detecting defects in point cloud data (Ma *et al.*, 2023; Márquez, 2013).

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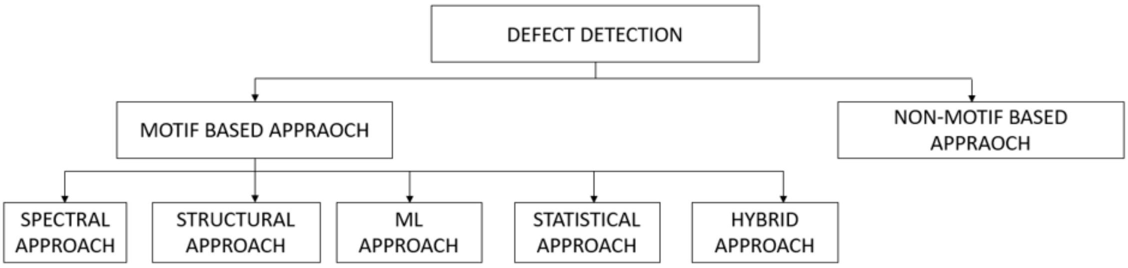

Figure 2. General approaches to defect detection; source automated fabric defect detection

Motif-based approaches for defect detection often use thresholding techniques to segment images and identify regions of interest. These techniques rely on statistical measures such as data distribution to determine appropriate thresholds. Such measures are commonly used in image processing applications (Yang *et al.*, 2022; Chrysochoos and Louche, 2000). Additionally, Cao *et al.* (2020) proposed a similarity measure that uses pixel intensity, which can be compared against a hard-coded threshold to determine the similarity between image regions. Whereas, traditional motif-based approaches have relied on threshold measures, often failing to detect defects accurately. Artificial intelligence has solved this problem, but methods such as convolutional neural networks (CNN) are limited by their need for extensively labelled data and their inability to handle varying surface geometries (Heslehurst, 2014). The wavelet detection algorithm was developed to overcome these limitations. This flexible algorithm considers the surrounding geometry and can highlight anything that stands out, making it an efficient and precise defect detection tool (Stopjakova *et al.*, 2005). Unlike traditional methods, the wavelet detection algorithm doesn't consider surface geometry, including sharp curves, as defects, making it even more efficient (Ying and Chen, 2013). The wavelet detection algorithm's accuracy, flexibility, and efficiency make it an ideal choice for defect detection in various industries (Shi *et al.*, 2004). From design to manufacturing, the wavelet algorithm can help ensure the quality and safety of products.

Upon conducting an extensive literature review on gap detection within point clouds, the current research in this field primarily focuses on addressing gaps in structural data. Studies rarely consider gap detection as a separate and crucial aspect of point cloud analysis. When gap detection is discussed, it typically involves creating triangular meshes to identify the boundaries of the gaps within a dataset. To address this gap in this research, various techniques to identify and assess gaps within point clouds are considered. One such technique is the density-based approach, which employs a nearest-neighbor technique within a kd tree (Eberly, 1999). This approach calculates the average density of the point cloud and using it as a threshold to compare against the points within the entire point cloud within a certain radius (Jones, 1995). This approach has emerged as a fundamental method for gap detection within point clouds, forming the foundation of the methodology outlined in this paper. In addition to the density-based approach, K-means clustering is explored, a widely used method for partitioning data into clusters (Lee *et al.*, 2023).

2. Methodology

This section follows a practical and systematic design research technique for investigating defect detection in a formed part using point cloud-based inspection and wavelet algorithms. This research follows the Design Research Methodology (DRM) by Blessing and Chakrabarti (2009) over other frameworks because it provides a thorough and structured approach to planning and executing investigations that involve different research methodologies tied to this work. Within the broad DRM, seven different types of design research are suggested by Blessing and Chakrabarti (2009) and this research follows the review-review-comprehensive-initial approach as illustrated in Table 1. This research follows the comprehensive literature review and highlights the gaps in the inspection methods used to detect the defects. Based on the comprehension of the research, another comprehensive literature review is carried out to find the existing methods to inspect the defects in a formed part. Based on the detailed research review, the initial framework is proposed, tested and evaluated on ten different formed parts for a concrete conclusion.

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Table 1. Design research project types and their primary objectives (Blessing and Chakrabarti, 2009)

No.	Research Clarification (RC)	Descriptive Study I (DS-I)	Prescriptive Study (PS)	Descriptive Study II (DS-II)
1	Review based	Comprehensive		
2	Review based	Comprehensive	Initial	
3	**Review based**	**Review based**	**Comprehensive**	**Initial**
4	Review based	Review based	Review based	Comprehensive
5	Review based	Comprehensive	Comprehensive	Initial
6	Review based	Review based	Comprehensive	Comprehensive
7	Review based	Comprehensive	Comprehensive	Comprehensive

2.1. Research Clarification

The Design Research Methodology's Research Clarification (RC) phase involves conducting a review of recent literature to clarify the research context, identify any existing challenges, and establish a solid foundation for the research as explained in Section 1.3. In this research, the RC phase focuses specifically on addressing the first part of RQ - " *In what way can point cloud-based inspection be effectively used to detect induced forming defects*?" which is to carry out the literature review on the existing inspection approaches to detect defects. To answer this part of the question, the review examines various algorithms that support the defect detection in design, including their accuracy, efficiency, and effectiveness. Moreover, the RC highlights the importance of defect detection in the early phase of design during forming process and can help minimize waste and improve product quality.

2.2. Descriptive Study 1: understanding the literature and identifying gaps

Defects in manufacturing processes are a common occurrence that can cause significant issues for processes (Marani and Campos-Delgado, 2023). Unfortunately, detecting these defects can be challenging until the process is complete and all the parameters have been assessed. To address this challenge, the research addresses the second part of the RQ, "How point cloud-based inspection can assist in detecting defects in a formed part?", which is focused on the effectiveness of PC-based inspection for defect detection in forming processes, the Descriptive Study 1 (DS-I) has been designed to follow the RC comprehensively. However, there is a solution: point cloud-based inspection for defect detection in forming processes.

After conducting a comprehensive review of the current literature on defect detection approaches, this research has identified certain inherent limitations of existing methods and established the prerequisites for an effective and precise techniques. The analysis has highlighted the need for a robust and accurate method that can handle intricate and irregular forming defects with ease (Jovančević *et al.*, 2017; Lee *et al.*, 2023; Marani and Campos-Delgado, 2023) that cannot be assessed through other inspection methods such as eddy current, xrays and thermography. The investigation results indicate that while statistical and structural approaches are precise to the geometry of the dataset, they are less adaptable when applied to a diverse range of datasets (Ma *et al.*, 2023). Furthermore, they are sensitive to data quality and often suffer from overfitting issues, which reduces their effectiveness. Several approaches, such as Machine Learning and Deep Learning, have been predominantly tested on pictorial representations, leading to qualitative accuracy. However, these models require significant amounts of labelled training data, often challenging to acquire (Márquez, 2013). Additionally, the training and deployment of machine learning models necessitates substantial computational resources, including robust hardware and memory (Zimmerling *et al.*, 2020). Therefore, the literature recommends the development of a robust and accurate technique that can handle intricate and irregular forming defects with ease while being adaptable to diverse datasets. The proposed approach should address the limitations of existing methods and ensure that the defect detection process is effective and precise (Zimmerling *et al.*, 2022).

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Regarding identifying defects, some methods use complex thresholding techniques capable of detecting both significant and minor defects with greater accuracy (Zhang *et al.*, 2016). However, these techniques often focus solely on detection and fail to consider the critical aspect of quantifying the precise extent of the defects (Lee *et al.*, 2023). This can lead to the rejection of entire components, even when only a tiny portion of the component is defective. One defect in a formed part that needs to be widely discussed in the literature is 'bridging,' which refers to the formation of tiny connections between different parts of a component during the forming process. The available techniques for identifying bridging rely on manual inspection, which is often highly unreliable (Croft *et al.*, 2011; Senthil *et al.*, 2013). The results can vary significantly depending on the data and the inspection's skill level, leading to inconsistencies and inaccuracies (Woigk *et al.*, 2018; Zöcke, 2010). To overcome these issues, an in situ real-time approach has been proposed to detect defects in the PC (Woigk et al., 2018; Zöcke, 2010). This method involves capturing data during the manufacturing process and analyzing it in real-time to identify defects as they occur. By doing so, it is possible to detect defects more accurately and quickly, minimizing the risk of rejections and improving overall quality control. After a thorough review on defect detection in point clouds, 'gaps' have emerged as a common defect within point cloud data caused during forming. Current methods lack clarity in explaining and dealing with these gaps. To address this gap, this research propose clustering methods to categorize similar defects within point clouds, making them easier to understand and manage. By focusing on defect-specific characteristics, clustering can lead to more precise and adaptable detection techniques, improving the accuracy and consistency of identifying and addressing gaps in point clouds.

2.3. Prescriptive Study: proposed framework

The prescriptive study (PS) is the third stage of the design research methodology, following DS-1, as outlined by Blessing and Chakrabarti (2009). The focus of the PS stage is to follow the comprehension-based facilitation in decision-making during the early stages of design and manufacturing. The PS stage builds on the previous stages, RC and DS-I.

The proposed approach for identifying defects is a highly advanced and nuanced method based on physical properties as illustrated in Figure 3. The approach incorporates input properties into a hybrid algorithm that combines spectral and statistical approaches, which are precisely fine-tuned to a point cloud to ensure accuracy. This algorithm is highly generic and designed to detect any geometry that stands out, whether wrinkles or carbon fibre threads. The proposed algorithm overcomes the limitations of spectral approaches, which often require graphs, by breaking down the 3D data into 2D slices.

Additionally, the algorithm's most notable feature is its ability to detect defects on multiple scales, providing highly detailed results for various applications. In the case of the 'Bridging' defect, the proposed algorithm relies on the simulated or CAD file of the ideal geometry. By aligning the defected PC and the CAD geometry, the defected region can be classified as the 'bridged region.' This method also incorporates statistical techniques to improve its results further and complement the 'Wrinkle' wavelet algorithm, enhancing the results even further. It ensures that major and minor defects are detected with greater accuracy. The DBSCAN clustering technique has emerged as an efficient and effective approach for handling large datasets (Bártová and Bína, 2019). One of its key advantages is using density-based thresholds, which are more effective than other clustering methods such as K-means. Determining the number of clusters can be challenging with K-means clustering, often requiring the elbow method. However, this approach tends to be time-efficient when dealing with extensive datasets. In contrast, DBSCAN clustering utilizes density-based thresholds, significantly improving its efficiency and accuracy. Additionally, DBSCAN clustering is adaptable, making it an ideal approach for a wide range of applications.

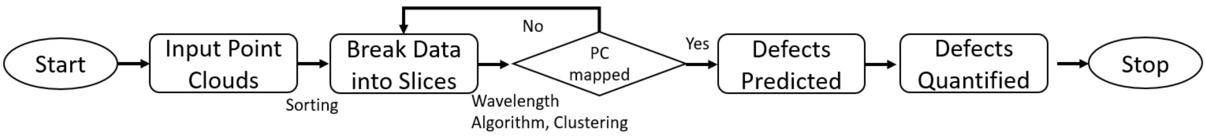

Figure 3. Proposed flowchart to detect the defects

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2.4. Descriptive Study 2: evaluating the proposed approach

The final stage of the Design Research Methodology is the Descriptive Study 2 (DS-II), which involves the validation assessment of the support created in the PS (Blessing and Chakrabarti, 2009) as shown in Figure 4. This stage presents promising techniques that confidently target the defects on the simulated and the formed parts and segment them, accordingly, surpassing any other existing method in terms of precision and accuracy by mapping them. This research iteratively tested the proposed framework on different parts for double dome geometry formed under different process and material parameters. These formed parts are compared with the simulations to have reliability. The proposed wavelet algorithm at the core of this approach is evaluated through a series of meticulously designed experiments conducted on diverse point clouds as explained in Figure 3. The results of these trials demonstrate the effectiveness of the proposed wavelet algorithm in detecting and segmenting defects, making it an indispensable tool for handling a wide range of real-world scenarios.

2.4.1. Wrinkles

To identify wrinkles and defected points precisely and comprehensively within the data (Boisse et al., 2018), this research has implemented the robust Wavelet Algorithm, primarily used for standard signal processing. Although typically used for 2D signals, the algorithm is tailored to the 3D PC data, resulting in an effective approach as shown in Figure 5.

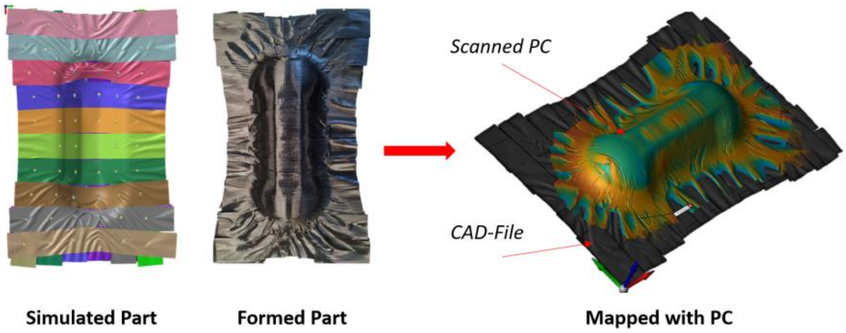

Figure 4. Real part that has the defects in comparison with the point-cloud image

The process segments the point cloud into 2D planes using the Wavelet Algorithm. This simplifies the representation, then compared to the original signal to identify deviations beyond a threshold. Statistical techniques like mean and standard deviation play a essential role, resulting in highly accurate identification (Kim *et al.*, 2010). The holistic algorithm is unique in that it not only integrates the Wavelet Algorithm but also incorporates various techniques based on the physical properties of the defects. This approach helps identify regions based on the type of defect they exhibit. The algorithm uses the multi-resolution capabilities of the Wavelet Algorithm and physical property-based classification to differentiate between normal and defective regions. Systematically dividing 3D point cloud data into 2D slices along each axis, the algorithm inspects the entire point cloud for irregularities. It also uses the Wavelet Algorithm's multi-resolution capabilities to identify fine-scale details and irregularities within the point cloud data. The approach offers flexibility to adjust the level of decomposition and variable thresholds inherent in the Wavelet Algorithm, resulting in highly accurate defect identification.

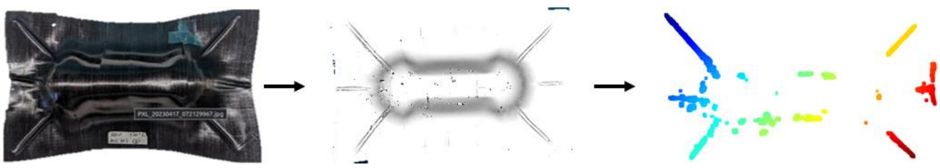

Figure 5. Original point cloud using cloud compare

2.4.2. Gaps

The gap detection (Boisse *et al.*, 2018) method is an essential tool for precise 3D spatial analysis within intricate point cloud datasets as illustrated in Figure 6. The authors use the DBSCAN algorithm to cluster

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nearby data points and identify isolated regions as noise. They transform the raw data into a structured NumPy array format for efficient data handling. The DBSCAN algorithm relies on two crucial parameters, epsilon (eps) and minimum samples (min_samples), to determine the radius for point clustering and the threshold for recognizing dense clusters. A KDTree is incorporated for optimized computational efficiency. The method systematically analyses each data point's neighbourhood to assess local density. The DBSCAN label assigned to each point is evaluated, and the local point density is compared to a user-defined density threshold (Margret *et al.*, 2021). The method yields a comprehensive compilation of gap points, indicating gaps within the point cloud dataset, and provides valuable support for defect characterization and in-depth analysis. The methodology is highly efficient and customizable to suit specific analytical objectives.

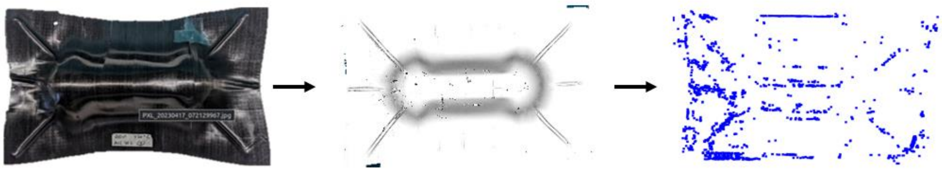

Figure 6. Detected gaps on original point clouds

2.4.3. Bridging

During the process of forming composites, a defect known as bridging can occur as shown in Figure 7. When this happens, the surface of the material being formed does not adhere properly to the tool being used, resulting in a measured distance between the surface and the tool (Boisse *et al.*, 2018). A bridging defect happens when the fibres or other reinforcing materials do not take on the desired shape as illustrated in Figure 7. This results in an unsupported area or gap between adjacent layers or within the composite structure. Bridging defects appear as low-density regions or irregular surface topology, indicating gaps or voids. Significant deviation may indicate their presence with a distance that determines the conformity of the surface, which is an essential factor in the overall quality of the formed product. Bridging is caused by the friction forces that prevent the material from sliding correctly, combined with high vacuum pressures that increase the forming force. These factors result in a defect that can compromise the structural integrity of the composite.

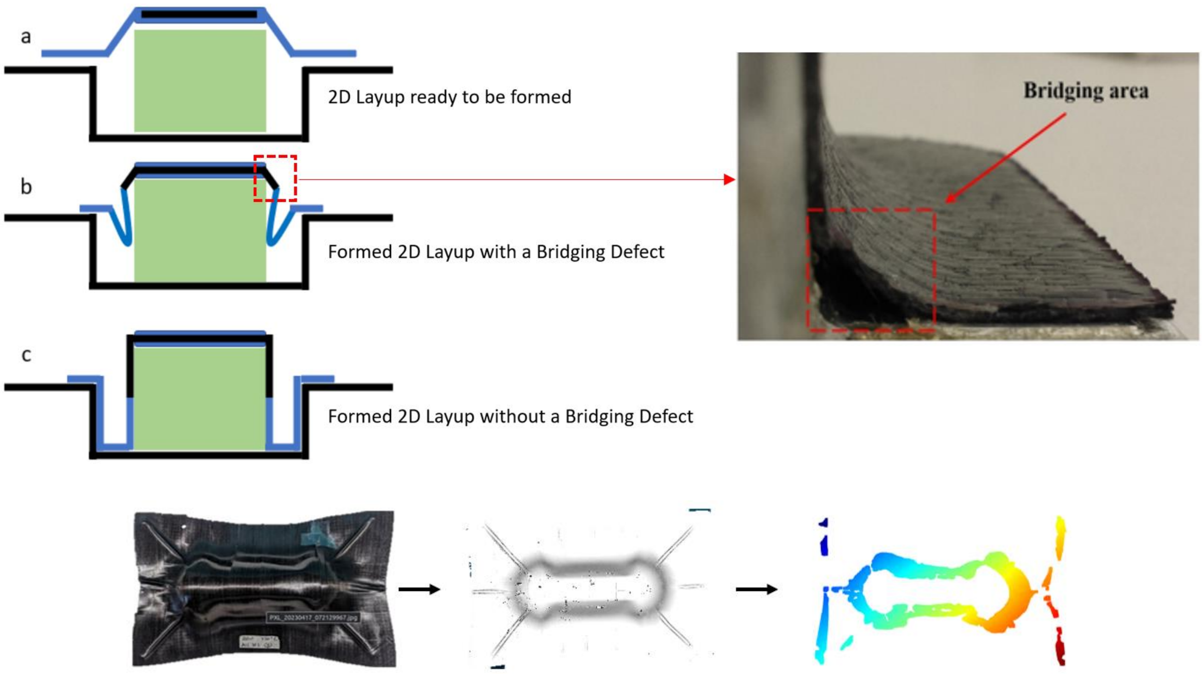

Figure 7. Illustration of bridging defect in 3D formed part

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The proposed algorithm for defect detection is based on a research paper and involves six fundamental steps (Zhang *et al.*, 2016),

- Select three or more corresponding points with defects and the ideal point cloud from the PC.
- Employ the Singular Value Decomposition (SVD) technique to generate an initial transformation matrix to align the two-point clouds.
- Refine with the Robust Iterative Closest Point (ICP) algorithm to enhance the alignment accuracy.
- Project the ideal and defected area in the PC dataset onto the x-y plane and isolate points below or above the defected PC dataset.
- Use the K Nearest Neighbours (KNN) concept to identify the three nearest points in the ideal PC corresponding to each point in the defective point cloud.
- Calculate the Z-axis differences between the two-point clouds to detect defects in 3D-formed parts accurately.

The proposed algorithm provides a reliable and robust method for defect detection.

3. Validations and discussion

The algorithms proposed for the particular problem have undergone rigorous and detailed validation, including multiple steps and iterations. These algorithms were carefully designed to address the challenges of the problem at hand and were validated using original PC data obtained from formed parts. The experiments conducted to evaluate the performance of these algorithms were carried out in a simulated practical setting, making it possible to assess their effectiveness in real-world scenarios as illustrated in Figure 8. To ensure that the proposed algorithms met the highest standards of accuracy and reliability, a quantitative analysis was conducted. This analysis involved comparing the results obtained through the proposed algorithms with the ground truth values, allowing for a high specificity level. A Statistical Outlier Filter was also applied to the algorithms to ensure they could handle noise in the data. This filter ensured the algorithms could deliver consistent and accurate results even in noise.

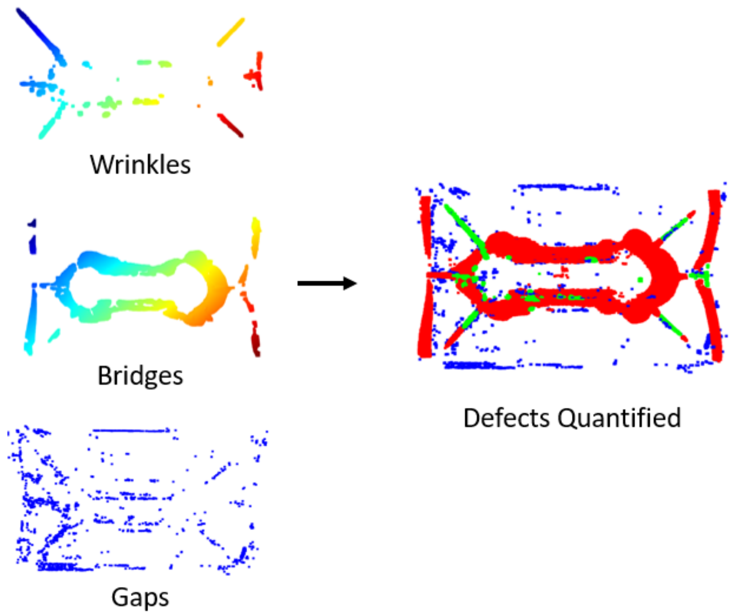

Figure 8. Comparison of defects in point cloud based scanned data

The proposed algorithms' robustness is a testament to their ability to provide accurate and reliable results, making them ideal for practical applications. Furthermore, these algorithms were tested on ten formed parts of dataset to ensure their efficiency and scalability in real-world scenarios. The results obtained through these experiments indicate that the proposed algorithms perform exceptionally well and can be considered a promising solution to the problem at hand.Overall, the validation process of

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these algorithms was thorough, and the results obtained are promising. These algorithms have been designed to deliver robust and reliable results in real-world scenarios, making them an ideal solution for practical applications.

The primary objective of identifying, classifying and detecting these defects techniques is to provide a cost-effective method while preserving the original properties of the double dome research geometry. In this regard, a statistical methods have been developed to support Figure 8, which can detect and classify defects without causing irregularities in the evaluation as illustrated in Table 2. However, the effectiveness of these techniques is significantly challenged when dealing with composite materials characterized by complex geometries, inhomogeneities, and intricate structures.

Table 2. Qualitative and quantitative analysis of the formed part

DEFECT	COLOR	QUALITATIVE	QUANTITATIVE
WRINKLE	GREEN	3.2%	35107
BRIDGING	RED	23.9%	360734
GAPS	BLUE	0.07%	1107

Notably, the results of these approaches are based on four likely outcomes, collectively referred to as the confusion matrix of detection. These include true positives, false positives, and false negatives. True positives indicate that the method accurately detects defects in the double dome geometry, while false positives indicate that the method identifies defects that do not exist. True negatives denote that the method correctly identifies the absence of defects, whereas false negatives indicate that the method fails to detect the presence of defects despite their existence. Figure 9 illustrates the confusion matrix, which displays the algorithm's performance in detecting defects. The wrinkles were manually extracted from the point cloud and used as a benchmark to assess the algorithm's accuracy. The results demonstrate a high level of accuracy, as evidenced by the True Positive and True Negative values. It's worth noting that the accuracy of the results is expected to be more qualitative despite the quantified values.

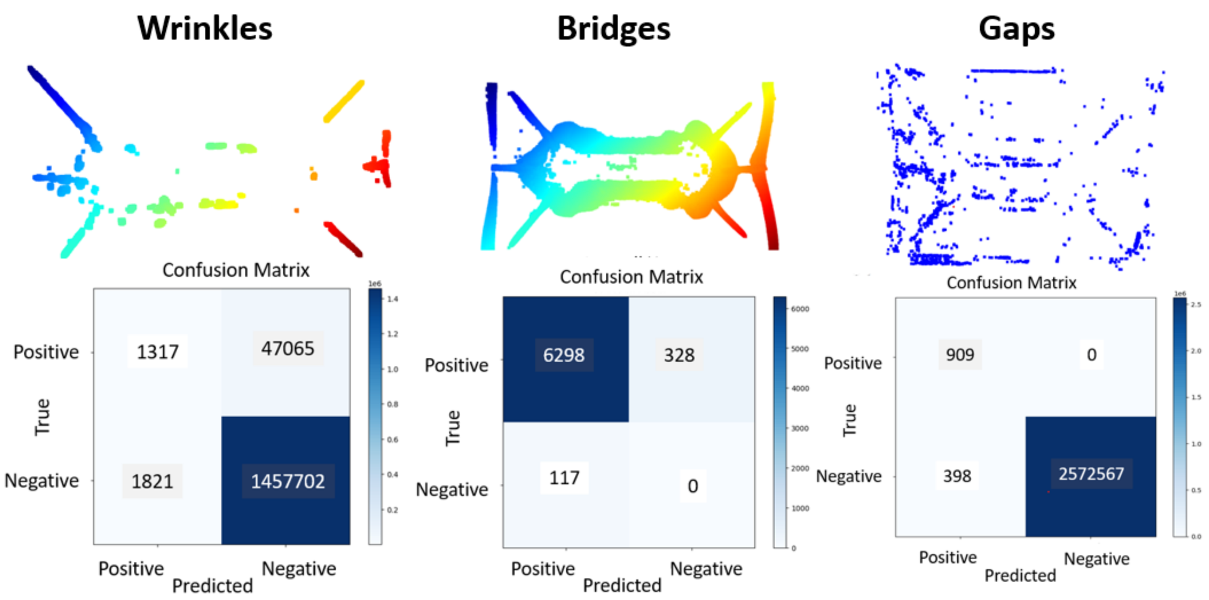

Figure 9. Confusion matrix of defects in PCD

4. Conclusion and outlook

The research paper outlines a novel and highly efficient approach for detecting forming defects in point cloud data. The proposed wavelet algorithm has demonstrated exceptional results in identifying and characterizing wrinkles as a defect with high accuracy. The algorithm can identify high and low wrinkle

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defects, exceeding the performance of other existing approaches. This makes it a reliable solution for quality control processes in forming. Furthermore, the algorithm can accurately detect the 'bridging defect' and refine wrinkle results to increase detection accuracy further.

This research significantly contributes to advancing the field of point cloud-based quality control in forming processes, providing a promising solution for manufacturers to improve their quality control processes and reduce waste. Although the algorithm's lack of quantitative accuracy is noted, the research proposes an alternative approach to supplement it. The proposed algorithm can be optimized for real-time applications, and an automatic method to vary the thresholds can be introduced in future research to enhance the algorithm's performance.

Overall, the proposed wavelet algorithm is highly effective for detecting forming defects in point cloud data. Its ability to accurately identify and characterize wrinkles and other defects in forming processes makes it a valuable tool for quality control processes in manufacturing. The research provides critical insights for future research and development in point cloud-based quality control, and the proposed algorithm can serve as a foundation for further innovation in the field.

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