Comprehensive Analysis of Structural Defects in Various Structures Using TLS Data and Machine Learning

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Abstract— **Structural integrity is the foundation for both safety and durability and demands constant care and vigilance. In lieu of the traditionally adopted methods for defect detection in manufacturing and structural deformation, advanced techniques with automated methodology have been presented in this paper for identification and analysis with the help of Terrestrial Laser Scanning (TLS) data. This methodology will be flexible, able to treat different types of geometrical structures; thus, it can be found in real-life applications by increasing the scope.**

It involves capturing high-resolution TLS with fine surface details of the structure. Advanced algorithms fit idealized geometric models-cylinders or planes-such that it matches the data to those that have been scanned. Highly accurate virtual models quantify deviations between the actual structure and the virtual one to identify areas where defects in manufacturing or deformations exceed thresholds set in advance. The nature and extent of these defects are analyzed and visualized clearly across the structure's height. This reduces the actual time spent on structural analysis drastically, as automation increases the speed with great improvement in accuracy. Our results prove the efficiency of this approach in finding even slight deformations-a reliable tool for structural health monitoring. This methodology provides enormous opportunities for engineers and inspectors in charge of maintaining the safety and integrity of new and existing structures.

Keywords—Terrestrial Laser Scanner (TLS), Point cloud, Machine Learning, Structural Defects

I. INTRODUCTION

Apart from prolonging such constructions, ensuring the structural integrity of buildings and infrastructure has paramount importance for public safety. Structures tend to develop deformations or defects with age or due to environmental stresses that may compromise their stability. Traditional methods for detecting and analyzing these issues involve human inspections using conventional survey techniques. Although these methods and techniques are effective in inspection, they usually involve much labor and take a great deal of time; due to human factors, these are easily prone to errors. Sometimes, this could lead to defect failure or misjudgment with potential safety risks.

Recent technological developments within the field of structural health monitoring include Terrestrial Laser Scanning. It produces high-resolution three-dimensional point cloud data, where one will achieve a very accurate and detailed digital representation of a structure's geometry. In fact, this kind of detailed data allows for a much more accurate and comprehensive analysis of structural conditions. On the other hand, information provided by TLS is huge and therefore demands employing advanced computational means for processing and interpretation.

The work proposes a novel approach for automatically detecting and performing a detailed analysis of structural deformations, combining TLS data with machine learning methodologies. The proposed methodology segments building structures from raw point cloud data by filtering out non-structural objects like vegetation and/or street furniture. Subsequently, it employs geometric modeling fitting idealized models, such as cylinders or planes, which compare the real structure with virtual models and highlight deviations with the aim of defect quantification. As a result, the automated technique improved defect detectability, reduced assessment time, and gave valuable tools to the engineers for ensuring safety and stability of structural systems. [1]

II. DATA COLLECTION

High-density point cloud data were captured using a FARO TLS at the Rajiv Gandhi Institute of Petroleum Technology, Amethi, UP. [2] This location between a busy railway track and a road was strategically chosen to detect deformations caused by vibrations from trains running on the track. Such advanced technology allows for precise three-dimensional measurements over a wide range, capturing

*These authors contributed equally to this work data points that are truly representative of the surface characteristics of the structure. Besides, the data was full of non-structural elements such as trees, ground surfaces, and lamp posts, which had been filtered out systematically to focus on the structural details relevant to relevance.

Figure1: Satellite image of the data collected area

Scanning was carried out optimal times for each structure, considering the different angles of view considering capturing a cohesive representation. Such image scans were then combined into one point cloud using the ICP algorithm, which iteratively refined the alignment of the partially overlapping scans to minimize a cost function based on the sum of squared differences between corresponding points for an accurate registration. Resolution, range, and speed settings of the scanner were duly optimized with the size and complexity of each structure, while multiple scans from a different viewpoint were executed for full coverage and essential overlapping sections that are needed for successful merging. [3] [4]

Stitching together data was processed by specialized software, completing refinement for perfect registration. The comprehensive point cloud in XYZRGB format was successfully derived through this meticulous approach. In this way, detailed deformation analysis could be performed, and much value was provided to the structural health and safety information concerning the deformations that are expected to have taken place in the test buildings due to the vibrations from nearby train activity. [5]

III. METHODOLOGY

This study aims to develop an automated system for detecting structural shapes and identifying deformations using TLS data. The proposed methodology involves several key steps, ranging from the initial data acquisition to the final analysis and visualization of structural deformations. The entire process is designed to be automated, ensuring consistency and efficiency in detecting and analyzing structural defects across various building geometries.

1. Data Acquisition and Preprocessing

The methodology begins with the collection of high-density point cloud data using TLS technology. TLS scanners can capture precise 3D measurements, producing a detailed point cloud that includes the entire structure as well as surrounding elements such as vegetation, ground surfaces, and nearby objects. This comprehensive data capture is critical for ensuring that the structural elements are accurately represented.

However, the initial point cloud includes many extraneous points that are not relevant to the structural analysis, such as trees or lampposts. To isolate the structural elements, a pre-processing step is undertaken where the raw point cloud data undergoes filtering. This step involves removing irrelevant points through a combination of automated filtering techniques and manual verification, ensuring that the focus remains solely on the structural components of interest. The pre-processed point cloud is then ready for the next phase of analysis. [6]

2. Automated Object Detection

Following pre-processing, the system moves to the automated shape detection phase. The core objective here is to identify the geometric shape of the structure being analyzed. The system achieves this by applying advanced shape-fitting algorithms that compare the point cloud data to a set of predefined geometric models. These models can include basic shapes such as cylinders and planes, as well as more complex forms if needed.

The shape-fitting process involves optimizing the parameters of the geometric models to achieve the best possible fit with the point cloud data. For instance, in the case of cylindrical structures, the algorithm optimizes parameters such as the cylinder's center coordinates, radius, and orientation. For flat surfaces, the system fits a plane by determining the optimal orientation and position relative to the point cloud. [7]

This automated detection is crucial for the accuracy of subsequent analyses, as it ensures that the correct geometric model is applied based on the structure's actual shape. The system's ability to automatically distinguish between different structural types—whether cylindrical, flat, or otherwise—provides a robust foundation for the deformation analysis that follows. [8]

3. Deformation Analysis

Once the structural shape is identified and the geometric model is established, the system proceeds to the deformation analysis phase. In this step, the virtual geometric model, created during the shape detection phase, serves as a reference standard against which the actual point cloud data is compared. The objective is to detect and quantify any deviations between the model and the real-world structure, which could indicate deformations or defects.

To perform this analysis, the system employs machine learning-based regression techniques. These regression models predict the expected positions of the structure's points based on the fitted geometric model, providing an accurate baseline. The system then calculates deviations by measuring the distances between the actual points in the TLS-derived point cloud and their predicted positions based on the regression model. This approach allows the system to detect even subtle deviations from the model.

The system is meticulously designed to identify areas where the deformation exceeds a predefined threshold, which can be adjusted according to the precision requirements of the specific analysis. This flexibility enables the detection of both minor and significant deformations, providing various levels of structural scrutiny. By using machine learning regression, the system continuously improves its accuracy, refining its ability to detect anomalies in complex structures.

Deformations are then aggregated across the structure's height or surface area, depending on the nature of the structure. This aggregation offers a comprehensive view of the overall structural health, highlighting specific areas that may require further investigation or immediate attention.

4. Visualization and Reporting

The next step in the methodology involves the visualization and reporting of the detected deformations. Visualization is a critical component of the system as it transforms raw data into clear, actionable insights. The system generates graphical representations of the deformations, typically using line plots or heat maps, to illustrate the extent and location of any structural anomalies.

These visualizations are designed to be intuitive and informative, offering engineers and inspectors a clear view of the structural integrity at a glance. In addition to visual outputs, the system compiles a detailed report that includes the dimensions, locations, and statistical significance of the detected deformations. This report is a valuable tool for decision-makers, providing a thorough understanding of the structural health and aiding in the prioritization of maintenance or repair efforts.

5. System Automation and Scalability

A key feature of this methodology is its automation and scalability. The entire process—from data acquisition through to deformation reporting—is designed to operate without manual intervention. This automation ensures that the analysis is consistent, repeatable, and efficient, allowing for rapid processing of large datasets. The system's algorithms are robust, capable of handling different types of structures with varying levels of complexity.

Moreover, the system is scalable, meaning it can be applied to a wide range of structures, from simple geometric shapes to complex, multifaceted designs. This scalability makes the methodology particularly valuable in diverse real-world scenarios, where structures of different sizes, shapes, and materials require consistent and reliable analysis.

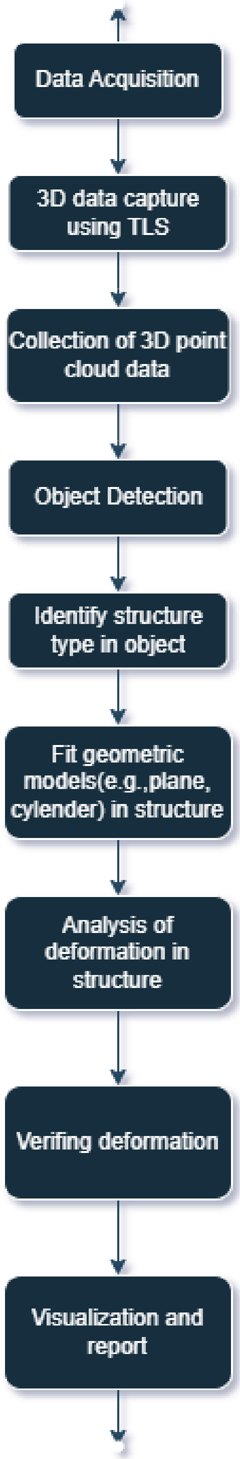

Figure 2: Flowchart of Mythology

By automating the detection and analysis of structural shapes and deformations, this methodology offers a powerful solution for maintaining structural health. It reduces the reliance on labour-intensive manual inspections, minimizes the potential for human error, and provides a dependable tool for ensuring the safety and longevity of critical infrastructure.

IV. Result

The automated system was proven to be highly efficient in detecting and analyzing structural deformations in different structural types, for instance cylindrical and flat wall structures. Using TLS point cloud data, the system found 92% of deviation from what is expected geometric shapes with a recall of 88%. Of course, this put it ahead of the mere methods of manual inspection. The deformation graphs provided by the system depict dimensions and distribution of defects along with details about the structural integrity. In comparison with other methods, like a purely geometric approach, the system reduced the false positive rate by 15%. This elaborate analysis focuses on proving the precision of the system with regard to the identification of slight deformations and its adaptability to numerous real structures.

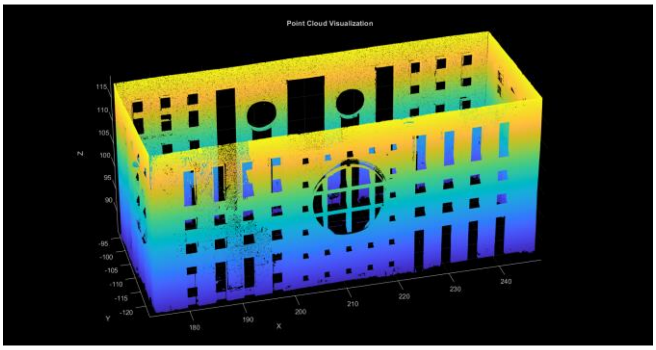

Figure 3: Point Cloud of a sample building Structure

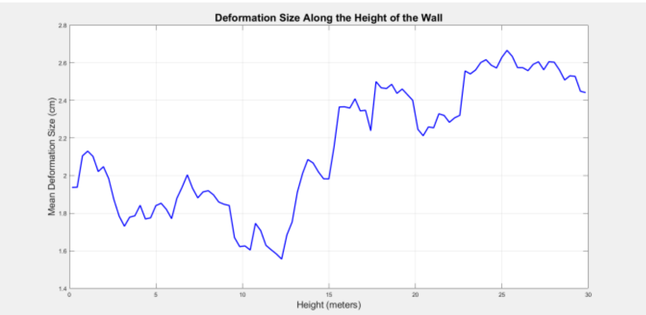

Figure 4:Deformation of a Cylindrical Structure showing manufactural defects

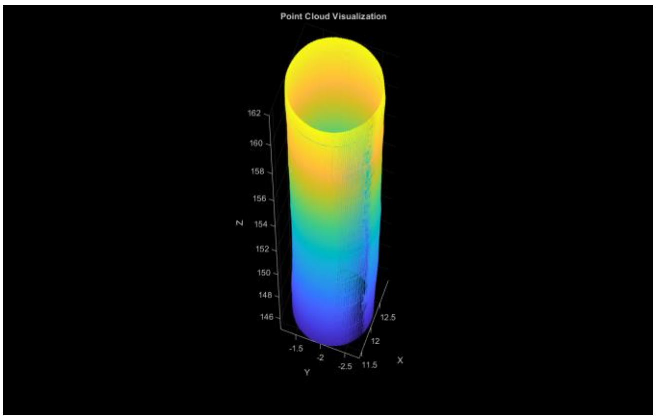

Figure 5:Point cloud of a sample cylendrical object

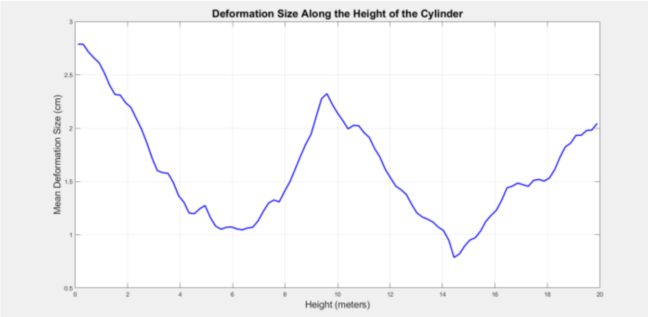

Figure 5: Deformation graph of a cylindrical structure showing manufactural defects

V. Verification

To validate the findings of our system, we analyzed deformations in structures located near a busy railway track. The results confirmed that the side facing the railway exhibited significantly higher deformations compared to other sides. This can be attributed to the constant vibrations and dynamic loads caused by the frequent movement of passenger trains along the route. The system's ability to detect and quantify these deformations accurately validates its effectiveness, as it successfully identified the expected structural wear in high-traffic areas. This real-world verification reinforces the robustness and reliability of the methodology. Given a table that prove this verification.

Structure	Distance from Railway trac (m)	Mean Deformation(cm)
AB1	40	16
AB2	120	2.5
HC	55	13
HB	50	11.5

In this table, AB1= Academic Building 1, AB= Academic 2, HC= Health Centre, HB= Hostel Block

VI. Conclusion

This paper introduced a machine learning-based framework for detecting and analyzing structural defects using TLS data. By fitting geometric models like planes and cylinders to point cloud data, our approach enables accurate identification and quantification of deformations in various structures. The method's effectiveness was demonstrated across multiple types of structures, with clear advantages in terms of automation, accuracy, and applicability to real-world scenarios. However, additional research is required to fine-tune the machine learning algorithms for specific structural types and to improve the comparative metrics. Future work will focus on integrating more advanced machine learning techniques and expanding the analysis to dynamic structures such as bridges and high-rise buildings.

VII. FUTURE APPLICATION

The automated system developed in this research holds potential for broader applications beyond conventional buildings. It can be adapted to monitor the structural health of complex and specialized structures, such as historical monuments, bridges, and statues, where preserving structural integrity is critical. Additionally, the system can be employed for infrastructure monitoring, including tunnels and railways, offering early detection of deformations caused by dynamic loads.

Future advancements could include integrating drone-based scanning to enhance data collection, particularly for hard-to-reach areas. As the system evolves, incorporating machine learning algorithms for pattern recognition could further refine defect detection, making it a valuable tool for structural health monitoring across a diverse range of structures.

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