Robotic IoT-Enabled 1D Line Scanner Integration for 3D Point Cloud Data Processing

Emre Ergin[1], Sven Stumm[1] and Sigrid Brell-Cokcan[1]

[1]The Chair of Individualized Production in Architecture, RWTH Aachen University, Germany
E-mail: office@ip.rwth-aachen.de

Abstract –

The integration of measurement systems and sensors is critical to advancing construction automation processes and aligning digital models with physical production realities. However, incorporating field measurement and inspection tools into digital fabrication is challenging due to the dynamic nature of construction sites. While point cloud sensors have been widely used in field robotics, there is still potential for more accurate, flexible measurement systems for component assembly. This paper presents progress in integrating an automated, precise measurement system into a robotic fabrication process to facilitate adaptive process planning and control, focusing on the prefabrication stage of structural steel assembly and node prefabrication. The implemented scanning system, a typically static 1D laser line profiler, is attached to an industrial robotic arm. Unlike traditional full system integration approaches, we adopt an extensible distributed network approach, that considers the sensor and robot as separate modular systems. By leveraging automated calibration and synchronization between robot and sensor, we achieve a 3D-capable approach. Our work describes an overarching, streamlined system that covers the entire process from calibration over registration up to mesh reconstruction, that proposes a modular integration through a network communications middleware. This will allow faster component replacement and system retooling without the need for typical hard wiring or embedded computation, allowing better integration or extension for potential multi-sensor data fusion. In addition, we propose an edge detection system for potential automatic adaptive weld path generation.

Keywords –

Line scanning, Robotics, Internet of Things, IoT, 3D Point Cloud, Sensor Calibration

1 Introduction

The Architecture, Engineering, and Construction (AEC) industry continues to evolve at a rapid pace, marked by the integration of innovative materials, methods, and new technologies. The increasing requirements of sustainability, high performance functionality, and complexity of structural forms is driving an ongoing digitalization in the industry. As new techniques emerge, they become an integral part of pushing the limits and reducing the constraints of manufacturability. This introduces new physical and digital systems that need to be integrated with low barriers to utilization, especially in manufacturing and construction phases where digital fabrication is becoming a more essential part of production. With the integration of digital processes comes the need for more data regarding processes, to both ensure quality, that is in need of precision due to the dominance of manual inspection in the industry, as well as monitor progress for optimization of production workflow. Monitoring of construction processes has been recognized as a critical factor in minimizing uncertainties [1].

Robotics have emerged as a transformative force in inspection and monitoring of prefabrication processes. Following research shows the potential in quality assurance of construction components through 3D laser scanning, such as [2], where non-contact measurement technique utilizing terrestrial laser scanning (TLS) is utilized, [3], proposes a comprehensive method integrating building information modelling (BIM) and 3D laser scanning technology, to assess the dimensions and quality of precast concrete panels, and [4] introduces a refined metric for evaluating point cloud quality in automated construction progress monitoring using the Scan-vs-BIM method. Most research in the area of construction application delves into the quality assurance by not explicitly detailing the 3D data gathering procedure.

For the visual inspection sensor integration to kinematic systems, two primary configurations are commonly utilized; eye-in-hand and eye-to-hand [5]. Each configuration offers distinct advantages. Eye-in-hand approach, which is utilized for the scope of this paper, ensures accuracy at tool center point (TCP) scale but offers limited environment sight, while eye-to-hand provides panoramic visibility albeit with slightly reduced precision at manipulator TCP.[5]

For the application of high-precision industrial inspections, line scanning sensors (1D, linear sensors, laser profilers) are widely implemented, where a single line of measurement points is collected at each exposure [6]. In order to integrate such measurement systems with other type of tools and systems, they need to be calibrated context-aware. A dynamic measurement system, where the laser profiler is integrated with a 6-DoF robotic arm, as opposed to the movement of a linear conveyor belt in the factory setting, requires precise identification of real-world coordinates for line scan image data, referred to as geo-referencing or mapping [7].

Achieving this requires accurate calibration of a sensor's intrinsic characteristics and extrinsic parameters. This is crucial considering that slight inaccuracies in calibration results in major deviations of scanned measurements based on changes due to orientation and distance to the object that is scanned. A method for compensation of measurement inaccuracies is the registration of line measurements against the already measured object. Within a distributed approach, the Internet-of-Things (IoT) aspect of implementation, the synchronization between robotic sensor positioning and the measurement is another important aspect that needs to be considered.

While using an IoT enabled or rather a distributed networked approach through an Industry 4.0 communication layer creates this additional challenge of data synchronization it also has a number of advantages such as:

- Easy retrofit for existing systems
- Easy expansion and replacement of sensor systems
- Capabilities for multi-sensor data fusion and mapping of data from multiple sources
- Easy upgrade of data processing systems
- Independence of data acquisition, processing, and visualization
- Data exchange for sensor-based process adaptation

This paper investigates the streamlined calibration of a 1D laser profiler and its integration with robot kinematics via IoT for precise 3D scanning. Our approach includes a modular system with IoT communication for synchronization, covering the entire process from calibration over registration up to mesh reconstruction. We further propose an edge detection method for adaptive weld path generation based on existing geometry.

2 Methodology and Evaluation

This section delves into the steps of implementing and setting up the required environment, starting from physical assets, tool calibration, IoT adaptation and finalizes at software development documentation a well as the results.

The test environment consists of KUKA KR30-3 F 6-axis robot arm equipped with Keyence LJ-X8400 Line Profiler measurement head, that is connected to the Keyence Raw Data Output Controller LJ-X8000A with dedicated cabling. The controller connection to a data processing computer is achieved through an Ethernet port. This project software is developed in Python environment, with the implementation of mainly Keyence LJ-X8000A Communication Library, Open3D, NumPy, Paho-mqtt, and SciPy-Spatial libraries amongst other peripheral packages.

The industry 4.0-compliant communication layer and IoT infrastructure is established through the use of Cloud Remote Control (CRC), developed by Robots in Architecture Research [8]. The CRC framework enables distributed registration, state, and command communication of various assets and facilitates easy integration of automation components to simplify the addition of new devices and replacement of devices in automated processes.

This setup ensures seamless data integration, enabling robots, devices, and sensors as network-connected things to communicate status and control commands to a centralized or multiple distributed control units in a local intranet. It also enables secure, gateway-controlled remote access to production environments and cloud computing. These potential features of remote access have not been realized in the approach described, and the benefits of Intranet-of-Things communication are more apparent.

The reference geometry to be scanned is a to-be-weld steel node connection, consisting of a perpendicular SHS 40x40x3 mm square tube and RO 42.5x2.5 mm round tube at 45º angle, on the upper surface of a HEA 200 steel beam, point weld for initial alignment as depicted in Figure 1.

Figure 1. Used reference object; steel node section.

2.1 Setup Environment

In the following section, the main components of the setup and the deployment process are described.

2.1.1 Tool Calibration

A Keyence LJ-X8400 Line Profiler measurement head is attached to the robot flange as shown in Figure 2. The device has a reference distance of 380 mm with measurement range of ±60mm in Z-axis and 210mm of line length at the reference distance[1]. Since the laser pointer is enclosed in the profiler itself, the reference distance and the middle of the line is chosen to be calibrated as TCP (where X is 105mm and Z 0mm). Unlike the traditional 4-point calibration method, where a sharp, physical calibration reference point is utilized in the robot work environment, the laser calibration is done by referring to a reflective marker and luminance values at given spot. The reason behind this is the occlusion between reflective mirror and laser projection at detecting sharp objects, as previewed in Figure 3.

[1] keyence.com/products/measure/laser-2d/lj-x8000 last visited 21/11/2023.

Figure 2. Keyence LJ-X8400 Line Profiler Head attachment to the flange of KUKA KR30-3 F Robot arm

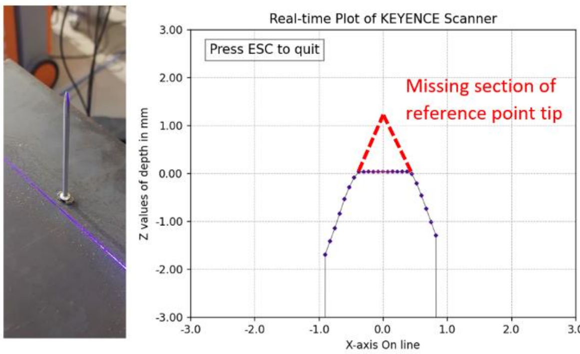

Figure 3. Preview of measurement occlusion and calibration

The proposed methodology of referring to a single reflective point is done by masking a reflective marker to a single tiny point and moving the laser middle to the reflective marker (see Figure 4 and Figure 5).

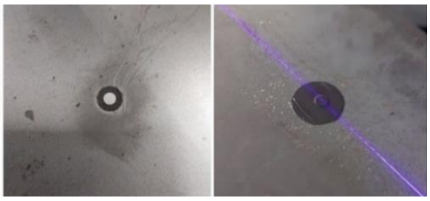

Figure 4. Scanning of reflective marker and masking to single point of reference

The achieved calibration point exhibits a measurement deviation of 0.19mm. The ABC 2-Point calibration procedure is conducted relative to a pre-calibrated robot base frame, a planar 300mm x 300mm steel plate of thickness 4mm.

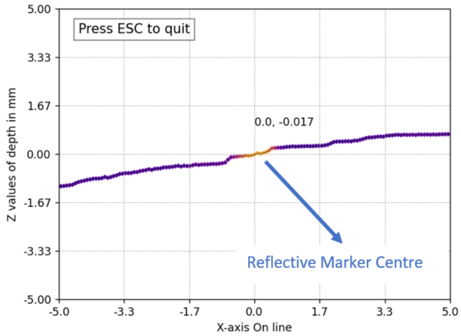

Figure 5. Determination of reflective marker center

The process involves aligning the laser consecutively with the planar surface edge for yaw axis (KUKA A), horizontal alignment in the scanned profile diagram over for pitch axis (KUKA C), and moving the robot along a trajectory, perpendicular to the laser projection, ensuring constant average height along the trajectory line for roll axis (KUKA B), as illustrated in Figure 6.

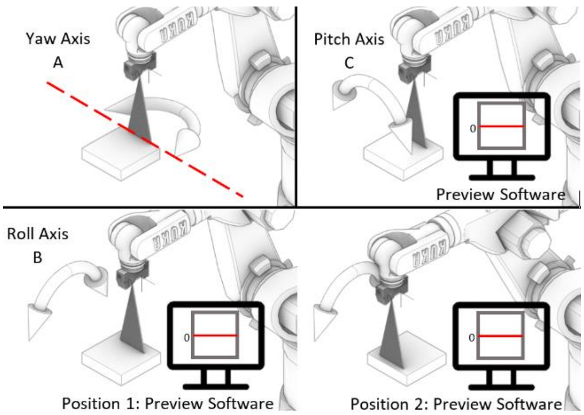

Figure 6. Calibration of orientation in Euler Angle

2.1.2 CRC Implementation of Robot

The objective of Cloud Remote Control (CRC) within the context of Industry 4.0 communication is to facilitate modular plug & produce work cells for robotic and other automated production systems. Therefore, the IoT part of CRC establishes a semantic networking interface for communication. This necessitates both seamless expandability and accessible adaptability of the automation equipment, such as KUKA industrial robot arm and various actuators as well as sensors. Central to this communication framework is the utilization of the JSON data format with standardized device-specific topics, enabling the seamless integration of novel devices into the system [8].

CRC establishes an Industry 4.0 communication or rather information layer based on the publish-subscribe model through MQTT (which can however be transferred to any publish subscribe communication protocols such as OPC-UA). This communication layer enables users to direct commands to specific devices by unique identifier while allowing devices to broadcast their statuses, facilitating coordination among various assets. The system integrates KUKA industrial robot arms, controlled via JSON strings sent to the *"devicename/cmd"* channel, managing diverse robot arm motions and commands. Moreover, device-specific states, such as selected tools, TCP velocity, and robot TCP frames, are consistently published to the *"devicename/state"* topic at approximately 50 Hz, ensuring effective synchronization and monitoring of device statuses within the defined environment.

2.1.3 CRC Integration of the Line Scanner

The software solution is designed to be integrated within the Cloud Remote Control (CRC) framework as an additional IoT device. As stated in the previous chapter, this framework enables seamless orchestration among individual assets within a workspace, facilitated by a control unit. Irrespective of the configuration or spatial arrangement of physical assets, the framework ensures wireless coordination among them.

For sensor systems the CRC differentiates between two basic types streaming and triggered sensors. As streaming sensors continuously stream their measurement data directly within their state message, these are only used for simple sensors that do not create too much load on the network. Triggered sensors can be identified by a command support, these sensors will only send out new data, if the appropriate command is sent. Figure 7 presents implemented commands that are supported by the processor for the 1D-Line sensor are as follows:

- "CapturePointCloud": Initiates the acquisition of a series of line scans to construct a 3D point cloud scan while the robot is in motion.
- "ExportPointCloud": Saves the recorded Point Cloud data locally in *.txt* and *.pcd* formats and generates a *.stl* mesh:
- "ClearPointCloud": Erases all recorded instances of point clouds.
- "CaptureSingleLine": Captures the current linear scan and stores the resultant point cloud data locally.
- "DetectEdge": Executes the edge detection script within the program, offering a preview of the results in an Open3D window.

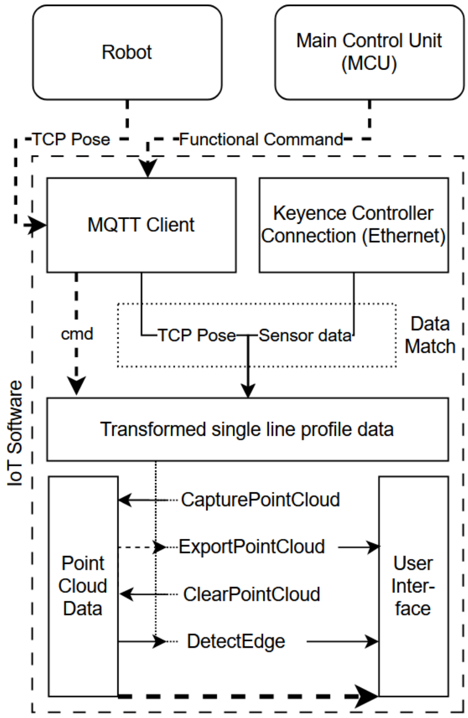

Figure 7. Line-Scanner Processor software architecture through MQTT

2.1.4 Device Synchronization

The need to synchronize laser profiler linear scan data with the robot TCP to acquire accurate 3D point cloud scans of specified objects is accomplished by transforming the sensorial data to the robot tool position in close to real time. To facilitate this process, a dedicated class called 'Transformer' has been developed.

The CRC robot controller integrates the robot as part of the network and streams the TCP values of the active tool in the KUKA frame data format {"X":0, "Y":0, "Z":0, "A":0, "B":0, "C":0} under the topic *"robotname/state"* approximately every 20 milliseconds. The Transformer class is initialized with the current TCP. This incoming data is then translated into a transformation matrix, thus allowing the transformation of the currently received instance of point cloud data from the Open3D library to seamlessly align with the calibrated robot TCP.

To synchronize the data from the different devices, the Point-Cloud-Processor adds arrival time stamps to the received data. Other forms of time synchronization using the NTP or PTP protocols are possible to account for network latency, but the results did not show the need to implement distributed clock synchronization. The use of timestamps at the time of measurement with synchronized clocks will be part of future research. However, the arrival timestamps are used to compare and align the laser profile data with the TCP.

2.1.5 Scanning and Meshing

The scanner was positioned approximately at a distance of 380mm from the geometrical center of the scan object. A total of 6 scanning paths are defined by a spherical coordinate system around this center with a range of ±40º in φ (KUKA C) and ±20º in θ (KUKA B) orientation. The scans were performed with a TCP speed of 3mm/sec (see Figure 8) and a linear path length of 150mm for each individual scan trajectory. The scanning trajectory, point cloud registration, and meshing is application and geometry dependent, the goal with the proposed node connection is to scan the intersections for the generation of welding paths.

First, the recorded mesh is down-sampled by a small value for the local deviation of each scan point (e.g., 0.5 mm) to account for scanner accuracy. Next, the point normals are estimated and aligned using Open3D functions to ensure consistent face orientation.

The mesh construction process uses the Poisson surface reconstruction method proposed by Kazhdan in 2006 [9] as implemented in Open3D. After the construction phase, the resulting mesh undergoes an additional smoothing process without compromising the authenticity of its shape [10]. Together, these filters contribute to the refinement of the mesh, ensuring a smoother appearance while preserving the true structure derived from the original point cloud data.

Figure 8. Constructed mesh preview with 6 scans, total computation time 8 minutes at robot speed of 3mm/sec.

2.2 Point Cloud Registration

The TCP shows an observable calibration error of 0.19 mm as further described 2.1.1 Tool Calibration. Despite its seemingly small value, this variance has significant implications for the alignment of the acquired data relative to the robot's base coordinates.

Figure 9 and Figure 10 show four different scans from two perspectives, each taken from previously mentioned 6 linear scan paths (2.1.5 Scanning and Meshing), to illustrate the noticeable differences in the results.

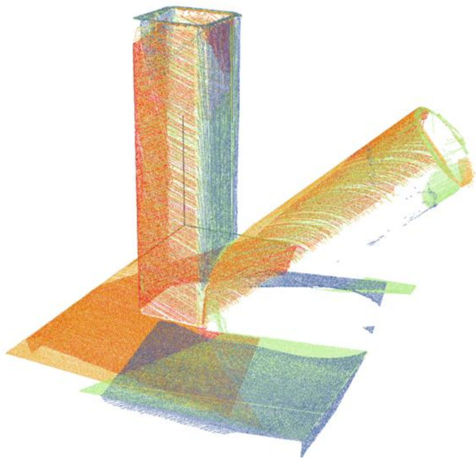

Figure 9. Comparison of four scans, from varying scanning angles, represented in red, orange, green and blue colored point clouds.

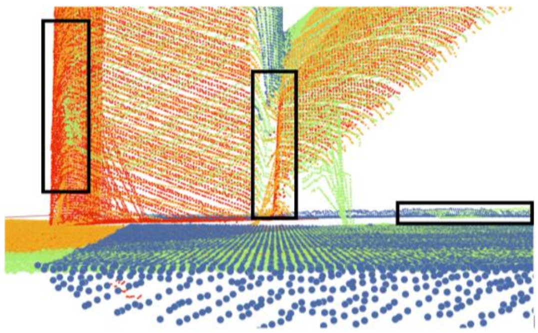

Figure 10. Close up comparison of four scans, from varying scanning angles, represented in red, orange, green and blue colored point clouds, visible unmatched points marked in black squares.

These visual representations indicate that all four scans are approximately aligned with the robot base frame in the context of world coordinates. While acknowledging the potential for improving global alignment through initial reference geometry, this discrepancy was ignored for the purposes of this work.

Upon closer inspection, as presented in Figure 10, there are noticeable misalignment of points between the point cloud collections. Such difference of orientation induces noise during meshing, consequently amplifying inconsistencies between the physical model and its digital representation.

To ensure increased quality results with minimal noise, an introduced approach involves employing a local point cloud registration method between captures, specifically leveraging the Open3D Multiway Registration[11]. This implementation integrates voxel down-sampling to optimize computation time while preserving data intensity. The optimization process is iterated twice: first to identify and prune uncertain alignments, then to refine the graph alignment.

Given the nature of linear point cloud scans, this implementation favors point-to-plane transformation estimation over the point-to-point Iterative Closest Point (ICP) registration method.

Figure 11 below shows a comparison between the meshed representations of six individual scans (shown in blue) and their counterparts after registration (shown in green). The contrast is present, where the surface quality and differs significantly, between the noisy unregistered point cloud and the registered point cloud collection with increased cleanliness.

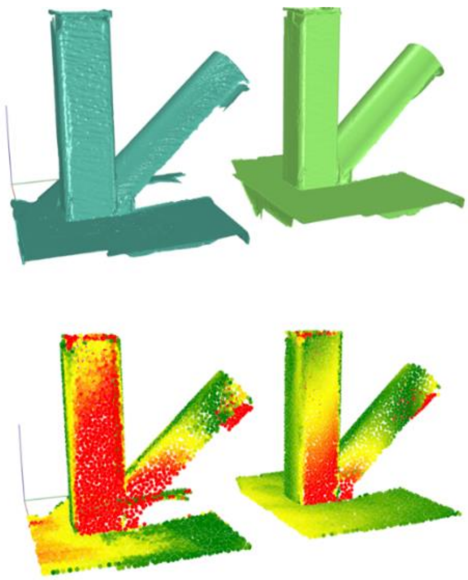

Figure 11. Mesh reconstruction without registration (top left) and with registration (top right) and at the bottom, corresponding deviation to the digital geometries presented in a gradient from green (less surface deviation) to red (more surface deviation)

The resulting registered 3D point cloud captures, and mesh construction provide a complex digital representation of the physical object and enable a wide range of data interpretation algorithms to be applied. In recent years, various researches have focused on the interpretation of point cloud data for gap detection[12], line segment extraction[13] and object detection[14] . Subsequent chapters will go through a simplified approach of edge detection algorithm for potential welding path generation as mentioned before.

2.2.1 Development of Edge Detection Approach

Integration of an edge detection process as described in [15][16]enables the extraction of vital information from the recorded point cloud data. As for the proof of concept, an edge detection approach is implemented within this project. The applied methodology within this paper leverages the eigenvalues of individual points, considering a specified number of neighboring points, to identify directional changes present at the edges within the collection [17].

A number of neighbor correspondences assigned as property for each point within the cloud and eigenvalues were calculated in each neighborhood, to be filtered by the distinctive eigenvalue changes, and masked with color red as to be seen in Figure 12.

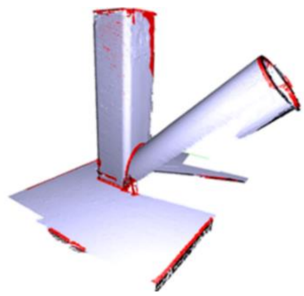

Figure 12. Potential candidates for detected edges depicted in red colored points.

Subsequently, potential edges are clustered using the Density-Based Scan Algorithm [18] implemented as part of Open3D, facilitates the grouping of the best-suited candidates in close proximity. The parameter of maximum correspondence distance to neighbors within a potential cluster is set to factor of 2.1 of the down-sampling value. Colored clustering is presented in Figure 13.

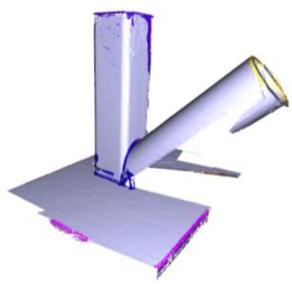

Figure 13. Density-based clustering of potential edges, represented in varying colors.

3 Outlook and Future Work

This proposed system presents an ideal solution for conducting detailed scans within smaller-scale assemblies. It can be seamlessly integrated with wide-range, 3D point cloud cameras mounted on robots to facilitate initial determination -offering global awareness to the robot- of the precise locations where detailed scans are to take place. An exemplar 3D detection workflow can be determined as Figure 14.

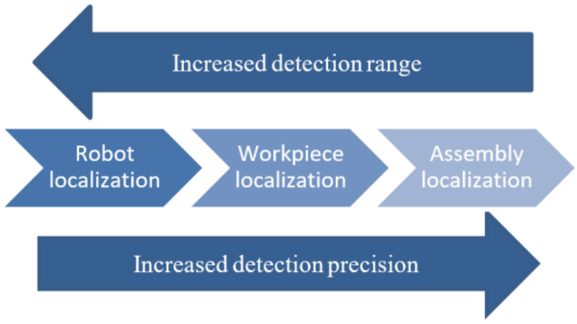

Figure 14. Potential 3D scanning workflow based on the relation between scan precision and range.

Beyond its visual quality assurance capabilities, this system opens doors for further advancements through the introduction of various algorithms tailored for detailed scanning. Potential optimizations of the system as well as a more comparative analysis of the chosen algorithms for each step will be part of future research. Beyond this some proposed developments could include:

1. **Layer Inspection and Height Comparison:** Specifically designed for wire-arc additive manufacturing applications, this algorithm can focus on analyzing sub-millimeter differences present in each layer, ensuring precise monitoring and quality control.
2. **Crack Detection and Repair:** A potential algorithm can address critical applications such as detecting cracks on steel bridge trusses and subsequent repair through welding, enhancing structural integrity and safety.
3. **Deflection Analysis:** Targeting welded workpieces, this application can conduct comprehensive deflection analysis. It identifies and analyzes deformations in assembly parts caused by high heat output, ensuring the structural integrity of the affected components.
4. **Individualized Scanning path planning:** Due to the directional and scalar limitations of the linear scanner, a path planning approach based on geometrical properties of the scanned objects, can be implemented to overcome the occluded parts at each individual scan.

4 Conclusion

Research and implementation of visual systems in robotics area all over the industries have been predominantly focused on global localization of mobile robotics. Such advancements benefit the construction industry as well, however, there's a noticeable absence of specific inspection methods catering to detailing, joining, and assembly in smaller scale. Additionally, the dynamic nature of construction environments necessitates adaptable process setups.

This paper presents a promising approach to enhance the capacity of a high-precision, single-dimensional laser profiler sensor by integrating it with a 6-DoF motion system, a robotic arm. The incorporation of IoT enables both systems to function independently and facilitates potential reconfiguration of the motion system, allowing for the potential of different types of kinematics-capable robots integration.

The results of the paper proved that the consistency in scale and detail as well as the location, relative to the robot base, of the scanned object with the physical world conditions. Additionally, the IoT infrastructure showed that the integration of various systems can be standardized, through a simplified M2M framework. While this proposed application lacks the real-time capability of model reconstruction, due to the high-loads of point cloud computation and the software only being deployed on prototyping level, the potential of implementing the controller software on cloud level and communication layer through potential 5G infrastructure remains to be implemented in the future development of this ongoing research project.

The precise comparison of digital to physical world can lead to new paradigms of individualized production in steel prefabrication. Enhanced automated inspection and quality control in steel construction assembly can streamline the regulation and safety assurance that is widely done manually in construction industry. This paper contributes to the foundational aspects of automating the digitalization process of real-world conditions, presenting a pathway for potential advancements in steel prefabrication within the construction sector in near future.

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