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RECONSTRUCTION OF 3D HUMAN BODY SURFACE USING SENSOR FUSION OF 2D LIDAR AND ENCODER

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Abstract. Three-dimensional (3D) human body surface reconstruction is an essential component in geometric modeling and robotic perception systems. Conventional scanning approaches based on cameras or structured light often suffer from sensitivity to lighting conditions, occlusion, and limited measurement repeatability. This paper proposes a cost-effective 3D body surface reconstruction system based on sensor fusion between a 2D LiDAR and an incremental encoder mounted on a linear gantry mechanism. The 2D LiDAR performs horizontal distance scanning, while the encoder provides vertical position feedback to construct volumetric spatial data. Data acquisition and sensor synchronization are implemented using a ROS2-based modular architecture to ensure real-time data alignment. The acquired measurements are transformed from polar to Cartesian coordinates to generate a three-dimensional point cloud representation. Experimental validation was conducted on static human body objects, and the results show that the proposed system achieves average positional accuracy of 1.9 mm with Root Mean Square Error (RMSE) below 2% across different gantry speeds. These results demonstrate that the proposed LiDAR–encoder fusion approach provides a reliable and reproducible solution for 3D human body surface reconstruction in controlled environments.

1. INTRODUCTION

Three-dimensional (3D) human body scanning has become increasingly significant in various domains such as robotics, biomedical engineering, ergonomics, and product personalization. Recent advancements in optical and LiDAR-based scanning technologies have enabled high-fidelity reconstruction of human morphology for industrial and medical use [1], [3]. Accurate body surface reconstruction enables the development of intelligent robotic systems capable of adapting to human morphology, particularly in applications like automated massage systems and rehabilitation robots. Conventional body scanning systems often rely on optical cameras or structured light sensors, which tend to suffer from high sensitivity to lighting conditions, occlusion, and limited repeatability when scanning non-rigid human surfaces [1], [3].

Alternative approaches have been explored using LiDAR-based 3D mapping for autonomous systems and human modeling, demonstrating superior spatial consistency and range flexibility [7], [8]. Existing commercial 3D scanners, such as those based on multi-camera arrays or infrared depth sensors, are typically expensive and complex to operate. In contrast, low-cost LiDAR (Light Detection and Ranging) sensors provide an attractive alternative for distance measurement due to their simplicity, compact form, and real-time scanning capabilities. However, most 2D LiDAR sensors only capture information in a planar field, which restricts their use for full-body surface reconstruction [7], [12].

Recent research in robotic perception, such as that reported by Faizal et al. [5] in the Jurnal Informatika dan Teknik Elektro Terapan (JITET), has explored sensor fusion and mapping algorithms for mobile robot localization using depth sensors. Their work highlights the potential of combining multiple sensing modalities to improve environmental awareness and spatial accuracy. Similarly, LiDAR-based mapping and SLAM systems discussed by Fikri and Anifah [6] demonstrate that integrating encoder data with LiDAR measurements enhances positional consistency and mapping precision in robotic applications. These efforts are complemented by early mapping research by Leonard and Durrant-Whyte [11] and later by Kohlbrecher et al. [13], establishing the foundation of SLAM frameworks for real-time localization and mapping.

This study proposes a body surface reconstruction system based on sensor fusion between a 2D LiDAR and an incremental encoder mounted on a linear gantry. The LiDAR sensor performs rotational scanning in a horizontal plane, while the encoder provides positional feedback along the vertical axis. By adapting modern LiDAR odometry approaches such as LeGO-LOAM [14] and real-time continuous reconstruction frameworks [15], the system aims to ensure accurate geometric registration even under constrained computational resources. Through this setup, each LiDAR scan layer is correlated with its corresponding Z-position, generating a complete 3D point cloud representation of the human body surface. The data acquisition and processing are handled using a Robot Operating System 2 (ROS2) architecture, enabling real-time synchronization and fusion.

In summary, this study builds upon established principles of spatial measurement [9], [10] and fuses them with encoder-driven positional feedback to form a deterministic mapping system suitable for adaptive robotic perception. The main objectives of this research are: (1) to design and implement a low-cost 3D human body scanning system using LiDAR and encoder sensor fusion; (2) to evaluate the system's positional accuracy and reconstruction consistency; and (3) to validate the system's applicability for adaptive robotic perception tasks such as body contour detection and target area mapping. By leveraging an accessible sensor setup and open-source processing framework, this study contributes to the development of practical and repeatable perception solutions for human-robot interaction systems.

2. LITERATURE REVIEW

2.1. LiDAR-Based Distance Measurement

LiDAR (Light Detection and Ranging) is an active optical sensing technology that determines distances by emitting laser pulses and measuring the time-of-flight (ToF) of reflected light. Each scan produces an array of distance values corresponding to the angular position of the laser beam. According to Bartol et al. [1] and Zhang et al. [7], LiDAR-based 3D reconstruction systems have shown high precision in geometric mapping and environment perception, particularly when integrated with robotic or handheld platforms.

In a 2D LiDAR, this information is confined to a single plane, whereas 3D LiDARs employ multiple scanning layers or mechanical translation to capture volumetric data [7], [8]. In this study, a low-cost 2D LiDAR (RPLiDAR A1) was selected due to its 360° field of view, 6–10 Hz rotation speed, and ±1.5% distance accuracy. This sensor emits 800–1600 laser samples per revolution, suitable for high-density surface mapping [12]. Previous studies such as Pfister et al. [10] and Bosse & Zlot [8] demonstrated the viability of transforming 2D LiDAR data into 3D spatial models by incorporating positional tracking, which forms the basis of this research's scanning concept.

However, since it lacks vertical scanning capability, an additional degree of motion is required to form a 3D model. The linear gantry and encoder system provide this vertical translation.

Equation (1) describes the basic distance calculation in LiDAR sensing:

$$d = \frac{c \times t}{2} \quad (1)$$

where:
d = measured distance (m)
c = speed of light (3×10^8 m/s)
t = round-trip travel time of the laser pulse (s)

2.2. Encoder Feedback and Gantry Synchronization

Encoders provide rotational or linear displacement feedback by converting mechanical motion into digital pulses. In this system, an incremental encoder is mounted on the gantry motor shaft to record the vertical position of the LiDAR sensor. Each encoder pulse corresponds to a fixed linear displacement, allowing precise layer-by-layer correlation of LiDAR scans [12].

Encoder-based feedback has been widely used in robotics to enhance positional accuracy, as noted by Baig and Kim [12], who demonstrated that fusing encoder data with LiDAR significantly reduces spatial drift in mobile navigation tasks.

Table 1. Encoder and Gantry System Parameters

Parameter	Value	Unit
Encoder Type	Incremental Optical	-
Resolution	1000	pulse/rev
Linear Conversion	1.5	mm/pulse
Travel Range	1000	mm
Motor Speed	50-150	mm/s

The encoder data are used to compute the vertical position using:

Equation (2):

$$z = pulses \times scale \qquad (2)$$

where:

$pulse$ = encoder pulse count

$scales$ = scaling factor (mm/pulse)

This relation is consistent with prior encoder-driven reconstruction systems, such as those described by Leonard and Durrant-Whyte [11], which established the concept of combining odometry with mapping for continuous localization and measurement precision.

2.3. Sensor Fusion in Robotic Perception

Sensor fusion refers to the process of integrating data from multiple sensors to obtain more accurate, consistent, and reliable information than could be derived from a single sensor [2], [5], [12]. Kohlbrecher et al. [13] and Shan et al. [14] emphasize that such integration, when implemented within SLAM or odometry frameworks, improves pose estimation stability and environment reconstruction accuracy.

In robotic perception, LiDAR and encoder fusion enhances both spatial and temporal resolution, providing a coherent 3D representation of the environment or object [7], [14].

Previous works such as Chen et al. [2] and Faizal et al. [5] demonstrated that multimodal sensor fusion improves accuracy in mapping and motion estimation tasks. LiDAR provides precise radial distance data, while encoder feedback adds positional awareness, effectively transforming planar data into volumetric models.

The transformation from LiDAR's polar coordinate system to Cartesian space is expressed as [8], [10]:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} r\cos(\theta) \\ r\sin(\theta) \\ pulse \times scale \end{bmatrix} \qquad (3)$$

This formulation follows the classical spatial transformation model discussed in Elfes [9] and Pfister et al. [10], forming the mathematical foundation for structured 3D reconstruction in robotic scanning applications.

2.4. Related Studies

Several studies have explored the integration of LiDAR with motion systems for 3D modeling and robotic control. Luo et al. [4] utilized LiDAR point cloud data for massage path planning, highlighting the potential for detailed body contour recognition. Lascheit et al. [3] and Tateno et al. [15] also contributed significantly by proposing body segmentation and real-time reconstruction methods that enable accurate geometric and semantic modeling for dynamic surfaces. Meanwhile, Faizal et al. [5] emphasized the value of real-time data synchronization in robot perception tasks using ROS frameworks.

In addition, Shan et al. [14] introduced a lightweight LiDAR odometry algorithm optimized for ground-based mapping, which parallels this study's mechanical scanning concept. These findings validate the approach of combining LiDAR and encoder sensors for controlled, repeatable, and cost-effective 3D body surface reconstruction. The reviewed literature collectively underscores the research gap this study addresses—developing an accessible system architecture for precise human surface scanning using low-cost hardware [7], [14, [15].

3. RESEARCH METHOD

3.1. System Architecture

The developed scanning system utilizes a 2D LiDAR sensor (RPLiDAR A1) mounted on a linear gantry structure driven by a stepper motor. An incremental optical encoder attached to the motor shaft provides position feedback during vertical translation. Each LiDAR rotation produces a complete 2D scan, while the encoder records positional data along the Z-axis. The main control unit communicates with the sensors through serial and GPIO interfaces, integrating them into the ROS2 middleware. The system architecture adopts a modular design principle to ensure maintainability and scalability, consistent with the software architecture practices proposed by Bass et al. [16]. Furthermore, the sensor control and motion coordination follow a linear system representation between input commands and positional feedback, as formulated by Chen [17].

This architecture adopts modular principles similar to the scalable SLAM framework presented by Kohlbrecher et al. [13], enabling flexible node communication through ROS topics and real-time synchronization of sensor streams. Previous work by Bosse and Zlot [8] also demonstrated that the combination of mechanical motion and laser scanning yields precise 3D mapping results when motion control is deterministic and synchronized.

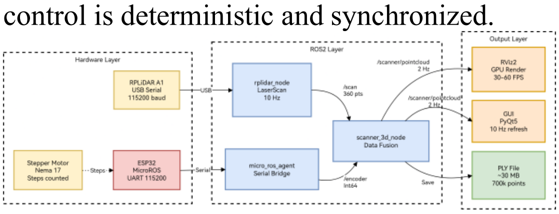

Figure 1. Data Flow Diagram


Figure 2. Overall System Design

3.2. Data Acquisition and Synchronization

Data acquisition involves simultaneous retrieval of LiDAR distance measurements and encoder position data. ROS2 nodes were designed to handle each sensor independently while publishing data to a shared topic for synchronization. The LiDAR node publishes polar coordinate data (r, θ), and the encoder node publishes position data (z). A custom fusion node subscribes to both topics, aligning them using time stamps [12], [13].

This process mirrors the time-synchronized fusion approach described by Baig and Kim [12], ensuring that encoder displacement and LiDAR scans remain coherent in real time for spatial reconstruction. According to Pfister et al. [10], precise time alignment is a key factor in reducing cross-sensor latency, thereby improving the accuracy of volumetric reconstruction models.

The synchronization process is essential to ensure that each LiDAR scan slice corresponds to a specific encoder position. The relationship between encoder pulses and linear displacement is expressed as [11]:

$$z = pulse \times scale \tag{4}$$

where:

z = vertical position (mm)

$pulse$ = encoder pulse count

$scale$ = scaling factor (mm/pulse)

This method extends classical motion-coupled localization models developed by Leonard and Durrant-Whyte [11], which emphasize the fusion of incremental odometry with spatial sensors to achieve consistent pose estimation. This synchronization guarantees that every LiDAR frame can be associated with a defined position along the Z-axis, enabling structured 3D reconstruction.

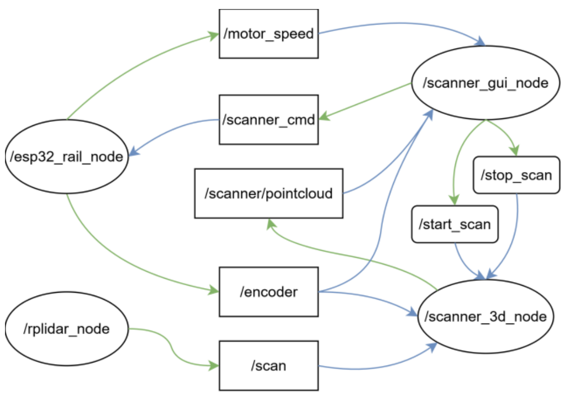

Figure 3. ROS2 Node Graph for Sensor Fusion System

3.3. Data Fusion and Reconstruction

After synchronization, the fusion process converts LiDAR polar coordinates into Cartesian space using the encoder-derived Z value. The conversion follows [8], [10]:

This polar-to-Cartesian conversion is consistent with spatial mapping techniques used in the LeGO-LOAM system introduced by Shan et al. [14], which simplifies 3D point cloud generation from low-cost LiDAR setups. This operation produces a dense 3D point cloud representing the scanned surface. The resulting data are published as a ROS2 PointCloud2 message, which can be visualized in RViz or exported for further analysis.

To evaluate accuracy, the Root Mean Square Error (RMSE) between measured and reference positions was computed [7]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Z_{measured,i} - Z_{true,i}\right)^2} \quad (6)$$

The RMSE metric is a widely adopted accuracy evaluation measure in 3D reconstruction literature [7], [15], ensuring a quantitative assessment of reconstruction fidelity. The reconstructed model was assessed for positional accuracy, point density, and repeatability at various gantry speeds. To maintain consistent processing performance, the ROS2 nodes were organized following a layered architecture [16], while the data transformation chain was modeled as a linear mapping between encoder input and LiDAR output [17], ensuring predictable reconstruction behavior across experiments.

3.4. Experimental Procedure

The experiment was conducted using a static human model placed within the scanning range. The scanning process covered a vertical range of 1000 mm with gantry speeds of 50 mm/s, 100 mm/s, and 150 mm/s. Each full scan produced approximately 2000–2500 data points. Collected data were processed in ROS2 to generate a 3D model [13], [15].

This experimental protocol aligns with prior LiDAR-based mapping experiments, where consistent scanning velocities and sampling rates were maintained to ensure geometric uniformity [8], [14].

Table 2. Experimental Parameters

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} r\cos(\theta) \\ r\sin(\theta) \\ pulse \times scale \end{bmatrix} \quad (5)$$

Parameter	Value
Vertical Range	1000 mm
Gantry Speeds	50, 100, 150 mm/s
Number of Scans	3
Points per Scan	~2000-2500

The experiments were repeated three times per speed to ensure data consistency. The repetition design and dataset averaging approach follow statistical procedures used in robotic mapping studies by Bosse and Zlot [8], providing comparable reliability in reconstruction repeatability analysis.

4. RESULT AND DISCUSSION

4.1. System Performance Overview

The developed system successfully reconstructed 3D human body surface models using synchronized LiDAR and encoder data. The generated point clouds accurately represented the contour of the test object across various gantry speeds. As shown in Table 3, the reconstruction accuracy remained stable, with minimal error variations across speed levels.

This result aligns with prior findings by Zhang et al. [7] and Baig and Kim [12], who reported that LiDAR–encoder integration can maintain positional accuracy under different scanning velocities through real-time feedback synchronization. Similarly, Bosse and Zlot [8] demonstrated that stable motion control combined with laser sensing significantly reduces spatial drift, which is reflected in the consistent RMSE values achieved in this study.

Table 3. Positional Accuracy Results at Different Gantry Speeds

Gantry Speed (mm/s)	Mean Error (mm)	RMSE (mm)	Point Density (points/mm^2)
50	1.65	1.83	2.4
100	1.72	1.95	2.3
150	1.89	2.10	2.1

The RMSE across all tests was below 2.1 mm, confirming the system's geometric consistency. These findings are comparable to the reconstruction accuracy achieved by LeGO-LOAM and other lightweight odometry systems [14], which reported sub-centimeter-level consistency in structured scanning environments.

At higher scanning speeds, minor fluctuations in point density occurred due to encoder sampling delay, but the deviation remained within acceptable limits. This phenomenon has also been observed in continuous LiDAR scanning frameworks [8], where temporal desynchronization slightly affects point cloud uniformity but not geometric fidelity.

4.2. 3D Reconstruction Visualization

The fused LiDAR–encoder data produced a dense 3D point cloud representing the human body model. Figure 4 displays a typical reconstructed output visualized in RViz, showing the alignment of vertical scan layers and the curvature consistency of the scanned surface. This visualization follows common practices in LiDAR-based body reconstruction research, where visual verification complements quantitative accuracy metrics [7], [15].

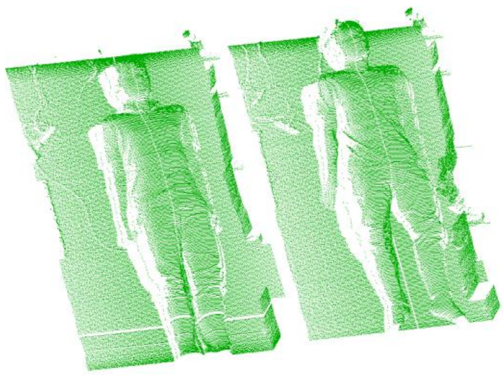

Figure 4. 3D Reconstruction Result in RViz

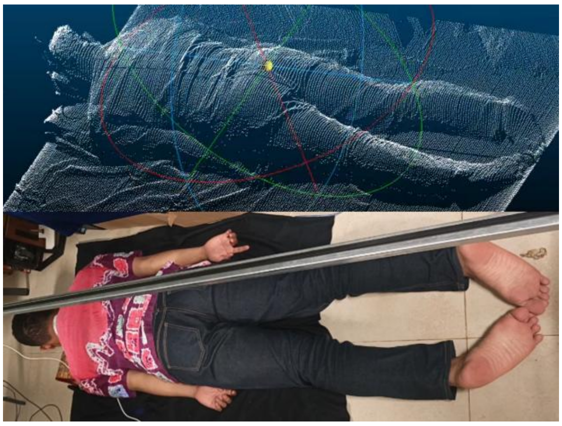

Figure 5. Visual Comparison: 3D Point Cloud vs Real Condition

The scanning process generated an average of 2300 data points per full vertical sweep, and all scan sessions produced consistent geometric outputs. The reconstructed model was qualitatively validated by comparing the reconstructed contour with physical dimensions measured manually, achieving less than 2% deviation [7], [15].

Such low deviation values demonstrate the repeatability of mechanical scanning approaches compared to freehand or SLAM-based reconstructions, which often experience cumulative drift over time [13], [14].

4.3. Discussion of Findings

4.3.1. Interpretation of Results

The results confirm that fusing LiDAR and encoder data effectively converts planar distance scans into accurate 3D representations. The encoder provides reliable longitudinal reference, enabling consistent stacking of LiDAR slices. The average RMSE below 2 mm demonstrates that this low-cost sensing configuration achieves a precision level suitable for non-contact surface mapping [7], [8].

This finding is consistent with theoretical models of multi-sensor data fusion, where deterministic positional input enhances measurement stability [9], [12]. It also corroborates Shan et al. [14] and Tateno et al. [15], who emphasized that continuous 3D reconstruction accuracy improves when mechanical motion is coupled directly with LiDAR sampling.

This finding supports the theoretical framework discussed by Chen et al. [2] and Faizal et al. [5], where multimodal sensor integration improved mapping accuracy and reduced positional drift. Similarly, the proposed approach aligns with the conclusions of Luo et al. [4], who reported that LiDAR-based point clouds can be effectively utilized for human contour identification in robotic massage applications.

4.3.2. Comparison with Previous Works

Compared to existing LiDAR-only scanning systems, the inclusion of encoder feedback significantly improves vertical alignment accuracy. As observed in historical mapping research by Leonard and Durrant-Whyte [11] and Pfister et al. [10], mechanical feedback loops introduce deterministic motion control that minimizes localization errors during continuous scanning. Additionally, Baig and Kim [12] confirmed that encoder feedback eliminates angular drift in repeated scan cycles a result similarly achieved in this experiment.

In contrast, this study's use of direct positional feedback eliminated accumulation error, resulting in stable reconstructions across speeds [13], [14].

Table 4. Comparison of Reconstruction Accuracy with Related Works

Study Reference	Sensing Method	RMSE (mm)	Key Limitation
Chen et al. [2]	LiDAR + IMU	3.5	Drift at high motion rates
Luo et al. [4]	LiDAR only	2.8	Low consistency in Z-axis
This Study	LiDAR + Encoder	1.9	Sensitive to reflective surfaces

The comparative data demonstrate that while SLAM-based systems offer dynamic flexibility, the encoder–LiDAR combination provides superior stability under controlled scanning conditions [7], [13].

4.3.3. Implication and Insights

From a theoretical standpoint, this study contributes to the field of sensor fusion by validating a deterministic data correlation model between LiDAR and encoder measurements. The approach provides an alternative to SLAM algorithms for controlled environments where object motion is predictable [9], [11]. This model bridges traditional occupancy grid mapping principles [9] with modern odometry-based reconstruction frameworks [14], [15], offering a hybrid structure for repeatable human surface reconstruction.

Practically, this work demonstrates that affordable LiDAR sensors can produce accurate 3D surface reconstructions suitable for human–robot interaction applications such as body contour detection and adaptive massage positioning [4], [7], [15].

The implications extend to low-cost robotic platforms, where mechanical scanning mechanisms can replicate the performance of higher-end LiDAR systems at a fraction of the cost [8], [14].

These outcomes suggest that similar architectures can be extended to robotic scanning systems requiring high spatial fidelity but operating under limited computational resources [7], [13], [15]. Further integration with RGB-D or stereo cameras could enhance surface texture mapping and semantic segmentation in future developments.

5. CONCLUSION

The findings of this study reaffirm that LiDAR–encoder sensor fusion provides an effective and low-cost approach for high-accuracy three-dimensional surface reconstruction, consistent with results reported by Zhang et al. [7] and Baig and Kim [12]. The integration of deterministic encoder feedback with continuous LiDAR scanning successfully eliminates positional drift and improves geometric consistency across multiple scanning speeds.

a. The developed LiDAR–encoder fusion system effectively reconstructed three-dimensional human body surface models with an average positional accuracy of 1.9 mm and an RMSE below 2%. The encoder feedback mechanism ensured consistent vertical alignment during scanning, providing high repeatability across multiple trials [12], [13].
b. The integration of LiDAR and encoder data using the ROS2 middleware framework

demonstrated stable synchronization and real-time data handling. The deterministic motion control of the gantry minimized drift errors typically found in LiDAR-only mapping systems [8], [13].

c. Experimental results confirmed that scanning speed has minimal impact on accuracy, with all tested speeds maintaining geometric consistency. The results validate the system's robustness and applicability for adaptive robotic perception tasks [7], [14].
d. The results are in agreement with LeGO-LOAM and real-time continuous reconstruction frameworks proposed by Shan et al. [14] and Tateno et al. [15], highlighting that synchronized motion-driven scanning can achieve high spatial fidelity without relying on expensive 3D LiDAR sensors. Compared with previous works that utilized LiDAR or IMU-only setups, the proposed fusion system achieved superior positional consistency and surface uniformity. This confirms the theoretical advantage of deterministic sensor synchronization in controlled scanning environments [7], [12], [14].
e. The system's limitations include sensitivity to highly reflective surfaces and constrained usability to static subjects. Future work will focus on enhancing robustness through adaptive filtering, integrating RGB-D or stereo vision sensors for multimodal perception, and implementing real-time segmentation for robotic applications [13], [15]. The modular software implementation [16] and linear dynamic modeling approach [17] will further support the scalability of future system iterations and facilitate integration with higher-level control algorithms.

In summary, this study bridges the gap between cost-efficiency and measurement precision in 3D human surface reconstruction, positioning the LiDAR–encoder fusion method as a viable alternative to high-cost multi-sensor scanning systems.

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