Development of a Two-wheel Vision-based Tactile Sensor for Continuous Sensing of Large Surfaces

Mohammad Amin Mirzaee[1], Hung-Jui Huang[2], and Wenzhen Yuan[1]

***Abstract*— Conventional vision-based tactile sensors (VBTS) offer high-resolution shape reconstruction, yet their limited sensing areas and susceptibility to damage during sliding make them unsuitable for continuous, large-scale inspections. To overcome these limitations, we present GelBelt, a novel VBTS capable of uninterrupted surface scanning. GelBelt utilizes an elastomeric belt guided by two wheels, enabling smooth movement across surfaces. Experimental evaluations demonstrate the sensor's effectiveness in 3D shape reconstruction of large-scale surfaces.**

I. Introduction

Automated surface inspection to reduce production defects and prevent component damage has long been demanded [1]. As industries expanded and increasingly integrated automation, the need for reliable inspection solutions became more demanded [2], [3]. Accurate surface evaluation is essential for maintaining high product standards, ensuring operational safety, and preventing system failure.

Vision-based tactile sensors (VBTS) offer a promising solution by balancing performance with cost-effectiveness. Systems like GelSight [4] use high-resolution cameras to gather precise surface information [4]–[8]. Although conventional VBTS designs offer high accuracy, they are limited by their small sensing areas and the rigidity of the elastomeric membrane. This design constraint makes it difficult to gather continuous data over large surfaces, as the sensor must be repeatedly lifted and pressed [9]. While cylindrical VBTSs [10], [11] with rolling mechanisms enable continuous sensing, they provide only narrow tactile frames with varying indentation depths, making them less practical for large-scale surface inspections.

This paper introduces GelBelt [12], a novel VBTS designed to address these challenges. GelBelt decouples the elastomer from the rigid plate, allowing it to function as a belt that rolls over two wheels. This configuration ensures uninterrupted tactile data acquisition while maintaining extensive surface contact within each frame. Our experiments validate the sensor's performance by comparing estimated surface normal maps with ground truth values. GelBelt achieved an average alignment score of 0.97 (dot product). We use markers to estimate contact forces up to 60 N and surface angles across ranges of -10° to 10° and -3° to 3°.

II. Sensor Overview

GelBelt features a two-wheel system with a flexible belt made from sensing materials, as shown in Figure 1 and Figure 2 E. During scanning, the belt moves across the wheels while the optical components, fixed between the wheels, capture surface contact data. Since elastomers tend to adhere to acrylic, we attach a thin, transparent low-friction layer to the inner side of the belt, facilitating the motion. The belt's outer surface is coated with reflective powder to capture fine details, with additional markers at the edges for position tracking. In addition to mounting the sensor on a robot arm or holding it in hand, GelBelt can traverse surfaces like a small vehicle by incorporating motors on the wheels, as shown in Figure 1. The overall dimensions of the sensor are 175 $mm \times 80\ mm \times 65\ mm$ $(L \times W \times H)$, with a sensing area of $40 \times 60\ mm^2$.

[1]Mohammad Amin Mirzaee and Wenzhen Yuan are with University of Illinois at Urbana-Champaign, Champaign, IL, USA {mirzaee2,yuanwz}@illinois.edu

[2]Hung-Jui Huang is with Carnegie Mellon University, Pittsburgh, PA, USA {hungjuih}@andrew.cmu.edu

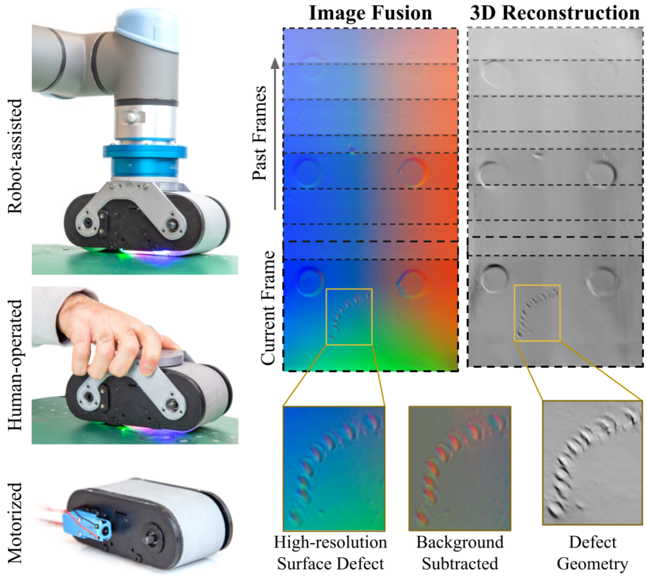

Fig. 1. The GelBelt sensor can be mounted on a UR5e robotic arm, operated by a human, or motorized to scan large surfaces.

We fabricated the belt using Silicone XP-565 (Silicone Inc.) coated with diffusive aluminum powder and laser-engraved markers along the belt's edges. A clear tape was used as the intermediate layer between the belt and acrylic. The tape is thin and flexible enough to wrap around the wheels while maintaining a stiff, low-friction surface against the acrylic.

GelBelt utilizes photometric stereo techniques for estimating surface normals [7]. We build on the method outlined in [13] to predict surface normal maps from GelBelt's tactile images using a simple MLP model. To reconstruct a larger surface, we combine data of multiple tactile images as the belt moves across it. We estimate the sensor's planar movement between consecutive frames using optical flow [14] initialized by marker movement and applied to the normal maps. We register each local normal map with the global map based on the estimated poses while averaging overlapping regions. We also use side markers to train and test a simple MLP model to estimate the contact angle and normal force. Markers are detected using the *blob_dog* function from the Scikit-image Python library.

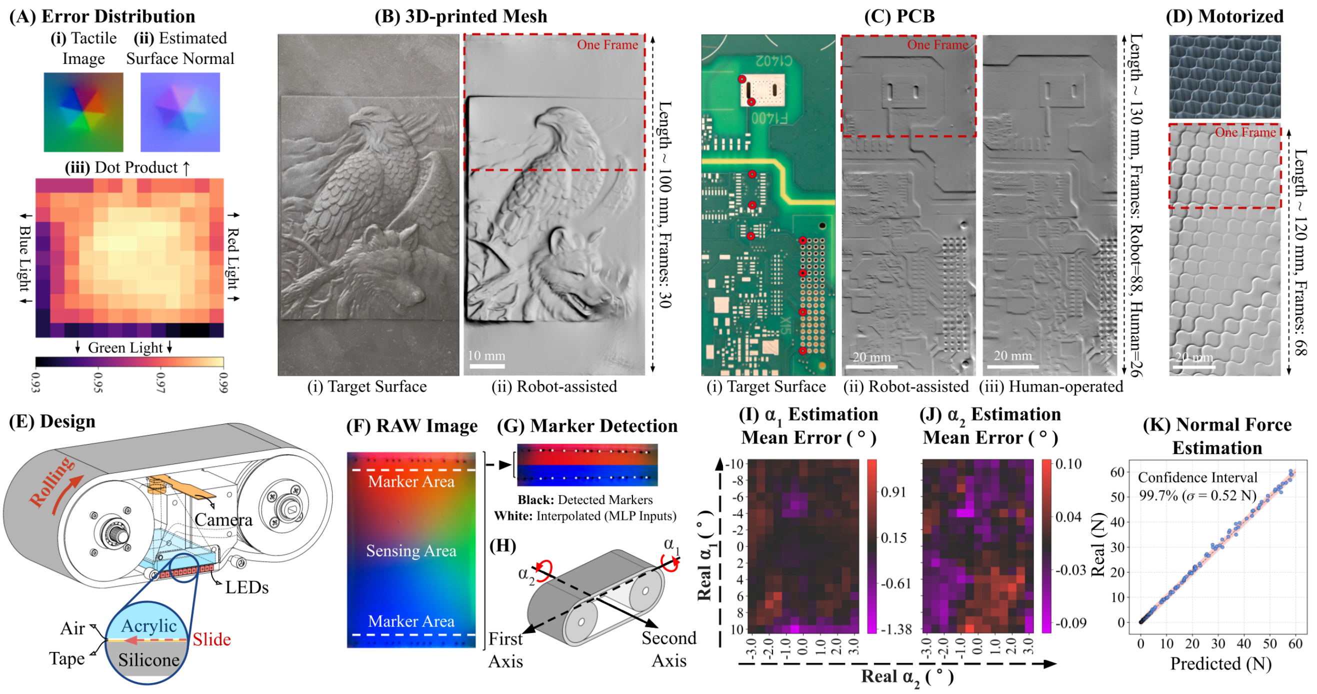

Fig. 2. (A) 2D normal estimation accuracy plot over the sensing area. (B) 3D-printed mesh surface reconstruction. (C) PCB surface reconstruction in robot-assisted and manual modes. We evaluate the planar distance and angle drift for the red control points. (D) We attached motors for standalone sensing. (E) Highlighted optical components. (F,G) Splines are fit to the detected side markers. 2×10 white points are interpolated as model inputs. (I,J) Mean errors of estimated angles. Maximum standard deviation is about 1 and 0.1 degrees for α_1 and α_2 (K) Normal force prediction plot.

III. Experiments

A. Surface Geometry Reconstruction

To quantify the reconstruction accuracy, we press a hexagonal indenter with known dimensions at 143 positions across the sensing area, arranged in a 13×11 grid. The sensor's surface normals are estimated for each indentation, and we compute the dot product between the predicted normals and the ground truth. The accuracy distribution for the 143 measurements is plotted in Figure 2 Aiii.

To reconstruct a larger surface, we combine data from multiple tactile images as the belt moves across it. Figure 2 Bii and Cii display 3D meshes reconstructed from a printed mesh (created using a Form 3+ printer by FormLabs) and a PCB, respectively using a UR5e robot. These results demonstrate GelBelt's capability to accurately stitch and capture fine surface details across extended areas, producing high-quality 3D models. To our knowledge, GelBelt is the fastest vision-based tactile sensor for continuous scanning, speeds up to 45 mm/s with the potential for even higher speeds.

We also tested GelBelt under manual operation, where a human operator guided the sensor across surfaces. As shown in Figure 2 Ciii, despite the inconsistencies introduced by manual handling, the sensor maintained accurate surface reconstruction, demonstrating its robustness even in less-controlled environments. We also explored autonomous sensing by attaching motors to the sensor, allowing it to roll over surfaces independently. Figure 2 D shows the results of motorized scanning on a honeycomb laser bed.

We analyzed the distances and angles of line segments formed by 9 control points (red circles in Figure 2 Ci) by comparing the real image (pixel-to-mm scaled via caliper) and reconstructed PCB surfaces to assess planar drift. The mean absolute errors in robot-assisted mode are 0.33 mm and 0.35°. In manual mode, they are 0.38 mm and 0.28°.

B. Contact Force and Angle

Figure 2 G shows a sample image of the marker area with detected markers (black dots), fitted spline, and feature points (white dots). We collected data for rotations in two axes, shown in Figure 2 H, using a UR5e robot. We change contact angles in the range of -3 to 3 degrees in the x-axis direction (wheelbase axis) and -10 to 10 degrees in the y-axis (wheel axis) with intervals of 0.5 and 1 degree, respectively, for 35 iterations while rolling the belt.

Figure 2 F-J show that the model accurately estimates contact angles for both axes. However, the estimation error is slightly higher for the x-axis compared to the y-axis, and the error increases with larger angles. Figure 2 K demonstrates that the force estimation model predicts the applied normal force with good precision.

Figure 2 K shows that the force estimation model can predict the applied force with good accuracy over the entire range of the study with an error of 1 N (95% confidence interval). Contact force and angle estimation results show the potential application of the markers' motion as feedback in future work on robust scanning of larger surfaces.

IV. Conclusion

This paper introduced a novel design approach for vision-based tactile sensors that enables rapid and efficient surface scanning. We presented the design, fabrication, and evaluation of the proposed GelBelt sensor, demonstrating its effectiveness in practical applications. The mechanical design features an elastomeric belt mounted on two wheels, facilitating continuous movement over surfaces and enhancing scanning versatility. Both qualitative and quantitative evaluations confirm the sensor's reliability, with low reconstruction and alignment errors. Future work will improve the sensor design to scan curved surfaces while maintaining sufficient contact using contact force and angle feedback.

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