Development of a High-Speed Event Vision-Based Roller Tactile Sensor for Large-Surface Inspection

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***Abstract*— Large-scale industrial surface inspection requires rapid capture of high-resolution 3D geometry. Vision-based tactile sensors (VBTSs) provide fine local shape sensing, but standard planar designs rely on slow press-and-lift acquisition, while continuous sliding, roller, and belt variants remain limited by friction, motion blur, and camera frame rate. We present a high-speed event vision-based roller tactile sensor for continuous large-surface inspection [1]. The sensor combines rolling tactile contact with a modified event-based multi-view stereo (EMVS) pipeline. At scanning speeds up to $0.5\,$m/s, the system achieves mean absolute error below $100\,\mu$m, approximately $11\times$ faster than prior continuous tactile sensing methods. We further demonstrate high-speed Braille reading at $2.6\times$ the speed of previous tactile approaches.**

I. INTRODUCTION

Surface inspection is critical in aerospace and automotive manufacturing, where sub-millimeter accuracy is needed to detect cracks, dents, and coating defects [2]–[4]. Non-contact optical scanners can cover large areas quickly but are sensitive to lighting and challenging reflectance [5]. Vision-Based Tactile Sensors (VBTSs) overcome much of this by using internal illumination and elastomer deformation to recover high-resolution local geometry [4], [6]. However, most VBTSs remain limited to slow "press-and-lift" acquisition, making large-area inspection impractical [7].

Continuous tactile scanning has been explored through roller- and belt-based VBTSs [8], [9], but frame-based cameras still impose strict speed limits through motion blur and low frame rates. Existing systems therefore operate below 0.1 m/s for 3D reconstruction [8], [9], which is inadequate for high-throughput inspection. Event cameras offer a compelling alternative: they asynchronously report brightness changes with microsecond temporal resolution and intrinsic robustness to motion blur [10]. Previous Neuromorphic VBTSs (NVBTSs) have exploited these properties for slip detection and grasp-related perception [11]–[13], but often at reduced spatial resolution due to sparse marker tracking, leaving continuous high-speed 3D tactile reconstruction largely unexplored.

This paper presents, to the best of our knowledge, the first high-speed event vision-based roller tactile sensor for large-surface inspection [1] (Fig. 1). The system combines rolling contact, a modified EMVS pipeline, and multi-reference Bayesian fusion to improve depth consistency on the curved roller surface. It achieves continuous 3D scanning up to $0.5\,$m/s with sub-$100\,\mu$m MAE, about $11\times$ faster than prior continuous tactile sensing, and also demonstrates high-speed Braille reading.

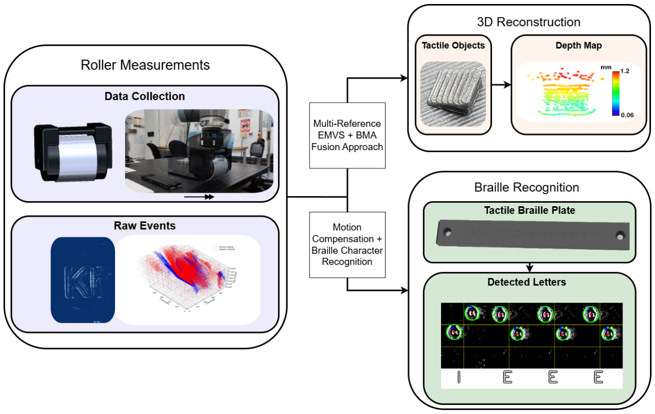

Fig. 1. The roller tactile sensor system (mounted on UR10 robotic arm) captures asynchronous events during continuous rolling (left) and utilizes event-based algorithms for both 3D surface reconstruction (top right) and fine feature recognition, demonstrated via Braille reading (bottom right).

II. METHODOLOGY

The proposed sensor consists of a cylindrical acrylic roller coated with a soft translucent elastomer (Smooth-On Sorta-Clear 18) and reflective membrane, viewed by an event camera (DVXplorer mini) under ring illumination (Fig. 2a). During rolling contact, local surface geometry deforms the elastomer and induces brightness changes on the reflective layer, producing an asynchronous event stream that encodes tactile structure. The prototype has a $47\,$mm roller radius and an effective sensing area of approximately $40\times 30\,$mm. To recover 3D geometry, we adapt Event-Based Multi-View Stereo (EMVS) [14] to rolling tactile sensing. Each event $e_k = (x_k, y_k, t_k, p_k)$ is assigned a camera pose by linearly interpolating the robot trajectory to the event timestamp. Events are accumulated over a $20\,$ms window and back-projected through a constrained disparity-space image (DSI) spanning the expected contact depth of 43–47 mm, discretized into 500 planes. For each reference view, local maxima in the DSI yield a semi-dense depth map. Constraining the search range using the roller geometry improves both efficiency and depth precision.

A single EMVS reference view is sensitive to the curved roller geometry, since the same surface patch is observed at different relative depths across the rolling window [15]. We therefore reconstruct three depth maps from the same event window using the start, midpoint, and end poses, denoted Z_s, Z_m, and Z_e. The start and end maps are warped to the midpoint frame using the calibrated camera model and relative pose transforms, and the final depth

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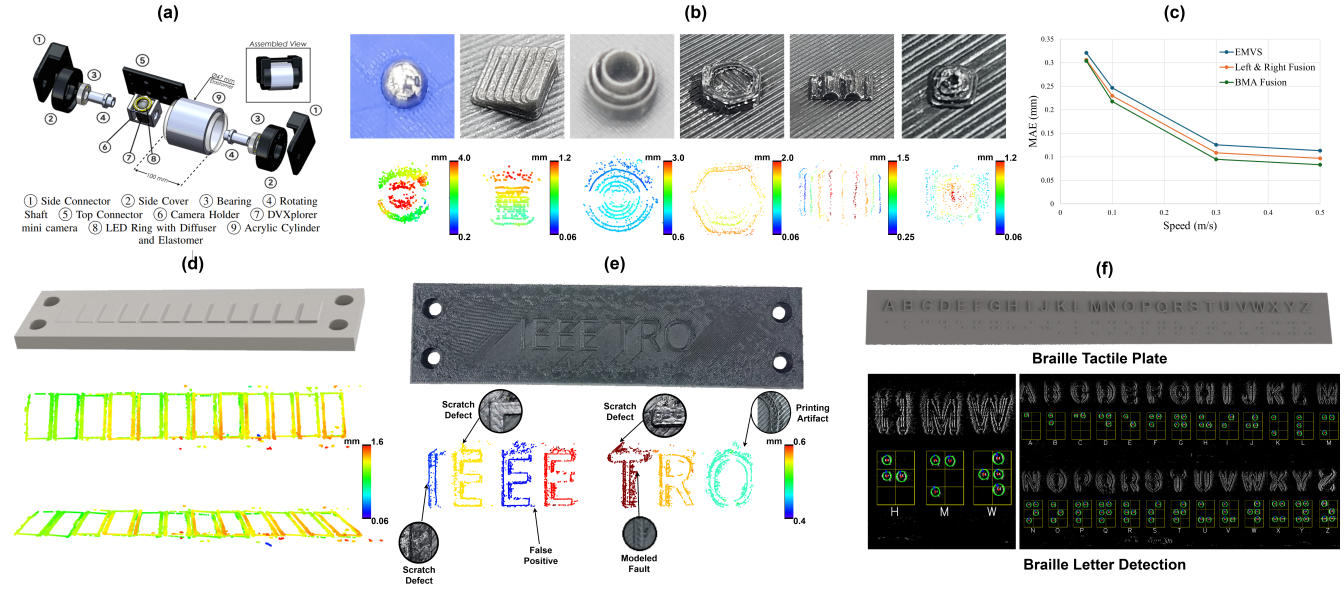

Fig. 2. **(a)** Mechanical design of roller with exploded and assembled view **(b)** Single object reconstruction **(c)** Speed (m/s) against MAE (mm) comparing baseline EMVS and BMA **(d)** 3D printed varying-height line array (top) and its corresponding reconstruction (bottom) **(e)** 3D printed letter plate with varying-height letters and induced defects (top) and its reconstruction (bottom) **(f)** High-speed braille reading demonstration on tactile plate.

estimate is computed by Bayesian model averaging: $Z_f = \sum_{i\in\{s,m,e\}} w_i \cdot W_i(Z_i)$, where $W_i(\cdot)$ warps the depth map from reference time t_i to the midpoint frame and w_i are fixed fusion weights, determined once by minimizing mean absolute error (MAE) on a calibration sphere of known geometry. This multi-reference strategy reduces curvature-induced bias, suppresses spurious DSI artifacts, and improves depth consistency during high-speed rolling. For 2D tactile feature recognition (e.g., Braille reading [16]), we use a contrast-maximization motion compensation pipeline [17], [18]. By warping asynchronous events using the sensor's known linear velocity, we accumulate an Image of Warped Events (IWE), producing sharp, high-contrast 2D representations even at high scanning speeds. The resulting IWE is then processed with a lightweight Braille-recognition pipeline: a single-cell Region of Interest (ROI) is denoised, divided into the standard 2 × 3 Braille grid, and analyzed with Hough circle detection to form a 6-bit code matched to a Braille lookup table.

III. EXPERIMENTS AND RESULTS

The sensor was mounted on a UR10 robotic arm and rolled across target surfaces at controlled speeds from 0.05–0.5 m/s. We evaluated six small objects with known geometry for single-contact reconstruction as seen in Figure 2b (4mm metal sphere, stairs, sparse sphere or concentric circles, bumps, pyramid, and a hexagon with a shallow recess), two larger 3D-printed plates for stitched large-surface inspection (Fig. 2d & Fig. 2e), and Braille plates for fine tactile feature recognition (Fig. 2f). Unless stated otherwise, results are averaged over five trials. Reconstruction accuracy is reported as mean absolute error (MAE) on valid reconstructed points within the contact region, using the known object geometry as ground truth.

The multi-reference BMA fusion consistently improved over baseline EMVS on the test objects, reducing average MAE by 25.2% at 0.3 m/s (Fig. 2c). The overall average MAE ± standard deviation was 0.0620 ± 0.0047 mm across all six test objects. Reconstruction was most accurate for objects with distinct edges or repeated discontinuities, such as the sparse sphere (0.0120 ± 0.0010 mm) and stairs (0.0581 ± 0.0026 mm), while smooth or self-occluding geometries such as the solid sphere (0.0946 ± 0.0081 mm) and recessed hexagon (0.0808 ± 0.0042 mm) were more challenging.

For larger surfaces, successive depth maps were stitched along the rolling trajectory with ICP refinement. On a varying-height line-array plate, the sensor achieved 0.0638 ± 0.0055 mm MAE across the full surface. On a letter plate with varying heights and induced defects, it achieved 0.0596 ± 0.0035 mm MAE while recovering local scratches and modeled faults (Fig. 2e). As illustrated in Figure 2f, the sensor was also used for Braille reading at 0.5 m/s, 2.6× faster than previous tactile approaches [16], indicating that the platform can also support high-speed fine-feature recognition beyond 3D reconstruction.

IV. CONCLUSION

This paper presented a high-speed event vision-based roller tactile sensor for continuous large-surface inspection. By combining rolling tactile contact with event-based multi-view stereo and multi-reference Bayesian fusion, the system achieved continuous 3D scanning at up to 0.5 m/s with sub-100 μm error, 11 times faster than prior continuous tactile sensors while maintaining comparable accuracy. The results show that event-based tactile sensing is particularly effective for sharp features and defects relevant to industrial inspection, while remaining more limited on smooth, featureless surfaces. All experiments were processed offline on a single laptop CPU, and future work will focus on denser reconstruction and force/contact control for curved surfaces.

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