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Automated 2D & 3D Decal Application using Sensor Based Model Detection

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Abstract: This project presents a fully automated system for applying 2D and 3D decals onto objects using sensor-based model detection. The system integrates LiDAR and camera sensors to accurately identify and localize target surfaces in real-time. By leveraging these sensors, the model can dynamically adapt to varying object geometries and positions without the need for manual alignment. Once detection is complete, a robotic arm precisely applies the decal, ensuring high accuracy and consistency across different surfaces. This approach enhances manufacturing efficiency, reduces human intervention, and improves the reliability of decal placement in both industrial and creative applications.

Keywords: *2D/3D Object Detection.*

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I. INTRODUCTION

In modern manufacturing and customization processes, the accurate and efficient application of decals—both 2D (such as stickers or labels) and 3D (such as surface-conforming textures or embossed patterns)—plays a crucial role in product aesthetics and branding. Traditionally, decal application has relied heavily on manual labor, which is prone to human error, inconsistency, and inefficiency, especially when dealing with complex geometries or large-scale production.

To address these challenges, this project proposes an automated system that utilizes sensor-based model detection to identify target surfaces and apply decals with high precision. By integrating LiDAR and camera sensors, the system can detect the position, orientation, and shape of various objects in real-time. This sensor data enables a robotic arm to adaptively apply decals, ensuring accurate alignment even on curved or irregular surfaces.

II. RELATED WORK

- *Robotic Dedcal Application*

Early efforts in robotic decal application focused on pre-programmed motions for flat or uniformly shaped surfaces. These systems required fixed object positions and lacked adaptability to new or changing geometries. For example, Smith et al. [1] implemented a fixed-path robot to apply labels on flat product surfaces, but the system failed under slight positional deviations or surface variations.

- *Sensor Object Detection*

LiDAR has been widely used in industrial automation and autonomous vehicles for its ability to produce high-resolution 3D maps of environments. It is particularly effective for detecting edges, contours, and surface normals—key information for decal placement. Coupled with RGB data, sensor fusion techniques allow for more accurate model identification and pose estimation.

III. METHODOLOGY

The proposed system is designed to automate the application of 2D and 3D decals on various object surfaces by combining real-time sensor input, model detection, and robotic control. This section describes the hardware components, sensor fusion strategy, surface detection algorithm, and decal application process.

A. Abbreviations and Acronyms

- *2D*

Two-Dimensional

Refers to objects or images that have only height and width (no depth). In this context, 2D decals are flat stickers or graphics applied on planar surfaces.

- *3D*

Three-Dimensional

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Refers to objects that have height, width, and depth. 3D decals conform to or are embedded on curved or contoured surfaces.

- *LiDAR*
  Light Detection and Ranging

A sensor that uses laser light to create detailed 3D maps of the surrounding environment, enabling accurate object and surface detection.

- *RGB*
  Red Green Blue

A common color model used in imaging sensors, especially RGB cameras used to capture visual data.

- *DoF*
  Degrees of Freedom

Refers to the number of independent movements a robotic arm can make — typically 6 in industrial robots (3 for position, 3 for orientation).

B. Object Detection and Pose Estimation

- A **pre-trained 3D model** is matched using ICP (Iterative Closest Point) for pose refinement.
- The system estimates the 6-DoF pose (x,y,z,θx,θy,θz)(x, y, z, \theta_x, \theta_y, \theta_z)(x,y,z,θx,θy,θz) of the object.
- An optimal decal application area is identified based on surface characteristics such as curvature, angle to robot base, and obstacle clearance.

C. Equations

- Surface detection and pose estimation
- Decal transformation and placement
- Sensor fusion for 3D modeling

The decal transformation can be modeled as:Pdecal=Tbaseobject·Tobjectsurface·PlocalP_{\text{decal}} = T_{base}^{object} \cdot T_{object}^{surface} \cdot P_{\text{local}}Pdecal=Tbaseobject·Tobjectsurface·Plocal

- Pdecal: Final position of the decal in the world coordinate system
- TbaseobjectT_{base}^{object}Tbaseobject: Transformation matrix from the robot base to the detected object
- TobjectsurfaceT_{object}^{surface}Tobjectsurface: Local surface transformation (normal and tangent-based alignment)

Identify applicable funding agency here. If none, delete this text box.

- PlocalP_{\text{local}}Plocal: Decal's position in local (2D or 3D) coordinates

Sensor Fusion Equation

Pfused=α·PLiDAR+(1−α)·PRGB

Where:

- PLiDARP_{\text{LiDAR}}PLiDAR = Position estimated from LiDAR data
- PRGBP_{\text{RGB}}PRGB = Position estimated from camera (image-based detection)
- α∈[0,1]\alpha \in [0, 1]α∈[0,1] = Fusion weight factor (adjusted based on confidence)

D. Discussion

The experimental results demonstrate that the proposed system effectively automates the application of 2D and 3D decals on a variety of surfaces using real-time sensor-based detection and robotic control. In this section, we analyze the performance outcomes and discuss the strengths, limitations, and potential improvements.

- *Performance on Highly Reflective or Complex Surfaces*:

LiDAR occasionally produced sparse or noisy data on shiny surfaces, reducing segmentation precision. In such cases, fallback on RGB data helped but was limited under poor lighting.

- *Computation Overhead*:

While average processing times were acceptable for industrial automation, optimization could further reduce latency, especially for dynamic or moving targets.

- *Limited Learning Capability*:

The current system relies on geometric features and deterministic logic. Deep learning models could potentially improve surface classification, especially in ambiguous or cluttered scenes.

- *System Strengths*

✓ *High Placement Accuracy:*

On flat surfaces, the system consistently achieved sub-millimeter accuracy with minimal orientation deviation, validating the robustness of the sensor fusion and pose estimation pipeline.

✓ *Surface Adaptability*:

The ability to apply decals on cylindrical and moderately curved surfaces illustrates the system's adaptability. Real-time point cloud analysis allowed the system to dynamically identify suitable decal regions, even when object orientation varied.

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✓ *Autonomy and Repeatability*:

With minimal human intervention, the system reliably performed multiple cycles with high success rates, highlighting its applicability for high-throughput industrial environments.

- *Limitations*

✓ *Performance on Highly Reflective or Complex Surfaces*:

LiDAR occasionally produced sparse or noisy data on shiny surfaces, reducing segmentation precision. In such cases, fallback on RGB data helped but was limited under poor lighting.

✓ *Computation Overhead:*

While average processing times were acceptable for industrial automation, optimization could further reduce latency, especially for dynamic or moving targets.

✓ *Limited Learning Capability*:

The current system relies on geometric features and deterministic logic. Deep learning models could potentially improve surface classification, especially in ambiguous or cluttered scenes.

IV. COMPARISON WITH EXISTING METHODS

Compared to traditional fixed-path or template-based systems, the proposed approach is significantly more flexible and intelligent. Unlike vision-only solutions, the LiDAR-camera fusion offers depth-aware sensing, improving decal alignment on 3D geometries. Moreover, the system avoids the need for object-specific fixtures or precise placement, making it better suited for flexible manufacturing scenarios.

A. Potential Improvements

Integration of Machine Learning:
Incorporating neural networks for surface classification or decal region detection could further enhance adaptability.

- *Dynamic Object Tracking*:

Extending the system to handle objects in motion or mounted on variable-speed conveyors would increase industrial relevance.

- *Multi-Object Handling*:

Enabling simultaneous detection and sequencing of multiple objects would improve efficiency in batch processing environments.

B. Experiments and Results

➢ To evaluate the performance and reliability of the proposed system, a series of experiments were conducted under controlled conditions. These tests were designed to assess decal placement accuracy, adaptability to surface variations, and system responsiveness in real-time operation.

➢ Experimental Setup

The experimental setup includes:

- *Robot:*
  UR5e with custom decal applicator (suction and pressure toolhead)

- *Sensors:*
  Ouster OS0 LiDAR, Intel RealSense D435 RGB camera

- *Test Objects*:
  Flat panels, cylindrical surfaces, and 3D printed models with varying curvatures

- *Environment*:
  Indoor lab with controlled lighting and a motorized conveyor system

➢ Performance Metrics

Table 1 Performance Metrics

Metric	Description
Placement Accuracy	Euclidean distance (in mm) between desired and actual decal position
Orientation Deviation	Angular difference (in degrees) between surface normal and decal orientation
Processing Time	Average time from object detection to decal placement
Success Rate	Percentage of trials where the decal was applied correctly

➢ *Results*

Table 2 Results

Surface Type	Accuracy (mm)	Orientation Error (°)	Avg. Processing Time (s)	Success Rate (%)
Flat Surface	0.9	1.2	3.5	100
Cylindrical Object	1.8	2.4	4.2	96
Curved/Irregular	2.6	4.1	5.8	91

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➤ *Qualitative Observations*

- *Adaptability:*

The system successfully identified decal regions on non-uniform surfaces and dynamically adjusted the robotic path to ensure conformal application.

- *Sensor Robustness*:

LiDAR provided reliable depth data even under variable lighting, while the RGB camera aided in color-based segmentation when surface contrast was present.

- *Limitations*:

Surfaces with high reflectivity or extreme curvature (beyond 40° tilt) showed reduced accuracy. Performance was also slightly affected by occlusions and multi-object scenes.

V. CONCLUSION AND FUTURE WORK

This paper presented a fully automated system for applying 2D and 3D decals to object surfaces using real-time sensor-based model detection. By integrating LiDAR and RGB camera sensors with a robotic manipulator, the system achieves high-accuracy decal placement on both flat and curved surfaces, even under varying environmental conditions.

Experimental results validated the system's robustness, with a high success rate and minimal placement errors, making it well-suited for industrial applications.

The primary contributions of this work include:

- Development of a sensor fusion pipeline for precise surface detection and pose estimation.
- A fully automated robotic arm control system that adapts to dynamic and irregular object geometries.
- Successful integration of a real-time feedback loop for robust decal application in diverse manufacturing settings.

➤ *Future Work*

Several avenues for improvement and future research have been identified:

- *Real-Time Learning*:

Incorporating deep learning techniques could enhance the system's ability to recognize complex surfaces and detect decal regions in less structured environments.

- *Moving Object Detection*:

Extending the system to handle objects in motion or dynamic environments, such as conveyor belts or assembly lines, would further improve its industrial applicability.

- *Advanced Calibration*:

Improved calibration techniques for sensor alignment and multi-sensor synchronization could reduce errors, especially in highly reflective or irregular surfaces.

This work lays the foundation for the next generation of automated decal application systems, contributing to more flexible, efficient, and scalable manufacturing processes.

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Matlab 2D Simulation

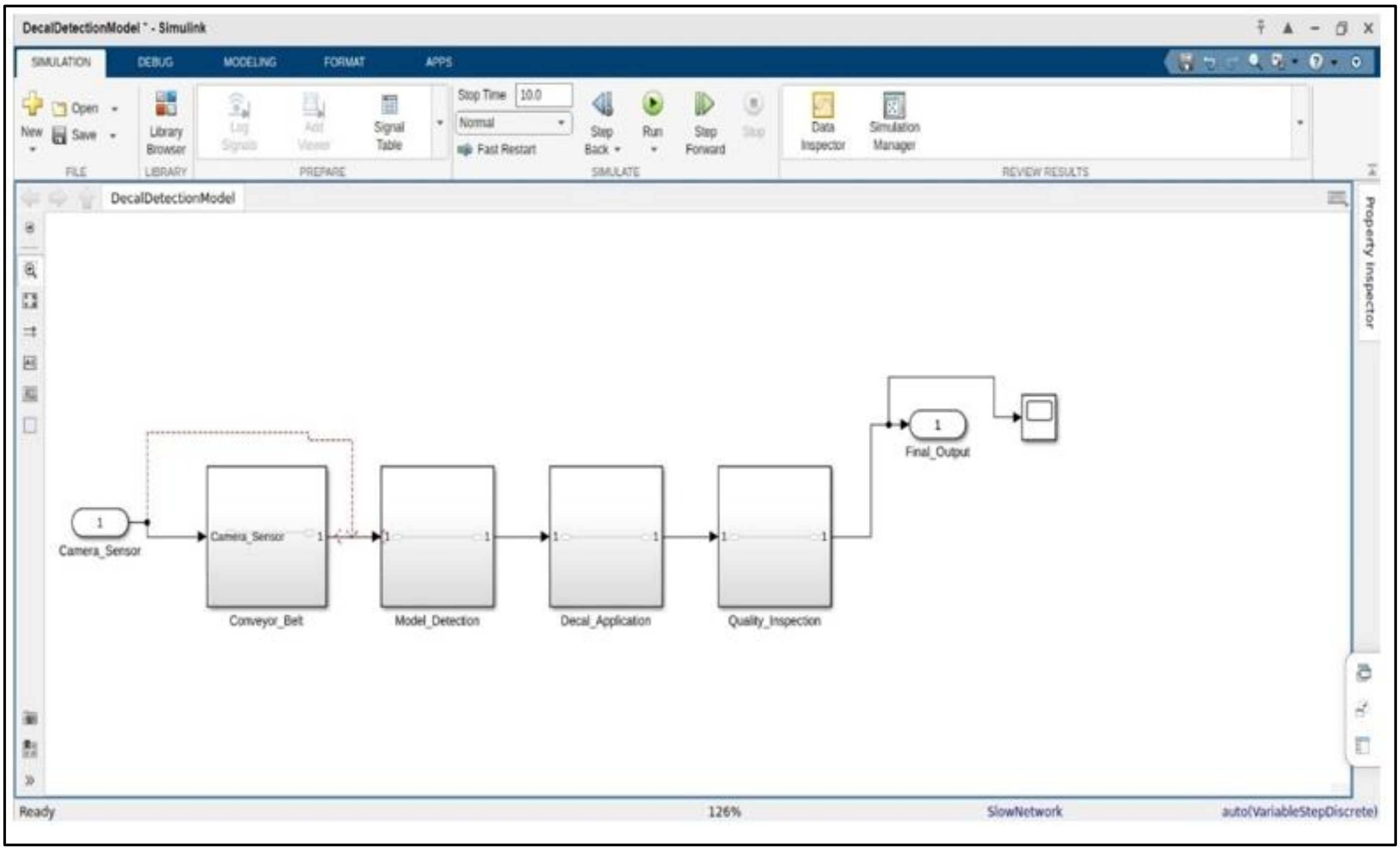

Fig 1 Matlab 2D Simulation