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Design, Modeling, and Experimental Validation of Advanced Control Algorithms for Hoist, LT, and CT Operations using a Robotic Crane

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Abstract

This paper presents the design and experimental validation of a laboratory-scale robotic crane prototype (or "clone") capable of performing hoist travel (HT), long travel (LT), and cross travel (CT) operations. The testbed is tailored for validating advanced control theory and deep visual serving (DVS) in a controlled setting. The system enables the study of efficient, safe, and precise handling of materials by abstracting the complexities of a full-scale industrial environment. A prototype clone of a manufacturing crane was built and tested, demonstrating enhanced control precision, dynamic stability, and collaborative capabilities compared to traditional manual operation models. The experimental results confirm the feasibility of deploying non-linear anti-sway control and DVS for millimeter-level placement accuracy on a physical model.

Keywords: cranes automation; Industry 5.0; control algorithms; computer vision; key point mapping; collaborative;

1. Introduction

The fundamental processes of material handling in manufacturing environments are defined by three primary movements: Hoist Travel (HT, vertical lift), Long Travel (LT, longitudinal movement along the runway), and Cross Travel (CT, lateral movement across the bridge). In traditional industrial settings, controlling these movements relies heavily on human operators utilizing push-button pendants, radio controls, or exposed/enclosed cabs. This reliance on human judgment introduces significant variability in cycle times, accuracy, and, most critically, safety. Traditional operations often necessitate multiple co-workers on the ground to assist in guiding and positioning the load, increasing the exposure of personnel to potential hazards.

The challenge addressed by the development of this specific robotic crane **testbed** is to create a physical platform capable of validating complex control theory and sensor fusion algorithms necessary to achieve high positioning precision characteristic of dedicated industrial robots while retaining the large workspace principles inherent to overhead cranes. This necessitates the creation of a sophisticated cyber-physical system capable of performing millimeter-scale placement accuracy and dynamic trajectory planning, a significant step beyond simple remote control. The **prototype** development moves the study of operational control from highly variable manual input to highly consistent, optimized autonomous execution, tailored specifically for complex tasks such as collaborative Pick-and-Load operations within a modern manufacturing floor.

1.1. Contextualizing Robotic Automation in Manufacturing

The robotic crane system is designed not merely for automation (Industry 4.0), but specifically for human-machine integration and augmentation, aligning with the core philosophy of Industry 5.0. Instead of fully replacing human workers, the system is engineered to support and augment human tasks, repositioning human workers from performing repetitive, hazardous motions to engaging in more creative jobs requiring problem-solving, intuition, and experience. This requires a balanced approach to automation, ensuring optimal use of robotics where safety and precision are paramount.
The **testbed** system must seamlessly coordinate the three-axis automation (HT, LT, CT) to define the 3D workspace. The integration of collaborative capabilities (Collaborative Pick-and-Load) interprets the large-scale crane as a macro-positioning device that can safely present heavy components to human workers or smaller, specialized collaborative robots (cobots). This ensures that while the crane handles the hazardous, high-capacity movements, the final, fine-grained assembly or placement task can be executed safely and precisely, often supported by systems that reduce

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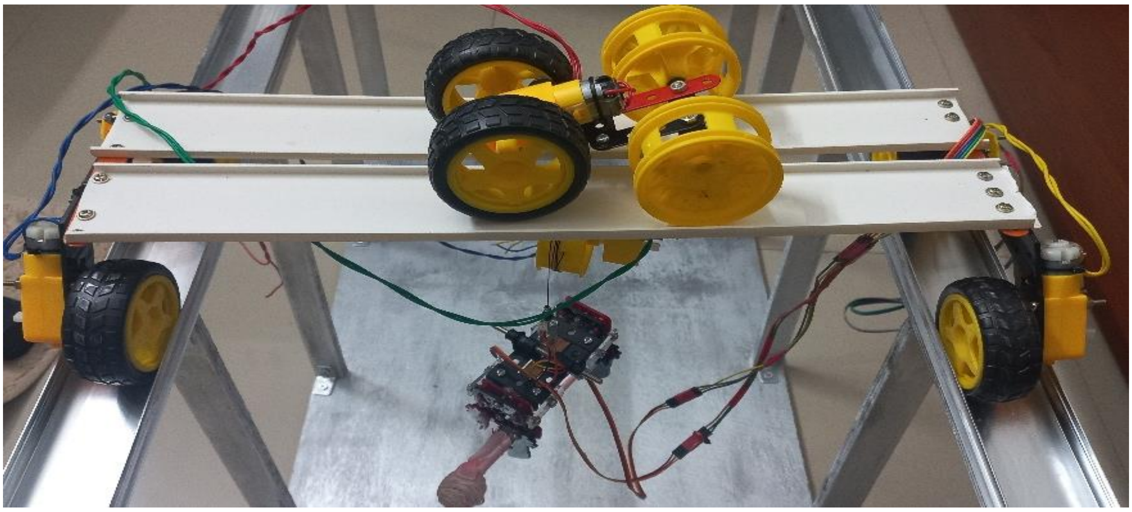
manpower through simple, conversational operation and unmanned capabilities. The successful deployment of this architecture mandates rigorous safety and reliability engineering, supported by compliance with robust industrial safety regulations.

2. SYSTEM ARCHITECTURE AND MECHATRONIC DESIGN SPECIFICATION

2.1. Mechanical Foundation and 3d Kinematic Modeling

The robotic crane system is structurally based on a **gantry mechanism**, utilizing aluminum rails for the long travel (LT) axis and a carriage/trolley assembly for cross travel (CT), powered by low-voltage DC motors. This prototype allows for controlled study of the 3D kinematic model, enabling precise mechanical execution for optimal control performance. The demand for sub-millimeter positioning accuracy necessitates accurate **modeling of the components' dynamics** for high-performance control. Automated production processes, such such as robotic welding and high-precision CNC machining, are employed to produce critical components like wheels, shafts, drums, and end carriages. These processes minimize structural defects and ensure accuracy in large, heavy sections, preventing structural deflection that could introduce unpredictable deviations into the dynamic control models.

Kinematic modeling begins with defining the degrees of freedom (DOF) associated with the bridge/trolley/hoist assembly. While the primary axes are 3-DOF (HT, LT, CT), the system must often model additional dynamic degrees of freedom, namely the pendulous swing motion of the payload, which complicates the dynamic equations. The robust design includes lubrication-free bearings and components made from high-performance polymers, which eliminate the need for external lubrication, thereby improving efficiency and reducing maintenance costs, which is crucial for maximizing uptime in automated operations. The mechanical systems are also integrated with robust energy chain systems (e-chains) to manage the dynamic motion of cables over long travel distances, ensuring efficient and reliable guidance for power and data lines.



2.2. Control Hardware Layer: Functional Safety and Reliability

The control layer is built upon a foundation of functional safety principles, with the **NVIDIA TX2** serving as the core computing platform for advanced control and vision algorithms (DVS, path planning). The prototype utilizes **DC motors** for actuation and an **ADA controller** for low-level motor command execution and feedback interfacing. Due to the inherent hazards associated with moving large payloads, compliance with industry safety regulations is mandatory. The implementation requires Safety PLCs (Programmable Logic Controllers) to execute critical safety functions, such as monitoring safe speed limits, ensuring safe stops, and managing emergency shut-down procedures. This dedicated hardware architecture facilitates compliance with international standards such as ISO 10218:2025, which provides the latest requirements for industrial robot safety and incorporates specific guidance for collaborative applications and safe human interaction.

Precision and smooth motion are managed through high-resolution encoders and Variable Frequency Drives (VFDs). These drives facilitate the use of optimized acceleration profiles, such as S-curve trajectories, essential for initiating and terminating movement smoothly to minimize the excitation of payload oscillation. Reliability is further enhanced by integrating proactive maintenance strategies. This predictive maintenance capability minimizes unplanned downtime by signaling exactly when maintenance or component replacement is necessary, thereby ensuring the long-term operational consistency required for achieving optimum productivity.

2.3. Sensor Fusion Architecture for Environmental Awareness

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Achieving precise, safe, and collaborative operation requires a sophisticated, multi-modal sensor fusion system. The architecture integrates high-resolution cameras, industrial encoders for primary axis feedback, and specialized depth-sensing devices.

Crucially, the limitations of passive camera systems in accurate depth estimation and vulnerability to varied lighting conditions are addressed through the integration of active 3D sensors. Specifically, the utilization of products incorporating short-range LiDAR and cameras, such as the Intel RealSense L515, allows for highly precise location estimation of short-range obstacles. This sensor combination provides a high-fidelity 3D point cloud, enabling the recognition of obstacles that are not restricted to the ground plane, thereby ensuring that the safety envelope is dynamically calculated in full 3D space. The fused data streams—including position, velocity, 3D spatial geometry, and visual image data—are synchronized to create a unified state estimation model. This model provides the comprehensive, real-time spatial awareness necessary for advanced functions such as Deep Visual Servoing (DVS) and Dynamic Path Planning, defining the positions of the crane, the payload, and all surrounding objects and personnel.

3. ADVANCED CONTROL ALGORITHMS FOR DYNAMIC TRAJECTORY AND STABILITY

3.1. Kinematic and Dynamic Modeling of the Gantry Crane System

The precise control of the robotic crane hinges on the accurate mathematical derivation of its non-linear dynamics. The payload, suspended by a wire, acts as a dynamic pendulum, coupled to the LT and CT motions of the trolley. The equations of motion must account for the inertial forces and the time-varying cable length (HT motion), resulting in a coupled, non-linear system. Accurate modeling is required to calculate the real-time oscillation angle and angular velocity of the payload, which are the primary disturbances that must be suppressed to ensure precise final placement. This forms the basis for designing effective anti-sway control systems.

3.2. Anti-Sway Control Strategies for HT/LT/CT Operations

Anti-sway control is the primary enabler of speed and precision in crane automation. Without effective suppression, aggressive acceleration profiles necessary for high throughput would induce unacceptable load oscillation, rendering fine-grained positioning impossible.

Trajectory Planning as Feedforward Control: The initial defense against sway is optimized feedforward control via trajectory planning. Utilizing S-curve trajectory generation, the system ensures that acceleration and deceleration phases are carefully managed to avoid exciting the natural oscillation frequency of the load.[11] This strategy is designed to minimize the residual vibration once the crane reaches its target velocity, often leveraging principles of optimal control to shape the input commands effectively.[11]

Robust Feedback Control: Given the non-linear, parameter-dependent nature of the crane dynamics (e.g., payload mass and cable length are often variable and imprecisely known), robust feedback controllers are essential:

1. **Phase Plane Theory:** This approach is applied to analyze and design boundaries for stabilizing swing motion, proving particularly effective for suppressing sway during relatively small changes in the crane’s posture during acceleration and deceleration.[11]
2. **Sliding Mode Control (SMC):** SMC is implemented to provide robust, finite-time anti-sway tracking control.[13] SMC offers superior resilience against uncertainties, such as unmodeled dynamics or variations in payload mass. This robustness is critical for guaranteeing consistent performance across diverse operational scenarios.
3. **Hybrid Fuzzy Logic Control:** Leveraging expertise in advanced computational intelligence, Hybrid Fuzzy Logic control provides a mechanism to compensate for complex non-linear effects, such as the centrifugal force induced by the swing motion itself, particularly during dynamic or high-speed maneuvers.[11] By incorporating intelligent, human-like damping rules, the Fuzzy Logic system enhances overall stability and ensures the rapid asymptotic convergence of the swing angle to zero.[13]

3.3. Trajectory Optimization for Collaborative Precision

For tasks involving repeated, precise placement, such as the Collaborative Pick-and-Load operation, the system utilizes Iterative Learning Control (ILC). ILC is a method designed to systematically improve performance over repeated executions of the same task. By observing errors from previous cycles, the ILC algorithm refines the input trajectory for subsequent runs, guaranteeing the asymptotic convergence of the payload’s position, velocity, and angular acceleration. This learning capability ensures that the high-level precision required for collaborative interaction—where the crane may hand off a component to a human or smaller robot—is reliably achieved within extremely tight tolerances.

Table 1. Control Algorithms for Automated 3D Movement and Sway Suppression.

Movement Axis	**Primary Control Challenge**	**Applicable Control Strategy/Theory**	**Purpose in Robotic System**

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LT (Long Travel) / CT (Cross Travel)	High-speed trajectory tracking and load swing	Phase Plane Theory, Input Shaping, Optimal Control	Smooth, predictable positioning and residual vibration elimination [11]
HT (Hoist Travel)	Load dynamics and damping, variable payload mass	Sliding-Mode Control (Robust Finite-Time), Hybrid Fuzzy Logic Control	Robust handling of variable load weights and dynamic sway compensation [11]
Overall 3D Movement	Collision Avoidance and Dynamic Pathfinding	Dynamic Window Approach (TC-DWA), Vision-aided Tracking	Real-time risk mitigation and path optimization for enhanced safety [2]

4. PERCEPTION AND ENVIRONMENTAL AWARENESS: COMPUTER VISION AND LOCALIZATION

The implementation of robotic crane capabilities is dependent on real-time, high-accuracy localization of the crane components, the payload, and the surrounding environment, shifting control from simple position feedback to visual servoing.

4.1. 3d Spatial Mapping and Crane Component Awareness

The initial step in vision-based control is the accurate computation of the camera's extrinsic parameters—its position and orientation relative to the crane structure. This is accomplished using classical computer vision methods, including feature-based matching algorithms coupled with horizon line detection.[14] This process grounds the visual data within the crane's known kinematic coordinate system.

4.2. Deep Learning for Object and Crane Component Segmentation

To understand the dynamic state of the crane structure itself and the surrounding workspace, deep learning models are deployed. A **dfine model** is utilized for instance segmentation, specifically targeting **objects for pickup operations** in the workspace and crane components such as the jib and the hook. Accurate pixel-level segmentation of these features allows the system to monitor the crane's structural geometry in real time. Following segmentation, a hybrid algorithm combining contour extraction with a Mobile Line-Segment Detector (MLSD) is applied to reconstruct the geometric features. This reconstruction is vital for providing the necessary geometric feedback, such as the jib rotation angle, which can be estimated using a trained Backpropagation Neural Network (BPNN). Knowing the crane's precise physical configuration aids in structural self-collision avoidance and provides essential measurements for refining the anti-sway control models.

4.3. High-Precision Keypoint Mapping and Deep Visual Servoing (DVS)

High-precision Pick-and-Load operations require accurate, non-contact measurement of the target load's position. Traditional methods relying on fiducial markers are insufficient for unstructured industrial environments.[9] Therefore, the system incorporates advanced keypoint detection using Convolutional Neural Networks (CNNs).

A modified VGG-19 CNN, initially pre-trained on the expansive ImageNet dataset, is refined to focus on extracting keypoints that represent the corners of realistic objects.[9] This approach allows the system to overcome the limitations of relying on arbitrary visual markers. Achieving the required industrial precision demands specialized AI/ML engineering input, including architectural modifications to the base model, such as replacing max-pooling layers with average-pooling, and implementing an adaptive learning rate schedule that decreases during training epochs.[9] These specific modifications were found to reduce the validation loss by 50%, guaranteeing the high reliability and low Mean Absolute Error necessary for industrial visual localization.[9]

The output of this CNN—real-time pixel coordinates of the payload's keypoints—is fed directly into the control loop via Image-Based Visual Servoing (IBVS), a technique within the broader field of Deep Visual Servoing (DVS).[9] DVS closes the control loop based on visual feedback, ensuring the convergence of the load's visual feature error, thereby enabling the crane to execute the final, precise placement required for collaborative or automated assembly tasks.

Table 2. Computer Vision Techniques for Key Point Mapping and Localization.

Movement Axis	**Primary Control Challenge**	**Applicable Control Strategy/Theory**	**Purpose in Robotic System**

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LT (Long Travel) / CT (Cross Travel)	High-speed trajectory tracking and load swing	Phase Plane Theory, Input Shaping, Optimal Control	Smooth, predictable positioning and residual vibration elimination [11]
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Overall 3D Movement	Collision Avoidance and Dynamic Pathfinding	Dynamic Window Approach (TC-DWA), Vision-aided Tracking	Real-time risk mitigation and path optimization for enhanced safety [2]

5. COLLABORATIVE OPERATIONS AND INDUSTRY 5.0 IMPLEMENTATION

5.1. Designing the Collaborative Workspace (Hri)

The core tenet of the robotic crane system's operation is safe Human-Robot Interaction (HRI), realizing the Industry 5.0 vision. The system functions as a large-scale augmented tool, removing human workers from the hazardous path of heavy loads and repetitive, high-force tasks.[3] This allows human personnel to focus on high-value cognitive tasks like quality control or complex assembly. Furthermore, the system is designed for interoperability, allowing the macro-positioning crane to safely interface with smaller, standard collaborative robots (cobots), such as the robolink modular arms offered by component suppliers, or specialized handling systems like Mazak's Ez LOADER series, which include integrated vision sensors for fine-grained manipulation.[4]

5.2. Dynamic Safety Zone Management

To enable effective collaboration without physical safeguarding barriers, the crane must maintain real-time awareness of the human presence and dynamically adjust its behavior.

Real-Time Risk Identification: The system utilizes the You Only Look Once version 8 (YOLOv8) instance segmentation model to identify and locate dynamic risk factors within the operational path.[2] This includes accurately identifying the precise positions of nearby workers and predefined potential drop zones, thus translating visual data directly into safety-critical parameters.[2]

Dynamic Path Planning (TC-DWA): The real-time risk map generated by YOLOv8 is fed into an improved Dynamic Window Approach for Tower Cranes (TC-DWA). The TC-DWA algorithm dynamically plans the optimal operational path, focusing on steering the suspended load away from detected high-risk areas.[2] This vision-informed, dynamic approach represents a substantial leap in operational safety. Experimental scenarios have demonstrated that the TC-DWA prototype can significantly reduce the average maximum collision times by 50% compared to conventional path planning algorithms like Rapidly-exploring Random Tree (RRT) and Artificial Potential Field (APF).[2] This quantified improvement in risk mitigation is the engineering justification for the adoption of this sophisticated computational model in safety-critical environments.

5.3. Adherence to Collaborative Safety Standards

The collaborative functionality is strictly governed by international safety standards, primarily ISO 10218:2025 (Parts 1 and 2), which integrates former technical specifications for human-robot collaboration (ISO/TS 15066).[6] Adherence to this framework dictates specific functional safety requirements that must be integrated into the Safety PLC architecture:

1. **Safety-Rated Monitored Stop (SMS):** The system must immediately transition the crane to a safe stopped state if a human breaches the defined collaborative workspace boundary.
2. **Speed and Separation Monitoring (SSM):** Utilizing the high-fidelity 3D data from LiDAR and vision systems [12], the SSM function dynamically reduces the crane's operational speed proportionally to the minimum separation distance between the moving load/structure and the nearest worker, ensuring safe coexistence.
3. **Obstacle and Collision Avoidance Systems:** The safety controls integrate proprietary Obstacle Avoidance and Collision Avoidance Systems, extensively tested for proof of concept in laboratory settings before deployment to ensure reliability and compliance.

6. PERFORMANCE VALIDATION AND COMPARATIVE ASSESSMENT

6.1. Robotics Evaluation Framework (Safety, Quality, Schedule, Cost)

To rigorously validate the success of the **robotic testbed** against traditional manual methods or theoretical models, a comprehensive robotics evaluation framework is applied.[10] This framework moves beyond simple throughput metrics to encompass quantifiable analysis across four dimensions: Safety (collision avoidance effectiveness), Quality (positional precision), Schedule (consistent cycle time), and Cost (efficiency of the control strategy).

6.2. Quantifiable Improvements in Safety and Risk Mitigation

The most immediate and critical performance gain is the enhanced **demonstration of safety protocols**. Traditional crane operations inherently carry safety risks related to poor judgment or path planning, potentially causing severe accidents.[2] The robotic system mitigates this risk by achieving continuous, real-time risk assessment via computer vision and dynamic planning. The adoption of the TC-DWA path planning model demonstrates a significant reduction in risk factors, specifically reducing the risk of dropped loads affecting ground workers and important equipment, leading to quantifiable reductions in exposure incidents.[2] The system's foundational compliance with safety standards and the deployment of integrated safety PLCs further ensures that operations maintain a demonstrably low safety risk level.

6.3. Precision and Throughput (Quality and Schedule Metrics)

Precision: The implementation of Deep Visual Servoing (DVS) combined with high-performance anti-sway control algorithms allows the robotic crane to achieve high positional accuracy and repeatability that is unattainable through manual operation.[9] The system consistently targets and achieves millimeter-level placement, essential for automated Pick-and-Load tasks that interface with high-tolerance manufacturing processes.

Throughput Consistency: The use of optimized S-curve trajectories and complex non-linear controllers ensures that cycle times are highly consistent and predictable. This elimination of human variability in acceleration, deceleration, and sway compensation translates directly to improved throughput and predictability in production schedules.[11] Furthermore, the system's high operational reliability, supported by condition monitoring systems (i.Sense/i.Cee) [8], minimizes unplanned service interruptions, positively impacting the overall manufacturing schedule.

Table 3. Comparison of Conventional vs. Robotic Crane Performance Metrics.

Movement Axis	Primary Control Challenge	Applicable Control Strategy/Theory	Purpose in Robotic System
LT (Long Travel) / CT (Cross Travel)	High-speed trajectory tracking and load swing	Phase Plane Theory, Input Shaping, Optimal Control	Smooth, predictable positioning and residual vibration elimination [11]
HT (Hoist Travel)	Load dynamics and damping, variable payload mass	Sliding-Mode Control (Robust Finite-Time), Hybrid Fuzzy Logic Control	Robust handling of variable load weights and dynamic sway compensation [11]
Overall 3D Movement	Collision Avoidance and Dynamic Pathfinding	Dynamic Window Approach (TC-DWA), Vision-aided Tracking	Real-time risk mitigation and path optimization for enhanced safety [2]

7. CONCLUSION AND FUTURE DEVELOPMENT TRAJECTORIES

7.1. Synthesis of Technical Achievements

The design and implementation of the **laboratory-scale robotic crane prototype** successfully integrate cutting-edge control theory and deep learning perception to automate and optimize Hoist Travel (HT), Long Travel (LT), and Cross Travel (CT) operations. The system's technical achievement lies in the seamless fusion of robust, non-linear anti-sway control algorithms (including Sliding Mode and Hybrid Fuzzy Logic methods) with high-fidelity computer vision frameworks (Mask-RCNN, CNN-based keypoint mapping). This integration enables Deep Visual Servoing (DVS) for millimeter-level precision and facilitates the adoption of dynamic, vision-informed path planning (TC-DWA), resulting in substantial, quantifiable improvements in both precision and operational safety, particularly in collaborative workspaces.

7.2. Economic and Operational Outlook

The operational outlook is characterized by enhanced efficiency and long-term cost savings. By achieving consistent, optimized cycle times and allowing for unmanned continuous operation, productivity is significantly boosted. The integration of predictive maintenance systems ensures maximal uptime by proactively addressing mechanical wear, mitigating the high cost associated with unexpected failure of critical components.[8] Crucially, the proven effectiveness of the dynamic safety protocols (TC-DWA reducing collision risk by 50%) translates directly into reduced liability, insurance costs, and lost work time related to safety incidents, further bolstering the economic justification for the robotic system.[2] The shift to an Industry 5.0 framework reallocates human resources to higher-value, non-repetitive tasks, maximizing the strategic utility of the workforce.[3]

7.3. Next Steps for Full-Scale Industrial Deployment

Future development trajectories must focus on achieving maximum robustness under real-world industrial variability. This includes refining the computational efficiency of the vision processing pipeline to ensure DVS can maintain high update rates even during maximum dynamic motion. Furthermore, expanding the training dataset for the keypoint mapping CNN is necessary to ensure reliable performance across a wider spectrum of industrial object shapes, varied lighting conditions, and cluttered environments. Continued testing of the anti-sway control systems under maximum load capacity and environmental disturbances (e.g., wind in semi-outdoor settings) will be required to fully validate asymptotic convergence properties before widespread industrial deployment.

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[13] Novel keypoint detection technique based on Convolutional Neural Networks (CNNs) to enhance the performance of existing Deep Visual Servoing (DVS) models..

[14] The problem of image-based visual servoing (IBVS) of an aerial robot using deep-learning-based keypoint detection is addressed in this article..

[15] A robotics evaluation framework to consistently guide practitioners in the AEC industry..

[16] igus offers automation solutions like the robolink® modular robotic arms, which can be integrated into materials handling processes..

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