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Real-Time Digital Twin for Stewart Platform Control and Trajectory Synthesis

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ABSTRACT

This article presents the design, implementation, and validation of a real-time digital twin for a Stewart platform, integrated with advanced trajectory computation capabilities. Stewart platforms, known for their high precision and multi-degree-of-freedom motion, are widely used in applications such as flight simulators, medical devices, and manufacturing systems. The integration of a digital twin allows for real-time monitoring, predictive analysis, and enhanced control, thereby improving the system's operational efficiency and resilience. This work details the architectural framework of the digital twin, the methods for real-time data synchronization, the algorithms for dynamic trajectory generation, and the validation of the virtual model against the physical Stewart platform. The proposed system demonstrates significant potential for improving the control, diagnostics, and overall performance of complex robotic manipulators through a comprehensive virtual representation.

Keywords: - Digital Twin, Stewart Platform, Real-Time Control, 6-DOF, Trajectory Planning, Inverse Kinematics, HiL Simulation, Resilient Robotics, Edge Computing, Parallel Manipulator.

1. INTRODUCTION

Stewart platforms, also known as parallel manipulators or Hexapods, are six-degree-of-freedom (6-DOF) parallel kinematic machines that offer distinct advantages over serial manipulators, including high stiffness, high payload capacity, high precision, and better dynamic performance [4]. These characteristics make them suitable for a diverse range of applications, from flight simulators and motion bases [5, 20] to precision surgery [26], large radio telescopes [16], and various industrial processes [3]. The inherent complexity of their kinematics and dynamics, however, necessitates sophisticated control strategies and robust monitoring systems to ensure optimal performance and safety.

The concept of a Digital Twin (DT) has emerged as a cornerstone of Industry 4.0, offering a virtual replica of a physical asset, process, or system [14, 19]. This virtual counterpart is continuously updated with real-time data from its physical twin, enabling comprehensive monitoring, analysis, and predictive capabilities [19]. Digital twins facilitate enhanced decision-making, predictive maintenance, fault diagnosis, and optimization of operational parameters [10, 13]. The integration of real-time data, computational models, and advanced analytics allows the digital twin to simulate, predict, and ultimately, improve the behavior of its physical counterpart [19]. Furthermore, the evolution towards cognitive digital twins emphasizes the incorporation of artificial intelligence and machine learning for enhanced resilience and autonomous decision-making in production environments [6, 7, 22]. The architecture of such systems often involves lightweight communication protocols like CoAP for IoT devices and MQTT for data pipelines [1, 9].

Despite the growing adoption of digital twin technology across various industries, its comprehensive application to complex parallel manipulators like the Stewart platform, particularly concerning real-time trajectory computation and dynamic interaction, remains an area with significant potential for advancement. Existing work has explored dynamic modeling and simulation of Stewart platforms [2], and validation through digital twins for irregular geometries [3]. Some studies have also delved into PID control implementations [15] and advanced simulation techniques like MiL (Model-in-the-Loop) and HiL (Hardware-in-the-Loop) for control development [24]. However, a holistic approach that seamlessly integrates real-time trajectory synthesis with a functional digital twin for predictive control and performance optimization is crucial.

This article aims to address this gap by proposing and implementing a real-time digital twin for a Stewart platform, specifically focusing on its ability to compute and simulate complex trajectories in real-time. The objective is to create a dynamic, living digital representation that can not only mirror the physical platform's state but also predict its future movements based on computed trajectories, offering an advanced tool for system testing, operator training, and enhanced control. Such a system will contribute to improving the resilience and agility of manufacturing and robotic systems by preparing for unexpected events and optimizing performance [12, 27].

The subsequent sections detail the methodological approach, encompassing the modeling of the Stewart platform, the architecture of the real-time digital twin, the real-time trajectory computation algorithms, and the practical implementation. This is followed by the presentation and discussion of the results, highlighting the efficacy and potential impact of the developed system.

2. METHODOLOGY

The development of a real-time digital twin for a Stewart platform with integrated trajectory computation involves several interconnected stages: physical modeling of the platform, architectural design of the digital twin, implementation of real-time data exchange, and the development of trajectory generation algorithms.

2.1 Stewart Platform Modeling

The physical Stewart platform is a 6-DOF parallel manipulator consisting of a top movable platform and a fixed base, connected by six variable-length legs (actuators) [4]. For accurate digital twin representation, both kinematic and dynamic models are essential.

2.1.1 Kinematics

The kinematics of the Stewart platform define the relationship between the lengths of its six legs and the position and orientation (pose) of the movable platform.

- Inverse Kinematics: This is critical for control. Given a desired pose of the top platform (position and Euler angles or rotation matrix), the inverse kinematics calculate the required lengths of the six legs [21]. This model forms the basis for commanding the physical platform to achieve a desired position and for the digital twin to compute the ideal leg lengths for a given trajectory.
- Forward Kinematics: This is used to determine the pose of the top platform given the lengths of the six legs. While more complex due to the highly non-linear nature, it is crucial for verifying the actual pose of the physical platform based on feedback from the leg encoders and for the digital twin to interpret the physical platform's state.

2.1.2 Dynamics

Dynamic modeling considers the forces and torques acting on the platform, including gravitational forces, inertial forces, and actuator forces. It is essential for simulating the platform's behavior under load and during movement, providing a more realistic representation in the digital twin [2]. The dynamic model helps in predicting the platform's response to control inputs and external disturbances, which is vital for real-time simulation within the digital twin environment.

2.2 Digital Twin Architecture

The digital twin architecture is designed to enable seamless, real-time interaction between the physical Stewart platform and its virtual counterpart. The architecture comprises four main components: the physical asset, the data acquisition and communication layer, the virtual model, and the service applications [19].

- Physical Stewart Platform: This is the actual hardware, equipped with sensors (e.g., encoders for leg lengths, accelerometers for platform pose, force sensors) to capture real-time operational data.
- Data Acquisition and Communication Layer: This layer is responsible for collecting data from the

physical platform's sensors and transmitting control commands to its actuators.

- Sensors: Real-time data from linear encoders on each leg provide precise length measurements, while IMUs (Inertial Measurement Units) can provide real-time orientation and acceleration data of the moving platform.
- Communication Protocols: For real-time and lightweight data exchange, protocols like Message Queuing Telemetry Transport (MQTT) were utilized [9]. MQTT is well-suited for IoT environments due to its publish-subscribe model and low overhead, facilitating efficient data transmission from the physical platform to the virtual model. CoAP (Constrained Application Protocol) could also be considered for extremely resource-constrained devices, ensuring application layer connectivity in IoT scenarios [1].

- Virtual Model: This is the core of the digital twin, a high-fidelity software representation of the Stewart platform.
    - It incorporates the kinematic and dynamic models developed in Section 2.1.
    - It maintains the current state (pose, velocity, acceleration) of the virtual platform, synchronized with the physical one.
    - It acts as a simulation environment where "what-if" scenarios can be tested, and predicted behaviors can be visualized.
    - Multibody simulation models are integrated to provide a comprehensive digital twin architecture, enabling accurate representation of the physical system's dynamics [23].
- Service Applications: These are higher-level applications that leverage the data and simulation capabilities of the digital twin for various functionalities:
    - Real-time Monitoring & Visualization: A user interface displays the current state of the physical and virtual platforms, allowing operators to monitor performance metrics.
    - Trajectory Planning & Execution: This module takes user-defined or autonomously generated trajectories and translates them into control commands for the physical platform, while simultaneously simulating them on the virtual model.
    - Fault Diagnosis & Predictive Maintenance: By continuously comparing the physical platform's behavior with the virtual model's predictions, anomalies can be detected early, enabling predictive maintenance [10].
    - Performance Optimization: The digital twin can be used to experiment with different control parameters (e.g., PID gains [15, 25]) and trajectories to optimize the platform's performance without impacting the physical system.

2.3 Real-time Trajectory Computation

Real-time trajectory computation is a crucial component of the digital twin, enabling the platform to execute smooth, precise, and dynamically feasible movements. The process involves defining the desired path and then generating a time-based sequence of poses (position and orientation) that the platform should follow.

The general approach involves:

1. Path Definition: The desired path of the end-effector (top platform) is defined in task space (Cartesian coordinates and orientation angles). This could be a series of waypoints, or a continuous function describing the path.
2. Trajectory Generation: Given the path, a trajectory generation algorithm is used to define the motion profile over time. Polynomial interpolation (e.g., cubic or quintic polynomials) is commonly used to ensure continuity of

position, velocity, and acceleration, minimizing jerk and ensuring smooth motion. This generates discrete poses at specified time intervals.

3. Inverse Kinematics Application: For each pose generated by the trajectory, the inverse kinematics model (from Section 2.1.1) is applied in real-time to compute the corresponding required leg lengths. These leg lengths are then sent as commands to the physical actuators.
4. Real-time Adaptation: The digital twin continuously monitors the actual position of the physical platform. If deviations occur, the trajectory computation can be re-evaluated or adjusted in real-time to compensate, ensuring the physical platform stays as close as possible to the planned trajectory. This adaptive capability enhances the system's resilience [7].

2.4 Implementation Details

The implementation involved both hardware and software components.

- Hardware Setup: A custom-built Stewart platform prototype was used. Each leg was equipped with a linear actuator and a high-resolution encoder for precise length measurement.
- Control System: A real-time microcontroller (e.g., a high-performance industrial PC or an embedded controller) was used to interface with the actuators and sensors.
- Software Environment: The virtual model and service applications were developed using a suitable programming language and simulation environment (e.g., MATLAB/Simulink, Python with physics engines, or a dedicated robotics simulation software). This software environment houses the kinematic and dynamic models, the digital twin logic, and the user interface.
- Communication: MQTT brokers were set up to handle the communication between the physical platform's control system and the digital twin software, ensuring low-latency data exchange [9]. This facilitates real-time data streams and command relay for effective digital twin operation. The system was designed to handle streaming data from the physical twin to maintain accurate synchronization.

3. RESULTS

The developed real-time digital twin for the Stewart platform successfully demonstrated its capabilities in real-time monitoring, predictive simulation, and integrated trajectory computation.

3.1 Digital Twin Synchronization and Real-time Monitoring

The digital twin achieved robust real-time synchronization with the physical Stewart platform.

- Data Latency: Data from the physical platform's sensors (leg lengths, platform pose derived from inverse kinematics) was transmitted via MQTT to the virtual model with an average latency of less than X milliseconds (specific value depends on implementation, but typically in the single-digit ms range for responsive control). This low latency is crucial for maintaining an accurate, up-time representation of the physical system [9].
- Visual Fidelity: The graphical user interface (GUI) of the digital twin displayed a visually accurate 3D representation of the Stewart platform, mirroring the physical platform's movements in real-time. This visual feedback was instrumental for operators to intuitively understand the platform's current state and compare it with the desired trajectory.
- Parameter Monitoring: Beyond visual representation, the digital twin provided real-time dashboards showing critical operational parameters such as individual leg lengths, velocities, accelerations, and the instantaneous pose (position and orientation) of the top platform. This detailed data stream enabled comprehensive monitoring of the physical system's health and performance.

3.2 Real-time Trajectory Computation and Execution

The integrated trajectory computation module demonstrated high accuracy and responsiveness in generating and executing complex motion profiles.

- Trajectory Accuracy: Various trajectories (e.g., linear movements, circular paths, complex spatial curves) were defined and executed. The digital twin's predictive simulation accurately showed the expected path, and the physical platform, under PID control [15], closely followed these trajectories. Deviations between the planned trajectory and the actual physical movement were consistently within acceptable operational tolerances (e.g., less than Y mm for position, and Z degrees for orientation). This validation aligns with findings on validating digital twins for complex systems [3].

- Smooth Motion: The use of polynomial interpolation for trajectory generation ensured smooth transitions in position, velocity, and acceleration, which is vital for reducing mechanical stress on the platform and achieving precise movements. The digital twin's simulation clearly illustrated the smooth velocity and acceleration profiles generated by the algorithms.
- Predictive Capabilities: A key result was the digital twin's ability to simulate future states of the platform based on the computed trajectory before actual execution on the physical system. This predictive capability allowed for:
    - Pre-flight Checks: Operators could visually and numerically verify the feasibility and safety of a planned trajectory in the virtual environment.
    - Collision Avoidance: Potential self-collisions or collisions with environmental obstacles could be detected in the virtual model, preventing costly physical errors.
    - Performance Forecasting: The digital twin could predict the power consumption, actuator loads, or dynamic stresses associated with a specific trajectory, enabling optimization.

3.3 System Resilience and Diagnostics

The digital twin's architecture facilitated improved system resilience and diagnostic capabilities.

- Anomaly Detection: By constantly comparing the real-time data from the physical platform with the ideal behavior predicted by the virtual model, the system could detect anomalies. For instance, if a leg length measurement significantly deviated from the virtual model's expected value for a given command, an alert would be triggered, indicating a potential sensor malfunction, actuator fault, or external disturbance. This aligns with the concept of using digital twins for proactive resilience management [12, 27].
- Fault Isolation: In cases of discrepancies, the detailed real-time data from all sensors, combined with the comprehensive state information of the virtual model, aided in quickly isolating the source of the fault. For example, a discrepancy in one leg's length, while others were tracking correctly, could point to a specific actuator issue.
- Enhanced Control Verification: The digital twin served as a real-time validation tool for the underlying control algorithms. The effectiveness of PID tuning [25] or other control strategies could be observed and refined by analyzing the physical platform's tracking performance against the ideal virtual trajectory.

Overall, the results demonstrated a functional and highly effective real-time digital twin for the Stewart platform, capable of providing deep insights into its operational state and enabling advanced trajectory management.

4. DISCUSSION

The successful implementation of a real-time digital twin for the Stewart platform, coupled with integrated real-time trajectory computation, represents a significant advancement in the control and operational management of complex parallel manipulators. This work bridges the gap between theoretical modeling and practical application, showcasing the tangible benefits of digital twin technology in robotics.

The high fidelity and low latency of the data synchronization between the physical and virtual models confirm the feasibility of creating a truly real-time digital twin [9, 23]. This real-time mirror allows for continuous, accurate monitoring, which is fundamental for ensuring system performance and detecting nascent issues. The choice of lightweight protocols like MQTT proved effective in maintaining this critical data flow, even in dynamic operational scenarios [9].

The capability to compute and simulate trajectories in real-time within the digital twin environment is a major strength of this system. Unlike offline simulations, this integrated approach allows for immediate validation of planned movements against the current state of the physical platform, reducing the risk of errors and enabling rapid adjustments [3]. The predictive power of the digital twin, allowing "what-if" analysis of trajectories, significantly enhances operational safety and efficiency. This goes beyond simple control by providing a foresight into the system's behavior under various movement commands. The work also supports the broader vision of utilizing digital twins for manufacturing resilience and agility [13].

The application of fundamental kinematic and dynamic models [2, 4] within the digital twin framework ensures that the virtual representation accurately reflects the physical realities of the Stewart platform. The integration of advanced control elements, such as PID controllers, which are essential for precise motion, further solidifies the practical utility of this digital twin [15, 25]. The system's ability to quickly identify deviations between the physical and virtual states underscores its potential for advanced diagnostics and predictive maintenance, contributing to the overall resilience of the robotic system [12, 27].

While the implementation demonstrated considerable success, certain challenges and limitations were noted. Accurate calibration of the physical platform is paramount for the digital twin's fidelity; any inaccuracies in physical measurements or actuator scaling can lead to discrepancies between the real and virtual systems. Furthermore, while the digital twin can predict and identify potential issues, the current system relies on human intervention for decision-making regarding fault resolution or control adjustments. Future work could explore the integration of AI and machine learning techniques within the cognitive digital twin framework [6, 8, 22] to enable autonomous decision-making for enhanced resilience and self-optimization. For example, AI algorithms could be trained on historical digital twin data to automatically suggest optimal trajectory adjustments or identify maintenance needs before failures occur.

Moreover, exploring more sophisticated communication architectures, perhaps incorporating edge computing for faster local processing and reduced cloud latency, could further enhance the real-time capabilities, especially for applications requiring ultra-low latency control [8]. Expanding the digital twin to include environmental factors (e.g., temperature, vibrations) and their impact on platform performance would create an even more comprehensive and robust virtual model. Finally, the scalability of this approach to multiple interconnected Stewart platforms or larger industrial systems could be investigated, moving towards the concept of a digital twin for an entire manufacturing chain [11, 17]. This article has provided a robust foundation for leveraging real-time digital twin technology to significantly advance the capabilities and operational integrity of Stewart platforms in diverse application domains.

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