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Research on the Construction of a Digital Twin System for the Long-Term Service Monitoring of Port Terminals

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Abstract: Structural damage is a prevalent issue in long-term operations of harbor terminals. Addressing the lack of transparency in terminal infrastructure components, the limited integration of sensor monitoring data, and the insufficient support for feedback on service performance, we propose a novel digital twin system construction methodology tailored for the long-term monitoring of port terminals. This study elaborates on the organization and processing of foundational geospatial data, sensor monitoring information, and oceanic hydrometeorological data essential for constructing a digital twin of the terminal. By mapping relationships between physical and virtual spaces, we developed comprehensive dynamic and static models of terminal facilities. Employing a "particle model" approach, we visually represented oceanic and meteorological elements. Additionally, we developed a multi-source heterogeneous data fusion model to facilitate the rapid creation of data indexes for harbor elements under high concurrency conditions, effectively addressing performance issues related to scene-rendering visualization and real-time sensor data storage efficiency. Experimental validation demonstrates that this method enables the rapid construction of digital twin systems for port terminals and supports practical application in business scenarios. Data analysis and comparison confirm the feasibility of the proposed method, providing an effective approach for the long-term monitoring of port terminal operations.

Keywords: digital twin; data-driven; port infrastructure; long-term service monitoring; multi-source heterogeneous data

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1. Introduction

The harsh marine environment in which harbor terminals operate is characterized by complex factors such as wind, waves, currents, temperature, salinity, and load conditions, leading to pervasive structural damage during long-term operations [1–3]. The terminal components are numerous and highly complex, with current safety and early warning measures primarily reliant on periodic manual inspections. However, existing inspection methods face challenges such as adverse working conditions, concealed internal damage, and low data accuracy, making it difficult to dynamically, continuously, and comprehensively reflect the safety status of the terminals. The deployment of sensors for automated and digital health monitoring has emerged as a new trend in recent years [4–6], offering a more effective approach to addressing these issues.

Digital twins are used in many disciplines to support engineering, monitoring, controlling, and optimizing cyber-physical systems [7]. Digital twin technology, a virtual representation of a physical entity, has revolutionized various industries, including port terminals [8–11]. Digital twin technology is a digital and technological concept, which means that is based on the integration and fusion of data and models. It accurately constructs physical objects in real-time in digital space and simulates, verifies, predicts, and controls the entire lifecycle process of physical entities based on data fusion and analysis prediction [12,13]. Digital twins can capture the combined usage of heterogeneous models and respective evolving data for the entire lifecycle [14]. The development of digital twin technology provides new solutions for the integration of virtual and real, real-time interaction, and iterative operation and optimization, as well as full factor digital transformation and the intelligent upgrading of port terminals. The key to the application of digital twins to ports lies in IoT (Internet of Things) perception and full element digital expression, massive data visualization rendering and data fusion, spatial analysis calculation and simulation deduction, etc. The core lies in the interaction and collaboration between the real scene and twin scene of the port, as well as the transmission and automatic construction of real-time data. Also key is the acquisition of data such as water depth measurements, sensor perception, and maintenance and operation history at the front of the port, ultimately achieving a multi-physical quantity, multi-scale, and multi-probability simulation process of the port.

By creating dynamic models of port operations, digital twin technology has become instrumental in advancing smart water transportation by offering real-time monitoring and predictive maintenance capabilities for port structures. A digital twin (DT) creates a revolutionary opportunity for smart ports' authorities, with the capability of high-fidelity digital representation of real-world things [15,16]. At present, digital twin technology has already been applied to numerous domestic ports [17–20]. Yu P. analyzed the key problems and technologies that need to be solved and used, respectively, in the specific implementation of digital twins of integrated port energy systems [21]. Hofmann proposed a digital twin for truck-dispatching operator assistance, which enables the determination of optimal dispatching policies using simulation-based performance forecasts [22]. Li Y proposed a framework integrating DT with the AdaBoost algorithm to realize the real-time optimization and security of the ACT(Automated Container Terminals) [23]. Martínez-Gutiérrez proposed a new DT design concept based on external service for the transportation sector [24]. Shanghai Port has employed digital twin technology to monitor the health of its infrastructure. By creating a virtual model of the port's structures, including piers and docks, the system can detect structural anomalies and predict maintenance needs, thereby enhancing safety and operational efficiency. Guangzhou Port has integrated digital twin technology with advanced sensors and IoT devices to detect structural integrity issues. The system analyzes data from these devices to provide insights into potential weaknesses and degradation patterns, enabling timely interventions. Shenzhen Port has developed a comprehensive digital twin-based health monitoring system. This system combines real-time data acquisition, simulation models, and predictive analytics to monitor the structural health of port facilities, ensuring long-term stability and reliability. Ningbo–Zhoushan Port has deployed a digital twin to monitor real-time operations and predict maintenance needs. The technology aids in efficient berth allocation, reducing vessel waiting times and improving overall port throughput. The Port of Rotterdam has implemented a digital twin system to continuously monitor the health of its infrastructure. The system uses real-time data to detect structural issues and predict future maintenance requirements, ensuring the safety and efficiency of port operations. Antwerp Port's digital twin framework integrates with various detection technologies, including LIDAR (Light Detection and Ranging) and sonar, to analyze the structural health of underwater and above-water components. This integration allows for the detailed inspection and timely maintenance of critical infrastructure. The Port of Los Angeles has constructed a robust digital twin-based health monitoring system that incorporates machine learning algorithms to analyze structural data. This system provides real-time insights and predictive maintenance recommendations, enhancing the port's operational resilience. Singapore Port has developed a comprehensive digital twin to manage complex logistics and improve service levels. The system supports real-time decision-making, asset management, and operational planning, leading to increased port productivity [25–27].

Structural health monitoring of terminals through sensor data collection allows for real-time safety assessments based on empirical values. However, there is a lack of effective support for feedback on the long-term service performance of terminal structures. This paper proposes a digital twin system methodology tailored for the long-term service monitoring of harbor terminals. Utilizing multi-source heterogeneous data from long-term service monitoring, we establish monitoring data resources encompassing terminal structures, environment, materials, and loads. By extracting characteristic parameters that represent the terminal's performance under marine environmental influences and using deployed sensors to collect status data, we investigate techniques for constructing a comprehensive digital twin of the terminal. The system is designed to handle large volumes of data with low latency and intelligent processing. This digital twin system enables data-driven visual management of structural safety through historical backtracking, monitoring and early warning, and future predictions, thereby illustrating the structural safety status of the terminal at different stages of its service life.

2. Methodology

The framework for the digital twin system construction method proposed in this paper is illustrated in Figure 1.

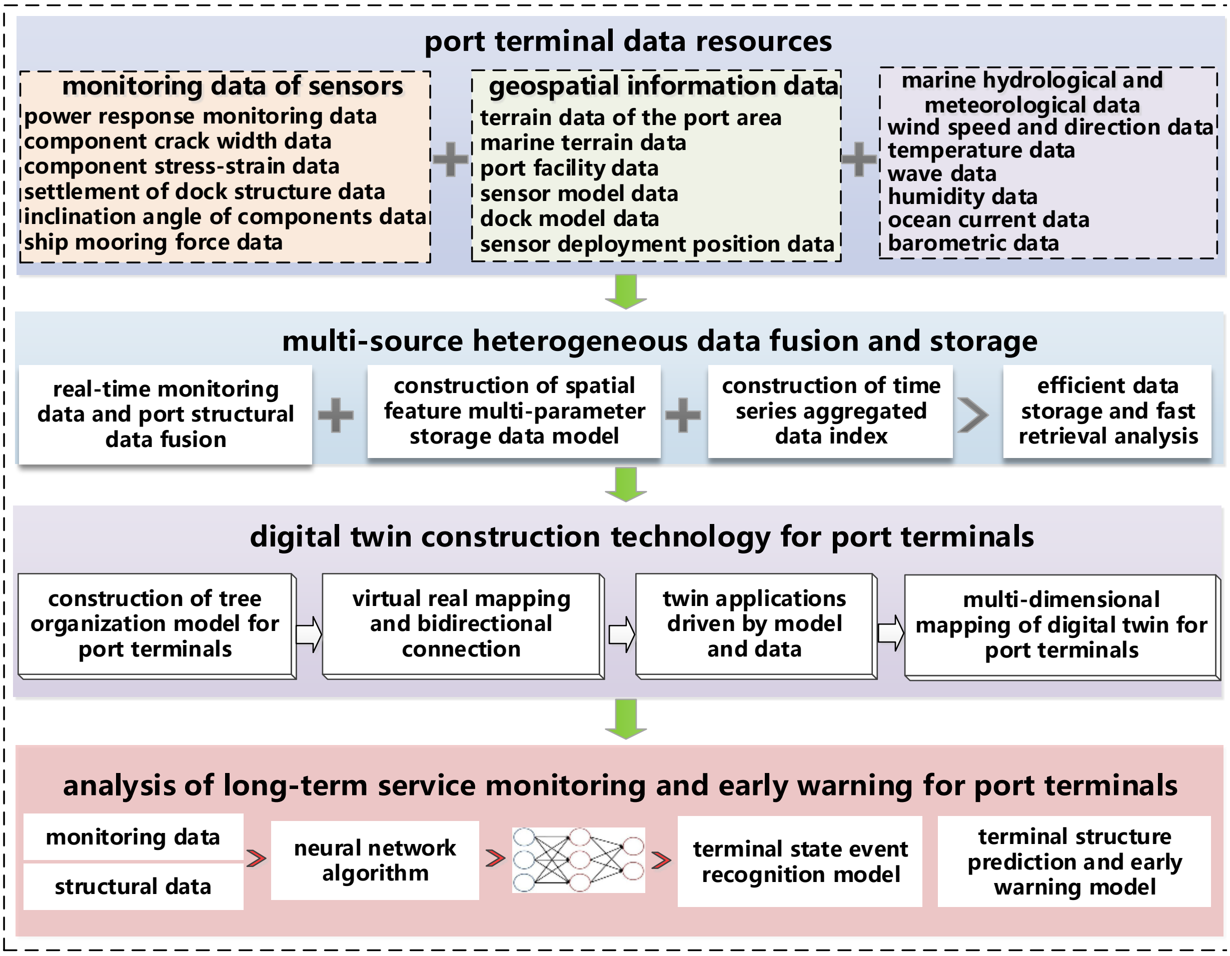


Figure 1. Construction framework of digital twin system.

Based on the physical information–mapping relationship between the physical space scene and the virtual space scene, the logic block diagram is shown in Figure 2.

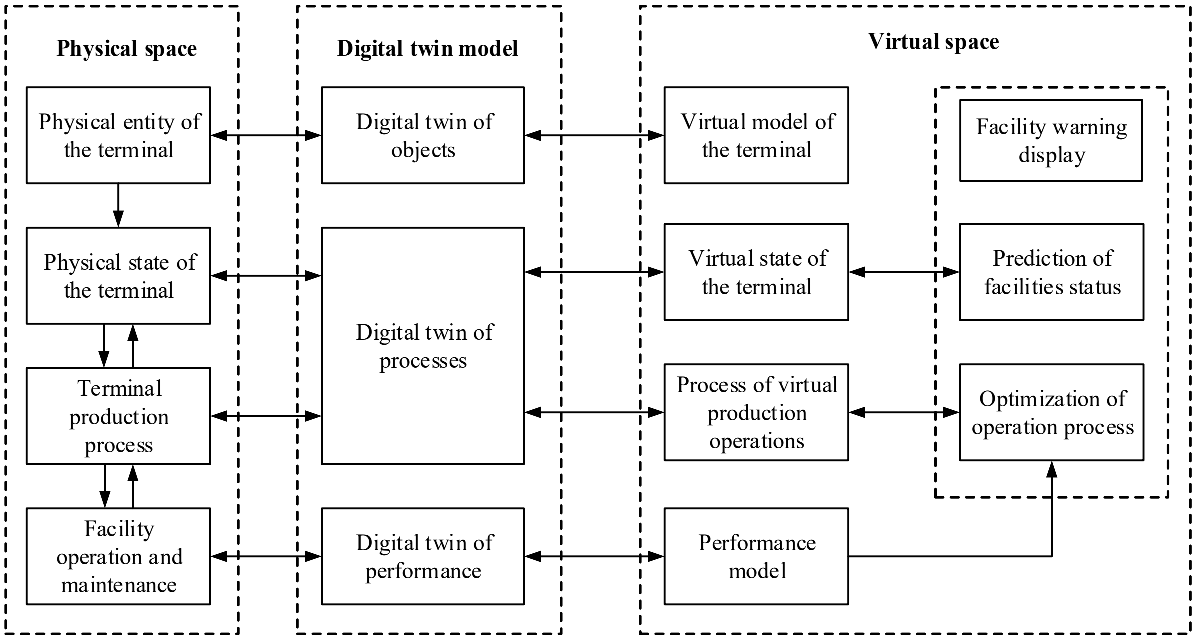


Figure 2. Terminal digital twin logic block diagram.

2.1. Port Terminal Data Resource

The construction of a digital twin for a seaport terminal encompasses foundational geospatial data, sensor monitoring data, and marine hydrometeorological data. These data resources exhibit semantic independence and heterogeneity, varying across temporal and spatial dimensions and storage formats. This includes unstructured data such as vector and raster maps of the port area, and detailed models of the terminal (as shown in Table 1), as well as structured data such as terminal stress–strain data, structural settlement data, and marine hydrometeorological information (as detailed in Table 2). The diverse acquisition methods, data content, and spatiotemporal characteristics necessitate varied approaches to data processing, structure, representation, and storage.

Table 1. Unstructured data.

Serial Number	Data Item	Data Description
1	Topographic data of port area	Including port infrastructure, elevation, and other data.
2	Port infrastructure data	Including data of docks and berths.
3	Marine topographic data	Including data such as the water depth at the wharf front.
4	Wharf model data	Including model data such as wharf components.
5	Sensor model data	Include sensor model data such as stress and strain.
6	Sensor layout position data	Includes sensor point, line, and area data.

Table 2. Structured data.

Serial Number	Data Item	Data Description
1	Dynamic response monitoring data	Including fundamental frequency, amplitude, acceleration, sensor position, and other data.
2	Stress and strain data of components	Including stress value, strain value, sensor position, and other data.
3	Dynamic inclination data of components	Including vibration, angle, sensor position, and other data.
4	Component crack width data	Include data such as crack length, width, and sensor position.
5	Settlement data of wharf structure	Include data such as settlement depth and sensor position.
6	Ship mooring force data	Including data such as stress and sensor position.
7	Marine hydrological element data	Including ocean wind, waves, currents, and other data.
8	Meteorological element data	Including temperature, humidity, air pressure, and other data.

2.2. Multi-Source Heterogeneous Data Fusion and Storage

Terminal monitoring and related data have the characteristics of large data volume, high concurrency, and strong real-time performance. For unstructured data, this study employs an XML-based (Extensible Markup Language) distributed spatial data organization and storage method. This approach supports deep-level nested expressions and tree-like storage structures, systematically managing metadata concerning data sources, types, information content, structure, and access methods. This framework establishes a unified spatial reference for terrain scenarios above, at, and below the waterline at the terminal's edge. On this basis, an integrated spatiotemporal dataset of port infrastructure is constructed, correlated by geographic location and attribute information, and stored using a combination of file systems and relational databases. Regarding structured data, the study first analyzes sensor monitoring data in terms of acquisition frequency, data format, and volume. Then, a time-series-based multi-parameter column storage database model for terminal monitoring is developed, specifying database entity attributes, data types, lengths, and precisions. A distributed storage system database is utilized for storing these data.

Following the organization and processing of these data, the CGCS2000 (China Geodetic Coordinate System 2000) geographic coordinate system is adopted as the reference to create a foundational geographic information basemap of the port. This basemap integrates terminal and sensor models, allowing for the real-time monitoring and collection of terminal safety status data, ultimately forming a unified digital twin data resource for the terminal.

2.3. Digital Twin Construction Technology for Port Terminals

2.3.1. Construction Method for Wharf Digital Twin

The construction of a digital twin for the terminal integrates physical models, simulation models, and data models through mutual coupling. Based on the mapping relationship between physical and virtual spatial scenarios, the process begins by constructing comprehensive models of static elements within the terminal's physical space in the virtual environment. Sensor perception data and structural state data are then fused. Subsequently, dynamic elements of the terminal are simulated, based on kinematic and dynamic characteristic models. Finally, data organization and the optimization of the digital twin model are performed, achieving the construction of a terminal structure digital twin scenario driven by both models and data. The specific steps are as follows:

(1) Construction of static element scenarios: This phase involves four stages: model creation, model establishment, texture mapping, and model baking. Utilizing 3ds Max for three-dimensional modeling, we develop high-precision 3D models of the natural environment within a 3 km radius of the terminal, including marine, terrain, and topographic features, as well as the relevant port infrastructure. Structural parameters, geometric parameters, material parameters, and state parameters are embedded within these 3D models. A multidimensional terminal scene model compatible with sensors is constructed, analyzing the rotation, translation, and orientation of the terminal scene model to determine the relationships between variables such as sensor inclination, angles, and positions. Real-time updates of model data are achieved through data interfaces, facilitating the information interaction and data synchronization between the physical entities and the digital twin.

(2) Construction of dynamic element scenarios: Building on the static model scenarios, dynamic elements of the terminal, such as movable equipment and facilities with action attributes, are modeled according to their motion characteristics. Corresponding animation frames are created, and a graphics engine is employed to execute related operational actions and commands. For complex motion models, elements are categorized and grouped based on the relative motion relationships of terminal components in a tree structure. Each dynamic element of the terminal is then modeled according to its structural characteristics, using kinematic and dynamic properties to construct physical simulation models. These models simulate kinematic and dynamic behaviors, providing parameters for the operational states of the terminal's digital twin (Figure 3).

Figure 3. Scene construction of dynamic element model of wharf.

Organization and rendering optimization of the digital twin model: This study employs a scene tree directory structure for the logical management and optimization of massive model data. The constructed terminal digital twin scene comprises billions of model nodes, each containing vast amounts of data such as triangles and polygons, materials, and textures. The scene graphics are organized using a top-down, hierarchical tree data structure. The root node is at the top, extending downward, with each group node containing geometric information and rendering state information to control its appearance. At the bottom of the scene graph, leaf nodes contain the actual geometric information constituting the scene's objects. Utilizing the rendering tools in 3ds Max, models are rendered in sequence according to the directory structure. This process involves adding materials, defining surface color, transparency, roughness, and texture, and incorporating the physical model's material parameters, structural data, and geometric data, along with optimizing boundary conditions. Additionally, rendering optimization is applied to the edges of the models.

2.3.2. Expression of Marine Hydrometeorological Elements

During the actual operation of a seaport terminal, risks to safety arise from adverse weather conditions, including wind, waves, and currents. To effectively integrate and display marine hydrometeorological data within the digital twin scenario, a dynamic evolution simulation method using "particle models" is proposed. This method involves performing coordinate transformation operations on particles and setting parameters such as color, texture, lighting, and fogging to achieve a three-dimensional dynamic visualization of marine hydrometeorological elements. The specific steps are as follows:

(1) Index Construction: Taking the ocean current field data of the demonstration port area as an example, the raw data are parsed to obtain the basic information of the grid. The values in the u and v directions are stored using two arrays. The data grid spacing is 0.03°, with each grid cell storing the parsed (u, v) values and the calculated flow direction and velocity information based on these (u, v) values.

(2) Parameter Initialization: The fundamental structure of a particle includes variables x, y, dx, dy, age, birthAge, and path, which are initialized to define position and velocity parameters. The initialization of particle position parameters involves generating random floating-point numbers within specified ranges. The initial lifespan (birthAge) is randomly generated. Once the particle position is determined, the corresponding velocity values from the flow field are obtained via bilinear interpolation. This interpolation method establishes a function based on two variables and linearly extends the function. It determines the value of function f(x) at point P using the known values at points Q_{11}, Q_{12}, Q_{21}, and Q_{22} (Figure 4).

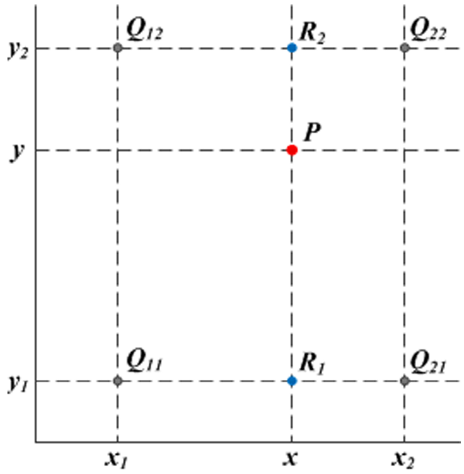


Figure 4. Bilinear interpolation diagram of flow field particles.

Firstly, bilinear interpolation is performed in the x-direction twice according to Formulas (1) and (2), as follows:

$$f(R_1) \approx \frac{x_2 - x}{x_2 - x_1} f(Q_{11}) + \frac{x - x_1}{x_2 - x_1} f(Q_{21}) \quad (1)$$

$$f(R_2) \approx \frac{x_2 - x}{x_2 - x_1} f(Q_{12}) + \frac{x - x_1}{x_2 - x_1} f(Q_{22}) \quad (2)$$

Subsequently, linear interpolation is conducted in the y-direction according to Formula (3), as follows:

$$f(P) \approx \frac{y_2 - y}{y_2 - y_1} f(R_1) + \frac{y - y_1}{y_2 - y_1} f(R_2) \quad (3)$$

(3) Data Computation Update: Based on the velocity values of the vector field, integration is performed to calculate the next position of the particle, continuing iteratively until the termination condition for integration is met. The lifespan of the particle corresponds to the period when integration of the particle's trajectory ceases. Assuming the velocity of the vector field is represented as $\vec{v}(\vec{r}(t))$, where t is the integration variable or time variable and $\vec{r}(t)$ is the position vector of the particle's trajectory, differential functions are utilized for computational solution. According to the integral equation of formula 4, the position of the particle at the next moment can be determined as follows:

$$\vec{r}(t) = \vec{r}(t_0) + \int_{t_0}^{t} \vec{v}(\vec{r}(t))dt \quad (4)$$

(4) Streamline Generation: After updating the particle position data, particles with different lifespans generate a series of points. These points can be connected using piecewise linear segments to form streamlines. To enhance the dynamic effect of the streamlines, transparency is adjusted based on the order of particle generation. This approach allows all particle points to be connected into line segments, forming cohesive streamlines.

2.3.3. Driven by the Fusion of Digital Twin Scenes and Feature Data

A complete digital twin of the port is established, based on the integration of digital models, sensor data collection, and marine hydrological and meteorological elements that reflect the authenticity of physical entities. Applications such as data perception, intelligent identification, and control prediction need to be driven by the fusion of twin scene and element data. Through multi-source sensor technology, real-time monitoring data of the port structure, environment, materials, loads, and other operational processes are collected.

Through multi-source heterogeneous data analysis, system functional integrity verification, and the iterative optimization of control algorithms, decision-making control, performance evaluation, and health predictions of the digital twin of the port are achieved, as well as real-time feedback and autonomous learning of the physical and historical states of physical entities. A digital twin driving model is established for the data-driven analysis and interactive mapping of digital twin data at the dock, integrating scene construction, element data access, and prediction and deduction. The model mainly includes the following:

(1) The description and precise characterization of dock equipment, equipment components, and system integration, achieving component coupling simulation and the precise characterization of digital twins.

(2) The dynamic data regarding virtual–real interaction at the dock is updated and visualized in real time. Through real-time updates of physical models, state parameters, operational data, and marine environmental data of in-service dock operation facilities, data-driven and interactive iterations, process monitoring, performance evaluation, and health predictions of the digital twin of all dock elements are achieved.

(3) The consistency mapping detection of dock digital twins and application systems is achieved through parallel intelligence, compressive sensing, and deep learning to generate and optimize digital twin interaction mapping, completing accurate data analysis and consistency mapping. We use data-driven models to express the characteristic elements of port terminal structural safety monitoring for different scene objects and application requirements, and map them to the application system through visualization.

2.4. Analysis of Long-Term Service Monitoring and Early Warnings for the Wharf

Based on the constructed digital twin model of the port, driven by real-time monitoring data, deep learning neural network algorithms are used to deeply analyze and mine the multimodal data collected from real-time monitoring of the port, in order to establish an accurate data analysis model, reveal the relationship and temporal characteristic trends between the structural data indicators of the port, improve the analysis ability of the digital twin of the port, and achieve accurate identification and warning of the safety status of the port.

By applying deep learning algorithms to real-time monitoring data such as settlement, displacement, and acceleration in dock structures, utilizing long short term memory neural networks (LSTM) and gated recurrent units (GRU), complex relationships and nonlinear features between data can be discovered. Extracting valuable information from massive monitoring data allows us to provide more accurate intelligent analysis support for digital twin structures at docks. By analyzing the characteristics of structural state monitoring data for specific events such as ship collisions, heavy load operations, extreme weather, etc., a deep neural network model is trained to identify these events and analyze their impact on structural state. We integrate the predictive analysis results into the digital twin system to achieve real-time control, historical review, and prospect prediction of port structural safety, thereby enhancing the safety analysis capability of port infrastructure.

3. Performance Optimization, Comparative Experiments, and Results

3.1. Efficiency Optimization Methods for Scene Data

Optimizing digital twin scenarios for port operations is a critical challenge, requiring the further enhancement of efficiency for the effective deployment of digital twin applications. Efforts have been directed towards optimizing the organization, management, scheduling, and visualization of scene data, incorporating multi-level detail, view frustum culling, asynchronous data loading, and request prediction. Additionally, a semantic-indexing model oriented towards the organization, transmission, and storage of heterogeneous data collected by sensors has been proposed. Furthermore, for the access and interactive visualization of massive ship data, a density clustering approach is employed to manage densely packed AIS (Automatic Identification System) data symbols, thereby reducing data display latency.

(1) Efficiency optimization of port scene data involves several key strategies. Firstly, employing multi-level detail (LOD) optimization gradually simplifies the surface details of models, in order to reduce geometric complexity. Thresholds are set and evaluated based on the ratio of view height to data size, in order to determine whether further decomposition into higher resolution data is necessary, thereby enhancing graphical rendering efficiency. Secondly, view frustum culling optimization controls the range of front and back clipping planes, defined by the field of view angles and projection matrix, to ascertain the size and depth of visible content within the visible view frustum. Thirdly, asynchronous data loading divides data among different threads; the main thread calculates required data through LOD algorithms and clipping. If not cached, data are added to the request queue. Once loaded, the main thread is notified for tile utilization and view refresh (Figure 5). Lastly, predictive request optimization forecasts data needs during continuous scene movement. Data are preloaded into buffers based on the predicted requirements, maintaining the invariant graphic projection frustum. Adjustments are made to frustum size and shape according to viewpoint movement direction and speed, thereby improving the accuracy and specificity of data retrieval predictions.

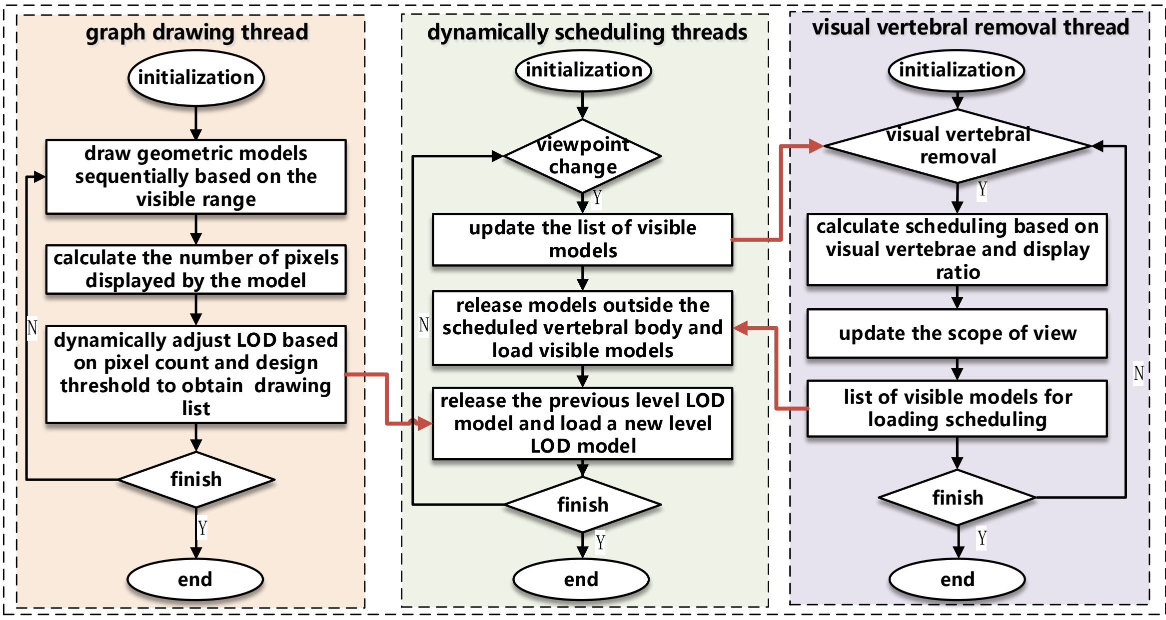
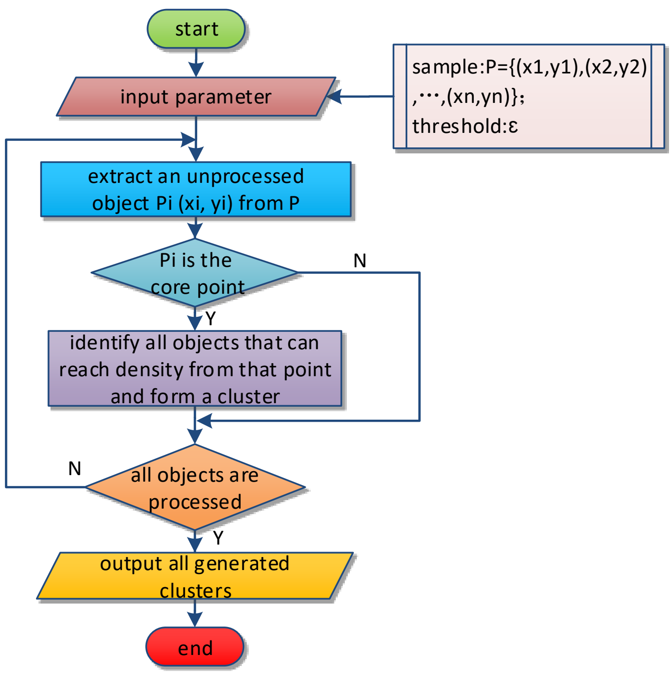


Figure 5. Optimal design of asynchronous data loading.

(2) The efficiency optimization of sensor monitoring data involves several strategic steps. Initially, the storage space for sensor monitoring data is partitioned into N grid regions, abstracting data entities and their attribute relationships into nodes and edges within a model. This enables the indexing of multidimensional features and associative relationships. Subsequently, prior to storage, sensor monitoring data undergoes normalization, where raw data are linearly distributed to achieve a normalized distribution within the [0, 1] interval. This transformation converts raw data into semantic vectors, establishing a semantic indexing structure. Furthermore, during the query–response phase, query requests are forwarded to an integrator module. The integrator module distributes the query to multiple relay modules for the parallel execution of searches. Each relay module is designed with multiple identical instances to ensure load balancing and fault tolerance. Results from queries are merged and returned to the integrator module. Lastly, for sensor monitoring data such as stress–strain and structural settlement data, feature extraction is performed. Multiple datasets are classified and their features correlated to construct a data classification and attribute inverted index. This facilitates the establishment of vector connectivity graphs for different types of data at the same moment in time.

(3) Ship data simulation and efficiency optimization in port twin scenarios involve the real-time integration of ship position data. Each update of ship data necessitates re-rendering to enhance the display's efficiency and reduce latency. This study employs density clustering to optimize dense ship AIS data, ensuring the efficient presentation of ships within the twin port scenario.

Building upon the DENCLUE (Density-based clustering) algorithm, this study optimizes the integration of ship AIS data in twin port scenarios (Figure 6a). For ship position points where the distance between two ships is d and the interaction range is set to ε, if $d \leq \varepsilon$, these points are considered to be within the same clustering range. Using Pi as the center and ε as the radius, the algorithm calculates the number of ship position points u within this neighborhood circle. It then calculates the number of points in the neighborhood of each point within the neighborhood of Pi and takes the maximum value v. If $u > v$, Pi is saved as a density attractor point for that region; if $u \leq v$, then Pi (where (x_2,y_2) are coordinates) with the maximum neighborhood density becomes the attractor point, and all ship position points within Pj's neighborhood, including Pi, are clustered around Pj. To prevent the sequential clustering of point coordinates, clustering is only performed if $d \leq \varepsilon$. This process is repeated for all ship position points to complete one clustering iteration. The pseudo code of the DENCLUE algorithm for ship density clustering is shown in Figure 6b. Based on the previous layer of clustering points, the threshold is incrementally increased, and clustering is repeated until the desired density point count is achieved. As more ship position points are clustered, the density attractor points gradually become the local maxima of global density. When the required density point count is reached, clustering is considered complete. Addressing the issue of low efficiency and display latency in rendering three-dimensional ship models, this method integrates the efficiency optimization techniques proposed earlier for port scene data. Starting from rendering, view frustum culling optimization dynamically loads ships within the view range as the viewpoint moves, simultaneously removing ship models outside the view frustum.



(a)

```
# Gaussian kernel function
def gaussian_kernel(distance, sigma):
    return exp(-distance**2 / (2 * sigma**2))

# Calculate the density of each point
def calculate_density(points, sigma):
    n = len(points)
    densities = [0.0] * n
    for i in range(n):
        for j in range(n):
            if i != j:
                dist = euclidean_distance(points[i], points[j])
                densities[i] += gaussian_kernel(dist, sigma)
    return densities

# Identify core points
def find_core_points(densities, threshold):
    return [i for i, d in enumerate(densities) if d > threshold]

# Expanding clustering from a core point
def expand_cluster(points, densities, core_index, sigma, visited):
    cluster = [core_index]
    visited[core_index] = True
    for i in range(len(points)):
        if not visited[i] and densities[i] > 0:
            dist = euclidean_distance(points[core_index], points[i])
            if dist < some_distance_threshold(sigma):
                cluster.append(i)
                visited[i] = True
    return cluster

#DENCLUE clustering algorithm
def denclue_clustering(points, sigma, threshold):
    densities = calculate_density(points, sigma)
    core_points = find_core_points(densities, threshold)
    clusters = []
    visited = [False] * len(points)
    for core in core_points:
        if not visited[core]:
            cluster = expand_cluster(points, densities, core, sigma, visited)
            clusters.append(cluster)
    return clusters
```

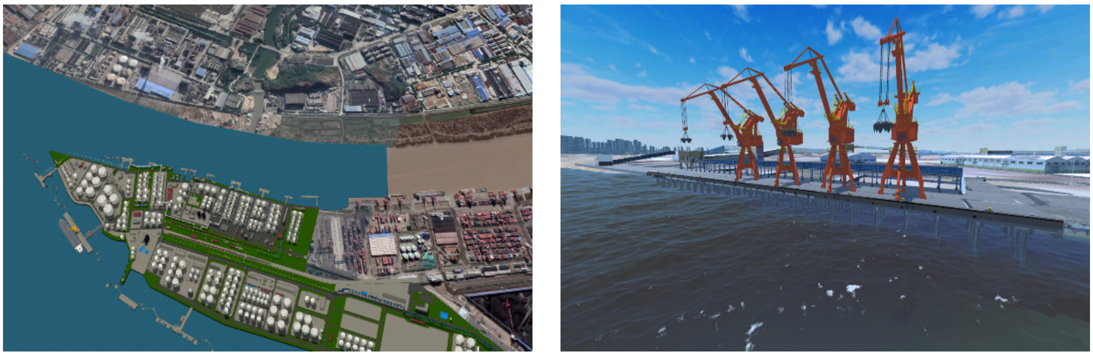
(b)

Figure 6. Optimization design of ship density clustering and pseudo code. (**a**) Optimization design process for ship density clustering. (**b**) Pseudo code of DENCLUE algorithm.

Through the aforementioned efficiency optimization design for scene data, several performance issues related to the organization, display, and scheduling of three-dimensional scenes have been addressed. Simultaneously, the real-time storage and query efficiency problems of sensor monitoring data have also been resolved. This integrated approach not only enhances the rendering and interaction capabilities of complex three-dimensional scenes but also ensures that sensor data can be stored, accessed, and queried efficiently in real time, thereby improving the overall system performance and user experience in digital twin applications for port environments.

3.2. Twin Scenes and Platform Construction

The demonstration utilizes the ore terminal berth of the demonstration port area. It employs unmanned aerial vehicles for photogrammetric data collection, integrating oblique photography with satellite imagery and spatial elevation data. This process establishes a spatial geographic information repository. Utilizing the methodology proposed in this study, a digital twin model of the port area (Figure 7a) is constructed. Surface and vertex/fragment shaders are employed to create realistic shadows, enhancing the fidelity of the terminal model imported into the Unity model library. These digital twins provide a perspective on the internal components of the terminal and the status of sensors (Figure 7b). The reason for choosing Unity in this article is that it has a good visual rendering effect, supports both Client/Server architecture for easy deployment and an efficient display, and supports publishing Browser/Server architecture for browser access when the display efficiency is not high.



(**a**) (**b**)

Figure 7. Construction of digital twin model. (**a**) Twin scene model of port area. (**b**) Refined dock model.

The development of the dock digital twin system (Figure 8) using the Unity3D base platform expands functionalities with the WebGL (Web Graphics Library) 3D graphics module. This integration of JavaScript and OpenGL for Embedded Systems provides hardware-accelerated rendering for HTML5 (HyperText Markup Language 5) Canvas, enabling the smooth display of dock digital twin scenes and models within web browsers. The system consists of four main components: a data layer, a service layer, a rendering layer, and a presentation layer. The data layer is structured according to dock feature data characteristics, encompassing geographic spatial data, sensor monitoring data, and hydrometeorological data. The service layer centrally manages basic geographic information services, dock feature services, hydrometeorological model services, and interfaces for sensor monitoring and perception data access. The rendering layer focuses on simulating and rendering dock component models, vessels, sensors, and marine hydrometeorological elements. Meanwhile, the presentation layer implements the functionalities of the digital twin system platform, including twin scene display, monitoring data presentation, monitoring alerts, and intelligent decision-making capabilities.

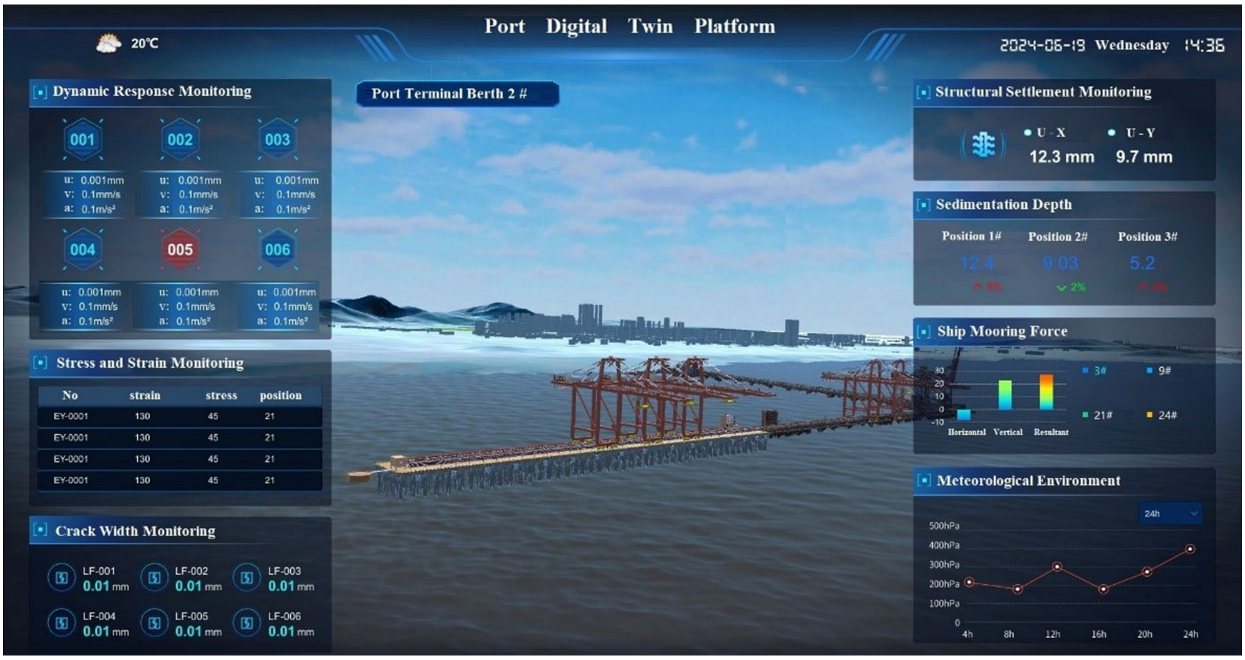
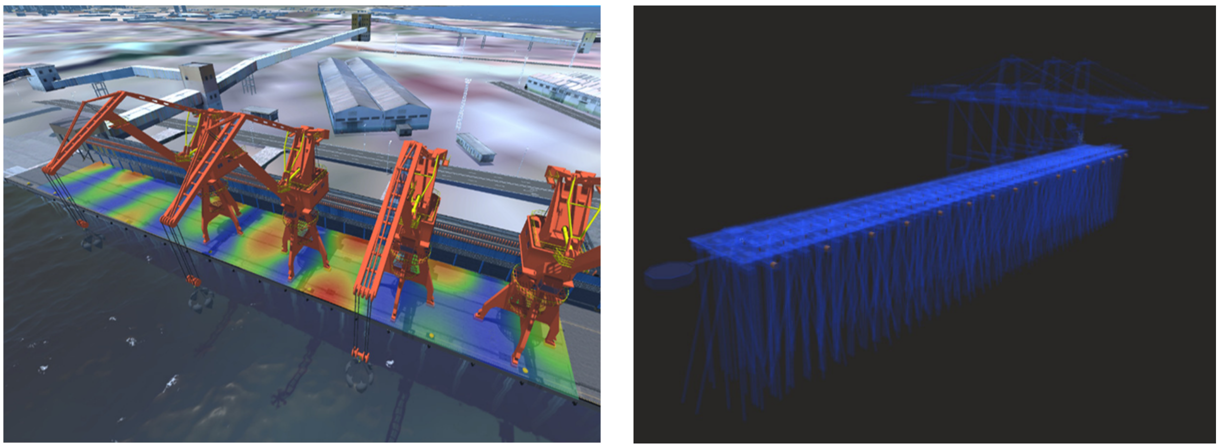


Figure 8. Digital twin system platform.

The paper applies a digital twin system for monitoring the safety status of port terminals. The monitoring data collected by sensors (stress and strain data, structural settlement data, siltation depth data, meteorological environment data, etc.) and spatial data (terminal refinement data, vector and grid map data, etc.) are used as input values. The characteristics of sensor data, collection frequency, and data volume are comprehensively analyzed, and the safety status of port terminals is used as the target output. A deep learning model for evaluating the structural status of ports is constructed to achieve an impact analysis of port structures. Based on monitoring data and numerical analysis results, we extract characteristic elements such as the settlement (Figure 9a) and stress (Figure 9b) of the dock structure, and use multi-dimensional simulation special effects technology to visualize and enable interaction with early warnings, using aspects such as particle effects, light and shadow materials, and grading colors.



(**a**) (**b**)

Figure 9. Application of digital twin platform. (**a**) Simulation of settlement of structure. (**b**) Simulation of stress of structure.

3.3. Efficiency Optimization Experimental Analysis

In the experimental setup, the raw data for constructing the dock digital twin model amounted to 4.56 GB. Rendering and analysis of the scene were conducted using various computational servers, where CPU (Central Processing Unit) usage rates encompassed the operational overhead of internal system processes. Findings indicated that, for a system with 16 GB of memory, CPU usage reached 58.7%, whereas, for a system with 64 GB of memory, CPU usage was 21.6%. Overall, these results suggest that the dock digital twin model construction is adaptable to lower-tier computational resources. However, for practical applications, consideration should be given to provisioning higher-tier computational resources.

In the experiment integrating monitoring data into the digital twin scene, comparisons were made between the initial rendering time and the subsequent rendering time after changes in the view. Before optimization, the initial rendering time was prolonged, increasing exponentially with larger datasets. Conversely, rendering times after changes in the view area were relatively faster and less affected by dataset size increments. After optimization, there was minimal difference between the initial rendering time and the rendering time after view changes. However, overall processing time significantly decreased (as detailed in Table 3). The formula for efficiency improvement rate is to subtract the efficiency before improvement from the efficiency after improvement, and then compare it with the efficiency before improvement.

Table 3. Comparative analysis of scene-rendering efficiency (ms).

Number of Access Data		100	865	1985	7582	13,500	21,000
Before optimization	First rendering time	150.14	681.84	1146.1	6095.36	15,652.38	36,034.96
	View change rendering time	130.22	319.32	461.38	641.96	1351.74	2977.05
After the optimization	First rendering time	148.82	345.96	393.22	667.04	1450.74	3036.52
	View change rendering time	146.3	270.24	273.34	558.56	1243.26	2560.84
Comparative analysis before and after	Efficiency improvement in first rendering	0.88%	49.26%	65.69%	89.06%	90.73%	91.57%
	Efficiency improvement in rendering after view changed	−12.35%	15.37%	40.76%	12.99%	8.03%	13.98%

In the experiment on the efficiency of displaying dynamic ship data, the real-time performance and smoothness of the digital twin scene model were analyzed before and after clustering optimization. This analysis focused on two aspects: monitoring the average frame rate after moving the scene view and comparing the time taken to switch between different ship symbols. The experiment involved 2896 ship data entries of various types, using the frame rate before loading ship models as a baseline. Compared with the situation before loading the ship data, the average frame rate showed a slight decrease post-loading, but the difference was minimal and did not significantly affect the smoothness of the visuals in practical applications. Regarding the time taken to switch between different symbols, the transition time between clustered ship positions and their three-dimensional models was only 368 milliseconds after optimization. As shown in Table 4, this demonstrates that the optimized three-dimensional visualization of ship data performs well in terms of display efficiency, meeting the requirement for smooth visuals.

Table 4. Rendering efficiency of multilevel symbolic modeling.

Display Model	Average Frame Rate/fps	Switching Rate/(ms)
Digital twin scene	18.53	-
Ship point (original)	34.49	0.183
Ship location (clustering)	23.94	0.245
Three-dimensional model of ship	21.65	0.159

4. Conclusions

This study explores the construction of a digital twin system for harbor terminals in an exploratory manner. Firstly, it designs the architecture of the digital twin system focusing on four aspects: data resources for harbor twin scenes, the integration and storage of heterogeneous data from multiple sources, the construction of the harbor digital twin body, and long-term service monitoring and early warning analysis. Secondly, it analyzes the data format of the harbor digital twin body, elaborates on data organization and processing methods, and proposes methods for constructing and simulating visualizations of harbor digital twin bodies and marine hydrometeorological data. Solutions are presented for organizing and scheduling massive data, optimizing twin scene efficiency, and addressing issues related to the visualization performance of scenes and the real-time storage efficiency of sensor monitoring data. Lastly, a digital twin system tailored for the long-term monitoring of ports is developed and experimentally applied at the demonstration berth of an ore terminal in a harbor area. Comparative efficiency analyses of twin scenes using the methods proposed in this study demonstrate their capability to integrate real-time sensor monitoring data, enhance the display of digital twin system data elements, and provide essential data support for practical applications of digital twin scene models.

This study has certain limitations in the interactivity of twin scenarios and deep learning-based analysis and prediction. It requires iterative training and upgrading of the model through long-term accumulated data, ultimately forming a warning analysis model suitable for the long-term service monitoring of dock structures, and achieving efficient collaboration between physical and twin scenarios.

The research outcomes presented in this paper are applicable to port operations and the analysis of vessel arrivals and departures. They provide technical support for the intelligent management of port infrastructure and the optimization of infrastructure health monitoring. The rapidly constructed comprehensive digital twin scenes of docks enhance cognitive efficiency and accuracy, facilitating the integration of next-generation information technologies with the maritime transport industry. The next focus of research includes two aspects. Firstly, in-depth research will be conducted on the interactivity of twin scenes and deep learning-based analysis and prediction. Secondly, research will be conducted on complex scene perception, collaborative control, scheduling organization, information security interaction, etc., to form ubiquitous, interconnected, efficient, and intelligent applications in port digital twin scenes. In the future, the rapid development of the shipping trade will drive automated container terminals towards intelligence, safety, and efficiency. Future research results can be further applied to the formulation of job scheduling tasks and the safety and stability of transportation paths [28,29].

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