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Digital Twin-Driven Intelligent Relocation System with AI-Based Path Planning and Reinforcement Learning

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Abstract. This paper proposes an AI-based intelligent house-moving system integrating digital twin technology with AI-driven planning algorithms and virtual–physical interaction technology to improve relocation process efficiency. Structure-from-Motion (SfM) approach combined with object detection techniques is applied to the system which generates semantically enriched digital twin models for indoor environment and objective objects. Based on this model, feasibility analysis and path planning are performed to evaluate whether large furniture can be moved through constrained spaces and hence generates collision-free movement paths for different scenarios under each case. Genetic algorithms are used for optimizing container space utilization, improving packing efficiency and reducing transportation cost, meanwhile, reinforcement learning is incorporated to enhance system adaptability. In addition, with the help of augmented reality (AR) module and digital twin visualization dashboard, the system can provide real-time guidance and monitoring for users. The proposed system improves efficiency, accuracy, and user experience compared to traditional relocation methods.

Keywords: Digital Twin, AI Reinforcement Learning, RRT Algorithm, Genetic Algorithm

1. Introduction

1.1. Research background and significance

Traditional house-moving processes rely heavily on manual experience. Users are required to manually estimate the volume and feasibility of transporting the furniture. This results in a range of critical issues, including fitting problems, time delays, inefficient operations, and potential damage to furniture during transportation. Digital twins, 3D scanning technology, and artificial intelligence technology provide new opportunities in relocation. Digital twins generate virtual duplications of physical environments, integrating artificial intelligence and algorithms in packing optimization, spatial planning and reinforcement learning, it is possible to efficiently develop an intelligent house-moving system that enables a more efficient, reliable, and user-friendly moving services in the process.

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1.2. Related work

Existing studies related to this paper can be categorized into four main areas: digital twin modeling, perception and scene reconstruction, path planning, and intelligent decision-making. In the field of digital twin technology, existing studies have demonstrated its effectiveness in creating virtual duplications of physical environments for simulation and analysis. Digital twins have been widely applied in manufacturing field and smart systems to enable data-driven decision-making and systematic optimization [1, 2]. These studies provide a foundation for applications in relocation scenarios.

1.3. Research content and contribution

The main contributions of this work are summarized as follows:

(1) Feasibility Analysis with Digital Twins. An indoor environment can be built with the use of digital twins to simulate an indoor space and layout.

(2) Intelligent Planning Algorithms. A combined planning system is established to improve efficiency and reliability in the process. This comprises collision detection, enhanced path planning using RRT and genetic algorithm container optimization.

(3) Virtual–Physical Interaction System. Virtual Physical Interaction System is proposed to provide instructions on the on-site functioning to enable users and workers to see the position of objects and their movement in the real world.

(4) Dynamic Planning that is based on reinforcement learning. It is suggested that during a movement, a reinforcement learning strategy can be used to address unforeseen challenges and make adaptable decisions based on the real-world conditions.

2. System composition & structure

To create an intelligent house-moving system that incorporates the use of digital twin technology and artificial intelligence, the system requirements should be defined. These requirements act as the basis of system design, and they make sure that the system design can effectively overcome the constraints of traditional processes prior to the design itself

2.1. System requirements

To begin with, the system can build virtual indoor spaces in the computer by collating multi-source data. The information of the indoor spaces enables the system to construct correct digital models of the environments. Moreover, the system should have the capability to identify and model target objects that households must be represented both geometrically and semantically. The ability is useful in making the system aware of the physical properties of objects. Depending on the built environment, the system can decide whether a large furniture can be moved across the constrained areas which may be doors, corridors and staircases hence produce logical movement routes. The optimization of container loading is another crucial need. The system ought to organize the available space rationally and efficiently to optimize the use and minimize operational expenses. In addition, the system must provide an augmented reality (AR)-based interaction module that assists users and moving workers with visualizing movement paths and location positions in the real world to enhance accuracy and minimize manual errors.

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2.2. Non-functional requirements

Besides functional requirements, there are a number of non-functional requirements to be taken into consideration. It is important to be accurate and reliable because any mistake of modelling and planning can result in an unsuccess of the task. The system must also have the ability to handle complex environment, but must be user friendly so that the users can use the system in the real world. Moreover, the physical environment and the digital twin need to be synchronized through data so that they are always consistent in the entire process.

2.3. System structure

The proposed system adopts a layered structure which integrates physical environments, data collection, algorithms, and user interaction into an unified structure. At the first level, the physical layer scans and duplicates the real-world environment, including indoor spaces, layouts and furniture's physical properties. This layer serves as the source of all spatial and operational data. At the next layer which is named data layer, the system is responsible for storing, and managing multi-source data collected before, such as images, point clouds, and object properties. This layer ensures that raw data from the physical environment can be efficiently processed.

The model layer constructs the digital twin of the environment by transforming collected data into structured 3D environment. It builds up a virtual duplication of the space where objects and environments can be simulated and analyzed accordingly. The algorithm layer is the core of the system, in where intelligent moving, planning and optimization algorithms are performed. This layer includes spatial planning algorithms for path generation, optimization algorithms for container loadings, and AI reinforcement learning for adaptive decision-makings.

At the final level, the interaction layer provides user interfaces for system operation. This includes AR-based visualization and digital dashboards, which enable users to interact with the system and monitor house-moving progress timely. This layered structure ensures an efficient integration of different system components, allowing each layer to be independently developed, monitored and optimized

2.4. Key technologies in the system

The adoption of this structure is based on various important technologies. The modeling technology of digital twins assists 3D construction. Path generation is done using planning algorithms, including RRT and genetic algorithms are employed in optimization. Technology of reinforcement learning promotes flexibility in changing conditions. Lastly, augmented reality (AR) increases the level of interaction between the system and its users.

3. Digital twin construction of indoor scenes

3.1. 3D scene data collection

The quality of the construction of an accurate digital twin model depends on a quality 3D data scan. In the present work, Structure-from-Motion (SfM) approach is adopted. Structure-from-Motion (SfM) is a technique that shows a three-dimensional scene by examining a series of images which have been taken using a camera at various angles [3, 4]. Once it has taken pictures of the room, it begins to find unique feature points, then compares across many pictures to approximate the positions and orientations of the cameras based on the position of tangible objects in the room. The

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triangulation of the spatial coordinates of the matched feature points then creates a 3D point cloud that serves as model. Their camera parameters and point positions can be optimised with iterative optimization, including bundle adjustment, to achieve a better modelling accuracy [5]. Consequently, the system generates a 3D model of the interior space, the interior layout, the location of the furniture and the camera motion path.

3.2. Instance modelling and semantic annotation

Now that we have the point cloud model as given by SfM, the next step is extracting and modelling individual objects in the scene. While SfM captures geometric information, it lacks object distinction and semantic meaning. So, to build a structured digital twin, more processing is needed. Most approaches use deep learning-based object detection and segmentation methods like YOLO [6] for common household items (sofa, bed, door) or Mask R-CNN [7]. Image-based detections are mapped into the 3D space by linking them to corresponding regions in point cloud from which instance 3D models can be calculated. These are also useful as simpler geometric representations of the objects for reducing the computational complexity by roughly estimating their dimensions and positions. Besides geometric modeling, we designate semantic attributes of each object including category, size, estimated weight and physical properties. These characteristics facilitate downstream process like path planning and container optimization, manifesting in a digital twin where every object is identifiable by its geometric and functional particulars.

3.3. Model optimization and cloud synchronization

For real-time modelling and interaction for these large-scale tasks, the digital twin model must be optimized for computational performance. Before the optimization, the points and geometries of the modeling data in raw 3D are massive and highly intricate, which leads to degradation in performance. A number of model simplification techniques are utilized to mitigate this problem. One such model is Level of Detail (LOD) techniques which change the 3D model's complexity in correspondence to its viewing and processing constraints [8]. In addition, simplification of 3D meshes can be performed by algorithms like edge collapse which lower the number of polygons while maintaining the geometric form [9].

4. AI based intelligent moving and planning algorithms

4.1. Feasibility analysis of moving large furniture in 3D space

Based on the digital twin environment constructed in Chapter 3, the system first evaluates whether large furniture can be transported through constrained indoor spaces. Geometric intersection methods such as the Separating Axis Theorem (SAT) is widely used for convex object intersection testing [10, 11], for house-moving, it can be used for collision detection. If a collision-free transformation and rotation is allowed during transportation path plan, then the object is considered transportable. This analysis is necessary for subsequent path planning process.

4.2. Path planning based on RRT algorithms

After the feasibility analysis, the system is able to generate suitable collision-free paths using the Rapidly exploring Random Tree algorithm. RRT explores the configuration space through random sampling which suits for high-dimensional motion planning problems [12]. To enhance convergence

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efficiency, a goal-directed sampling method is applied, and denser sampling is used for precious detection in narrow regions such as corridors and doorways. Compared to traditional search-based methods, RRT-based approach is more effective in complex environments [13].

4.3. Container space optimization based on genetic algorithms

Genetic algorithms are applied to optimize the container loading arrangement of furniture. Each solution is encoded as a chromosome which represents object positions and orientations [14]. The fitness function evaluates space utilization and penalizes overlap. The algorithm can iteratively improve solutions through selection, crossover, and mutation [15]. This approach is widely used in solving complex combinatorial optimization problems which is effective in container loading process.

4.4. Dynamic obstacle avoidance based on AI reinforcement learning

Reinforcement learning has been widely applied in dynamic path planning and decision-making tasks [16]. To handle dynamic changes and some unexpected situations, a reinforcement learning strategy can be applied. The system is modeled as an agent which interacts with the environment, where states represent object positions and actions include movement and rotation. Reward function is set for successful movement while penalization is set for collisions. Through reward and penalize functions, the system can learn and adapt a suitable decision iteratively.

5. Virtual physical interaction in system

5.1. AR-based on-site navigation and placement guidance

An augmented reality (AR) based module which overlays virtual information onto the physical environment is developed to provide instructions for moving process. The system uses real-time camera tracking technology to align virtual spaces with physical spaces. The camera pose is continuously estimated by using Simultaneous Localization and Mapping (SLAM) technology which creates accurate projection of planned paths and object positions [17]. Navigation paths can be displayed as visual signs, such as arrows, in the dashboard to guide users along paths without collision. Also, virtual models of furniture appear in target places, so employees can set things up exactly as indicated in the layout.

5.2. Digital twin visualization dashboard

A digital twin visualization dashboard for monitoring the real-time relocation is developed, where users can access the status, location of objects, and the progress of tasks. The dashboard can visualize and represent all the furniture in the digital twin. Each furniture has a progress status that can be "not moved," "in transit," or "placed," to assist the user in tracking progress in a dynamic way. Additionally, the seamless updates of the physical environment and its digital twin enable real-time synchronization. To achieve seamless updates, the system employs a data synchronization strategy that uses network communication methods so that in the case of any updates related to the physical environment, the virtual model is updated without delays [18]. The relocation visualization dashboard enhances transparency and improves the relocation overview for the system users.

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5.3. System development environment and technical framework

Unity or Unreal Engine is used for 3D visualization and AR interaction and offers real-time rendering for immersive user experience. Core algorithms are developed using Python-based frameworks, which include object detection, path planning and reinforcement learning. These AI techniques enable smart decision making and updatable system behavior [19, 20]. Data storage systems like MySQL or MongoDB are used for scene data and system states storage, which allows quick access to data and real-time updates. This overall architecture maximizes flexibility and efficiency across all components.

6. Conclusion

This paper proposes an AI-based intelligent house-moving system integrating digital twin technology, planning algorithms, and virtual–physical interaction to enhance efficiency and user experience. Using Structure-from-Motion (SfM), indoor environments are reconstructed from multi-view images to generate digital twin models, which support object modeling and semantic annotation. Based on this, feasibility analysis, RRT-based path planning, genetic algorithm optimization, and reinforcement learning are applied to improve relocation efficiency and adaptability. In addition, AR-based guidance and a digital twin dashboard provide visual assistance for users which improves efficiency and user experience compared to traditional methods.

Compared with traditional relocation processes and experience, the proposed system demonstrates improved efficiency, flexibility and better experience. But the system is still highly dependent on the accuracy of the models and can have problems in highly complex situations. The next steps include improving real-time capabilities, accuracy of models, precision of reconstructing, and even the possibility of incorporating robotic systems to assist in the relocation of large and heavy objects. Moreover, this system also can use multi-sensor data fusion and cloud processing to assist with scalability and complete user experience. In addition, it can be used to improve the user interaction design and embrace feedback of users in order to adopt Virtual Reality technology in a way that will allow better user interaction making this system useful for many real-life scenarios.

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