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Digital Twin System for Home Service Robot Based on Motion Simulation

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***Abstract*—In order to improve the task execution capability of home service robot, and to cope with the problem that purely physical robot platforms cannot sense the environment and make decisions online, a method for building digital twin system for home service robot based on motion simulation is proposed. A reliable mapping of the home service robot and its working environment from physical space to digital space is achieved in three dimensions: geometric, physical and functional. In this system, a digital space-oriented URDF file parser is designed and implemented for the automatic construction of the robot geometric model. Next, the physical model is constructed from the kinematic equations of the robot and an improved particle swarm optimization algorithm is proposed for the inverse kinematic solution. In addition, to adapt to the home environment, functional attributes are used to describe household objects, thus improving the semantic description of the digital space for the real home environment. Finally, through geometric model consistency verification, physical model validity verification and virtual-reality consistency verification, it shows that the digital twin system designed in this paper can construct the robot geometric model accurately and completely, complete the operation of household objects successfully, and the digital twin system is effective and practical.**

***Index Terms*—Service Robot, Digital Twin, Motion Simulation, Particle Swarm Optimization Algorithm**

I. INTRODUCTION

Home service robots, as an important medium to improve the quality of human life, are able to replace humans to complete domestic work. However, in the face of complex domestic service tasks, relying solely on physical robotic platforms, the execution of tasks is highly unstable, and often unpredictable problems occur, which are likely to cause irreversible damage to expensive physical robots or the home environment, with a high degree of risk and uncertainty. Therefore, it is very necessary to design a digital twin system for home service robots to simulate various situations that may occur in real environments, to try to discover and solve problems that may occur when the physical robot platform actually operates, and to guide the physical robot to perform home service tasks reliably and efficiently.

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In this paper, we argue that the main things that a robot can rely on to complete domestic service tasks are the movement of its robotic arm and chassis. Most physical engines already integrate path planning internally to enable chassis movement, so this paper focuses on how to simulate the real motion of the robotic arm in a virtual environment and build the digital twin system based on it.

Digital twin refers to the construction of a virtual mapping of the physical entity in the whole life cycle of a system, through data fusion, information interaction, and virtual simulation [1], to describe the operational state of the physical space [2] [3]. The first generic framework for the digital twin was modeled in terms of physical entities, virtual models and connections [4]. For monitoring of complex objects, the five-dimensional model that adds services and digital twin data to the three-dimensional model was proposed [5].

Driven by the development strategies of various countries [6] [7], the application of digital twin has become a hot spot [8]–[10], including the field of robotics [11] [12]. Through virtual reality technology, [13] proposes a digital twin-based programming method for industrial robot demonstrations, which improves the human-robot interaction of robot demonstrations. Reference [14] proposes a digital twin-based approach for flexible robot work cell development, which speeds up the overall commissioning process.

Digital twin is rapidly developing in the industrial robot field, but it is not yet targeted for home service robots. The home environment is unstructured, and has a number of manipulable objects, so the digital twin construction method for industrial robots cannot be applied to home service robots directly. This paper proposes a digital twin system for home service robot based on motion simulation. The system integrates geometric, physical, and functional information. A parser for URDF [15] (Unified Robot Description Format) files is designed to build the robot geometric model automatically. An improved partcle swarm optimization algorithm is proposed to solve the inverse kinematics problem and achieve rational motion of the robot arm in digital space. Functional model is also proposed to describe the semantic information of household objects. Finally, the validity and practicality are demonstrated by geometric consistency verification, physical validity verification and virtual-reality consistency verification.

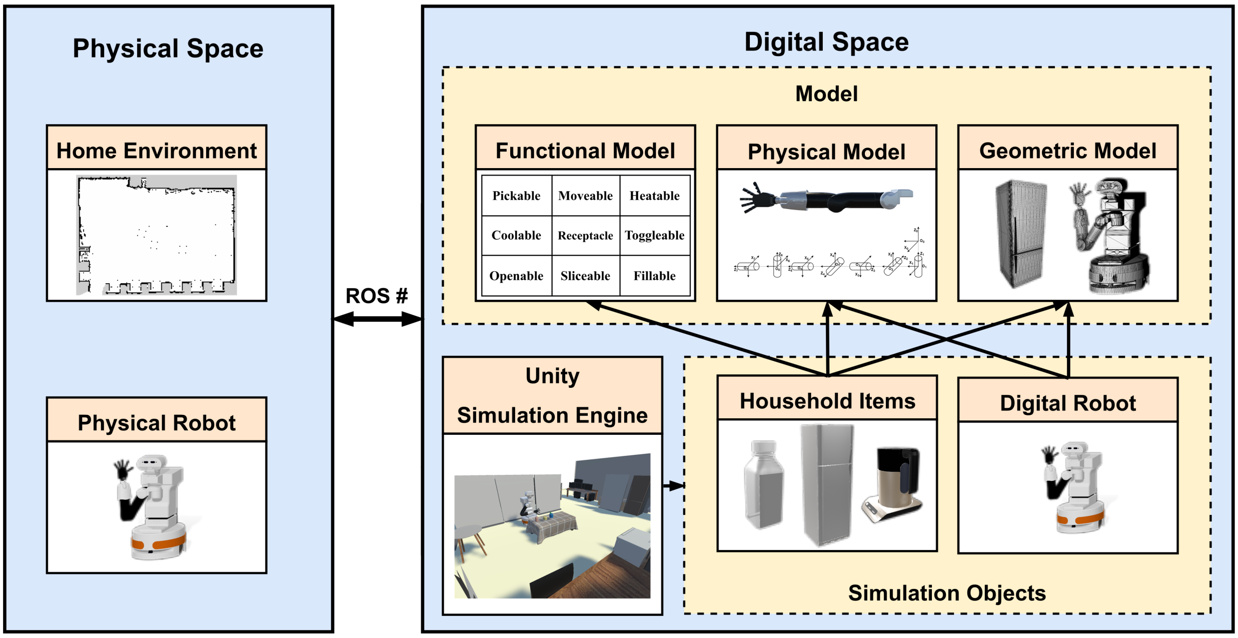


Fig. 1. Framework for the digital twin system for home service robot based on motion simulation.

II. Overall Description of the System

A. System Framework and Workflow

The framework of the proposed system is shown in Fig. 1, which mainly includes physical space, digital space and connections. The physical space is consisting of service robots and home environment. The digital space is composed of the digital robot platform and the virtual home environment, which is required to map the physical space realistically. The connection of this digital twin system is based on ROS#, which reliably exchanges twin data.

During the operation phase of the system, the physical robotics platform monitors various operational data in the physical space in real time, including odometer information, robot arm status, and so on. This data is connected to the digital space via ROS#, which helps map the physical space to the digital space with high fidelity. In the digital space, the robot simulates the operation of the real environment in the digital space to guide the physical robot platform.

B. Model Composition and Correlation Analysis

The digital twin model M consists of the geometric model G_v, the physical model P_v and the functional model F_v:

$$M = G_v \cup P_v \cup F_v, \tag{1}$$

where, G_v is the 3D models, including the shape and material properties of all objects in the physical twin space, which has the most intuitive impact on the visual effect of the digital space; P_v describes the physical properties of the robot platform and household objects, such as gravity, which determine the similarity between physical and digital spaces; F_v is used to describe the functional properties of household objects, which determine the behavior of the robot in digital space that is consistent with real-world common sense.

III. Construction Method of Digital Twin System

This section introduces the construction method of the digital twin system for home service robot, described in terms of the robot and the home environment, respectively.

A. Geometric Modeling of Robot

The robot model contains joint and kinematic parameters that can be constructed with the help of URDF files. URDF files can be obtained from the ROS and can be parsed by the Gazebo software, but cannot be used directly in Unity3D. Therefore, the URDF file parser is implemented in Unity3D.

The URDF parser uses the $System.xml$ namespace of C# to parse the URDF file, and gets the robot's Joint and Link information, as well as the robot's description file and material file. The above information can form the basic framework of the model, so that the robot's URDF model can be imported into Unity3D as a $GameObject$.

In this paper, we use the TIAGo robot as the physical robot platform. This platform has a 7 Dof robotic arm, a Hey5-type 5-finger manipulator, and a PMB-2 type mobile chassis, to flexibly move and manipulate tiny objects in indoor environments [16].The geometric model of the TIAGo robot obtained by 3D stereoscopic display is shown in Fig. 1.

B. Forward Kinematic Modeling of Robot Arm

The robot arm of the TIAGo robot has 7 Dof. As shown in Fig. 2, the coordinate system at each joint of the TIAGo robot arm can be established.

By denoting the 7 joint variables of the TIAGo robot arm as $\theta_1, \theta_2, ..., \theta_7$, the forward kinematic equations of this robot

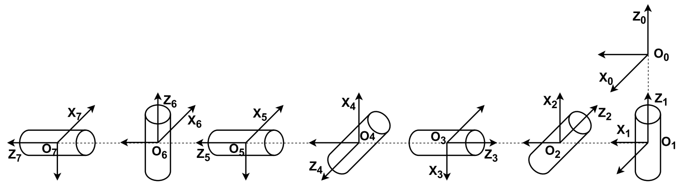


Fig. 2. Coordinate system of each joint of TIAGo robot arm.

arm can be established using the D-H parameter method. By reviewing the relevant information, the D-H parameter of the TIAGo robot arm are shown in Tab. I, where α_k and a_k are the angle and length of rotation from the Z_{k-1} axis to the Z_k axis along the X_{k-1} axis, respectively. θ_k and d_k are the angle and length of rotation from the X_{k-1} axis to the X_k axis along the Z_k axis, respectively.

TABLE I
D-H PARAMETER OF TIAGO ROBOT ARM.

Joint Index k	α_k/rad	a_k/mm	d_k/mm	θ_k^l/rad	θ_k^u/rad
1	0	0.15505	-0.151	0	2.75
2	1.57	0.125	-0.0165	-1.57	1.09
3	-1.57	0	-0.0895	-3.53	1.57
4	1.57	0.02	-0.027	-0.39	2.36
5	-1.57	0.02	0.162	-2.09	2.09
6	1.57	0	0	-1.41	1.41
7	-1.57	0	0	-2.09	2.09

The transformation matrix between the $(k-1)^{th}$ joint and the k^{th} joint of the TIAGo robot arm is shown in (2), where C_θ and S_θ donate $\cos\theta$ and $\sin\theta$, respectively:

$$T(\theta_k)_k^{k-1} = \begin{bmatrix} C_{\theta_k} & -S_{\theta_k}C_{\alpha_k} & S_{\theta_k}S_{\alpha_k} & a_kC_{\theta_k} \\ S_{\theta_k} & C_{\theta_k}C_{\alpha_k} & -C_{\theta_k}S_{\alpha_k} & a_kS_{\theta_k} \\ 0 & S_{\alpha_k} & C_{\alpha_k} & d_k \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

Substituting the parameter in Tab. I, $T(\theta_1)_1^0$, $T(\theta_2)_2^1$, ..., $T(\theta_7)_7^6$ can be found sequentially, and multiplying them together gives:

$$M(\theta_1, \theta_2, ..., \theta_7) = \prod_{k=1}^{7} T(\theta_k)_k^{k-1} = \begin{bmatrix} R & P \\ 0 & 1 \end{bmatrix} \quad (3)$$

where R and P are the pose matrix and position matrix of the end-effector, respectively. $M(\theta_1, \theta_2, ..., \theta_7)$ is the position&pose matrix of the end-effector, which is the forward kinematic model of the robot.

C. Inverse Kinematic Modeling of Robot Arm

Since the motion of the robot arm joints is physically constrained, and the degrees of freedom are redundant, this paper uses the particle swarm algorithm to solve the inverse kinematics of the robot arm. The particle swarm algorithm is suitable for the case where the robot has redundant degrees of freedom and has strong robustness.

In the particle swarm algorithm, the optimal particles include the historical optimal particle $pBest$ and the global optimal particle $gBest$. Each particle iteratively updates its velocity v and position x with $pBest$ and $gBest$ as references to explore the solution space:

$$\begin{aligned} v(t+1) = W \cdot v(t) + C_1 \cdot rand() \cdot [pBest(t) - x(t)] \\ + C_2 \cdot rand() \cdot [gBest(t) - x(t)], \end{aligned} \quad (4)$$

$$x(t+1) = x(t) + v(t+1), \quad (5)$$

where $W \in [0, 1]$ is the inertia weight, reflecting the effect of the original velocity on the subsequent motion; C_1 and C_2 are the learning factors, indicating the ability of the particle to utilize its own experience and the ability to absorb the experience of other particles, respectively.

From the current joint variables θ_1, θ_2, ..., θ_7, the current position&pose matrix M_C, pose matrix R_C and position matrix P_C of the end-effector can be calculated by (3). In addition, the desired position&pose matrix M_O, pose matrix R_O and position matrix P_O are given.

Define the position error E_P as the 2-norm of the difference of the position matrix, i.e.

$$E_P = \|P_C - P_O\|_2 \quad (6)$$

The current pose R_C and the desired pose R_O are transformed into quaternions (x_c, y_c, z_c, w_c) and (x_o, y_o, z_o, w_o). Define the pose error E_R as

$$E_R = 2\arccos\left(x_o \cdot x_c + y_o \cdot y_c + z_o \cdot z_c + w_o \cdot w_c\right) \quad (7)$$

In order to obtain a unique solution that conforms to the constraint, this paper adds additional conditions with the help of the optimal flexibility rule. For the TIAGo arm, the optimal flexibility is defined as

$$\min\{\sum_{k=1}^{7}[\omega_k(\theta_k(j) - \theta_k(j-1))]^2\}, \quad (8)$$

where $\theta_k(j) - \theta_k(j-1)$ is the difference between the current angle and the previous angle of the joint θ_k. ω_k is the weighting factor, following the principle of "more movement of the lower arm and less movement of the upper arm" to achieve more stable movement. In this paper, we take $\omega_1 = 1$, $\omega_2 = \omega_3 = 0.5$, $\omega_4 = \omega_5 = \omega_6 = \omega_7 = 0.1$.

According to the position error E_P, pose error E_R and the optimal flexibility rule (8), the fitness function is

$$f = \omega_P E_P + \omega_O E_O + \sum_{k=1}^{7}[\omega_k(\theta_k(j) - \theta_k(j-1))]^2, \quad (9)$$

where $\omega_P = rand(0, 1)$ and $\omega_O = 1 - \omega_P$ are the weighting coefficients of E_P and E_O, respectively. The smaller the f of the particle, then the better its quality, i.e., the smaller the difference between the current position&pose matrix M_C and desired position&pose matrix M_O.

To improve the global convergence performance of the algorithm, this paper lets the inertia weights W and the learning factor C_1 and C_2 make adaptive adjustments with the number of iterations:

$$
\begin{aligned}
W(t) &= (W_s - W_e)(\frac{t}{T})^2 + (W_e - W_s)(\frac{2t}{T}) + W_s \\
C_1(t) &= (C_{1s} - C_{1e})(\frac{t}{T})^2 + (C_{1e} - C_{1s})(\frac{2t}{T}) + C_{1s} \\
C_2(t) &= (C_{2s} - C_{2e})(\frac{t}{T})^2 + (C_{2e} - C_{2s})(\frac{2t}{T}) + C_{2s}
\end{aligned} \tag{10}
$$

where T and t are the final and current number of iterations, respectively. Take $W_s = 0.9$ and $W_e = 0.4$ to denote the initial and final values of $W(t)$, respectively. As the number of iterations t increases, $W(t)$ will gradually become smaller, then the particle swarm can explore the whole solution space at the beginning of the iteration and quickly locate the local area where the optimal solution is located. At the later stage of exploration, the particle swarm can launch a detailed search for the optimal solution locally. Taking $C_{1s} = 1.5$ and $C_{1e} = 2.5$ to denote the initial and final values of $C_1(t)$, and taking $C_{2s} = 2.5$ and $C_{2e} = 1.5$ to denote the initial and final values of $C_2(t)$, respectively, which can prevent the algorithm from falling into local optimum at the beginning and enhance the search accuracy at the end.

The improved particle swarm optimization algorithm is used to solve the inverse kinematic problem, as shown in the Alg. 1.

Algorithm 1 Solution of the inverse kinematic problem.

Input: Desired position&pose matrix M_O;
Output: Joint variables $(\theta_1, \theta_2, ..., \theta_7)$ of the robot arm;

```
Randomly initialization of 50 7-dim particles;
while t < T do
    Calculate the fitness of each particle according to (9);
    Update the pBest and gBest;
    Update the weights and learning factors by (10);
    Update the particles by (4) and (5);
end while
Select the global optimal solution gBest;
return  The 7 joint variables corresponding to gBest.
```

D. Geometric and Physical Modeling of Home Environment

The home environment contains a diverse range of objects. To build the digital twin system here, it is necessary to model the household objects. Household objects do not contain complex joint structures and can be modeled directly using Blender software. The basic shape is constructed first, and then given the materials to obtain a realistic model display effect. The open source SLAM (Simultaneous Localization and Mapping) technology allows the robot to explore the environment and obtain a environment map. The geometric model of the home environment can be completed by manually placing the household object and the room structure model in the digital space according to the map.

In order to simulate the manipulation of household items, physical modeling of them is also indispensable. In the Unity3D, physical properties such as gravity and collision can be easily added to various items through various components.

E. Functional Modeling of Household Objects

When interacting with household objects, robots cannot only consider physical properties. In order to bring robot behavior closer to that of humans, it is also necessary to describe the functional properties of each household item.

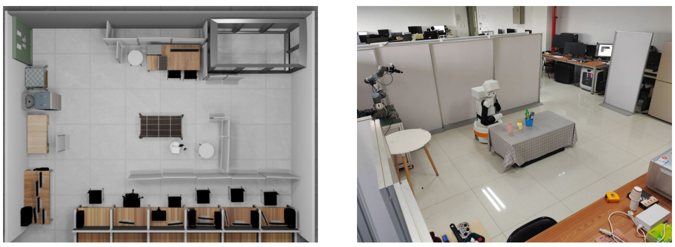
In [17], 22 attributes are proposed to describe the functionality of objects in home environment. In this paper, however, we argue that some of these attributes are only relevant to humans and not to robots to accomplish tasks, such as Sittable. There are also some attributes that can be combined into one. For example, Puttable, Rotatable and Moveable can be unified and described by Moveable. In this paper, we use a total of nine functional attributes as shown in Tab. II to describe the functional semantic information of household objects.

F. Connection of Home Service Robot Digital Twin System

Regarding the data interaction in the digital twin system, this paper focuses on the acquisition and transmission of the real-time status of the physical robot platform during its operation, and the control commands from the digital space to the physical robot. Specifically, this paper uses ROS to acquire and manage the various data of the physical robotics platform, and then uses ROS# to achieve two-way communication between the data in ROS and Unity3D.

IV. Experimental Verification and Analysis

To validate the proposed approach in this paper, a digital twin system for home service robot is built in laboratory environment as shown in Fig. 3. In the digital space, the virtual environment uses Unity3D 2021.3.11f1c1 as the development engine. The computer is equipped with a GTX1080 graphics card with 8GB memory, an i7-8700 CPU, and 16GB of RAM.



(a) The digital space of home environment **(a) The physical space of home environment**

Fig. 3. Simulated home environment built in the laboratory.

A. Geometric Model Consistency Verification

By measuring the real robot, its geometric parameters can be obtained, which allows the calculation of the accuracy of the geometric modeling. In addition, the number of components is

TABLE II
THE DESCRIPTION OF FUNCTIONAL ATTRIBUTES

Functional Attribute	Describe
Pickable	These objects can be picked up or put down into receptacles.
Moveable	These are non-static objects that can be moved around the scene.
Heatable	These objects can increase the temperature of other objects.
Coolable	These objects can decrease the temperature of other objects.
Receptacle	Receptacle objects allow other objects to be placed on or in them.
Toggleable	These objects can be toggle on or toggle off.
Openable	These objects can be opened or closed.
Sliceable	These objects can be sliced into smaller pieces.
Fillable	These objects can be filled with liquid.

known by consulting relevant information, and by comparing the real number with the modeled number, it is possible to indicate whether the robot geometric model has completeness.

Tab. III shows the measured data of the physical TIAGo, the modeling data of the digital TIAGo, and the error between the two. All data are in centimeters, except for the number of components. "Height" refers to the overall height of the robot, "Chassis" is the robot's movable chassis, and "Laptop Tray" is the platform behind the head of TIAGo. From the data in Tab. III, it can be seen that the modeling error of the geometric model of TIAGo is not large and all the components of TIAGo are modeled, so the geometric model has high accuracy and completeness.

The coordinates of a vertex of some household objects in the physical space and digital space are measured separately. Since objects are affected by gravity, only the two-dimensional coordinates of object on the map plane are of interest. The consistency of the geometric model of the home environment is verified by calculating the difference between the coordinates.

The coordinates of some objects in physical and digital space obtained from the measurements are shown in Tab. IV, and all data are in centimeters.The error is the Euclidean distance between two coordinates. The data in Tab. IV shows that the modeling error of the geometric model of the home environment is small, and therefore the geometric model of the home environment is geometrically consistent.

B. Physical Model Validity Verification

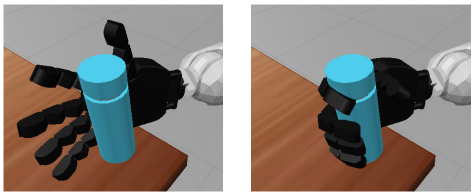
This experiment realizes the trajectory planning of the robot arm in the joint space according to the inverse kinematics model by the fifth polynomial interpolation method. The validity of the physical model is verified by using the example of TIAGo grasping a water cup.

To ensure the stability of grasping, the action of TIAGo robot is divided into two stages, approaching and grasping. Fig. 4 shows the process of robot approaching the water cup. The robot drives the robot hand to gradually approach the water cup through the position&pose adjustment of the robot arm until it is close to the water cup.

(a) Robotic Arm Initial State (b) Robotic Arm Movement (C) Robotic Arm Reach Cup

Fig. 4. The process of TIAGo robot hand approaching the water cup.

After approaching the water cup, the robot hand needs to perform a grasp action, as shown in Fig. 5.



(a) Prepare to Grip (b) Complete Grip

Fig. 5. The process of TIAGo robot hand grasping the water cup.

From the experimental results, it can be seen that the physical model enables the TIAGo robot to complete the water cup grasping task smoothly, which meets the expected requirements.

C. Virtual Reality Consistency Verification

Since the effective execution of all home service tasks requires robot movement, the virtual-real consistency is verified from the operation of movement command in the digital twin system.

Firstly, the Localization module that comes with the physical robot is used to obtain its initial position&pose, and to initialize the position&pose of the digital robot. Secondly, a movement command is sent to the robot, which will move and display the status and the home environment in real time. The movement of the robot is synchronized in the digital space, and the effect is shown in Fig. 6.

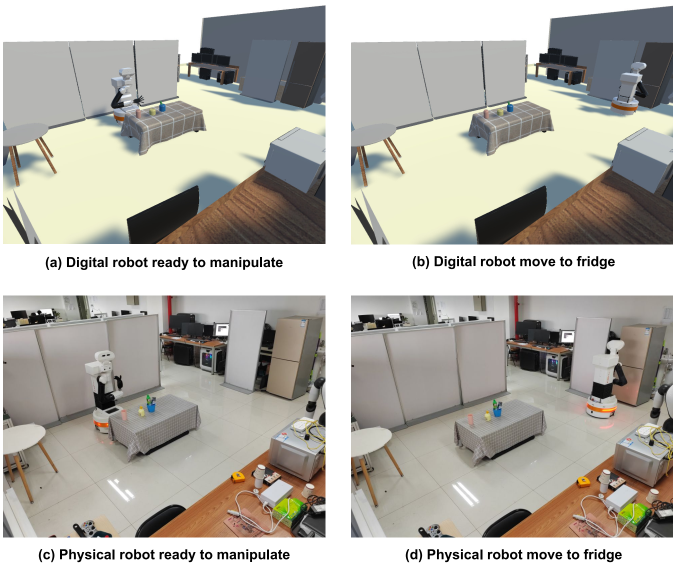
As can be seen from Fig. 6, the digital and the physical space can achieve the same execution effect when performing the same task, and the digital space can be synchronized with the physical space in real time. This proves that the digital twin system established in this paper has virtual-reality consistency.

TABLE III
GEOMETRIC PARAMETERS AND ERRORS OF ROBOT

Space	Components Number	Height(cm)	chassis		Laptop Tray		
			Height(cm)	diameter(cm)	Height(cm)	Width(cm)	Length(cm)
Physical	89	110	30	54	60	28	33
Digital	89	110.0998	30.0384	53.172	60.4548	28.476	33.264
Error	0	0.998	0.384	0.828	0.4548	0.476	0.264

TABLE IV
GEOMETRIC PARAMETERS AND ERRORS OF HOME ENVIRONMENT

Space	Fridge	Table1	Table2	Desk	Microwave	Television
Physical	(107 ,348)	(412, 157)	(334, 347)	(493, 213)	(405, 163)	(427, 152)
Digital	(105.423, 348.525)	(414.205, 156.423)	(333.012, 345.423)	(491.432, 212.433)	(406.429, 162.956)	(425.912, 153.422)
Error	1.662	0.612	1.861	1.667	1.430	1.790



(a) Digital robot ready to manipulate
(b) Digital robot move to fridge
(c) Physical robot ready to manipulate
(d) Physical robot move to fridge

Fig. 6. Operational effect of the digital twin system.

V. CONCLUSION

This paper proposes the motion simulation-based digital twin system for home service robots and its implementation method, to meet the practical need of complex home environment. This system integrates geometric, physical and functional models for accurately map the robot and its working environment. 3 aspects of validation experiments demonstrate the accuracy and practicality of the proposed method and system, providing a feasible approach to completing complex tasks for home service robots.

There are, however, still missing areas that need a lot of research, such as auto-adaptation to different homes, implementation of more atomic actions, and so on. Therefore, subsequent work will further refine the system.

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