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Intelligent Cloud Platform for Interior Design Based on Digital Twins

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In order to improve the human-machine interaction and intelligent control capabilities of smart homes, the researchers designed a new smart home human-machine interaction system. A dynamic equation for the Internet of Things in smart urban areas was constructed based digital twin technology. The expected output of the smart interior design platform was established by utilizing the mapping relationship between the continuous packet loss and the maximum delay value in smart interior design. Combined with the design of information quality management algorithms for smart interior design services, the software design of the platform was completed, achieving automated management of smart interior design. By utilizing data fusion technology to establish a big data fusion model for human-machine interaction in smart homes, data fusion output is carried out to optimize the control of human-machine interaction instructions in order to achieve the design of a smart home human-machine interaction system. The experimental results indicated that the login and operation functions of the platform meet user requirements, reducing the packet loss rate of the platform, decreasing the time delay effect, and ensuring the stable operation of smart indoor design. The information accuracy of the system during human-computer interaction is higher, although the accuracy may fluctuate due to uncontrollable factors, both are higher than the two comparison methods, and the fastest complete human-machine interaction can be achieved within 4 seconds, and the accuracy of human-machine interaction instructions is as high as 97%. Test results demonstrate that the intelligent cloud platform for interior design based on digital twins has good performance and certain application value.

Keywords: Digital twin technology, expected output, smart home, human-computer interaction

1. INTRODUCTION

According to the "Guidelines for Classification of Smart Home System Products" formulated by the Intelligent Committee of the China Interior Decoration Association in April 2012, the products of smart home systems can be divided into 20 categories including electrical control, lighting control, security alarm control, home network system, home wiring system, multimedia system, etc. [1]. It can be said that smart homes have taken into account various aspects of people's daily lives, and can bring practical enjoyment and convenience to everyday activities. However, to date, smart homes have not been popular mainly due to the lack of unified standards between the country and the industry, resulting in product incompatibility. Also, the system architecture is complex, which makes it difficult to maintain and upgrade. When wired remote control is used, there are wiring issues, poor system scalability, and poor mobility of household appliances, which increases the cost and difficulty of installation and debugging. The high cost is beyond the economic capacity of ordinary families.

A smart home control system is a control and management system built on the platform of smart home systems, utilizing network communication, automatic control, audio and video technology, and security prevention technology. It offers the smart-home owner security as well as comfortable and intelligent assistance in the control of household appliances. In this study, the researchers investigate the current system and

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design a smart home control system based on digital twin and RF technology. The system utilizes the nRF905 RF module to design networking for multiple indoor microcontrollers. Users send control signals for household appliances to the main control center built on the digital twin platform through mobile SMS or universal remote control, and then the main control center sends them to several communication nodes or smart sockets, achieving wireless remote control of various household appliances [2]. After researching and analyzing the actual requirements and feasibility of video surveillance, the researchers devised an implementation scheme for the main control center based on digital twin embedded technology. This system is based on the perspective and needs of general household applications, and therefore is significant and has good application prospects.

2. LITERATURE REVIEW

In 2010, the term "digital twin" appeared for the first time in a technical report by NASA (National Aeronautics and Space Administration), and was first applied in the aerospace field for issues such as fault prediction of spacecraft, design and maintenance of aircraft, etc. The term "digital twin" is applied to entities in the real world, such as a part, a factory, or the structure of an organism, while the other part of the twin is a digital mirror created using digital technology of the aforementioned entities, known as the "digital twin" [3]. This digital twin is a digital mirror of real entities and can also fully simulate the various behaviors of these entities in the real world using data such as physical models, sensor updates, and operational history, thereby reflecting the entire lifecycle process of the entities [4–6]. Hecheng developed a comprehensive distribution model for collection control and management control, and proposed a flow process for understanding the accuracy of field sample content and secondary evaluation of reserve content. In addition, it is expected to provide a good data interface for Internet of Things (IoT)-level input and output data for ongoing research data [7]. Qian, conducted an analysis of interior sound quality of electric vehicles using intelligent algorithms and neural networks. First, an appropriate standard-based noise test was used to record the interior noise of various electric vehicles and models. Second, the evaluation method was applied and the SQ is evaluated using the evaluation method [8]. Ku, designed and published IoTA Tangle, an IF4BT smart food safety service platform that adapts and integrates hazard analysis and key management information to improve information transparency. Deep learning systems are based on long and short memory and Siamese networks to extract important rare information with high risk, abnormal and noisy from daily monitoring and auditing [9].

Nowadays, urbanization is gradually increasing, and smart interior design poses many problems in regard to automated operation and management, with and increasing number of potential safety hazards are emerging. The establishment and improvement of an automated management platform and emergency response mechanism for smart interior design has become a priority of smart city management for the prevention of emergencies and decreasing the number of responses to emergencies. The development of Internet of Things technology provides an effective means of operating and managing smart urban areas.

In response to the above issues, the researchers propose a smart-home human-computer interaction system based on digital twins, in order to improve the human-computer interaction in smart homes.

3. METHODS

3.1 Digital Twin and GIS Technology Application

The construction of digital twin cities will trigger disruptive innovation in urban intelligent management and services. The management of "cloud based united front" utilizes the concept of digital twins to create a twin united front management scene in a virtual three-dimensional world, applying the twin concept to all the elements of united front in the real world. In the digital twin united front application scenario, all people, objects, events, buildings, roads, united front equipment and facilities in the physical city have corresponding virtual images in the digital world [10]. Attribute information and dynamic change information are visible, trajectories can be followed, and states can be checked; there is synchronous operation of virtual and real, blending of emotions and scenes; it is traceable and capable of providing safety accident warning and anticipating external development trends With the development of society, people's demand for housing is becoming increasingly diverse. By utilizing digital twins and GIS technology, designers can conceive more innovative interior or housing design methods to meet the needs of people of all ages[11].

3D laser scanning is a new technology that has emerged in recent years and is receiving an increasing amount of research in China. It uses the principle of laser to quickly obtain various elevation points of a surface, including their three-dimensional coordinates, effects and textures, and to collect more graphical information on measured objects such as three-dimensional models, lines and areas, and vol. The three-dimensional modeling process is shown in Figure 1.

3.2 General Steps and Key Technologies for Constructing Digital Twins

The key technologies required to construct a digital twin include data collection and transmission, modeling, simulation, visualization, and immersive interaction. In addition, technologies such as artificial intelligence, big data, cloud edge collaborative computing, and the Internet of Things are incorporated into the digital twin technology system, making these technologies an important component of digital twin technology. For example, when processing high-dimensional data, in order to improve computational speed and eliminate redundant data, dimensionality reduction technology is required for high-dimensional data [12].

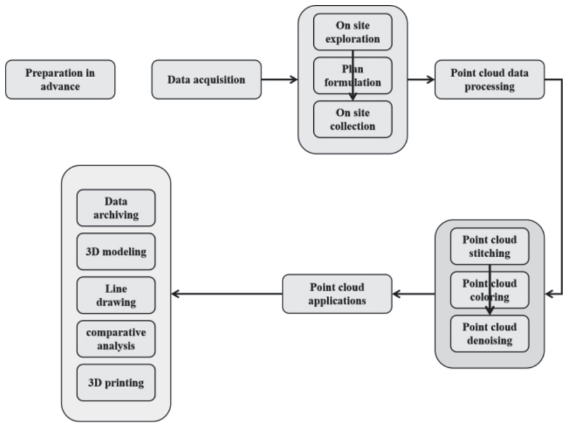

Figure 1 3D Model Construction Process.

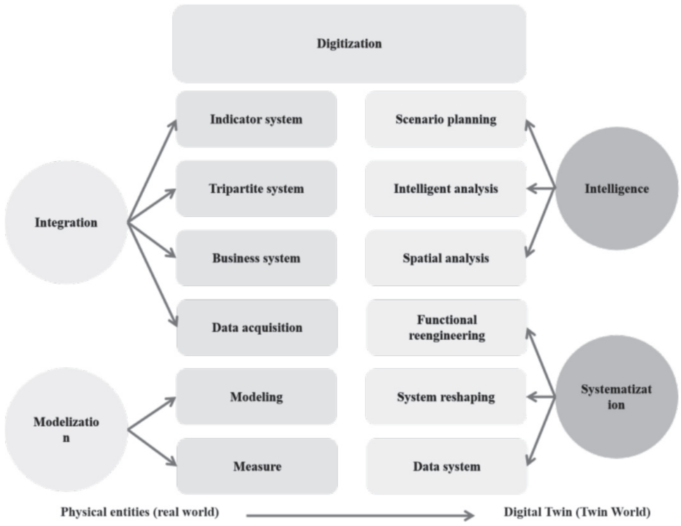

Figure 2 Digital Twin World Methodology V Model.

In the "Digital Twin World White Paper" released by the Digital Twin World Enterprise Alliance and Hangzhou Yizhi Micro Technology Co., Ltd., the model of the digital twin world methodology drawn by the author reflects the integration of various key technologies in the digital twin. The methodology model of the digital twin world is shown in Figure 2.

1) Modelization

Digital twins are required in order to achieve real-time control and prediction of various attributes throughout the entire lifecycle of physical entities. Therefore, establishing a digital model of physical entities is the core technology for achieving digital twins. Firstly, detailed measurement and modeling of physical entities (real world) must be performed. Not only should all models correspond to physical entities one by one; they also have to measure the environment of the physical entities and the objects with which they come into contact and interact [13].

2) Integration

The second step is to unify and integrate the existing system, including using various IoT devices (such as sensors) to collect various required data. The business system includes operation and maintenance systems, transaction systems, and other business-related systems, as well as some third-party systems. Only by analyzing, correlating, and integrating the data of these related systems can the target physical entity (real world) be accurately characterized.

3) Digitization

In the third step, digitization, we should achieve comprehensive digitization of digital twins, and establish a comprehensive indicator system.

4) Systematization

The fourth step is the systematization stage, where the digital twin is actually a system with its own architecture that requires us to reshape the original system and recreate the required functions. At the same time, it is necessary to ensure the data and task alignment between the real world and the twin world, in order to improve the collaboration efficiency of various subsystems or participants [14].

5) Intelligence

Finally, there is the intelligent stage, during which the intelligent applications are implemented. In intelligent analysis, we can retrieve images for the purpose of comparison and image recognition of a specific object, etc. based on the training results of machine learning.

After implementing the five main steps above, the simulation technology of digital twin models becomes the core technology used to ensure the accurate mapping of physical entities corresponding to digital twins. For highly complex digital twin systems, it is necessary to have a thorough understanding of their structure, operational mechanisms, and various environmental factors. Based on this, data-driven methods are used to update and improve the model in real-time, in order to approximate the real-time state of the target system and predict its future state.

3.3 Setting the Expected Output of a Smart Interior Design Platform Based on Digital Twin Technology

For smart interior design, network latency and packet loss rate are the main factors that affect the automation management process of IoT service information. Digital twin data such as physical models, sensor updates, and operational history are fully utilized to construct dynamic equations for smart interior design, expressed as

$$m_l = \sum s^j \frac{k_p \oplus c_m}{\beta_o} \tag{1}$$

where s^j represents a positive integer; k_p represents the upper limit value of the time delay of the Internet of Things; c_m represents the response coefficient matrix of smart interior design; β_o represents the delay indicator of IoT data in transmission [15].

Due to the influence of many factors during the operation of smart interior design systems, the response coefficient matrix of the Internet of Things presents two situations: time delay and no time delay, represented as

$$n_p = \frac{m_o}{j_o} \sum_{k=1}^{o} \frac{g_o\left(x_o \mp w_l\right)}{d_i \mp we_y} \left\{y_j\right\}^k \tag{2}$$

$$we_y = \frac{m_o}{j_o} \sum \frac{g_o\left(x_o \mp w_l\right)}{d_h \mp x_o} \tag{3}$$

where m_o represents the internal workload of smart interior design; J_o represents the external workload of the Internet of Things; g_o represents the maximum value of m_o and j_o; x_o represents the maximum time delay value of the IoT response coefficient matrix; w_l represents the sampling period of IoT data; d_h represents the type of time delay in the response coefficient matrix of the Internet of Things; $\left\{y_j\right\}^k$ represents the IoT response coefficient vector during the k-th sampling period.

Using digital twin technology, the mapping relationship between the continuous packet loss number and the maximum delay value is calculated with the formula:

$$U_r = \sum_{y=1}^{\emptyset} m_y \frac{h_j}{s_t} \tag{4}$$

where m_y represents the number of consecutive packet losses in the Internet of Things; h_j represents the expected output of IoT information mapping in virtual space; s_t represents the expected output value of IoT information; Ø represents the mapping time.

According to the mapping relationship between the continuous packet loss and the maximum delay value, the expected output of the smart interior design platform is obtained with:

$$m_o = \frac{s_t \left\langle m_l m_{k_p} \right\rangle}{n_p} U_r \tag{5}$$

where m_{kp} represents the constraint on the information of the Internet of Things.

The dynamic equation of smart interior design was constructed using digital twin technology above, and the mapping relationship between the continuous packet loss and the maximum delay value of smart interior design was set to set the expected output of the smart interior design platform.

According to the expected output of the smart interior design platform, the service information is laid out with:

$$E_t = \frac{1}{m_j p_j} \prod x(\overline{d}) \frac{R^* \propto \lambda_y}{k_h} \tag{6}$$

where m_j represents the distribution function of IoT service information; p_j represents the distribution threshold of IoT service information; $x(\overline{d})$ represents the hierarchical status of IoT service information; R^* represents the initial value of the state of the Internet of Things; λ_y represents the equilibrium function of IoT service information; k_h represents the noise factor that affects the quality of information in IoT services.

If the residuals of all nodes in smart interior design are defined as w_o, then the contribution correlation between service information in smart interior design is

$$v_u = \frac{m_j w_o}{l_j(k-1)} \eta_h \tag{7}$$

where l_j represents the spatial estimation value of the IoT structure; η_h represents the clustering center for the information quality of IoT services.

Utilizing the contribution rate correlation between service information in smart interior design, the statistical features of service information are extracted from the smart interior design system, namely:

$$q^* = \frac{\sigma_p}{m_{k_l}} + s_l \tau_p \tag{8}$$

where σ_p represents the attribute characteristics of service information; m_{k_l} represents the constraint conditions for service information fluctuations; s_l represents the uncertain variable that affects the quality of the service information; τ_p represents the dynamic variability of service information.

Due to the randomness of intelligent interior design service information in automated management, it is represented as μ^*, so utilizing equation (9) can achieve automated management of information quality in smart interior design services, namely:

$$R_d = \frac{d_e + E_t}{R_t q^*} \frac{v_u}{\mu^*} \tag{9}$$

where d_e represents the constraint function of information quality management for smart interior design services; R_t represents the quality coefficient of service information.

In summary, the expected output of the smart interior design platform was established using digital twin technology,

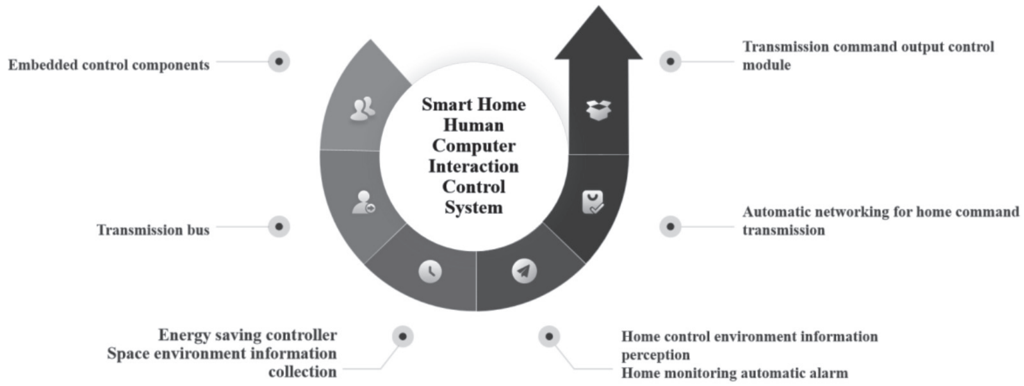

Figure 3 Design of Overall System Structure.

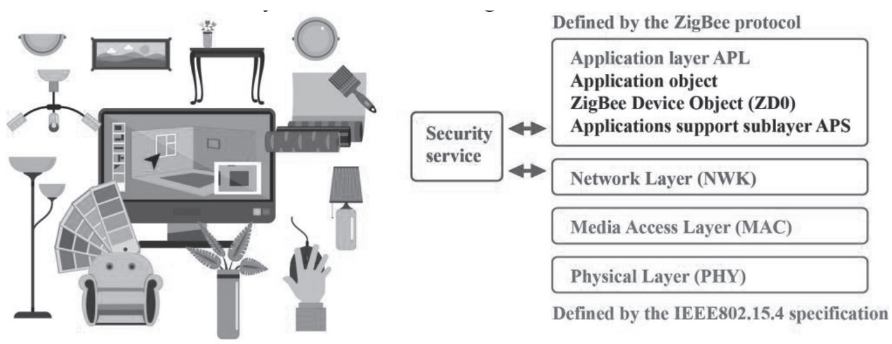

Figure 4 Three-layer architecture of human-computer interaction for smart homes.

and the software design of the platform was combined with algorithms designed for information quality management in intelligent interior design services [16].

3.4 Overall Design and Data Transmission Structure

In order to achieve the mining and automated acquisition of human-computer interaction instructions in smart homes, the overall system structure is first constructed. Using ZigBee for automatic control and remote control of the smart home human-machine interaction control system, SMA and UFL interfaces are used in the system, DSP is used as the information processor, and the fusion of diverse feature information is used to construct a storage structure model for human-machine interaction instructions in smart homes. Combined with the fusion control method of target and observation nodes, instructions for human-machine interaction in smart homes are transmitted. The overall structure of the system is shown in Figure 3.

Figure 3 shows the overall structure of the human-machine interaction control system for smart homes. The three-layer network architecture of the system is shown in Figure 4.

Figure 4 shows that in the ZigBee network structure diagram model, a hierarchical model management method is used to construct the application layer and application support sublayer for human-machine interaction in smart homes. A three-layer architecture is used to design the standard control protocol for human-machine interaction in smart homes.

A command control database is built for human-machine interaction in smart homes, and the methods of centralized database interface control and middleware data integration control are used to establish a big data analysis model for human-machine interaction in smart homes. Applying the principles of Hadoop architecture and distributed architecture, intelligent home human-machine interaction control is carried out. Assuming that the attribute set of the transmission model for human-machine interaction instructions in the smart home is $X = \{x_1, x_2, ..., x_n\}$, the fsimage instruction parameter set and log file for human-machine interaction in the smart home are established using the HRMS end-user transmission control method[17]. The characteristic components of the instruction transmission for human-machine interaction in the smart home are obtained using the semi-structured data source labeling method:

$$\begin{aligned} H(t) &= \varphi_1((s_1, a_1), (s_2, a_2), ..., (s_n, a_n)) \\ &= \Delta\left(\sum_{j=1}^{n} w_j \Delta^{-}1(s_j, a_j)\right) \end{aligned} \tag{10}$$

where $(s_1, a_1), (s_2, a_2), ..., (s_n, a_n)$ represents a relational database, w_j represents adaptive weight adjustment, and $\sum_{j=1}^{n} w_j = 1, \overline{s} \in S, \overline{a} \in [-0.5, 0.5]$ represents the dynamic parameter set configured on the server. Assuming $(s_1, a_1), (s_2, a_2), ..., (s_n, a_n)$ is a set of semantic feature distribution sets that describe the clustering of human-machine interaction instructions in smart homes, a statistical analysis model for the clustering of human-machine interaction instructions in smart homes is established based on this. A relational database is established in the fuzzy grid area for adaptive scheduling of human-machine interaction instruction output in smart homes, and the data transmission

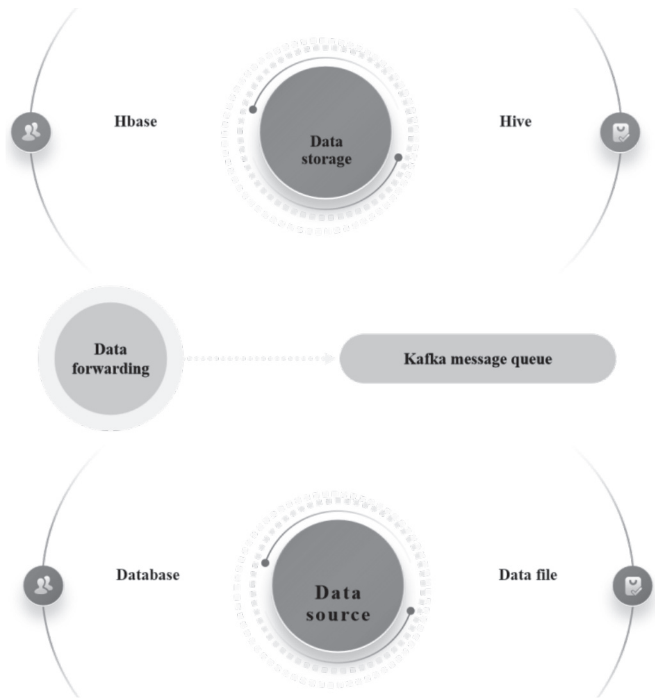

Figure 5 Data transmission architecture for human-computer interaction in smart homes.

architecture model of human-machine interaction in smart homes is obtained as shown in Figure 5.

3.5 Algorithm Design

Data fusion technology is used to establish a big data fusion model for human-machine interaction in smart homes, the application layer and data structure layer of the smart home human-machine interaction control system are constructed, and the optimal solution association rule feature set for the transmission of smart home control commands is obtained:

$$\theta_{j,k} = D_{j,k}^T V_j^{-1} D_{j,k} \tag{11}$$

where the carrier frequency characteristic component of V_j smart home control command transmission, $D_{j,k}$ is the baud interval characteristic distribution of smart home human-machine interaction command data transmission, V_j^{-1} is the feedback load of human-machine interaction command data, and $D_{j,k}^T$ is the transposition of $D_{j,k}$. At the HRMS terminal, construct a smart home human-machine interaction instruction allocation structure model, and obtain the offset value $w = (w_1, w_2, ..., w_n)^T, w_j \in [0, 1]$. The equivalent constraint control methods for channel equalization control of smart home human-computer interaction system are combined. Random linear fusion and analytical control methods are used to balance the transmission of human-machine interaction instructions in smart homes. The result is a distributed fusion model for human-machine interaction instructions in smart homes. The data fusion output is:

$$x(t) = \sum_{k=0}^{\infty} a_k(t) cos\,[2\pi k f_m t + b_k(t) + \theta_k] \tag{12}$$

where f_g is the frequency distribution of the same frequency window, f_m is the dynamic distribution spectrum of human-machine interaction in the smart home, a_k (t) is the amplitude of human-machine interaction instructions, k is the baud interval parameter, and b_k (t) is the dynamic migration parameter, θ_K is the dynamic feature output of human-machine interaction instructions [18].

Based on this, the fusion output of human-machine interaction data in smart homes is achieved.

Data fusion scheduling is used to dynamically control the interaction between various data sources and middleware in smart home human-machine interaction, AD/DA converters collect and convert pulse information in the smart home human-machine interaction control system, a system structure model is established for smart home human-machine interaction, and the interface allocation is obtained for the transmission of smart home human-machine interaction instructions, as shown in Figure 6.

Using dynamic parameter adjustment and overall control methods, obtain the unit vector set of human-machine interaction instructions for smart homes:

$$E_n = \sum_{l=1}^{n} y_l \varphi_l \tag{13}$$

Find its 1 eigenvalues λ_1, λ_2, λ_1. By combining the output conversion control of control instructions, it achieves optimized acquisition of human-machine interaction instructions for smart homes. Based on the data integration mode of data warehouse, a smart home human-machine interaction control model is obtained by combining Hadoop cloud platform control for the allocation of data between available computer clusters, and the control command output is completed:

$$min(f) = \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} X_{ij} \tag{14}$$

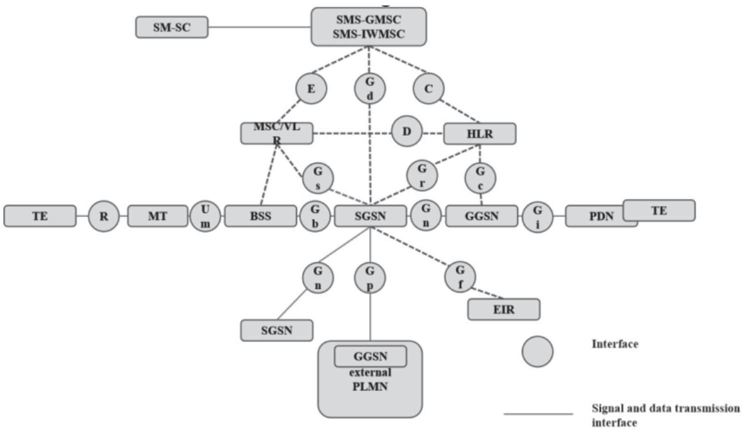

Figure 6 Interface allocation for human-machine interaction instruction transmissions in smart homes.

Table 1 User Login Test Case.

Testing procedure	Test data	Expected results	test result
Enter user account	The platform has completed the registration of the user's account and password	Registered users can log in normally; Unregistered users display user registration in the prompt box	Pass through
Enter password			
Obtain verification code			
Enter verification code			
Click the login button			

$$s.t \begin{cases} \sum_{j=1}^{m} X_{ij} = a_i, i = 1, 2, ..., m \\ \sum_{i=1}^{m} X_{ij} = b_i, j = 1, 2, ..., m \\ X_{ij} \geq 0. i = 1, 2, ..., m, j = 1, 2, ..., n \end{cases} \quad (15)$$

where C_{ij} represents the autocorrelation function of human-machine interaction in smart homes, X_{ij} represents the number of cross-correlation features, m, n represent the distribution dimension and state feature parameters of human-machine interaction control in smart homes, and a_i, b_i represent the feature parameter set of relational data.

This completes the design of a smart home human-computer interaction system based on digital twins.

4. SIMULATION EXPERIMENTS AND RESULT ANALYSIS

After completing the hardware and software design of the intelligent indoor design automation management platform based on digital twin technology, it is necessary to establish an experimental testing environment. The testing environment will affect the effectiveness of the platform's testing results. The environment of the proposed automation management platform is as follows:

Operating System: In order to ensure that the operating system version tested on the platform is above Windows XP, the researchers chose the Windows 10 operating system for testing.

Memory: The requirement for testing environment memory is>4GB, and the hard disk memory must be at least 1GB.

Browser: Chrome browser and IE browser are the main browsers for platform testing. Due to its wide applicability, the researchers chose Chrome browser.

CPU: The automation management platform requires a relatively high version of the CPU, and the researchers chose the i5–4768U2.5GHz version of the CPU [19].

The testing of the proposed platform is done in two stages. The first stage is the functional testing of the platform. The calculation formula for these two indicators is:

$$\varepsilon_{loss} = \xi_p \frac{q_r \eta_l}{l_o} \quad (16)$$

$$?_u = \frac{q_r}{l_o \eta_l} \varepsilon_{loss} \quad (17)$$

In the equation: ξ_p represents the value of the actuator when the platform loses packets; q_r is the robustness of service information in smart interior design; l_o represents the number of consecutive packet losses in smart interior design.

In the functional testing, it is necessary to ensure that the platform's backend system can operate normally. The user login function test results are shown in Table 1, and indicate that the login function of the platform is normal and can meet the user's requirements.

The user's operational function test results are shown in Table 2. The results indicate that the user's operational functions based on the proposed platform design meet the user's requirements.

To determine the performance level of the platform, the packet loss rate and delay effect during operation were tested using the number of executions as the independent variable. The results are shown in Figure 7 where the number of times that users execute the platform increases, the packet loss rate and latency effect of the automated management

Table 2 User's Operational Function Test Cases.

Testing procedure	Test data	Expected results	Test result
Enter the IoT device list page	New IoT devices: detector modification information: geographic location book delete IoT devices	Successfully added IoT devices, successfully modified IoT device information	Test passed
Click on the add button, enter the information of the new IoT device, and click confirm			
Click the modify button, enter the field information that needs to be modified, and click confirm			
Click the delete button, then click confirm			

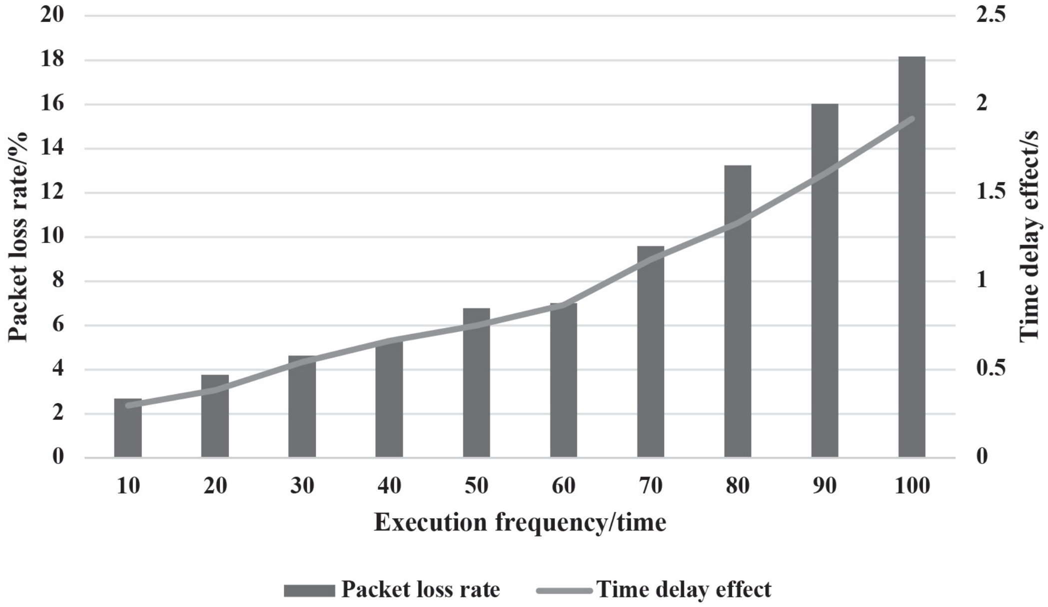

Figure 7 Platform Performance Test Results.

Table 3 Parameter Configuration.

Control nodes	Control data scale	Correlation dimension	Spectral gain/dB
Node1	43193	31	11.776
Node2	41130	38	12.025
Node3	41599	34	14.645
Node4	41073	115	12.655
Node5	43257	98	13.672
Node6	41990	8	12.878
Node7	43169	6	13.272
Node8	42514	3	12.113
Node9	41231	82	14.379
Node10	43205	33	11.955
Node11	41208	18	14.701
Node12	40483	13	13.203

platform show an increasing trend, in the packet loss rate test, the platform in the article is always controlled within 20%.

In the smart home's human-machine interaction process, the interval period for the collection of instruction is set at 2.5 seconds, and the sample size of instruction data is 1000MB. Other parameter configurations are shown in Table 3.

In order to demonstrate the effectiveness of the proposed system, it was compared with Traditional Method 1 and Traditional Method 2 to test the response time of human-

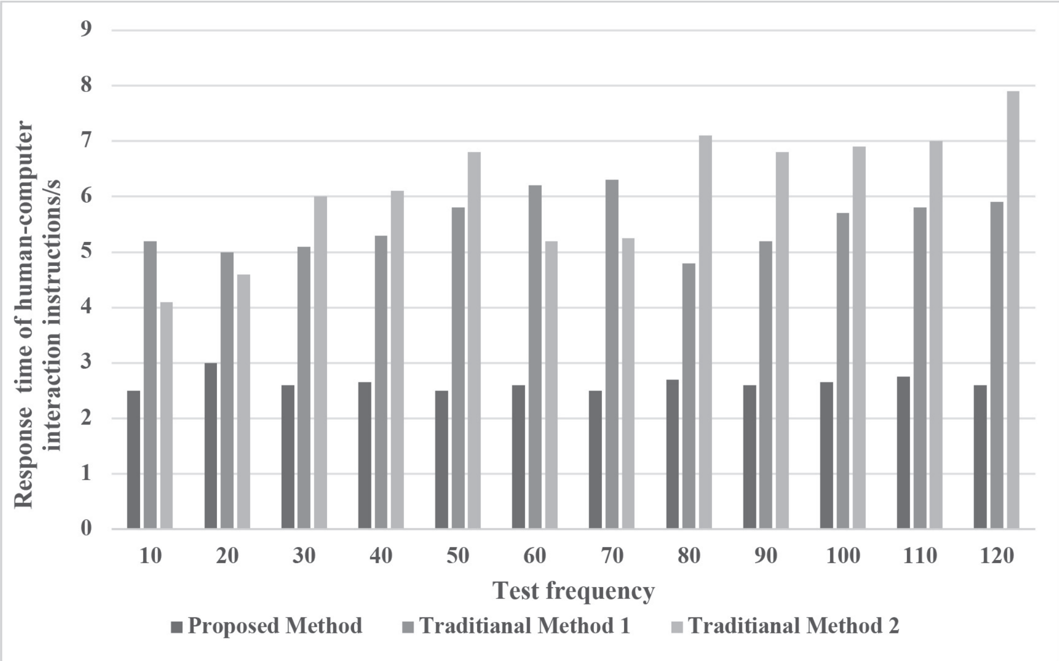

Figure 8 Control Instruction Input/Output Sequence.

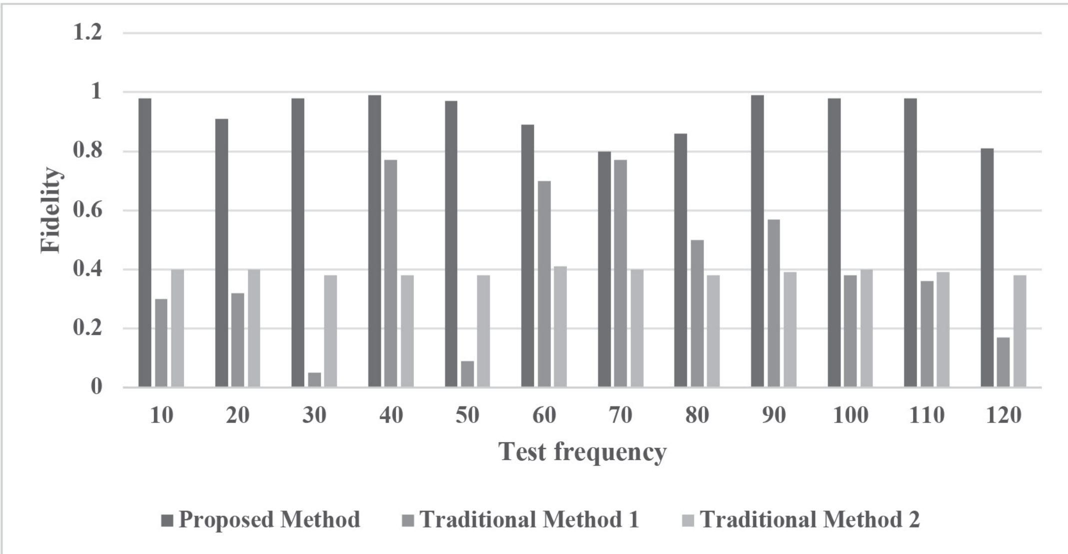

Figure 9 Accuracy testing of control instruction interaction.

machine interaction instructions using different methods. The test results are shown in Figure 8.

Figure 8 shows that no matter how many tests are conducted, the proposed system can respond to human-machine interaction commands within 3 seconds, with a small difference in response speed.

In order to further demonstrate the application effectiveness of the designed system, the accuracy of human-machine interaction between the three systems was compared again. The results are shown in Figure 9.

From Figure 9, it can be seen that the information fidelity of the system during human-computer interaction is higher. Although the accuracy may fluctuate due to uncontrollable factors, it is higher than the two traditional methods. This indicates that the design of the system can preserve the authenticity of human-computer interaction instructions while ensuring the reaction speed of human-computer interaction, which can improve the interaction accuracy [20–22].

In summary, the designed smart home human-computer interaction system based on digital twins has good performance and certain application value.

5. CONCLUSION

The researchers propose an intelligent indoor design automation management platform based on digital twin technology. Firstly, the overall system structure and data transmission structure are designed, followed by the design of intelligent home human-machine interaction algorithms. Using data fusion technology, a large data fusion model for intelligent home human-machine interaction is established for data fusion output, and then the control optimization of intelligent home human-machine interaction instructions is carried out in order to achieve the design of a smart home human-computer interaction system. Finally, simulation experiments were conducted to determine whether the functionality and performance of the platform can meet the user's requirements.

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