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RESEARCH ON SMART BUILDING DESIGN BASED ON DEEP LEARNING

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Abstract. In order to enhance the intelligent attribute features of buildings, smart building design was carried out based on twin deep learning networks. Firstly, the smart building is divided into building layer, sensor layer, network layer, knowledge layer, and decision-making layer, based on which the architecture of the smart building is constructed. Secondly, the intelligent algorithm for the decision-making layer was designed, using twin deep networks as the main framework, and detailed designs were made for the spatial attention mechanism and channel attention mechanism. Finally, an experiment was conducted on a certain architectural scene. The experimental results show that smart buildings can automatically adjust room temperature based on sensor information (adjust the temperature of Room 1 to 25.8 degrees and Room 6 to 25 degrees) and accurately alert rooms in case of fire. The experimental results fully confirm the effectiveness of our design work.

1. Introduction

Architecture is the fundamental carrier that provides services necessary for people's lives and work[2]. The architecture of human society has roughly gone through the development process of traditional architecture, intelligent architecture, and smart architecture [11, 16, 13]. Traditional architecture only has relatively independent control over various equipment such as water supply and drainage, power distribution, lighting, and ventilation. The independent operation of each system consumes a lot of energy and is difficult to control comprehensively. Compared to traditional buildings, the most prominent feature of smart buildings is integration[8]. By designing information systems or control platforms, various internal systems of buildings can be integrated together to facilitate comprehensive analysis and processing of information[1].

Smart building is a platform that combines building equipment, office automation, and communication network systems. Smart buildings are the optimal combination of building structure, systems, services, and management[12]. Smart buildings provide people with a safe, efficient, comfortable, and convenient building environment. The integration of building intelligence is not the purpose of smart buildings, but an important technical method and means to achieve a safe, efficient, convenient, and comfortable working and living environment for smart buildings[3]. Smart integration serves the social, economic, and environmental benefits of smart

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buildings, rather than integrating for the sake of integration. Intelligent integration is only a means rather than the ultimate goal.

Ramamurthi pointed out that smart buildings are composite systems that rely on buildings as the supporting space and comprehensively consider multiple conditions. The intelligence attribute of smart buildings is reflected in the autonomous decision-making and adaptive control of various subsystems [10]. Fang believes that the intelligence attribute of architecture is set by human standards. The decision-making system in smart buildings will actively adjust and improve the temperature and air quality in the environment based on human livability[5]. Iqbal pointed out that smart buildings must first have the ability to perceive complex environments, such as temperature, humidity, oxygen content, and hazards within the building space. So to achieve intelligent design of buildings, it is necessary to first build an IoT system that includes multiple sensor nodes [6]. Tinhinane believes that the Internet of Things system is the core and framework of smart buildings. It obtains data on the building environment through bottom end sensors, extracts and processes this data to obtain effective information, and then integrates this information through decision-making modules to form new control and adjustment instructions, ultimately achieving real-time changes to the building environment to meet human requirements such as safety and comfort[14]. Vilares believes that the key difference between intelligent buildings and smart buildings is that smart buildings can not only passively collect environmental information, but also adjust various subsystems attached to the building platform to make changes that are beneficial to human needs. Intelligent buildings are limited to the functional level, while smart buildings have reached the decision-making level [15]. Djenouri has developed a framework for smart buildings using the Internet of Things system architecture, and designed multiple subsystems within it. Based on the decision tree method, the framework forms the core control unit of the entire building, giving it some intelligent attributes [4]. Kuttichira uses the Kalman filter model to predict and estimate multi-sensor control information within the Internet of Things, providing an automated control solution for smart buildings [7]. Northardt conducted research on energy consumption in Pakistan and pointed out that buildings have the greatest potential for energy conservation. Based on this, he concluded that using efficient light-emitting diodes and sunlight for lighting and heating can significantly reduce building energy consumption [9].

From the previous research work, it can be seen that smart buildings have higher decision-making level attributes compared to smart buildings. Smart buildings cannot do without the framework of the Internet of Things system, and decision models are the core of realizing their intelligent attributes. In this article, an IoT framework for smart buildings is constructed, and twin deep learning networks are used to achieve intelligent control of buildings, thus achieving the architecture design of smart buildings.

2. Architecture design and decision-making method design for smart buildings

2.1. **Architecture Design of Smart Buildings.** Smart buildings are complex systems. In order for a building to have intelligent attributes, it should contain at least 5 levels: first, the building level, which includes various building units, equipment, and environments. Secondly, the sensor layer is responsible for collecting status information from devices and the environment. Common sensors include temperature sensors, humidity sensors, oxygen sensors, and carbon dioxide sensors, but are not limited to these. Thirdly, the network layer is responsible for connecting sensors at various locations into a network. It is precisely through this layer that smart buildings form an Internet of Things in the physical dimension. Fourthly, the knowledge layer analyzes and organizes various data and information transmitted from the network layer to form knowledge that can be used by the decision-making layer. Fifth, the decision-making layer utilizes intelligent algorithms to form autonomous decisions based on the knowledge transmitted from the knowledge layer. Based on this, the architecture design of smart buildings is presented as shown in Figure 1.

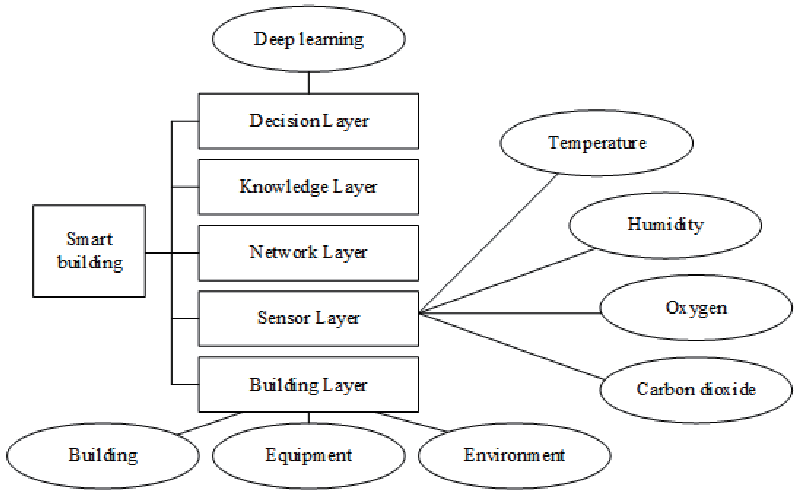

FIGURE 1. Architecture Design of Smart Buildings

From Figure 1, it can be seen that the key to realizing the intelligent attributes of architecture lies in the decision-making level. The decision-making level needs to have the ability of intelligence. Without human intervention, it can form autonomous decisions based on sensor information and self built knowledge base, adjust equipment parameters autonomously, and achieve the effect of changing building and environmental characteristics, improving building livability and safety. Obviously, in order for decision-makers to achieve their expected goals, they need to process a large amount of data and conduct effective analysis and processing of this data in order to obtain the best decisions. Therefore, the algorithm configured by the decision-making level is the core content of smart building design. In this article, twin deep learning networks are used as the core algorithm for the decision-making layer.

2.2. **Design of Deep Learning Method for Smart Building Decision making Layer.** Deep learning networks can learn complex data with multiple variables and achieve a stable internal structure through a large number of iterative processes.

At this point, deep learning networks can generate reasonable outputs or decisions based on new inputs. In the design of smart buildings, building information, equipment information, and environmental information are all collected through various sensors, which become inputs for deep learning. The goal of deep learning networks is to determine whether a building is safe and livable based on this data. If the ideal values of safety and livability are not achieved, autonomous adjustments need to be made to provide adjustment values at the output of the deep learning network. It can be seen that this process should fully refer to human judgment standards for safety and livability.

In the deep learning network we construct, we need to consider not only the various information collected by sensors, but also the reference information of human standards. Therefore, we designed a twin network with two channels, as shown in Figure 2.

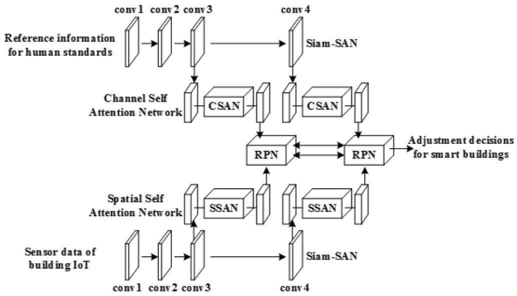

Figure 2. Deep Learning Framework of Twin Networks

From Figure 2, it can be seen that the twin deep learning network contains two learning channels. This structure is significantly different from single channel deep learning networks. For example, general deep networks such as CNN and RNN are single channel structures that learn and train directly based on input to obtain output. The dual channel structure in Figure 2 is responsible for inputting and processing human standard reference information, which corresponds to the reasonable values of sensors at various nodes of the smart building. The following channel is responsible for inputting and processing the true values measured by the sensors. The mutual reference and borrowing between the two channels greatly increases the credibility of the output results. The module units and structures of the two channels are exactly the same, both containing multiple convolutional layers, attention mechanism layers, and so on. The processing results of the two channels provide a basis for the final adjustment and decision generation of smart buildings.

In twin deep learning networks, the only difference between the two channels is that human standard reference information is fed into the channel attention module for processing. And the true value of the sensor is sent to the spatial attention module for processing. Firstly, let's observe the structure of the channel attention module, as shown in Figure 3.

In Figure 3, the keywords extracted from the human standard reference information are represented $A \in R^{C\times H\times W}$ and it can be reshaped $R^{C\times N}$, $N = H \times W$.

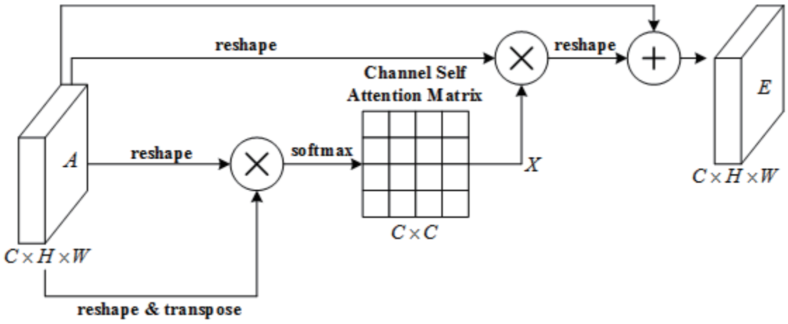

FIGURE 3. Structure of Channel Attention Module

The further operation is to perform a multiplication operation on $R^{C\times N}$ and the transpose of A, which is fed into the Softmax function to generate an attention map $X \in R^{C\times N}$, as shown in Equation (2.1):

$$X_{ji} = \frac{\exp\left(A_i \cdot A_j\right)}{\sum_{i=1}^{N} \exp\left(A_i \cdot A_j\right)} \tag{2.1}$$

Here, A_i is the variable at the i-th position in the channel module, A_j is the variable at j-th position in the channel module, N is the total number of variables, and X_{ji} is the mutual influence between the two channels.

Furthermore, A and the transpose of X is performed multiplication, followed by β scaling. Finally, $E \in R^{C\times H\times W}$ can be obtained by Equation (2.2).

$$E_j = \beta \sum_{i=1}^{N} \left(x_{ij} A_i\right) + A_j \tag{2.2}$$

At this point, all the features of the human standard reference information have been associated and assigned different weights, improving the reliability of subsequent learning.

The structure of the spatial attention module in the processing channel of the sensor's real information is shown in Figure 4.

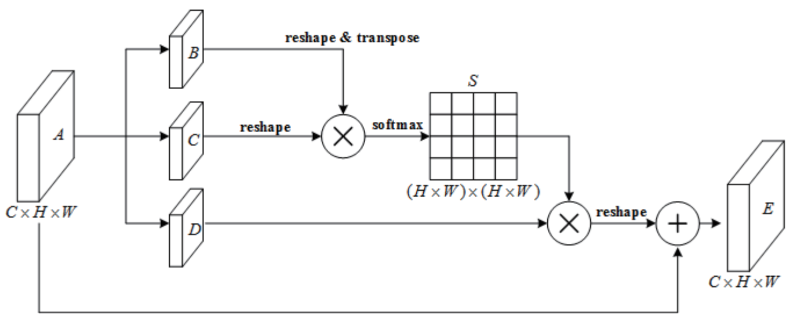

FIGURE 4. Structural Design of Spatial Self Attention Network

In Figure 4 , the keywords $A \in R^{C\times H\times W}$ extracted from the sensor's real information are convolved to feature maps B, C, and D. Feature map B correspond to query features $Q \in R^{C\times N}$. Feature map C corresponds to key features $K \in R^{C\times N}$. Perform multiplication processing between Q and K, and send the result to Softmax to generate an attention map $S \in R^{C\times N}$, as shown in Equation (2.3):

$$S_{ji} = \frac{\exp\left(B_i \cdot C_j\right)}{\sum_{i=1}^{N} \exp\left(B_i \cdot C_j\right)} \tag{2.3}$$

Here, B_i is the variable at the i-th position in the spatial module, C_j is the variable at the j-th position in the spatial module, N is the total number of variables, and S_{ji} is the impact between the two channels.

Furthermore, the transpose of S is multiplied with the eigenvalues, then scaled by α. Finally E_j can be obtained by Equation (2.4).

$$E_j = \alpha \sum_{i=1}^{N} \left(S_{ij} D_i\right) + A_j \tag{2.4}$$

Here, α is the scaling factor, D_i is the i-th eigenvalue in the module.

3. Experimental results and analysis

In the previous work, the architecture of smart buildings was designed and an algorithm based on twin deep networks was constructed for their autonomous decision-making. To verify the effectiveness of the aforementioned research work, further experimental studies will be conducted.

The scene in the experiment is set on a certain floor inside the building. This floor contains a total of 10 rooms, distributed on both sides of the hallway, with 5 rooms on each side. The planar structure diagram of the experimental scene is shown in Figure 5.

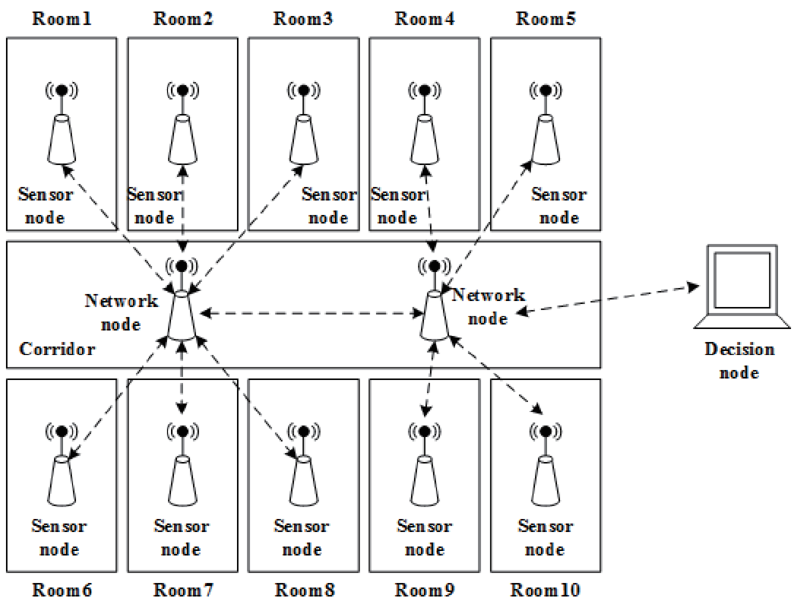

Figure 5. Plan structure diagram of experimental scene

In Figure 5, sensor nodes are arranged in each room, which can carry temperature sensors, humidity sensors, carbon dioxide sensors, carbon monoxide sensors, etc., to collect environmental information in the room. Here, the selection of sensors should match their coverage capability. For example, if the room area is large, sensors with a larger coverage range should be selected. If a sensor cannot cover the room area, it is necessary to increase the number of sensors. Taking temperature sensors as an example, we have chosen the PT1000 temperature sensor, which has a large coverage area, high sensitivity, and low power consumption.

Meanwhile, the sensor nodes are equipped with wireless communication modules that can communicate with network nodes in the hallway. The wireless communication mode here has chosen the ZigBee wireless communication protocol. ZigBee wireless communication has low power consumption and also has a good auxiliary effect on building energy conservation.The network nodes in the hallway then transmit the information to the decision computer nodes. A decision algorithm based on twin deep learning networks, running on a decision computer. The decision computer can control the air conditioning equipment, alarm devices, etc. in each room based on information from sensor nodes. For example, when the temperature is not suitable, the decision computer can control the air conditioning in the room to automatically adjust the temperature; When a fire occurs in the room and the concentration of carbon monoxide increases, the decision computer can control the alarm equipment in the room to emit an alarm sound.

Sensor data has a significant impact on the decision-making process of the entire system, and selecting sensors with high sensitivity and reliability can increase the credibility of the decision-making process. Of course, unexpected environmental conditions or force majeure may result in inaccurate or variable sensor data. Due to space limitations, a detailed explanation of the calibration and error checking mechanisms for sensors will be provided in an additional submission. Here, only the normal operation of the sensor is considered.

The first experiment is to automatically adjust the temperature of different rooms in the experimental scene. In the experiment, room 1 and room 6 were selected respectively. These two rooms are located on both sides of the hallway, with room 1 having better lighting and room 6 having relatively poorer lighting. After the twin deep learning network algorithm on the decision-making computer of the smart building has been trained, it will be used for temperature monitoring and automatic adjustment in these two rooms. The temperature variation curves of two rooms over time are shown in Figure 6.

From Figure 6, it can be seen that the temperature curve of Room 1 is generally higher than that of Room 6. There is a certain temperature difference between room 1 and room 6 because room 1 is located on the sunny side with sufficient sunlight, resulting in a higher temperature. And Room 6 is located on the shaded side, with insufficient lighting and therefore a lower temperature.

This is because the two rooms have set different suitable temperatures according to the needs of different people. As time passed, the temperature in both rooms reached its peak between 11 and 12 o'clock. At this point, the temperature information collected by the sensor nodes in the two rooms will be transmitted back to the decision layer through the network nodes. The decision-making layer automatically

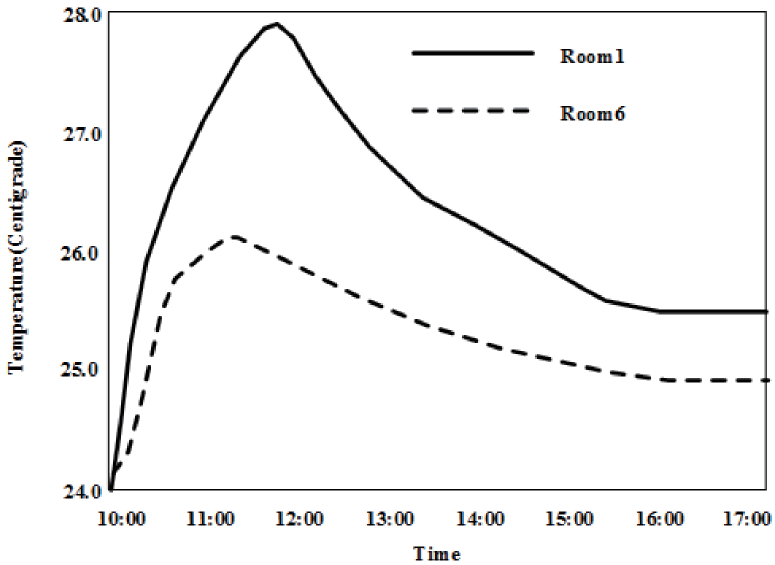

FIGURE 6. Temperature variation curves of two rooms over time

adjusts the air conditioning equipment in the room based on the algorithm of the twin deep learning network, referring to the suitable temperatures already set for the two rooms. The temperature in room 1 gradually adjusted to 25.8 degrees, and the temperature in room 6 gradually adjusted to 25 degrees. It can be seen that after the adjustment of the twin deep learning network, the building has reached a better suitable temperature, demonstrating the attributes of a smart building.

The second set of experiments will be conducted from a safety perspective for verification. Set up a fire source in room 9 to simulate the situation when a fire occurs. The sensor nodes in the room simultaneously monitor the oxygen content and carbon monoxide gas content in the room, and the concentration change curves of the two gases are shown in Figure 7.

From Figure 7, it can be seen that at the initial monitoring moment, the oxygen content in room 9 is at a normal level. Afterwards, the fire source in the room was ignited, and oxygen gradually decreased as it participated in the combustion. At first, the trend of oxygen reduction was relatively slow, but as the fire continued to intensify, the trend of oxygen reduction became more intense. The concentration of carbon monoxide gas in the room increased significantly after 40 seconds, and then gradually expanded with a more obvious increasing trend. After the sensor nodes in the room effectively capture this information, the deep learning algorithm on the decision computer can already determine that a fire has occurred in the room and control the alarms in the room and hallway to beep. The above experiment confirms that the smart building we designed has the ability to autonomously judge safety.

However, this research is still in its early stages and has not been thoroughly considered for some complex situations. For example, there may be deviations in the adaptability of different users to high and low temperatures. After different users enter the same room, they need to manually adjust the input data of the upper

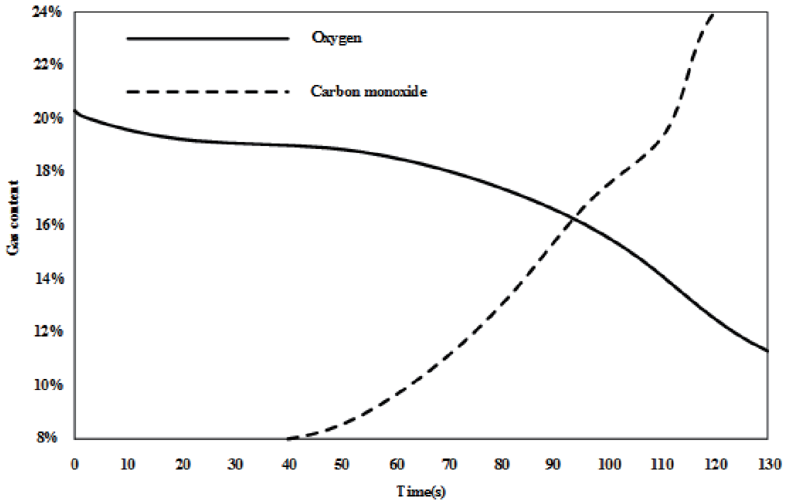

FIGURE 7. Concentration variation curves of two gases

channel in the deep network in order to enable the autonomous decision-making of smart buildings to meet their needs. These will be further analyzed and discussed in subsequent research. In future research, the autonomous perception capability of smart buildings can be further expanded to include the ability to control and solve problems, such as autonomously extinguishing fires after detecting them.

4. Conclusions

Smart buildings have become the future development trend of the construction industry. Smart building is a further improvement on the basis of smart building, with better intelligent attribute characteristics. In this article, the architecture of smart buildings was first designed. According to the five levels of division, the design of the Internet of Things hierarchy has been carried out for smart buildings. In the design of intelligent algorithms at the decision-making level, a deep learning architecture based on twin networks was adopted, and detailed designs were made for spatial attention mechanism and channel attention mechanism. During the experiment, a scene consisting of 10 rooms was set up. Experiments were conducted from two aspects: temperature adjustment and fire alarm, and the experimental results proved that the proposed deep learning algorithm endows buildings with intelligent attributes.

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