An intelligent wheelchair is a kind of service robot. The most critical part of its research field is the safe navigation control of a wheelchair, and path planning is the core part of the navigation control system. The use of a reasonable obstacle avoidance algorithm can not only ensure the safe navigation of the wheelchair but also protect the personal safety of users. This paper analyzes the actual needs of the wheelchair following system according to the application scenarios and determines the way to follow the target. The sensor scheme and the wheelchair mobile platform are selected through the analysis of the following methods and the characteristics of each sensor, and the overall architecture of the wheelchair hardware system is designed. Then, the key components such as processor, laser ranging radar, signal strength positioning module, and ultrasonic sensor in the hardware system are selected, and the corresponding peripheral circuit is designed according to the interface type and working voltage of the sensor. In order to solve the problems of the complex calculation process, one-way reasoning, and poor accuracy of the original fault tree method, this paper designs an expert knowledge inference machine based on the Bayesian network. After completing the definition of component vulnerability, the inference engine can be activated, the construction of the directed acyclic network is completed based on the knowledge model mapping of the fault tree, the conditional probability table definition of the directed edge is completed, and the bidirectional probability inference of the Bayesian network can be started. Diagnostic inference obtains the posterior probability to characterize the system impact degree of the bottom event failure. Based on a comprehensive analysis of the research status and research trend of intelligent wheelchair obstacle avoidance path planning methods, this paper mainly studies the intelligent wheelchair path planning method. The environment modeling and path planning of global path planning for static obstacles and dynamic obstacles are realized, and a simulation platform for wheelchair obstacle avoidance path planning based on MATLAB is designed, and simulation experiments are carried out on this basis. The effectiveness of the studied algorithms and strategies in the dynamic obstacle environment is verified by simulation experiments.

1. Introduction

Due to the decline of physiological functions and the disability of some limb functions, most of the elderly and disabled people need to use wheelchairs as means of transportation in their lives [1]. At present, most of the wheelchairs on the market can only enable the occupants to achieve their own purpose of moving, and there are hidden dangers of safety and lack of humanization [2]. According to medical statistics, after a period of training, there are still about 1 in 10 elderly people who have difficulty using wheelchairs, and some elderly people cannot learn to use wheelchairs at all, especially in the face of turning. In the event of an emergency collision and parking, that number quickly rose to 40 percent. With the rapid development of artificial intelligence and mobile robot technology, research on intelligent and humanized wheelchairs will be an inevitable trend. The development of an intelligent wheelchair suitable for
most groups will greatly reduce the burden on the society in caring for the elderly and the disabled, allowing the elderly and the disabled to regain the ability to move autonomously and to reestablish the ability to face life [3, 4].

As a simple means of transportation, wheelchairs provide many conveniences for people with reduced mobility. There are two main types of wheelchairs on the market at this stage, namely, manual wheelchairs and electric wheelchairs. Manual wheelchairs rely on human power to propel the wheelchair movement, while electric wheelchairs use joysticks to control wheelchair movement [5]. These wheelchairs are only controlled manually by the user during operation, which will not only cause driving fatigue but also may not be ideally controlled due to the user’s personal factors, and even a safety accident may occur in serious cases. The intelligent wheelchair applies artificial intelligence technology and robotic technology to the wheelchair. Compared with ordinary wheelchairs, this kind of wheelchair has better decision-making autonomy, human-machine interaction, and environmental adaptability, which greatly improves the quality of life of the elderly and the disabled [6]. Indoor mapping and autonomous navigation are the basic functions of intelligent wheelchairs, so they have very important research value and significance.

This paper sets three modes of wheelchair, namely, autonomous following mode, remote control mode, and joystick control mode. The hardware architecture of the wheelchair system is designed, key components such as wheelchair platform, processor, and sensor are selected, and the corresponding peripheral circuits are designed. At the same time, the original wheelchair controller is improved to complete the construction of the wheelchair hardware system. This paper introduces the viability evaluation process of the fuzzy Bayesian network: the determination of system model and node information, the fuzzification of knowledge, the determination of Bayesian network inference, the defuzzification of fuzzy Bayesian network inference, and the defuzzification and regression of inference results. The fuzzy processing of expert experience knowledge based on triangular fuzzy membership function is designed, and the fuzzy processing of expert experience and vulnerability level is carried out. The defuzzification algorithm using the area mean method is used to obtain the exact probability value after inference. The spacecraft survivability assessment algorithm of the fuzzy Bayesian network is designed. First, the fuzzy definition of the Bayesian network model is completed, that is, the construction of the fuzzy conditional probability distribution matrix corresponding to the risk level of the first and second generation. Then, three kinds of algorithmic reasoning, causal reasoning, diagnostic reasoning, and risk level clustering, are designed. The overall planning process under dynamic obstacles is determined, and then, the description of path planning under dynamic obstacles is given, including the conditions and objectives of dynamic path planning. The simulation environment model under dynamic obstacles is introduced, and the search process and obstacle avoidance strategy of global path planning and online replanning are proposed according to the obstacles that the intelligent wheelchair may encounter in motion. In practice, sensors are mainly used to detect dynamic obstacles. In the simulation test in this paper, it is mainly based on the distance between the moving obstacles and the intelligent wheelchair to judge whether to perform online replanning and obstacle avoidance. Finally, a simulation experiment is carried out based on the MATLAB platform, and the experimental results are analyzed to verify the feasibility of the planning algorithm and obstacle avoidance strategy.

2. Related Work

Path planning is one of the most basic problems in intelligent robot research [7]. It has been widely used in many fields, but there is no effective solution that can adapt to various complex environments. Scholars at home and abroad have proposed many methods for solving path planning problems [8]. Common path planning methods include visual graph method, graph search algorithm, artificial potential field method, etc. Some scholars also apply intelligent algorithms such as neural networks, genetic algorithms, and particle swarm optimization to path planning. Each of these methods has its own advantages and disadvantages. Neural networks, genetic algorithms, and other intelligent path planning algorithms have great advantages in path optimization, but their disadvantages lie in poor real-time performance or slow convergence speed. These shortcomings make them unable to meet the requirements for efficiency in practical applications. A*, D*, probabilistic roadmap methods, and other similar algorithms can overcome the shortcomings of the above intelligent path planning algorithms without considering the nonholonomic constraints of mobile robots, but in practical applications, due to unavoidable nonholonomic constraints, the effectiveness of the above algorithm is greatly reduced [9].

Obstacle location refers to distinguishing obstacles that affect the passage and determining their range. The indoor environment is complex, changeable, and unpredictable, and the shapes and colors of obstacles are diverse. Therefore, it is also a research difficulty to detect and locate obstacles in the indoor environment. At present, there are many methods that can be used for obstacle detection and localization. The common point of these methods is that they are very dependent on the sensors they use. According to the sensors used, obstacle detection and positioning methods can be divided into detection and positioning methods based on monocular vision, binocular vision, laser ranging, and ultrasonic waves [10]. Since it is difficult for a single sensor to obtain comprehensive and accurate environmental information, the fusion of information from two or more of the above sensors is a research hotspot in obstacle detection and localization in recent years [11].

Related scholars apply the Gauss-Seidel relaxation method to the optimization of SLAM, by traversing the nodes and updating the position of the nodes according to the constraints of the nodes [12]. When there is a closed loop, the error of this method is larger. Aiming at this problem, the multilevel relaxation method is applied to the optimization, and the multinetwork method is used to solve the
planning from global path planning, local path planning has higher efficiency and real-time performance, but because only the current local environment information is considered, the planned path is usually not globally optimal. The method based on least squares is to formulate the SLAM problem as a least squares problem and solve it. According to the different processing methods, the method can be divided into incremental-based methods and batch-based methods. The incremental-based optimization method optimizes the pose while moving the robot [14]. The batch-based method only optimizes the trajectory and map of the entire mobile robot at the end. There are the proposed iSAM algorithm and the improved iSAM2.0 algorithm based on the incremental least squares optimization method.

A heuristic search algorithm is an efficient search algorithm containing heuristic information, which is represented by the A* algorithm. The A* algorithm is developed on the basis of Dijkstra’s algorithm by adding heuristic terms and is a commonly used algorithm in global path planning [15]. However, when the A* algorithm faces large-scale path planning, the search time and space complexity are high. In recent years, many researchers have improved the A* algorithm and obtained a variety of heuristic search algorithms [16]. Based on the D* algorithm, relevant scholars have proposed an improved D* algorithm for different terrains, which improves the efficiency of path planning in different terrains [17].

Local path planning is that in an unknown environment, the robot only perceives the surrounding environment information and its own state information through its own sensors and plans an obstacle avoidance path in real time according to the obtained information [18–20]. Different from global path planning, local path planning has higher planning efficiency and real-time performance, but because only the current local environment information is considered, the planned path is usually not globally optimal. Commonly used local path planning methods include dynamic window method and artificial potential field method.

The dynamic window method is an algorithm that considers robot kinematics and dynamics [21]. The DWA algorithm builds the robot’s surrounding environment information into a window and realizes the path planning through the loop calculation window [22]. The algorithm can quickly adjust the robot’s path according to the changes of the environment information. Relevant scholars combined the DWA algorithm with the Ackerman robot to realize the autonomous obstacle avoidance function of the Ackerman robot. Related scholars applied the least squares method to DWA-based path planning, which improved the accuracy of robot navigation in unknown environments [23–25].

### 3. Methods

#### 3.1. Selection of the Sensor Scheme

Sensors are used to collect external environment or stimuli and perceive physical, chemical, biological, and other signals. With the development of sensor technology, various sensors are constantly updated and developed, and the types and accuracy of signals that can be collected by sensors are greatly improved. The main technical process of the target following system includes three parts: environmental perception, dynamic decision-making, and motion control. Environmental perception is usually the premise and condition of decision-making. The type of sensors selected determines the surrounding environment information that the wheelchair can obtain. The design of the system and the control scheme of the entire system play a decisive role.

Table 1 shows the respective characteristics of some perceptual methods adopted by target following. Vision sensors mainly include monocular, binocular, and panoramic vision. In the existing research, visual sensors show certain advantages in object recognition and tracking, but they are easily affected by the lighting environment, and it is not easy to accurately detect the distance of objects. Even if a camera with strong robustness to lighting changes is used, it is still difficult to accurately identify and follow a specific target in a more complex environment (such as multiple sports personnel). Distance sensors mainly include laser ranging radar.
ultrasonic sensors, and infrared ranging sensors. Compared with visual sensors, distance sensors can easily obtain the distance information of objects, but it is difficult to distinguish between interfering personnel and target personnel within the detection range.

Considering that the wheelchair system needs to accurately locate the target person and obstacles, the use of distance sensors to obtain environmental information around the wheelchair has a smaller amount of data and is easier to process. LiDAR has a wide detection range and high ranging accuracy, but the scanning frequency is relatively low.

The detection range of the ultrasonic sensor is relatively fixed. It mainly detects objects within a certain angle range and cannot measure the exact coordinates of the object. However, its detection frequency is high and the measurement data is reliable. As long as the object can be accurately detected within the measurement range, it is very suitable for emergency obstacle avoidance.

Although the RSSI positioning method has low ranging accuracy, it can match a specific target according to the ID of the hardware device, which has certain advantages in target recognition.

Therefore, in this paper, RSSI positioning is used to determine the approximate position of the target person, combined with laser ranging radar to accurately detect the environmental information around the wheelchair and the position information of the target person, and the D-S evidence theory is used to fuse the detection results to distinguish the target person from obstacles.

3.2. Wheelchair Platform Selection. This paper takes the KY110A electric wheelchair of Kaiyang Medical Technology Group Co., Ltd. as the basic platform to develop the wheelchair following system. The wheelchair has a four-wheel structure and is driven by a synchronous belt and dual-motor rear wheels. By controlling the rotational speed of the two driving wheels, a difference in rotational speed between the two wheels is formed, thereby realizing the differential steering effect. The motor, reducer, and driver are packaged together to form a single module, and the wheelchair controller, as another module, processes the signal input from the joystick, buttons, etc. to form instructions to control the start, stop, and movement of the wheelchair. The user controls the wheelchair to move forward and backward, turn left, turn right, and perform other actions through the joystick. The wheelchair is also equipped with a driving wheel automatic electronic braking system, which automatically brakes when the wheelchair is not controlled. This wheelchair is simple in structure, stable in control, safe, and reliable and is suitable as a mobile platform for a follow-up system.

The original controller of the KY110A electric wheelchair can only control the wheelchair through the joystick, and the control instructions formed after the environmental perception and data processing system analyzes the sensor data cannot be connected to the wheelchair controller. Therefore, this paper adds a microcontroller and DA chip on the basis of the original controller, simulates the joystick signal access to the bottom drive interface of the wheelchair, and sends the control commands of the environment perception and data processing system to the improved wheelchair through the IIC bus. The improved intelligent wheelchair control system can well inherit the stable and reliable advantages of the original electric wheelchair system. At the same time, it can also realize multimode control of the wheelchair through the communication between the smart phone and the environment perception and data processing system.

3.3. Hardware Architecture Design. The hardware system of the wheelchair must meet the following two requirements:

(1) Strong real-time performance

In real life, the operating environment of a wheelchair may be more complicated. The movement speed and direction of the target person can change at any time, and there will be interfering people and obstacles around the wheelchair. Therefore, the wheelchair system must have a fast response speed to ensure that the wheelchair can accurately follow the target person and avoid it reliably.

(2) Scalability

In the process of developing a wheelchair system, due to the different requirements of different application scenarios, developers usually need to select different hardware devices and build different hardware structures according to the actual application characteristics. The modular design is conducive to the update and upgrade of the wheelchair following system, enhances the scalability of the system, and shortens the development cycle.

The logic flow of sensor signal acquisition, command transmission, and execution during wheelchair operation is called the control architecture. The primary task in the design of the wheelchair following system is to determine its control architecture. The control architecture is divided into three types: hierarchical, inclusive, and hybrid according to cognition and behavior.

The hierarchical structure includes three levels: organization level, coordination level, and control level. The typical representative in this structure is SPA, which consists of three parts: environment perception, decision planning, and instruction execution. The control process is relatively simple, the division of labor among the components is clear, and the structure is clear. However, the general robot control system is relatively complex, and each part needs to be coordinated and organized, so there is a certain delay, resulting in poor real-time performance of the system.

The sensing modules of the inclusive structure are independent of each other, process the information obtained by the sensors, and make decisions based on their own information. The flexibility and reliability of the system are relatively good, but due to the independent work of each module and the lack of overall planning, the purpose of the system is poor.

The hybrid structure has the characteristics of ladder type and inclusive type, that is, to ensure the globality of
the system, to implement the analysis decision and motion control hierarchically, and to take into account the flexibility of the system, each module works in parallel, and data is exchanged through the bus.

The most intuitive embodiment of the control architecture is the hardware architecture of the robot. Traditional robots usually use a centralized hardware architecture because they are mostly controlled in a hierarchical structure. The system is mostly composed of a main controller and multiple sensing modules and execution modules, with simple structure, fast data transmission speed, and strong anti-interference ability. However, with the rapid development of robotics technology, the functional requirements of the system have increased rapidly, resulting in more and more sensing modules and execution modules, and the control system has become more and more complex. In practical applications, the traditional centralized control system is too complicated, and there are many connections between modules, which makes debugging and maintenance very difficult; because the system is built in a centralized manner, each functional module is inconvenient to expand, and it is difficult to update and upgrade. Most systems are designed for specific needs, with long development cycles and high costs.

In a distributed control system, each module has an independent microprocessor, which communicates with the main controller through buses such as UART, IIC, and SPI. The microprocessor inside the sensor preprocesses the acquired original signal, converts it into specific information, and designs it into a data packet in a certain format.

It is transmitted to the main controller through the bus, and the main controller directly analyzes and decides according to the processed information, which reduces the processing process and reduces its own data processing burden.

The distributed control system combines the functions of perception processing, decision control, and data communication, with high processing efficiency and convenient function expansion, which can meet the needs of various applications.

The system adopts a hybrid control architecture, and the hardware is designed as a distributed control method. The overall structure of the hardware system is shown in Figure 1. It is mainly divided into three parts: environmental perception, data processing, and wheelchair control. Adopting a dual-controller structure, the main control microprocessor obtains the data of the laser ranging radar, RSSI positioning module, and ultrasonic sensor through the

Figure 1: Overall structure of the hardware system.
UART and IIC bus and fuses these data to form decision-making instructions and then transmits them to the modified sensor through the IIC bus.

3.4. Design of the Inference Engine Based on the Bayesian Network. The knowledge in the expert system is the rule expression of the fault tree model, so it can also be said that the knowledge is mapped from the fault tree, so when the Bayesian network model is established, it can be regarded as a Bayesian model based on the fault tree. The network model was transformed.

In the failure model, solving the probability of the occurrence of the top event corresponds to the result of the vulnerability analysis of the spacecraft, and the evaluation of the spacecraft survivability is the probability that the top event does not occur. In addition, the vulnerability of the subnode probability spacecraft subsystem and the posterior event does not occur. In addition, the vulnerability of the subnode probability spacecraft subsystem and the posterior event does not occur. In addition, the vulnerability of the subnode probability spacecraft subsystem and the posterior event does not occur.

For the same child node, there are multiple states, and each state corresponds to a full probability, and the sum of the probability values of all states of the node is 1. This time, the full probability of the node needs to be “normalized.” In addition, assuming that the child node is in a certain state, all parent node events that cause the child node are the complete set of events, and the sum of the probabilities of the complete set is 1. Therefore, it is necessary to sum up the exact probability values that cause a certain state of the child node and perform “normalization” processing of the posterior probability.

In this system, the parent node in the Bayesian network model is used as the activation inference rule, and a complete prior probability needs to be defined. When a component does not have a corresponding failure mode, the prior probability of the node is defined as 0. The parent node is connected to a single or multiple child generations through directed edges, and the corresponding conditional probability can be found in the expert system. Similarly, the conditional probability of the directed edges of the second generation and the child generation can also be obtained.

(1) Determine the prior probability of the parent node

The prior probability of the parent node is the corresponding failure mode probability of the failed component. It can be obtained from the S3DE survivability software, or the bottom event failure probability can be customized in the user interface.

(2) Determine the node conditional probability table (CPT)

The conditional probability between nodes is defined by the developer of the expert system, and the conditional probability between nodes is the confidence of the expert knowledge.

(3) Inexact conditional probability processing

When a reliable basis cannot be found in the expert system, it is considered that the resulting probability of subsystem failure caused by component failure is equal, and the corresponding conditional probability value is 1.

(4) Natural language parameters

Expert experience is difficult to assign specific values to certain nodes when passing the probability, and only natural language descriptions of experience habits can be given, such as affirmative, frequent, very likely, and unlikely to occur. And this kind of natural language description belongs to the data uncertainty description.

The full probability $P'_j$ of the $S_j$ node can be obtained through causal inference:

$$ P'_j = \sum_{i=1}^{n} P(X_i)P(X_{i+1})P(S_j|X_{i+1}). \tag{1} $$

The causal reasoning can also obtain the full probability $P_K$ of the vulnerability of the second-generation child nodes corresponding to the $m$ child generation nodes:

$$ P_K = \sum_{j=1}^{m} P(K|S_j)P(S)P(K|S_{j+1}). \tag{2} $$

The fact probability of the node is determined, and the diagnostic reasoning is carried out in combination with the Bayesian formula. It can be obtained that when the vulnerability probability of the top event system is assumed to be 1, the posterior probability of the bottom event is the relative importance of the component failure, and the failed component corresponding to the maximum posterior probability is the weak link of the determined system.

$$ P(X_i|K) = 1 - \frac{P(K|X_i)P(X_i)}{\sum_{i=1}^{n} P(K|X_j)[1 - P(X_j)]. \tag{3} $$

3.5. Evaluation Process Based on the Fuzzy Bayesian Network. The expert experience knowledge without precise description is subject to probability fuzzification, and the polymorphic Bayesian network and risk clustering of the spacecraft survivability index are used in inference. According to the requirements of the improved function, the evaluation process of the fuzzy polymorphic Bayesian network is designed as shown in Figure 2.

(1) Determination of system information

Determine the failure components and the corresponding probability, activate the Bayesian network-directed acyclic graph drawing of the expert system, and determine the existing node conditional probability value and expert experience expression.
(2) Fuzzification of knowledge

It is determined that the expert experience is combined with the existing conditional probability value, and fuzzy processing is performed to generate the corresponding fuzzy CPT table. Then, the spacecraft system level is fuzzed for the realization of the clustering reasoning algorithm.

(3) Determine that the Bayesian network can be reasoned

Determine the completeness of the Bayesian network graph, the prior probability of the failed components, and the completeness of the conditional probability between nodes. If the information is lacking, it can be obtained from the knowledge engineer and user through the human-computer interaction interface.

(4) Reasoning of fuzzy polymorphic Bayesian networks

First, use causal reasoning to obtain fuzzy subsystems, the vulnerability levels corresponding to the system, and the corresponding probability intervals; then, the levels corresponding to the probability intervals of the system are obtained through risk-level clustering.

(5) Defuzzification and normalization of inference results

Since the calculated results are all fuzzy numbers expressed according to the structure of the membership function, the area mean method will be used to defuzzify the fuzzy mean probability to express the probability value of the fuzzy set. When evaluating the vulnerability risk level, it is necessary to normalize the sum of the risk probability of each node to 1.

3.6. Fuzzification of Knowledge and Defuzzification of Inference Results. The fuzzy processing of knowledge is a necessary condition for fuzzy processing of inaccurate empirical knowledge for fuzzy reasoning. Fuzzy linguistic variables take values according to the influence of the lower level on the upper level variable in the two upper and lower variables, and the scale of the influence relationship is fuzzified with an appropriate membership function. Triangular membership function, trapezoidal membership function, and normal distribution membership function are three kinds of membership functions commonly used in the field of fault diagnosis. In fuzzy systems, choosing a fuzzy membership function suitable for inference is crucial to the realization of inference process and the accuracy of inference results. In the process, the selection of different membership functions cannot be defined by various fields and reasoning methods, and the selection process is constantly selecting the best in practice.

The numerical value after fuzzy inference is still an interval of a triangular membership function. The task of defuzzification is to select a value with maximum accuracy to represent the eigenvalue of the fuzzy set through a suitable algorithm. Commonly used methods for defuzzification include maximum membership principle, area mean method, center of gravity method, etc. Among them, the area mean method not only is simple to calculate but also does not cause the loss of fuzzy information. It is very suitable for defuzzification of triangular membership function fuzzy results.

3.7. Fuzzy Bayesian Network Algorithm. For the three-layer directed acyclic graph of the Bayesian network of this system, it is still transformed from the fault tree model, but when the probability characterization of nodes is performed, the parent node layer is a component-level failure. The sub-generation layer has $n$ nodes and is an imprecise data layer, and the second-generation sublayer has 1 node belonging to the imprecise data layer and needs to be obfuscated.

If the child node has $n$ parent nodes, it corresponds to $4n!$ groups of fuzzy conditional probabilities. At this time,
the determination of the conditional probability table not only depends on the logic gate conversion rules but also corresponds to the fuzzy interval of the node conditional probability of the four vulnerability levels. When acquiring model data, the conditional probability table can be expressed as a matrix as follows:

$$C_{2 \times (n+12)} = \begin{bmatrix} T_{2 \times 12} & 1 \\ -1 & E_{2 \times n} \end{bmatrix}. \quad (4)$$

The spacecraft survivability evaluation of the fuzzy polymorphic Bayesian network, through the Bayesian probability inference, obtains the probability of spacecraft subsystem and system vulnerability level, and the diagnostic reasoning of the Bayesian network obtains the relative vulnerability of the failure components corresponding to the vulnerability level. Importance analysis and risk-level description will be divided into systems to carry out the corresponding description of the viability index.

The probability fuzzy value of each vulnerability level of the first-generation and second-generation nodes is obtained according to the prior probability set of the parent node, and the full probability value of the child node is obtained after defuzzification. First, the probability value of the independent basic event combination is solved, and the corresponding prior probability value matrix distribution is generated.

$$F_{2n \times 2n} = \begin{bmatrix} -1 & \cdots & 0 \\ \prod_{i=1}^{n} e_{2i} & \cdots & \prod_{i=1}^{n} e_{1i} \\ \cdots & \cdots & \cdots \\ \prod_{i=1}^{n} e_{2i} & \cdots & \prod_{i=1}^{n} e_{1i} \\ 0 & \cdots & -1 \end{bmatrix}. \quad (5)$$

Then, the full probability inference results of failure modes corresponding to all combinations of child nodes are obtained.

$$P_{2n \times 12} = F_{2(n-1) \times 2(n+1)} \times T_{2(n+1) \times 2n} = \begin{bmatrix} 0 & P_{21} & \cdots & P_{21} & P_{21} & \cdots & -1 \\ P_{21} & P_{22} & \cdots & P_{21} & P_{21} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ P_{21} & P_{21} & \cdots & P_{21} & P_{21} & \cdots & P_{12} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ -1 & P_{21} & \cdots & P_{21} & P_{21} & \cdots & 1 \end{bmatrix}. \quad (6)$$

Finally, the probability values of the same failure level are summed, which is the probability distribution of the failure level of the child nodes.

$$P_{1 \times 12} = \left[-1 \sum_{j=1}^{2} P_{j} + \cdots + \sum_{j=1}^{2} P_{1} + \sum_{j=1}^{2} P_{j} \cdots 1\right]. \quad (7)$$

In the reasoning of the fuzzy Bayesian network, since it is impossible to classify the nodes of the subgeneration as a whole, when solving the weak links of the system, the influence of the system survivability is directly solved.

$$P(X_i | K) = \left[1 - P(X_{i-1})\right] \cdot \frac{P(K | X_i) P(X_i)}{\sum_{j=1}^{n} P(K | X_{i+1}) P(X_{i-1})}. \quad (8)$$

4. Results and Analysis

4.1. Description of Path Planning under Obstacles. Path global planning refers to a series of key path points of the shortest path obtained by calling the A* algorithm according to the global map, the starting point, the ending point, and several process points specified by the user before the intelligent wheelchair navigation starts.

Local path planning or online replanning refers to the online replanning that is started according to the information returned by the sensor during the movement of the intelligent wheelchair robot.

The simulation in this paper is to determine whether to start online replanning by moving the minimum safe distance between the obstacle and the intelligent wheelchair. During the online replanning process, the system first modifies the map.

With this node as the starting point and the target point as the end point, the algorithm planning path is called again to complete the online replanning, and a new path is obtained, and then, the wheelchair will move according to the new path.

The conditions for initiating online replanning in a dynamic environment are as follows:

1. The obstacle and the intelligent wheelchair robot move towards each other and are outside a safe distance.
2. The obstacle is approaching behind the intelligent wheelchair, and the speed is greater than the speed of the intelligent wheelchair and is outside the safe distance.
3. The obstacle is in front of the robot movement, and the movement speed of the obstacle is lower than the movement speed of the intelligent wheelchair robot and is beyond a safe distance.
4. A moving obstacle is detected in a narrow corridor.
5. If the obstacle approaches the intelligent wheelchair robot in the vertical path direction, the waiting algorithm is executed to wait for the obstacle to pass and then move on.

The goal of path planning in a dynamic environment is to perform global planning according to the path searched by the A* algorithm before encountering a dynamic obstacle, start online replanning according to the minimum safe distance when encountering a dynamic obstacle, and require the path after obstacle avoidance to satisfy condition:
The intelligent wheelchair does not collide with any obstacle. (2) The obstacle avoidance path is as short as possible, and the running time is as short as possible. (3) Before avoiding the obstacle, the intelligent wheelchair and the moving obstacle keep a certain safe distance.

4.2. Simulation of a Single Obstacle

(1) The intelligent wheelchair and the obstacle move in the same direction in the wide corridor environment

The projected size of the obstacle person on the map is a circular object with a diameter of 0.4 m, and the moving speed of the obstacle is 0.04 m/s. During the program simulation, the intelligent wheelchair robot is guaranteed not to collide with obstacles. The size of the simulation environment is $10 \times 18$, the speed of the intelligent wheelchair robot is 0.25 m/s, and the turning speed is 0.1 m/s. The distance between the driving wheels is $b = 0.5$ meters, and the distance between the driving and driven wheels is 0.45 m. The radius of the wheel is $r = 0.05$ m, the speed of the wheel is 11.45° per second when the wheel is turned on the spot, and the turning radius is 1 m. Figure 3 shows the success rate of the intelligent wheelchair avoiding obstacles in the same direction in the wide corridor environment.

(2) Movement of intelligent wheelchairs and moving obstacles in a narrow corridor environment

The size of the simulation environment is $18 \times 8$. The simulation test is carried out by taking the moving obstacle approaching in front of the intelligent wheelchair robot as an example, and the moving speed of the obstacle is 0.16 m/s. The intelligent wheelchair robot finds obstacles in the narrow corridor and performs the braking procedure and regards the corridor as impassable and performs online replanning of the optimal path. In the simulation, the obstacle motion priority is the precondition. Figure 4 shows the
success rate of smart wheelchairs avoiding moving obstacles in a narrow corridor environment.

4.3. Simulation of Multiple Moving Obstacles. In the environment of a single moving obstacle, the intelligent wheelchair can effectively avoid the moving obstacles in the opposite and the same direction and at the intersection. We use the digital map of a hospital as a simulation environment to verify that the intelligent wheelchair avoids obstacles in the case of multiple moving obstacles. The size of the simulation environment is set to 29 * 19 m², the width of the corridor is 2 m, the width of the doorway is 1.5 m, the grid division scale is 1 m, the total number of grid nodes is 551, the linear speed of the intelligent wheelchair robot is 0.25 m/s, and the turning speed is 0.1 m/s. The distance between the driving wheels is \( b = 0.5 \) m, the distance between the driving wheel and the driven wheel is 0.45 m, the wheel radius is \( r = 0.05 \) m, the turning radius is 1 m, and the speed of the wheels adjusted in place is 11.45° per second. The projected size of the obstacle on the map is a circular object with a diameter of 0.5 m, and the intelligent wheelchair robot cannot collide with the obstacle in the simulation test.

(1) Two moving obstacles

In the simulation environment, there are two speed directions of moving obstacles, horizontal and vertical. In
In this section, it is assumed that the moving obstacles move from top to bottom or bottom to top. When the moving obstacles meet the walls in the environment, they will disappear; at the same time, the starting point of the obstacle will again generate a moving obstacle with the same parameters; the two moving obstacles we appear are named 1 and 2, respectively. Let the velocity of the obstacle be 0.12 m/s. The success rate of smart wheelchair avoidance under two obstacles is shown in Figure 5.

In the vertical direction, there is an obstacle passing through the next node of the intelligent wheelchair robot movement. According to the speed of the obstacle and the speed of the intelligent wheelchair, the distance between them can be found to be outside the safe distance. The intelligent wheelchair robot executes the waiting algorithm. The intelligent wheelchair detects the movement of the obstacle in real time until the distance between the obstacle and the intelligent wheelchair is within a safe distance and executes the command to move forward. It is detected that there is an obstacle in the direction of the crossing path, and the time-consuming waiting for the obstacle to pass is shown in Figure 6.

(2) Four moving obstacles

Through simulation, it is found that the intelligent mobile robot can successfully avoid two moving obstacles to verify the effectiveness of the algorithm. In this section, four moving obstacles are set.

![Figure 7: The success rate of smart wheelchair avoidance under four obstacles.](image1)

![Figure 8: When four moving obstacles are detected, there are obstacles in the direction of the crossing path and the time spent waiting for the obstacles to pass.](image2)
The case of four obstacles only gives the final path avoidance result. Moving the obstacle in the horizontal direction moves from left to right, and moving the obstacle in the vertical direction moves from top to bottom. When the obstacles in both directions encounter wall obstacles, they will regenerate moving obstacles at their respective starting points. Other parameters are the same as above. The success rate of smart wheelchair avoidance under four obstacles is shown in Figure 7. In the case of four moving obstacles, an obstacle is detected in the direction of the cross-path, and the time spent waiting for the obstacle to pass is shown in Figure 8.

The intelligent wheelchair robot successfully reached the finish line after avoiding obstacles twice and waiting once. The effectiveness of the algorithm under dynamic obstacles is verified, and then, we can directly apply the algorithm to practical situations.

5. Conclusion

According to the actual needs of this subject, the technical scheme of the wheelchair following system is proposed. Three modes of the wheelchair are set, namely, autonomous following mode, remote control mode, and joystick control mode. The hardware architecture of the wheelchair system is designed, the specific implementation method of the hardware system is proposed, the key components such as the wheelchair platform, processor, and sensor are selected, and the corresponding peripheral circuits are designed. At the same time, the original wheelchair controller is improved and designed. In order to solve the “inaccuracy” of fault tree analysis, a two-way inference machine based on the Bayesian network is designed, which realizes the probability calculation of survivability evaluation of the knowledge model. Based on expert knowledge, a system survivability model is established, and the node prior probability and the conditional probability table between nodes are determined. The grade evaluation is proposed, the knowledge fuzzification and defuzzification processing algorithms are designed, and the fuzzy Bayesian network survivability evaluation algorithm implementation and example analysis are carried out. This method can effectively apply expert knowledge and improve the accuracy of viability assessment results. In the dynamic environment, a path planning method based on global path planning and online replanning is adopted, and obstacle avoidance strategies for moving obstacles and intelligent wheelchairs in the same direction, in opposite directions, and at intersections are proposed, respectively. The conditions and objectives of path planning in dynamic environment are described. The path planning process and local obstacle avoidance strategy flow chart in the entire dynamic environment of the intelligent wheelchair are introduced, and the selection of the minimum safe distance when the intelligent wheelchair avoids obstacles is discussed. Simulation experiments are carried out to verify the effectiveness of the search algorithm and obstacle avoidance strategy.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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