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Performance Test, Index System Establishment, and Comprehensive Evaluation of Earthquake Rescue Robots

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Abstract: To effectively enhance the adaptability of earthquake rescue robots in dynamic environments and complex tasks, there is an urgent need for a comprehensive evaluation method that encompasses establishing an evaluation index system, testing performance indexes, and conducting performance evaluation. Firstly, four main criterion and twenty-three sub-criterion indexes are established by conducting a comprehensive review of existing assessment measures for rescue robots across diverse domains. These indexes are validated through test modules developed by the National Earthquake Response Support Service to obtain corresponding values for each criterion. Moreover, a method for establishing the index system is proposed based on the fuzzy clustering analysis and grey correlation analysis methods. This method effectively addresses issues related to excessive subjectivity, redundancy, and ambiguous stratification of indexes. Subsequently, the DEMATEL is employed to scrutinize the interrelationships and causal connections among each index within the established index system, leading to the identification of input and output indexes based on the analysis outcomes. Finally, as an empirical example, three earthquake rescue robots are comprehensively evaluated and ranked using the super efficiency DEA model. Alongside analyzing results regarding input redundancy and output deficiency, targeted improvement suggestions are provided for each earthquake rescue robot. Additionally, comparison analysis with the entropy weight method and VIKOR method verifies the effectiveness of our proposed method.

Keywords: earthquake rescue robots; performance test; index system; comprehensive evaluation; redundant input; inadequate output

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1. Introduction

As a crucial equipment for earthquake rescue operations, a series of performance indexes can be used as key evaluation criteria to reflect various aspects of gait ability, perceptual acuity, endurance capacity, and so forth [1]. Therefore, it is necessary to conduct a scientific and comprehensive evaluation of the performance of these earthquake rescue robots based on a series of performance indexes. This evaluation should accurately quantify the overall performance of earthquake rescue robots in dynamic post-disaster environments, enabling horizontal comparison and evaluation when confronted with multiple options, thereby aiding rescuers in accurately selecting the earthquake rescue robot with optimal overall performance.

Numerous theories have been proposed to evaluate the performance of rescue robots. Li, Yutan et al. [2] have evaluated the walking performance of coal mine rescue robot in terms of various performance indexes, including the maximum trench width, maximum obstacle height, maximum climbing angle, and stair climbing capability. Zhang, Di et al. [3] have assessed the locomotion capabilities of an earthquake search and rescue robot in terms of its performance in flat terrain traversal, climbing steps, rotational movement, ascending slopes, and aerial maneuverability. Zhao, Jing et al. [4] have evaluated the efficiency of quadruped rescue robot based on its capabilities in survival, locomotion, operation, and environmental interaction. Baek, Jun et al. [5] have conducted an analysis on the impact factors of mobile rescue robots for human body detection, encompassing communication time and live body identification. However, solely relying on these performance indexes is insufficient for evaluating the performance of earthquake rescue robots. Additionally, there is limited literature available on exploring the hierarchical index system of performance evaluation indexes specifically designed for rescue robots. Therefore, further research is required to develop a evaluation method for rescue robots.

A suitable evaluation method for performance indexes helps analysts and evaluators efficiently evaluate alternatives and determine the optimal alternative. When using performance indexes to select among different options, it is important to consider conflicting performance indexes [6]. For example, when choosing a high-performing rescue robot, conflicting criteria could be the mass-volume ratio and walking performance. Increasing the mass–volume ratio may negatively impact walking performance. Therefore, it is necessary to address this issue by using a method that considers multiple performance indexes [7]. This can be effectively achieved through multi-criteria decision-making (MCDM), which involves several stages [8], including (1) defining objectives, (2) selecting measurement criteria, (3) establishing an evaluation index system, (4) utilizing appropriate mathematical algorithms for evaluation, and (5) conducting analysis.

Numerous methodologies have been proposed and employed in the existing literature to establish the index systems in MCDM. Fang, Z et al. [9] proposed an evaluation index system for disaster rescue robots based on expert knowledge, encompassing the working structure, mechanical structure, geometric parameters, motion parameters, dynamic parameters, and system adjustable parameters. The evaluation index system for a quadruped rescue robot was proposed by Li, L et al. [4] based on expert subjective experience. This system encompasses four key aspects: survival ability, motion capability, operational proficiency, and environmental interaction. The evaluation index system proposed by Chi, Y et al. [10] for the substation inspection robot encompasses four key characteristics: safety, reliability, coordination, and quality based on the key performance indexes (KPIs). Li, Y et al. [2] proposed an evaluation index system for the walking mechanism of crawler-type coal mine rescue robots, which includes walking ability, explosion-proof capability, maneuverability, and reliability. This system was developed by summarizing appropriate evaluation indexes for assessing the performance of such mechanisms. In other engineering fields, the research primarily focuses on establishing an index system through correlation analysis of indexes and eliminating redundant ones. The index evaluation system of the transmission tower was quantified through association rules proposed by Wei et al. [11], and an evaluation system of the key index of the transmission tower was established based on principal component analysis. Yang et al. [12] constructed a maximum dispersion model for evaluating index screening in the entire process of distribution network planning, based on correlation analysis, which allows for elimination of indexes with high repeatability. Ge et al. [13] utilized grey correlation analysis to measure the degree of correlation between each index by analyzing the shape proximity of the sequence curve in evaluating the operational state of distribution networks. However, the establishment methods in the field of rescue robots primarily revolve around subjectively determining reserve indexes through expert knowledge and subsequently constructing a hierarchical index system based on expert experience. Based on the aforementioned approaches to establishing an index system in the field of rescue robots and other engineering fields, although the earthquake rescue robot's index system covers various factors that influence their rescue capabilities, it fails to consider application scenarios specific to earthquake ruins. Additionally, this established index system lacks flexibility for improvement and expansion according to new perspectives on rescue evaluation. Moreover, it does not adequately reflect the redundancy relationship between certain indexes of earthquake rescue robots; hence, applying data mining methods becomes necessary for eliminating redundant indexes.

The process of fuzzy clustering analysis categorizes data with similar characteristics into the same group and assigns data with dissimilar characteristics to different groups [14].

It ensures minimal differences among individuals within the same category and significant differences between individuals in different categories, allowing for quantitative assessment of individual similarities within a study and facilitating rational classification objectives. In the absence of predefined classifications, fuzzy clustering analysis organizes data based on sample similarity and is widely used in various domains such as index merging, classification, and hierarchical partitioning. Guo, J. et al. [15] employed fuzzy clustering analysis to merge and classify the maintenance support ability indexes of rescue equipment, thereby constructing a well-organized and comprehensive system for evaluating equipment maintenance support ability index. Koulouriotis, D. E. et al. [16] utilized fuzzy clustering analysis to determine the membership degree of robot performance index values and subsequently categorized robots based on these membership degrees. Su, P.Y. et al. [17] applied fuzzy clustering analysis to categorize and segment the functional indexes of teaching robots, while also establishing a learning-oriented functional index system that investigates key factors influencing robot functionality. The grey correlation analysis method determines the relative relationships between a certain index and other indexes in an index system, allowing for identification of more relevant indexes through ranking [18]. A major advantage of this method is its minimal sample size requirement and independence from typical distribution assumptions, while still yielding results consistent with qualitative analysis [19]. The grey correlation analysis method has gained widespread application in the screening and optimization of indexes. Athwale, V. M. et al. [20] employed a combination of grey correlation and expert scoring to screen performance indexes for industrial robots, taking into account both their correlation and importance. Datta, S. et al. [21] optimized the indices of industrial robots by systematically analyzing the factors influencing their performance using the grey correlation method, thereby establishing a comprehensive index system for evaluating robot performance.

Numerous methods have been suggested in the existing literature and employed to tackle various MCDM issues [22]. The technique for order preference by similarity to ideal solution (TOPSIS) is a multi-attribute decision-making method based on distance measurement, which calculates the distance between each attribute and the ideal solution, as well as the distance between each attribute and the anti-ideal solution. The relative preference of each attribute is determined by calculating the weighted sum of these two distances, and the optimal alternative can be determined [23]. However, when the information in the environment is incomplete or inaccurate, TOPSIS technology may not fully consider these uncertain factors, resulting in inaccurate decision results. The Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) is a decision-making approach based on the ideal point method, which comprehensively considers the discrepancy between the evaluation scheme and the positive ideal solution from multiple perspectives [24]. This enables it to offer compromise solutions for conflicting scenarios while fully incorporating subjective preferences of decision makers. Compared with TOPSIS method, VIKOR method can approximate the ideal solution more comprehensively. However, the results of this method can also be influenced by the selection of criterion weights and the standardization approach for criteria. As a multi-factor analysis method, the fuzzy analytic hierarchy process (FAHP) enables the systematic handling of complex problems by considering the interdependencies and correlations between each layer. It facilitates an integrated approach that combines qualitative and quantitative aspects, resulting in more comprehensive and rational analysis outcomes [25]. However, due to its involvement in evaluating multiple layers and factors comprehensively, there exists a certain level of subjectivity and uncertainty when determining the weights for each factor. The entropy weight method is a multi-index decision analysis technique that enables the determination of index importance without subjective assignment, thereby mitigating the influence of subjectivity on decision outcomes. This approach is particularly suitable for scenarios characterized by weak correlations between indexes, and can effectively address interdependencies among them [26]. However, it may encounter challenges in cases where indexes exhibit strong correlations, potentially leading to issues with weight distribution. Furthermore, this method does not account for interaction and combination effects among indexes, limiting its ability to comprehensively assess their relative importance in practical applications. In conclusion, the aforementioned comprehensive evaluation methods inherently necessitate the calculation of index weights. However, due to the absence of a standardized calculation criterion for these weights, different weight calculation approaches may yield disparate evaluation results.

The technique of data envelopment analysis (DEA) is widely employed to assess the relative efficiency of multiple inputs and multiple outputs and to rank alternatives based on their measured efficiency. The efficacy of this approach has been demonstrated in effectively addressing performance decision-making challenges encountered by rescue robots. Kao, C. et al. [27,28] have employed DEA to evaluate the technology performance including the purchased cost, the repeatability, the load capacity and the velocity for scheme selection during the design and manufacturing process of some rescue robots for a manufacturing company in Taiwan. Sun, Y. [29] has designed the system considering the DEA analysis and applied the system into an underwater robot control system and general intelligent control. Karsak et al. [30] and Toloo, M. et al. [31] have evaluated twelve robots using four engineering attributes as outputs: handling coefficient, load capacity, repeatability and velocity, and cost by the improved DEA method. The primary advantage of the DEA method lies in its ability to overcome the limitation of manual weight assignment and circumvent the intricate process of parameter unification. The super efficient DEA model can further rank effective decision units when there are multiple simultaneous effective decision units. It is worth noting that the DEA method excessively emphasizes the characteristic differences of the evaluation units, disregarding the objective causal logic relationship between the indexes. Moreover, the illogical input–output index system may yield evaluation results that deviate from objective reality.

Currently, the determination of the input–output index system is commonly based on the following principles: for an evaluation system, a higher output index indicates better performance, while a lower input index suggests better efficiency. However, this principle fails to consider the inherent relationships among indexes. As the index system becomes more extensive, intricate interdependencies or even causal relationships may arise between indexes, resulting in an absence of scientific precision. Decision-making trial and evaluation laboratory (DEMATEL) is a widely used method for analyzing the influence relationship between internal elements of a system by using matrix and graph theory [32]. It can scientifically analyze the input-output logic relationship between indexes, and its organic combination with DEA can effectively solve the problem of the inherent logic fusion between the evaluation index system and the evaluation model, and obtain scientific measurement results.

The present study focuses on investigating the performance testing, establishment of an index system, and development of a comprehensive evaluation method for earthquake rescue robots. The key contributions can be summarized as follows:

(1) The objective is achieved by establishing a hierarchical structure of performance evaluation, which proposes four main criteria and twenty-three sub-criteria indexes. Subsequently, three types of alternatives for earthquake rescue robots are evaluated through performance tests to obtain a comprehensive evaluation set for the corresponding criteria.

(2) The present paper proposes a method for establishing an evaluation index system of earthquake rescue robots. Firstly, experts construct the initial subjective evaluation index system and define the determined, undetermined, and central indexes. Subsequently, the fuzzy clustering method is employed to classify the undetermined indexes. Then, the group grey correlation degree method is utilized to determine which indexes should be screened, while employing evidence theory to fuse expert credibility regarding these screened indexes. Finally, closed-loop adjustments are made to eliminate redundancy in the screened indexes based on the results of credibility fusion.

(3) The present paper proposes an evaluation method for earthquake rescue robots. Firstly, the DEMATEL model is used to analyze the correlation and causality between the indexes in the established system. Based on this analysis, an input–output evaluation index system is established. Subsequently, the performance criteria in this index system are analyzed, followed by a comparative assessment of different types of such robots using a super efficiency DEA model. According to the results of this research, rescuers can accurately select the earthquake rescue robot with the best overall performance to improve the rescue effect. Considering the wide variety of robots with different performance characteristics, this research provides guidance for practical application.

2. Evaluation Criteria Selection and Initial Index System Establishment

Before constructing the index system, a comprehensive review of evaluation criteria for industrial robots and land mobile robots in the existing literature was conducted. The fundamental performance requirements of industrial robots and land mobile robots encompass robust survival ability to ensure seamless access to rescue sites, versatile motion ability for diverse mission execution, precise detection and perception capabilities to enhance rescue efficiency, and rapid communication abilities for enhanced human–robot collaboration and further improved rescue efficiency [33,34].

The performance evaluation of rescue robots is a comprehensive problem involving multiple factors and levels. To enhance the depth and professionalism of our criteria research, we collaborated with an experienced team of experts who possess rich practical experience and excellent theoretical knowledge in the field of rescue robots. These experts have profound expertise in mechanical engineering, automation control, information and communication engineering, as well as disaster prevention and mitigation engineering. Their professional knowledge and unique perspectives provide robust support for our research endeavors. Through extensive collaboration with them, we engaged in thorough discussions regarding the performance evaluation criteria for rescue robots. The evaluation criteria in this paper are classified into two levels, namely main criteria and sub-criteria, the main criteria for evaluating rescue robots encompass survival ability, motion ability, detection perception ability, and communication control ability. The following section provides a comprehensive overview of the concepts related to the performance evaluation of industrial robots and land mobile rescue robots, and the concise explanations regarding the interpretations, industry norms, and factors that influence the sub-criteria.

2.1. Survival Ability

The survival ability of rescue robots primarily reflects the reliability of the robot, while ensuring an adequate power supply is crucial to sustain uninterrupted rescue operations. The power supply unit is often identified as a limiting factor in the performance of rescue robots, as frequently reported in numerous literature studies [35,36]. The resilience of rescue robots is directly proportional to the operational duration and walking distance when supplied with energy by the power unit [37,38]. Additionally, their continuous ability to initiate and cease operations ensures sustained execution of rescue missions [39]. Therefore, the survival ability evaluation criteria are presented in Table 1, providing comprehensive details for analysis.

Table 1. The survival ability evaluation criteria.

Main Criteria	Corresponding Criteria	Literature Sources
Survival ability	Continuous walking distance with an independent power supply	[34–37,40]
	Continuous walking time with an independent power supply	[34–37,39]
	Success rate of continuous start, working, stop	[38,41,42]
	Continuous working time	[36,37,39]

2.2. Motion Ability

The motion ability of rescue robots is paramount for effective disaster relief efforts. Only with robust motion ability can they adeptly navigate the complex disaster environment, expeditiously and efficiently execute rescue tasks, and provide timely assistance to trapped personnel. When designing a robot for rescue missions, it is crucial to consider its ability to operate in confined spaces, such as collapsed buildings, caves, or rugged terrains. Factors like debris, uneven terrain, and narrow passageways impose limitations on the physical design of the rescue robot, hence it must be compact. Consequently, optimizing the size and mass of the rescue robot becomes essential for maneuvering through narrow spaces and overcoming obstacles. To ensure effective operation in these environments, designers need to meticulously evaluate the positioning of the rescue robot's center of gravity [43]. Specifically when crossing obstacles, maintaining a low center of gravity is imperative to ensure optimal traction capability [44,45]. This precautionary measure prevents tipping over or loss of balance that could hinder task completion. Therefore, designers must thoughtfully consider both structure and weight distribution to achieve an appropriate center of gravity position. In addition to the aforementioned factors, the continuous advancement and widespread use of re-configurable modular rescue robots have made mechanical transformation success rate a crucial factor affecting the motion ability of such robots. This is because their ability to smoothly adapt and transform into different forms in complex environments directly impacts their task completion success [46,47]. Meanwhile, the rescue robot deployed in disaster sites must possess exceptional climbing, obstacle-crossing, running, and turning capabilities to effectively adapt to diverse terrain environments [48,49]. Furthermore, the rescue robot must possess flexible control proficiency and robust load-bearing capacity to efficiently transport rescue equipment and materials, promptly reach trapped individuals, and execute rescue operations. [50,51]. Therefore, the motion ability evaluation criteria are presented in Table 2, providing comprehensive details for analysis.

Table 2. The motion ability evaluation criteria.

Main Criteria	Corresponding Criteria	Literature Sources
Motion ability	Mass-to-volume ratio	[43–45,52]
	Subversive resistance on complex road surfaces	[37,43–45,53]
	Maximum speed of wheel motion	[37,43,48,49,53]
	Success rate of mechanism transformation	[46,47,54]
	Success rate of maneuvering through narrow spaces	[43,46,49]
	Minimum turning radius	[55–58]
	Unit pressure exerted by the tracked device on the ground	[2,39,59,60]
	Maximum width across trenches	[43,48,49,61,62]
	Maximum height of obstacles to be overcome	[43,48,49,61,63]
	Maximum angle for climbing	[43,48,49,61,64]
	Number of steps climbed per unit time	[43,48,49,61,65]
	Success rate of path planning	[50,51,66–68]

2.3. Detection Perception Ability

The significance of rescue robots in rescue operations is self-evident, primarily due to their advanced environmental perception and detection capabilities, as well as their exceptional capacity to efficiently locate and identify victims. In hazardous, unpredictable, and intricate rescue environments, the prompt and accurate identification and localization of victims under harsh conditions while covering extensive search areas within limited timeframes are pivotal factors for evaluating the detection and perception abilities of rescue robots [69–71]. Therefore, the detection perception ability evaluation criteria are presented in Table 3, providing comprehensive details for analysis.

Table 3. The detection perception evaluation criteria.

Main Criteria	Corresponding Criteria	Literature Sources
Detection perception ability	Probability of live body identification	[69–73]
	Maximum radius for effective search	[69–73]
	Maximum depth for effective search	[69–71,73]

2.4. Communication Control Ability

The communication control ability of rescue robots plays a crucial role in the successful execution of their missions. This ability primarily involves real-time communication between the operator and the rescue robot [74], ensuring precise control by the operator and effective information collection and transmission by the rescue robot to better assist rescue personnel in accomplishing tasks. Key elements of the communication control ability encompass command accuracy and comprehensive signal processing [75]. Therefore, the communication control evaluation criteria are presented in Table 4, providing comprehensive details for analysis.

Table 4. The communication control evaluation criteria.

Main Criteria	Corresponding Criteria	Literature Sources
Communication control ability	Time required for establishing communication	[35,40,74,75]
	Success rate of the operating interface	[72,74–76]
	Accuracy of data transmission	[70,71,74,75]
	Maximum distance for wireless control	[74,75,77]

2.5. Initial Index System Establishment

The corresponding hierarchical structure of these criteria is established based on the above comprehensive analysis and quantification of the evaluation criteria for rescue robots, as illustrated in Table 5. The hierarchical structure allows for a clear evaluation of the rescue robot's performance on each individual criteria and how these criteria impact the overall performance of rescue robots.

Table 5. The initial index system of rescue robots and test results of the samples.

Total Aim	First-Grade Index	Second-Grade Index	Test Results of the Samples		
			Sample A	Sample B	Sample C
Performance of rescue robots	Survival Ability X_1	X_{11} Continuous walking distance with independent power supply/(m)	3000	6000	4000
		X_{12} Continuous walking time with independent power supply/(h)	3.13	20	4.35
		X_{13} Success rate of continuous start, working, stop/(%)	100	90	90
		X_{14} Continuous working time/(h)	5.23	22	6.85
	Motion Ability X_2	X_{21} Mass-to-volume ratio/(kg/m^3)	1083	1442	980
		X_{22} Subversive resistance on complex road surfaces (mm/s^2)	2	7	2
		X_{23} Maximum speed of wheel motion/(m/s)	328	100	350
		X_{24} Success rate of mechanism transformation/(%)	90	100	90
		X_{25} Success rate through narrow space/(%)	100	100	100
		X_{26} Minimum turning radius/(mm)	30	15	20
		X_{27} Unit pressure exerted by the tracked device on the ground/(Pa)	2200	4688	2500
		X_{28} Maximum width across trenches/(mm)	300	250	300
		X_{29} Maximum height of obstacles to be overcome/(mm)	250	200	250
		X_{210} Maximum angle for climbing/(deg)	34	30	34
		X_{211} Number of steps climbed per unit time/(pc)	20	16	20
		X_{212} Success rate of path planning/(%)	90	70	90

Table 5. *Cont.*

Total Aim	First-Grade Index	Second-Grade Index	Test Results of the Samples		
			Sample A	Sample B	Sample C
Performance of rescue robots	Detection perception Ability X_3	X_{31} Probability of live body identification/(%)	70	70	80
		X_{32} Maximum radius for effective search/(m)	18	15	20
		X_{33} Maximum depth for effective search/(m)	9	7	12
	Communication control ability X_4	X_{41} Time required for establishing communication/(s)	40	60	50
		X_{42} Success rate of the operating interface/(%)	90	80	90
		X_{43} Accuracy of data transmission/(%)	90	80	90
		X_{44} Maximum distance for wireless control/(m)	500	600	800
Undetermined index 1		Smoothness of walking on complex road surfaces/(mm/s^2)	4	5	4
Undetermined index 2		Motion speed under standard load/(m/s)	286	95	310

Meanwhile, experts in the field of rescue robots have supplemented and classified the criteria outlined in Table 5. They have further incorporated two additional indexes: Smoothness of locomotion on complex road surfaces and Motion velocity under standard load. These indexes have been categorized into determined and undetermined indexes. It is important to note that the determined indexes correspond to those presented in Table 5, while the undetermined indexes encompass two supplementary measures not depicted in Table 5. Furthermore, the experts have also identified the representative indexes among the second-grade indexes included in each first-grade index. These representative indexes are defined as the central indexes. The central indexes identified by the experts are presented in Table 6.

Table 6. The central indexes given by experts.

First-Grade Index	Central Indexes
X_1 Survival ability	X_{14} Continuous working time
X_2 Motion ability	X_{23} Maximum speed of wheel motion X_{210} Maximum angle for climbing
X_3 Detection perception ability	X_{31} Probability of live body identification
X_4 Communication control ability	X_{43} Accuracy of data transmission

3. Performance Testing

At present, a wide range of earthquake rescue robots are available in the market, each with distinct characteristics and functionalities. To comprehensively understand and evaluate their performance, it is essential to have diverse samples for testing and research purposes. Therefore, this paper selects three types of earthquake search and rescue robots developed by the Shenyang Institute Of Automation as the subjects of investigation. The robot is denoted as Sample A, Sample B, and Sample C, with their prototypes depicted in Figure 1. The aforementioned three types of robots are exemplary, and are extensively employed for conducting search and rescue operations in earthquake ruin environments. And the three types of land mobile robots exhibit unique design concepts, functional configurations, and practical applications. Subsequently, a detailed analysis and comparison of these three robots is conducted.

- Sample A: This is a deformable robot for searching ruins with the mass of 20 kg and the volume of 520 mm $\times$ 420 mm $\times$ 250 mm. The robot is designed for exploring ruins and features three independently driven tracks. The position of these tracks can be adjusted to suit various rescue environments and tasks, allowing the robot to transform into linear, triangular, or side-by-side configurations. Meanwhile, the robot can penetrate into the ruins and utilize its own infrared camera and sound sensor to transmit real-time image and voice information from inside the ruins back to the console, enabling rescuers to promptly identify survivors' locations and assess their surrounding environment.

- Sample B: This is a wheel-track composite exploration robot with the mass of 15 kg and the volume of 360 mm × 320 mm × 280 mm. According to the terrain characteristics in rescue environments, the robot's track geometry can be adjusted to enable it to switch between wheeled and tracked motion modes. Meanwhile, the robot is capable of entering hazardous situations and conducting survivor search and environmental detection tasks using its own camera, temperature and humidity sensor, as well as toxic and harmful gas sampling device. Additionally, the cloud platform can be deployed vertically alongside the robot into elevator shafts and caves to enhance rescuer' visibility range.
- Sample C: This is a intelligent life detection robot with the mass of 25 kg and the volume of 520 mm × 420 mm × 250 mm. The mobile mechanism adopts a modular chain structure to ensure its capability to navigate complex terrains. Depending on different rescue environments and tasks, the robot can transform into three distinct configurations: triangular, *D*-shaped, and side-by-side. Meanwhile, the robot integrates life detection technology with life detection radar, video, and audio information. Additionally, it is capable of penetrating non-metallic materials to effectively detect the vital signs of survivors using this life-detection technology.

(**a**) (**b**) (**c**)

Figure 1. Prototype of the three types of earthquake rescue robots: (**a**) Sample A; (**b**) Sample B; (**c**) Sample C.

The performance test of the three types of earthquake rescue robots is conducted to obtain the values of evaluation criteria. In this paper, a series of test modules designed by national earthquake response support service are used to test the performance of the three types of earthquake rescue robots [78]. The real arrangement of each module is shown in Figure 2. The next section will present the specific content of each module.

1. The dynamic slope test module is a linkage mechanism consisting of a hydraulic lifting platform and a slope device, featuring an adjustable continuous slope ranging from 15° to 60°. Additionally, the module allows for variation in the slope material to assess the climbing ability under different friction conditions.
2. The adjustable cross-cone turning module is designed with a 90° turning angle, allowing for adjustable cone slope and automatic twisting of the guide frame on both sides to adapt to the cone. The flexibility of turning and lateral balance ability at different speeds can be tested.
3. The adjustable ridge side slope module consists of multiple plates joined together by twisted plates. The slope can be adjusted, and the complexity of the side slope can be modified by altering the direction in which the plates are joined, allowing for testing of both passing ability and balance capability.
4. The complex pavement interspersed construction module consists of a grid and multiple wooden piles. By adjusting the interspersed positions of wooden piles, it is possible to simulate intricate terrains and assess flexibility and passing capacity.
5. The test module of the pipeline consists of torsional splicing techniques. By rotating the entire pipeline, it simulates complex pipelines and tests their ability to pass through narrow spaces by adjusting the vertical position.
6. The adjustable wave pavement module is constructed by combining multiple plate strands to form a collapsible fan shape. The handle allows for modification of the

wave spacing, while one end of the simulated staircase can be elevated to assess the performance on uneven road surfaces and steps.

7. The adjustable slope-crossing module consists of two sets of independent slopes connected face to face, and the spacing can be adjusted according to the need to test the ability to cross the gully.
8. The test module consists of multiple depressions that can be filled with various materials (such as sand, stone columns) to simulate different road conditions.
9. The re-configurable terrain test module consists of a vertical arrangement of hundreds of wooden cubes, forming a rectangular square matrix. Each individual cube is equipped with an independent lifting and locking device, enabling adjustable height settings. This design allows for the simulation of various complex terrain structures and facilitates testing of irregular pavement traversal capabilities.

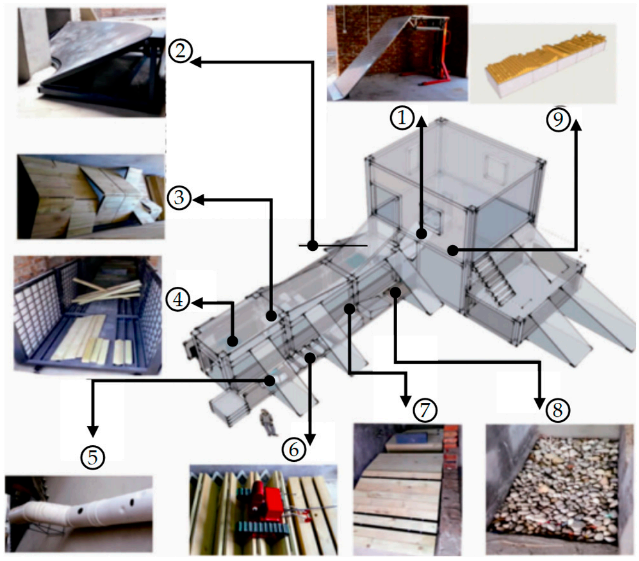

Figure 2. The real arrangement of each module.

The test environment is equipped with real-time monitoring functions. It includes a total of eleven monitoring cameras, a temperature and humidity sensor, six fixed installation wireless nodes, and six randomly scattered wireless nodes. By utilizing the multi-source wireless environment-sensing network, remote monitoring of testing process and environmental information are achieved, as depicted in Figure 3.

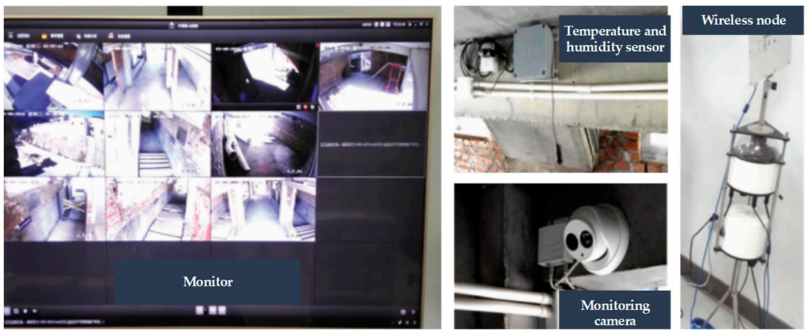

Figure 3. Real-time monitoring and detection hardware.

In this paper, the test standard for each criterion shown in Table 5 is based on the General specifications of ground robots for search and rescue in ruins (GB/T 37703-2019) [79]. The index test methods are derived from the existing methods [80] used at the National Earthquake Emergency Rescue Training Base. All tests for performance indexes were conducted three times, and the average value was considered as the test result. The performance criteria test results are presented in Table 5. Additionally, a comprehensive list of testing methods for all performance indexes is presented below.

1. Testing the values of continuous walking distance with independent power supply. The robot walks in the constructed ruins environment. Whether the robot can pass through the gravel road, wave road, slope road, and climb over the obstacle in the ruins environment is visually observed. The walking distance can be measured by using a measuring ruler with the CMC. Manual intervention is not allowed during the testing process. The recorded distance can be taken as the continuous walking distance with independent power supply.
2. Testing the values of continuous working time with independent power supply. When the battery is fully charged, turn on the power switch and operate the robot at low speed (one third of its the maximum speed of wheeled motion) until the robot automatically shuts down due to low power. When the robot starts moving, the stopwatch starts, and when the robot stops moving, the stopwatch stops. The recorded time can be taken as the value of continuous working time with independent power supply.
3. Testing the success rate of continuous start, working, stop. The robot is initiated on a level concrete surface and subsequently maneuvered in various directions, including forward, backward, left, right, and rotational movements at different velocities. Eventually, the robot comes to a halt. This is measured ten times, and the probability of success is calculated as the success rate of continuous start, working, stop.
4. Testing the values of continuous working time. When there is no external power supply and the battery is fully charged, the robot continues to perform tasks in the constructed ruins environment. When the robot enters the working state, start timing with a stopwatch, and when the control unit or terminal stops working, stop timing. The robot is not allowed to supplement energy during the testing process. The recorded time can be taken as the continuous working time.
5. Testing the values of mass–volume ratio. When weighing the robot, remove any accessories and place it horizontally on a platform scale with a weight exceeding 50% of its nominal weight. For measuring volume, determine the maximum dimensions of length, width, and height during movement, considering the outer edge of the wheel as the boundary. Both mass and volume are measured three times to obtain average values. The ratio of mass to maximum volume can be taken as the mass–volume ratio.
6. Testing the values of subversive resistance on complex road surface. The complex bumpy rubble road surface with a length of 50 m is set up. Two acceleration sensor are installed on the body device, one in the left–right direction and the other in the front–rear direction. The robot travels at a uniform speed at 50% of its maximum wheel motion speed. After movement, the acceleration curves in the left–right direction and front–rear direction are output, and the average values of each peak of curves in the two directions, which are represented as a_x and a_y, are calculated. The value of $\sqrt{a_x^2 + a_y^2}$ can be taken as the subversive resistance on complex road surface.
7. Testing the values of maximum speed of wheel motion. On a flat cement ground, the robot walks in a straight line at maximum wheel speed. Begin measurement after the robot walks for 2 m, the time and distance of movement are recorded, and the speed value can be calculated. This is measured three times, and the average speed value is taken as the maximum speed of wheel motion.
8. Testing the values of success rate of mechanism transformation. The robot walks in the constructed ruins environment, the robot continuously passes through the gravel road, wave road, slope road, and climb over the obstacle, and then the different types of the robot are transformed. If the motion type transformation can be achieved, it is considered successful; otherwise, it is considered unsuccessful. This is measured five times, and the probability of successful transformation is calculated as the success rate of mechanism transformation.

9. Testing the values of success rate through narrow space. The robot enters the interior of the ruins stably and safely from the entrance in the constructed ruins environment. Whether This is measured ten times, and the probability of successful passing is calculated as the success rate through narrow space.
10. Testing the values of minimum turning radius. The minimum turning radius is an index used to measure the ability of the robot to turn in narrow space. The robot is placed on a horizontal cement ground, and the robot rotates 360° in both the left and right directions. The distance between the center of the circular trajectory of a robot during rotational motion and the center of mass of the robot is measured. This is measured three times in both the left and right directions, and the average distance value is taken as the minimum turning radius.
11. Testing the values of unit pressure exerted by the tracked device on the ground. The unit pressure of the tracked walking device on the ground can be expressed as $P_0 = Fa/(2 \times L \times b)$, where *Fa* is the weight of the robot, *L* is the length of the track in contact with the ground, and *b* is the width of the track. When the robot moves on the soft ground, the lower the unit pressure on the ground, the smaller the amount of ground subsidence, and the easier it is for the robot to pass through.
12. Testing the values of maximum width across trenches. Taking 15 cm as the starting value, the trenches' width is measured three times. If at least one of the three times passes, the trenches' width is increased by 2 cm. If none of the three times passes, the trenches' width is reduced by 2 cm. Then, the measurement is continued for three times, and the maximum value is recorded until the trenches' width cannot be further increased or the trenches' width does not need to be further reduced. The maximum value is recorded as the maximum width across trenches.
13. Testing the values of maximum height of obstacles to be overcome. Taking 10 cm as the starting value, the obstacle height is measured three times when the obstacle width is 5 cm. If at least one measurement passes, the height is increased by 2 cm; otherwise, it is reduced by 2 cm. The measurements are then repeated three more times, and the maximum value is recorded until the height cannot be further increased or reduced. The maximum value is recorded as the maximum height of obstacles to be overcome.
14. Testing the values of maximum angle for climbing. Taking 30° as the starting value, the angle is measured three times when the slope length is 5 m. If at least one of the three times passes, the angle is increased by 5°. If none of the three times passes, the angle is reduced by 5°. Then, the measurement is continued for three times, and the maximum value is recorded until the angle cannot be further increased or the angle does not need to be further reduced. The maximum value is recorded as the maximum angle for climbing.
15. Testing the values of number of steps climbed per unit time. A continuous step with 70% of the maximum obstacle crossing height and 70% of the maximum climbing angle is selected, and the number of steps climbed by the robot per unit time (30 s) is recorded as the number of steps climbed per unit time.
16. Testing the values of success rate of path planning. The robot continues to perform tasks in the constructed ruins environment. Whether the robot can effectively plan its path and search a designated ruins space completely can be inspected, and whether the walking trajectory is reasonable can be inspected. This is measured ten times, and the probability of successful inspection results is calculated as the success rate of path planning.
17. Testing the values of probability of live body identification. The living organisms are placed at 70% of the maximum effective search radius and 70% of the maximum effective search depth. This is measured five times, and the probability of successful perception is calculated as the probability of live body identification.
18. Testing the values of maximum radius for effective search. Taking 10 m as the starting value, the search radius is measured three times. If at least one of the three times

passes, the search radius is increased by 1 m. If none of the three times passes, the search radius is reduced by 1 m. Then, the measurement is continued for three times, and the maximum value is recorded until the search radius cannot be further increased or the search radius does not need to be further reduced. The maximum value is recorded as the maximum radius for effective search.

19. Testing the values of maximum depth for effective search. Taking 5 m as the starting value, the search depth is measured three times. If at least one of the three times passes, the search depth is increased by 1 m. If none of the three times passes, the search depth is reduced by 1 m. Then, the measurement is continued for three times, and the maximum value is recorded until the search depth cannot be further increased or the search depth does not need to be further reduced. The maximum value is recorded as the maximum depth for effective search.
20. Testing the values of time required for establishing communication. The time it takes for the control unit to establish successful communication with the robot. This is measured ten times, and average value is taken as the time required for establishing communication.
21. Testing the values of success rate of the operating interface. The robot continues to perform tasks in the constructed ruins environment. Whether the interface is clear, easy to operate, and aesthetically pleasing in design is visually inspected. This is measured ten times, and the probability of successful inspection results is calculated as the success rate of the operating interface.
22. Testing the values of accuracy of data transmission. The robot continues to perform tasks in the constructed ruins environment. The robot is manipulated at 70% of maximum wireless control distance. This is measured ten times, and the probability of effective data transmission is calculated as the accuracy of data transmission.
23. Testing the values of maximum distance for wireless control. Taking 10 m as the starting value, the wireless control distance is measured three times. If at least one of the three times passes, the wireless control distance is increased by 1 m. If none of the three times passes, the wireless control distance is reduced by 1 m. Then, the measurement is continued for three times, and the maximum value is recorded until the wireless control distance cannot be further increased or the wireless control distance does not need to be further reduced. The maximum value is recorded as the maximum distance for wireless control.
24. Testing the values of smoothness of walking on complex road surfaces. A complex bumpy rubble road surface with a length of 50 m is set up. An acceleration sensor is installed on the robot body device in the vertical direction. The robot travels at a uniform speed at 50% of its maximum wheel motion speed. After the movement, the acceleration curves in the vertical direction is output, and the average value of peak of curve which is represented as a_z is calculated. The value of a_z can be taken as the smoothness of walking on complex road surfaces.
25. Testing the values of motion speed under standard load. If the technical specification provides a standard load value, it shall be adhered to accordingly; in the absence of such provision, 80% of maximum load will serve as the standard. On a level cement surface, the robot will travel at maximum speed with standard load while moving in a straight line. Timing begins when the robot has walked 2 m, and distance traveled within one minute is recorded. Three tests are conducted, and the average speed can be calculated as the motion speed under standard load.

4. Establishment Method of Index System

The evaluation index system of earthquake rescue robots is constructed by integrating subjective and objective elements, based on the preliminary classification of experts and the performance index values obtained from testing. This system further subdivides undetermined indexes, clarifies the screening indexes, and effectively manages these screening indexes to achieve closed-loop adjustment.

4.1. Using Fuzzy Clustering Method to Classify the Undetermined Indexes

By employing fuzzy clustering analysis, the index dataset is effectively partitioned into distinct classes, ensuring maximum dissimilarity between each class while minimizing differences within each class [81]. Consequently, the utilization of fuzzy clustering method enables the classification of undetermined indexes. The specific steps for employing fuzzy clustering method to classify undetermined indexes are as follows:

1. Determine the number of fuzzy clusters, the cluster center, and classified index. The fuzzy cluster number corresponds to the number of the first-grade indexes in Table 1, while the cluster center represents the central index, and the classified index denotes the undetermined index. $\boldsymbol{X}$ is an $m \times n$ dimensional matrix comprising the original data of classified indexes, where $x_{jk}(j = 1, 2, \cdots, m; k = 1, 2, \cdots, n)$ refers to an element within $\boldsymbol{X}$. Here, m signifies the number of classified indexes and n indicates the number of features associated with these indexes. $\boldsymbol{Y}$ is a $b \times n$ dimensional matrix composed of original data from central indexes, where $y_{jk}(i = 1, 2, \cdots, b; k = 1, 2, \cdots, n)$ represents an element within $\boldsymbol{Y}$. In this case, b stands for the number of central indexes and n also denotes their feature number.
2. Standardize the indexes' data in matrix $\boldsymbol{X}$ and matrix $\boldsymbol{Y}$.

$$d_j(k) = \frac{x_{jk} - \overline{x}(k)}{\overline{s}(k)} \tag{1}$$

$$d_i(k) = \frac{y_{ik} - \overline{y}(k)}{\overline{s}'(k)} \tag{2}$$

where $d_j(k)$ is the data of x_{jk} after standardization; $\overline{x}(k) = \sum\limits_{j=1}^{m} \frac{x_{jk}}{m}$; $\overline{s}(k) = \left\{ \sum\limits_{j=1}^{m} \frac{|x_{jk} - \overline{x}(k)|}{m-1} \right\}^{\frac{1}{2}}$;

$d_i(k)$ is the data of y_{jk} after standardization; $\overline{y}(k) = \sum\limits_{j=1}^{b} \frac{y_{ik}}{b}$; $\overline{s}'(k) = \left\{ \sum\limits_{i=1}^{b} \frac{|y_{ik} - \overline{y}(k)|}{b-1} \right\}^{\frac{1}{2}}$.

3. Calculate the fuzzy similarity matrix r. r_{ji} is the element in r, and the absolute value subtraction method is used to calculate the similarity r_{ji} between the classified index j and the central index i.

$$r_{ji} = 1 - c\sum_{k-1}^{n} |d_j(k) - d_i(k)| \tag{3}$$

where c is the coefficient, and c = 0.1 in this paper.

4. Classify the classified indexes. According to the fuzzy similarity matrix calculated by Equation (3), the central index with the highest fuzzy similarity to the classified index can be identified. Consequently, the classified index (undetermined index) can be assigned to the first-grate index that encompasses the central index.

4.2. Using Group Grey Correlation Method to Determine Screening Indexes

In this paper, each first-grate index is treated as an independent unit to analyze the correlation among second-grate indexes. The group grey correlation method is employed for identifying screening indexes and eliminating redundant ones within the second-grate indexes. If there are multiple central indexes in a first-grate index, the group grey correlation method is utilized to calculate the degree of correlation between the second-grate indexes within that specific first-grate index, thereby determining the screening indexes [21]. Conversely, if there is only one central index, the grey correlation method is applied to determine the screening indexes. The specific steps for employing the group grey correlation method to determine screening indexes are as follows:

1. Construct reference index group. The central index in each first-grate index are formed into a reference index group in this paper. The central index reference matrix is $\boldsymbol{Y}$. $y_i = [y_{i1}, y_{i2}, \cdots, y_{in}]$ is the reference vector of the central index $i(1 \leq i \leq b)$. The

comparison indexes are the remaining indexes that do not include the central indexes in each first-grate index. The reference matrix of the comparison indexes is as follows:

$$X' = \begin{bmatrix} x'_{11} & \cdots, & x'_{1n} \\ x'_{21} & \cdots, & x'_{2n} \\ \vdots & \vdots & \vdots \\ x'_{N1} & \cdots, & x'_{Nn} \end{bmatrix} \quad (4)$$

where $x'_j = [x'_{j1}, x'_{j2}, \cdots, x'_{jn}]$ is the reference vector of the comparison index $j(1 \leq j \leq N)$ and N is the number of comparison indexes in the first-grate index, and the feature number of the comparison index is also n.

2. Calculate the correlation coefficient and correlation degree. The correlation coefficient of x'_{jk} and y_{ik} at the k-th feature is as follows:

$$\xi_j^i(k) = \min\left|y_{ik} - x'_{jk}\right| + 0.5\max\left|y_{ik} - x'_{jk}\right| / \left(\left|y_{ik} - x'_{jk}\right| + 0.5\max\left|y_{ik} - x'_{jk}\right|\right) \quad (5)$$

The correlation degree between comparison index j and central index i is as follows:

$$r_j^i = \frac{1}{n}\sum_{k=1}^{n} \xi_j^i(k) \quad (6)$$

3. Calculate the group grey correlation degree.

$$\widetilde{r}_j = \frac{1}{b}\left[\sum_{w=1}^{b}\left(r_j^i\right)^p\right]^{1/p} \quad (7)$$

where $\widetilde{r}_j$ is group grey correlation degree between the j-th index and all the central indexes in the corresponding first-grate index, p is the coefficient, and p = 2.

4. Determine the screening indexes based on the group grey correlation degree. The principle of determining the screening indexes is: if $\widetilde{r}_j > \alpha$, α is the group grey correlation threshold, then the j-th index is the screening indexes; otherwise it is not. Assuming that the threshold of the general grey relational degree is ε, the threshold value of the group grey relational degree can be obtained according to Equation (7), as follows:

$$\alpha = \frac{1}{b}\left[\sum_{w=1}^{b}(\varepsilon^{\omega})^2\right]^{\frac{1}{2}} = \varepsilon\sqrt{b}/b \quad (8)$$

4.3. Using Evidence Theory to Fuse Expert Credibility to Process Screening Indexes

In this paper, four experts were invited to provide their expert opinions on screening indexes, and the credibility of these experts was fused using evidence theory. Based on the fusion results, redundancy indexes were eliminated [82]. The specific steps for fusing expert credibility using evidence theory to screening indexes are as follows:

1. Establish experts' trust distribution table for a certain screening index. The trust distribution of two experts is shown in Table 7. m_i and m_j are basic probability assignment functions of two experts.
2. Calculate the distance between m_i and m_j.

$$d(m_i, m_j) = \frac{1}{N}\sqrt{\sum_{k=1}^{M}(m_i(A_k) - m_j(A_k))} \quad (9)$$

where N is the number of experts, M is the number of possible cases, and M = 3 in this paper. A_k is any subset in an identification framework consisting of M pairwise different propositions.

3. Calculate the credibility of experts. The similarity between m_i and m_j is as follows:

$$\mathrm{sim}(m_i, m_j) = 1 - d(m_i, m_j) \tag{10}$$

The support of evidence m_i is as follows:

$$\sup(m_i) = \sum_{j=1, j\neq i}^{N} \mathrm{sim}(m_i, m_j) \tag{11}$$

The credibility of the experts is as follows:

$$\mathrm{Dcrd}(m_i) = \frac{1}{N-1}\sup(m_i) \tag{12}$$

4. The combination rule of credibility of the experts.

$$m(A) = m_1 \oplus m_1(A) = \begin{cases} \sum\limits_{X\cap Y=A} m_1(X)\cdot m_2(Y) + \delta(A) & A \neq \phi \\ 0 & A = \phi \end{cases} \tag{13}$$

$$\delta(A) = \sum_{A\cap Z=\phi} \rho(A,Z) + \sum_{A\cap Z=\phi} \sigma(A,Z) \tag{14}$$

$$\rho(A,Z) = \begin{cases} \mathrm{Dcrd}_1 \cdot m_1(A) \cdot \frac{m_1(A)\cdot m_2(Z)}{\mathrm{Dcrd}_1\cdot m_1(A)+\mathrm{Dcrd}_2\cdot m_2(Z)} \\ (\mathrm{Dcrd}_1 \cdot m_1(A) + \mathrm{Dcrd}_2 \cdot m_2(Z) > 0) \\ 0 \\ (\mathrm{Dcrd}_1 \cdot m_1(A) + \mathrm{Dcrd}_2 \cdot m_2(Z) = 0) \end{cases} \tag{15}$$

$$\sigma(A,Z) = \begin{cases} \mathrm{Dcrd}_2 \cdot m_2(A) \cdot \frac{m_2(A)\cdot m_1(Z)}{\mathrm{Dcrd}_2\cdot m_2(A)+\mathrm{Dcrd}_1\cdot m_1(Z)} \\ (\mathrm{Dcrd}_2 \cdot m_2(A) + \mathrm{Dcrd}_1 \cdot m_1(Z) > 0) \\ 0 \\ (\mathrm{Dcrd}_2 \cdot m_2(A) + \mathrm{Dcrd}_1 \cdot m_1(Z) = 0) \end{cases} \tag{16}$$

Table 7. Expert trust distribution on a certain screening index.

Title 1	Credible	Incredible	Unknown
m_i	0.98	0.01	0.01
m_j	0	0.01	0.99

According to the results of credibility fusion, the screening indexes can be processed. The processing principle of the screening indexes is as follows:

1. When the credible probability is highest, indicating that experts consider the event to be credible, delete the corresponding screening index.
2. When the incredibility probability is highest, indicating that experts consider the event to be incredible, retain and do not delete the corresponding screening index.
3. When the unknown probability is highest, closed-loop adjustment is required.

4.4. The Closed-Loop Adjustment of Index System

The principle of closed-loop adjustment is as follows: if the screening indexes is the central index, the index is initially determined by the experts, and then return to Section 2.5, and the experts will re-specify the central index, and the original screening indexes will be processed according to Sections 4.1–4.4; otherwise, return to Section 4.1, and the index is re-classified by the fuzzy clustering method, and the screening indexes are re-processed according to Sections 4.1–4.4.

In the closed-loop adjustment, two situations may arise: (1) the screening index belongs to the initial determined index determined by experts, but the evidence fusion results show that experts do not really understand the index, so the index should belong to the undetermined index, so we should go back to Section 4.1 and use the fuzzy clustering method to objectively classify the index; (2) the screening index belongs to the initial undetermined index. The fusion result of expert credibility shows that the unknown probability of the screening index is the largest, and experts can not give subjective judgment. Therefore, the screening index is re-defined as undetermined index, and the evidence fusion result proves the correctness of the initial judgment. When the central index remains unchanged, the deletion can only be judged based on the group grey relevance of the index before adjustment.

After integrating the aforementioned steps, the index system of earthquake rescue robots is established based on the flow chart depicted in Figure 4.

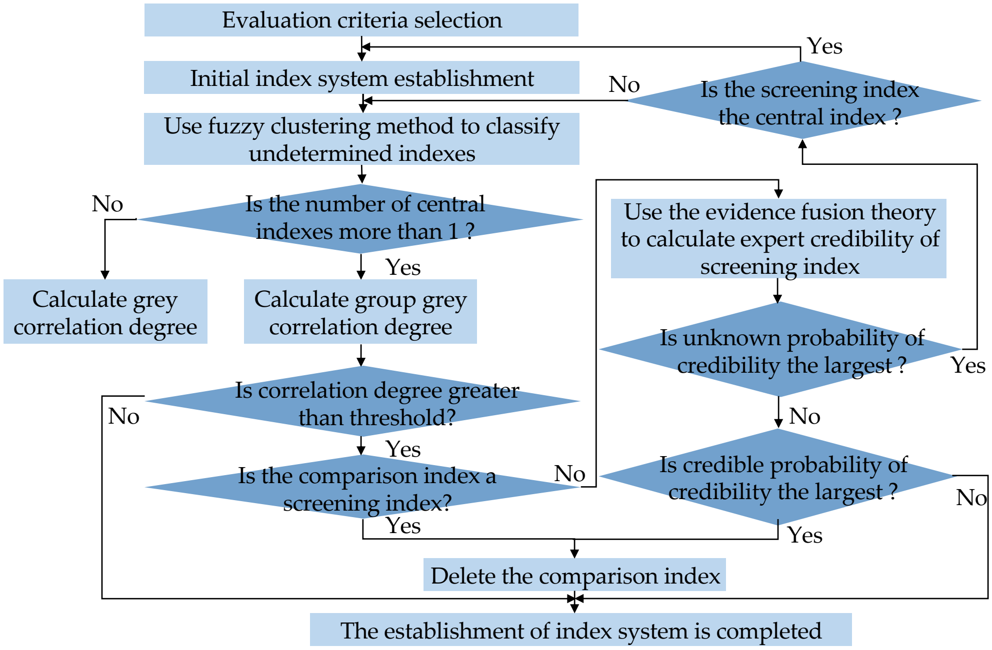

Figure 4. The flowchart of index system establishment method.

5. Construction of a Evaluation Method Based on DEMATEL Super Efficiency DEA

The present paper proposes a evaluation method based on the DEMATEL super efficiency DEA model. Firstly, DEMATEL is employed to determine the input and output indexes, along with their corresponding weights. Subsequently, by utilizing the super efficiency DEA model, the optimal value of performance, as well as the optimal slack variables for both input and output indexes, can be obtained. Finally, through evaluating and optimizing the redundancy of input parameters and insufficiency of output parameters for earthquake rescue robots, we aim to enhance their overall performance while successfully accomplishing rescue tasks.

5.1. The DEMATEL Model

The primary procedures of the fuzzy DEMATEL method [83] are as follows:

1. Establish a direct influence matrix. The expert group consists of L experts, denoted as $D = (D_1, D_2, \cdots, D_L)$. Each expert independently constructs a semantic direct influence matrix based on the direction and magnitude of mutual influence between criteria. The total direct influence matrix is obtained by aggregating the weights assigned by each expert.

$$A^k = \begin{bmatrix} 0 & a_{12}^k & \cdots & a_{1n}^k \\ a_{21}^k & 0 & \cdots & a_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}^k & a_{n2}^k & \cdots & 0 \end{bmatrix} \tag{17}$$

$$a_{ij} = \sum_{k=1}^{L} \omega_k a_{ij}^k = \left(\left(\underline{a_{ij}}, a_{ij}, \overline{a_{ij}} \right); \omega_{a_{ij}}, u_{a_{ij}} \right) \tag{18}$$

$$A = \begin{bmatrix} 0 & a_{12} & \cdots & a_{1n} \\ a_{21} & 0 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 0 \end{bmatrix} \tag{19}$$

where a_{ij}^k represents the assessment value of expert k on the direct influence of index i on index j, n denotes the total number of indexes, and ω_k signifies the weight assigned to expert k, $\sum_{k=1}^{L} \omega_k$.

2. Calculate the normalized direct influence matrix. Firstly, the elements in the total direct influence matrix are defuzzified based on Equation (16), yielding the defuzzified direct influence matrix E. Subsequently, E is standardized using Equations (20) and (21), resulting in the standard direct influence matrix X.

$$E = \begin{bmatrix} 0 & a_{12} & \cdots & a_{1n} \\ a_{21} & 0 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 0 \end{bmatrix} \tag{20}$$

$$s = \min \left\{ 1 \Big/ \max_{1 \le j \le n} \sum_{i=1}^{n} a_{ij} \, , 1 \Big/ \max_{1 \le i \le n} \sum_{j=1}^{n} a_{ij} \right\} \tag{21}$$

$$X = [x_{ij}]_{n \times n} = s \cdot E \tag{22}$$

3. Calculate the comprehensive influence matrix T as follows:

$$T = \lim_{k \to \infty} \left(X + X^2 + X^3 + \cdots + X^k \right) = X(I - X)^{-1} \tag{23}$$

where I represents the n-order identity matrix.

4. Calculate the influence and influenced degree. The calculation of the influence degree P and the influenced degree Q of index i can be expressed as shown in Equations (24) and (25), respectively.

$$P = [P_i]_{n \times 1} = \left[\sum_{j=1}^{n} x_{ij} \right]_{n \times 1} \tag{24}$$

$$Q = [Q_j]_{1 \times n} = \left[\sum_{i=1}^{n} x_{ij} \right]_{1 \times n} \tag{25}$$

5. Calculate the centrality and causal degree. The calculation of centrality and causal degree of index i are expressed as shown in Equations (26) and (27), respectively.

$$M_i = P_i + Q_i \tag{26}$$

$$U_i = P_i - Q_i \tag{27}$$

The centrality degree of index M_i reflects its position and importance within the index system, while the causal degree of index U_i indicates its pure influence on the system. A positive value for $U_i > 0$ suggests that this index is a causal factor (input index) with significant influence on other indexes, whereas a negative value for $U_i < 0$ implies that this index is a result factor (output index) greatly influenced by other indexes. When $U_i = 0$, it signifies that the impact on other indexes is equal to the impact of other indexes on it, rendering the possibility of eliminating this particular index.

5.2. The Super Efficiency DEA Model

The traditional DEA method typically employs the CCR model to perform modeling analysis on the system [84]. Assuming a total of n decision-making units, each with m inputs and r outputs, the optimization model aims to achieve optimal relative efficiency of the system.

$$\max\left(\alpha^T y_j / \beta^T x_j = \sum_{s=1}^{r} \alpha_s y_{sj} \Big/ \sum_{i=1}^{r} \beta_i x_{ij}\right) \left[st.\alpha^T y_j / \beta^T x_j \leq 1; x_j, y_j \geq 0, j = 1, 2, \cdots, n; \alpha, \beta \geq 0\right] \quad (28)$$

where $X_j = (x_{1j}, x_{2j}, \cdots, x_{mj})$, x_{ij} represents the i-th input index of the j-th decision making unit; $Y_j = (y_{1j}, y_{2j}, \cdots, y_{rj})$, y_{sj} denotes the s-th output index of the j-th decision making unit; and $\alpha = (\alpha_1, \cdots, \alpha_r)^T$ and $\beta = (\beta_1, \cdots, \beta_m)^T$ represent the output weight and input weight, respectively.

The model presented in Equation (28) represents a fractional programming problem, which can be transformed into a linear model using the Charnes–Cooper transformation [85]. Taking the o-th decision making unit DMU$_o$ as an example (with input X_o and output Y_o), as depicted in Equation (29).

$$\min(\rho) \left[st.\sum_{j=1}^{n} X_j \lambda_j + S^- = \rho X_0; \sum_{j=1}^{n} Y_j \lambda_j - S^+ = Y_0; \lambda_j \geq 0, j = 1, 2, \cdots, n; S^-, S^+ \geq 0\right] \quad (29)$$

where λ_j represents the weight coefficient and S^- and S^+ denote the relaxation variables of input and output, respectively.

The optimal solution can be derived from the model presented in Equation (19), denoted by variables ρ , S^- , and S^+ , with specific interpretations as delineated below:

- When $\rho = 1$, $S^- = 0$, and $S^+ = 0$, DMU$_o$ is considered to be DEA efficient, indicating that the system has achieved optimal output Y_o given input X_o.
- When $\rho = 1$, $S^- \neq 0$, and $S^+ \neq 0$, DMU$_o$ is considered to be weakly DEA efficient.
- When $\rho < 1$, DMU$_o$ is considered to be DEA invalid.

When the DEA analysis fails to yield effective results for DMU$_o$, it indicates that the evaluated unit possesses either redundant input ΔX_o or insufficient output ΔY_o . In order to enhance the effectiveness of DMU$_o$ in DEA, one can either reduce the input ΔX_o while keeping the output unchanged, or increase the output ΔY_o while maintaining a constant level of input. The refined inputs and outputs of improved DMU$_o$ are denoted as X_o and Y_o, respectively.

$$\begin{cases} X_0 = \rho_0 X_0 + {S_0}^- \\ Y_0 = Y_0 + {S_0}^+ \end{cases} \quad (30)$$

where ${S_0}^-$ and ${S_0}^+$ are input and output relaxation variables of DMU$_o$, respectively.

The input redundancy and output deficiency are illustrated as follows:

$$\begin{cases} \Delta X = X - X = (1-\rho)X + S \\ \Delta Y = Y - Y = S \end{cases} \quad (31)$$

The rates of input redundancy and output deficiency are presented as follows:

$$\begin{cases} RE_{io} = \frac{\Delta X_{io}}{X_{io}} = 1 - \rho_0 + \frac{S_{io}^-}{X_{io}}, i = 1, 2, \cdots, m \\ NE_{so} = \frac{\Delta Y_{so}}{Y_{so}} = \frac{S_{so}^+}{Y_{so}}, s = 1, 2, \cdots, r \end{cases} \quad (32)$$

where RE_{io} represents the redundancy rate of the i-th input index of DMU$_o$ and NE_{so} represents the deficiency rate of the s-th output index of DMU$_o$.

The efficiency value obtained from the traditional DEA model ranges between 0 and 1. When the efficiency value reaches 1, it becomes challenging to further differentiate the effective decision making units and identify the optimal ones. The super efficient DEA model provides an objective ranking of both effective and ineffective decision units [86]. The implementation method of this model is to exclude the o-th decision unit from the set of decision units when evaluating the o-th decision unit, so that the efficiency measured value of the decision unit that is effective in the original model is greater than 1 in the super efficient DEA model, and the efficiency measured value of the decision unit that is ineffective in the original model remains unchanged in the super efficient DEA model. The super efficient DEA model is shown in Equation (33).

$$\min(\rho)\left[st.\sum_{j=1,j\neq 0}^{n} X_j\lambda_j + S^- \leq \rho X_o;\sum_{j=1,j\neq 0}^{n} Y_j\lambda_j - S^+ \geq Y_0;\lambda_j \geq 0, j = 1,2,\cdots,n(j\neq 0);S^-,S^+ \geq 0\right] \quad (33)$$

6. Practical Application

6.1. Establishment of Index System for Earthquake Rescue Robot

In this paper, when establishing the index system for earthquake rescue robots, each index data adopts the average value of the performance test values of three samples of such robot. Since there are four first-grade indexes listed in Table 5, the number of fuzzy clusters is also set as four. The central indexes for each first-grade index shown in Table 6 represent the cluster centers. The threshold value of the general grey correlation degree ε is 0.8. When the number of central indexes b = 2, the threshold of group grey correlation degree can be obtained according to Equation (8), $\alpha = 0.5656$.

For the aforementioned two undetermined indexes in Table 5, employing Equations (1)–(3), we utilize the fuzzy clustering method to compute the fuzzy similarity matrix between these indexes and each cluster center. The obtained fuzzy similarity results are presented in Tables 8 and 9, correspondingly.

Table 8. The fuzzy similar matrix of the walking smoothness on complex road surfaces.

Index	X_{14}	X_{23} [1]	X_{31}	X_{43}	Undetermined Index 1
X_{14}	1.0000	0.4178	0.4943	0.5612	0.4083
X_{23}	0.4178	1.0000	0.2433	0.4569	0.4609
X_{31}	0.4943	0.2433	1.0000	0.4469	0.3971
X_{43}	0.5612	0.4569	0.4469	1.0000	0.4308
Undetermined index 1	0.4083	0.4609	0.3971	0.4308	1.0000

[1] When there are multiple central indexes, the index numbered in front is the central index.

Table 9. The fuzzy similar matrix of the motion speed under standard load.

Index	X_{14}	X_{23} [1]	X_{31}	X_{43}	Undetermined Index 2
X_{14}	1.0000	0.4178	0.4943	0.5612	0.4439
X_{23}	0.4178	1.0000	0.2433	0.4569	0.5911
X_{31}	0.4943	0.2433	1.0000	0.4469	0.5947
X_{43}	0.5612	0.4569	0.4469	1.0000	0.3526
Undetermined index 2	0.4439	0.5911	0.5947	0.3526	1.0000

[1] When there are multiple central indexes, the index numbered in front is the central index.

According to Table 8, the walking smoothness on complex road surfaces exhibits the highest similarity (0.4609) with central index X_{23}, indicating its association with motion ability X_2, and can be designated as X_{213} in sequential order. According to Table 9, the motion speed under standard load demonstrates the highest similarity (0.5974) with center index X_{31}, suggesting its affiliation with detection perception ability X_3, and can be denoted as X_{34} in sequential order. The grey correlation method is employed to calculate the grey correlation degree of the second-grade indexes for X_1, X_3, and X_4, since they have a central index. However, as X_2 has two central indexes, the group grey correlation degree method is used to determine the group grey correlation degree. The calculation results based on the group grey correlation degree method are presented in Table 10.

Table 10. The (group) grey results of index and their threshold.

Index Number	(Group) Grey Relational Degree	Threshold	Central Index
X_{11}	0.8460	0.8	X_{14}
X_{12}	0.7212	0.8	X_{14}
X_{13}	0.7450	0.8	X_{14}
X_{21}	0.6589	0.8	X_{23}, X_{210}
X_{22}	0.8354	0.8	X_{23}, X_{210}
X_{24}	0.5849	0.8	X_{23}, X_{210}
X_{25}	0.6254	0.8	X_{23}, X_{210}
X_{26}	0.6667	0.8	X_{23}, X_{210}
X_{27}	0.6398	0.8	X_{23}, X_{210}
X_{28}	0.6238	0.8	X_{23}, X_{210}
X_{29}	0.7567	0.8	X_{23}, X_{210}
X_{211}	0.7533	0.8	X_{23}, X_{210}
X_{212}	0.6028	0.8	X_{23}, X_{210}
X_{213}	0.7359	0.8	X_{23}, X_{210}
X_{32}	0.4213	0.5656	X_{31}
X_{33}	0.3596	0.5656	X_{31}
X_{34}	0.6426	0.5656	X_{31}
X_{41}	0.4123	0.5656	X_{43}
X_{42}	0.4896	0.5656	X_{43}
X_{44}	0.4356	0.5656	X_{43}

The results presented in Table 10 demonstrate that the correlation coefficients of X_{11} (0.8460 > 0.8), X_{22} (0.8354 > 0.8), and X_{34} (0.6426 > 0.5656) exceed the predefined threshold, thereby confirming the three indexes X_{11}, X_{22}, and X_{34} as screening indexes. This paper invites four experts to provide credibility probabilities for the three screening indexes X_{11}, X_{22}, and X_{34}. The expert trust distributions of these indexes are fused using evidence theory with conflict degree. Table 11 displays the resulting expert trust distributions, while Table 12 shows the fusion process and results for all three screening indexes.

Table 11. Expert trust distribution of the three screening indexes.

Expert	The Reliability Probability of Each Expert for the Screening Indexes.		
	Credible Probability	Incredibility Probability	Unknown Probability
1	0.4/0.5/0.4	0.5/0.5/0.4	0.1/0/0.2
2	0.6/0.7/0.3	0.4/0.2/0.6	0/0.1/0.1
3	0.1/0.8/0.8	0.8/0.1/0.1	0.1/0.1/0.1
4	0.5/0.9/0.1	0.5/0/0	0/0.1/0.9

Table 12. Results of expert reliability based on evidence fusion.

Index	Credible Probability	Incredibility Probability	Unknown Probability
X_{11}	0.7300	0.2507	0.0194
X_{22}	0.3547	0.6447	0.0006
X_{34}	0.3338	0.1035	0.5627

It can be seen from Table 12 that the credible probability of X_{11} is the largest, the incredibility probability of X_{22} is the largest, and the unknown probability of X_{34} is the largest. Therefore, the index X_{11} should be deleted and the index X_{22} cannot be deleted according to the processing principle of the screening indexes. And the experts cannot judge the index X_{34}, so it is necessary to adjust the index X_{34} in a closed loop.

The index X_{34} is not the central index, and belongs to the initially given undetermined index. The index X_{34} is re-defined as an undetermined index according to the evidence fusion result. The fuzzy classification and correlation degree of the index have been carried out when the central index has not changed, so the group grey correlation degree of X_{34}

before adjustment should be 0.6424 according to the principle of closed-loop adjustment in Section 4.4. The group grey correlation degree of X_{34} is greater than the threshold (0.6426 > 0.5656), so the index X_{34} should be deleted.

According to the aforementioned steps, the fuzzy clustering method is employed for classifying the undetermined indexes, namely walking smoothness on complex road surfaces and motion speed under standard load. The walking smoothness on complex road surfaces corresponds to motion ability X_2 and can be denoted as X_{213} in a sequential manner, while the motion speed under standard load pertains to detection perception ability X_3 and can be designated as X_{34} accordingly. Subsequently, the group grey correlation degree is utilized for identifying X_{11}, X_{22}, and X_{34} as screening indexes. According to the treatment method of the screening indexes, the index X_{11} should be deleted. The index X_{22} should be retained. The index X_{34} should be enter closed-loop adjustment. And then, according to the principle of closed-loop adjustment, the index X_{34} should be deleted. So far, the code name of each index is redefined and the final index system of earthquake rescue robots is established, as shown in Figure 5.

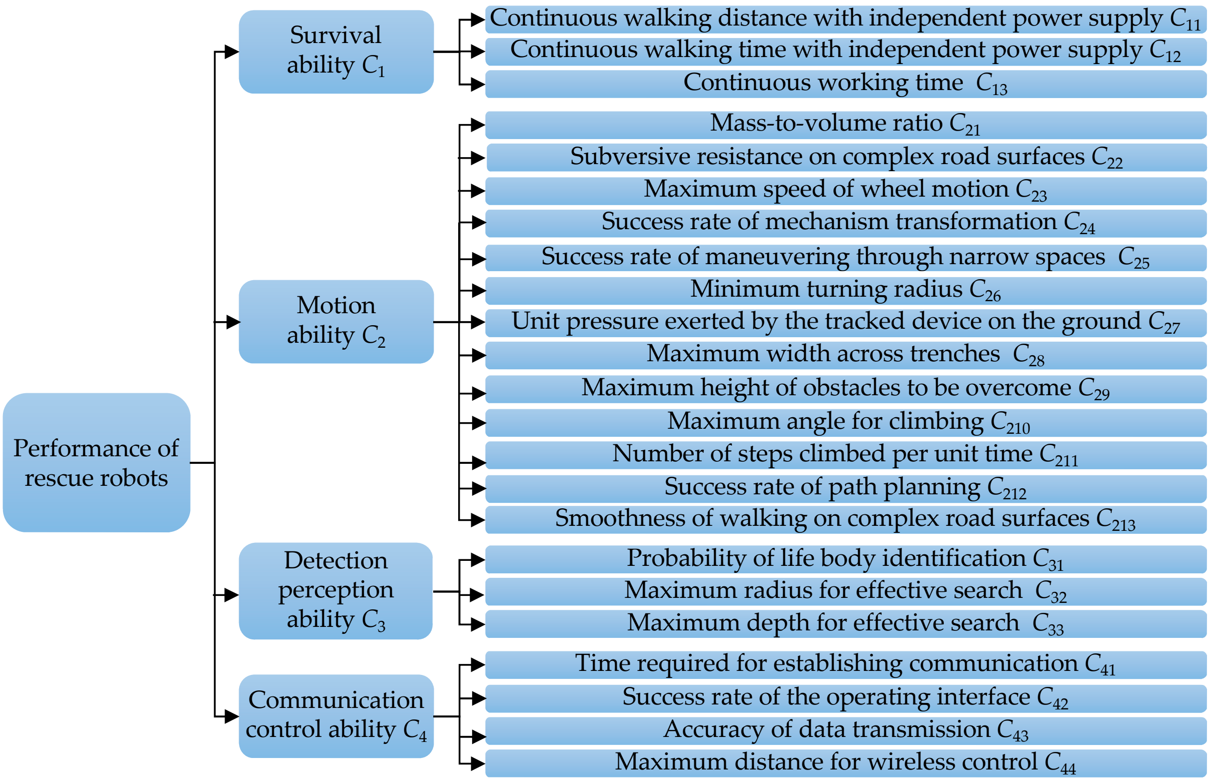

Figure 5. The final index system of earthquake rescue robots.

6.2. Comprehensive Performance Evaluation for Earthquake Rescue Robot

The direct influence matrix was constructed through a pairwise comparison method involving four experts who consistently assigned evaluation weights. The normalized comprehensive influence matrix can be computed based on Equations (27)–(30). Subsequently, the influence degree, influenced degree, centrality, and causal degree of each index can be determined using Equations (31) and (32), as presented in Table 13.

The centrality–causal degree scatter plot in Figure 6 is generated based on the calculation results of causal degree and centrality presented in Table 13. The index can be defined as an input index if the degree of causal is greater than 0, whereas it can be defined as an output index if the degree of causal is less than 0. From Figure 6, it can be observed that the input indexes include C_{22}, C_{25}, C_{26}, C_{27}, C_{213}, and C_{41}, while the output indexes consist of C_{11}, C_{12}, C_{13}, C_{21}, C_{23}, C_{24}, C_{28}, C_{29}, C_{210}, C_{211}, C_{212}, C_{31}, C_{32}, C_{33}, C_{42}, C_{43}, and C_{44}, respectively.

Table 13. Results of DEMATEL.

Index	Influence Degree	Influenced Degree	Centrality Degree	Causal Degree
C_{11}	1.7038	0.7523	2.4623	−0.9456
C_{12}	1.0512	0.6862	1.7372	−0.3666
C_{13}	0.4638	1.2336	1.6995	−0.7656
C_{21}	0.9911	0.4768	1.4662	−0.5123
C_{22}	0.3364	0.7873	1.1242	0.4503
C_{23}	0.4825	0.2748	0.7523	−0.2075
C_{24}	0.6621	0.2215	0.8845	−0.4420
C_{25}	0.3095	0.1468	0.7562	0.4631
C_{26}	0.3576	0.7311	1.0886	0.3715
C_{27}	0.2878	0.5482	0.8205	0.2785
C_{28}	1.2031	0.5232	1.7260	−0.6798
C_{29}	0.4834	0.2748	0.6586	−0.2095
C_{210}	0.8256	0.2645	1.0856	−0.5623
C_{211}	0.6042	0.5792	1.1856	−0.0256
C_{212}	0.5643	0.7579	1.3225	−0.1932
C_{213}	0.2726	0.8276	1.1023	0.5545
C_{31}	0.6001	0.2113	0.8026	−0.3976
C_{32}	0.8256	0.2645	1.1882	−0.5605
C_{33}	0.8062	0.7185	1.5245	−0.0876
C_{41}	0.2015	0.2956	0.4956	0.0925
C_{42}	1.0423	0.6683	1.7146	−0.3781
C_{43}	0.6273	0.7662	1.3921	−0.1382
C_{44}	1.3920	1.1402	2.5232	−0.2532

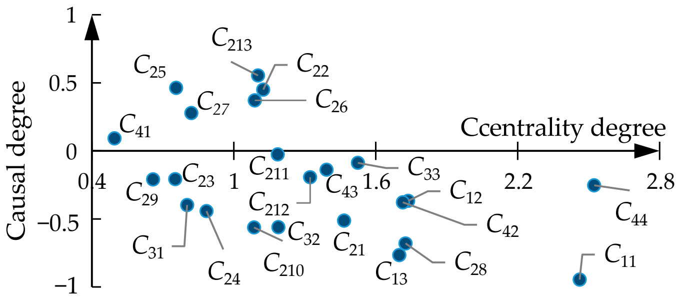

Figure 6. The centrality–causal degree scatter plot.

According to the input–output index system determined using DEMATEL, the DEA model and super efficient DEA model are adopted to comprehensively evaluate the performance of three types of earthquake rescue robots (Sample A, Sample B, and Sample C). The performance evaluation results of three types of earthquake rescue robots are shown in Table 14.

The comprehensive evaluation results (CER) in Table 14 demonstrate that the traditional DEA model effectively evaluates the three types of earthquake rescue robots. Sample C achieves a comprehensive efficiency value of 1, indicating its suitability for conducting search and rescue operations in post-earthquake scenarios. However, there is still room for improvement in terms of input and output for both Sample A and Sample B. After conducting a thorough analysis using the super efficient DEA model, we have obtained the measurement results for the three earthquake rescue robots as follows: Sample C (CER = 1.2978) > Sample A (CER = 0.5678) > Sample B (CER = 0.3256). The comprehensive performance evaluation reveals that Sample A emerges as the optimal choice, while Sample B exhibits the worst performance. Specifically, compared with Sample C, Sample A exhibited significant room for improvement in terms of its detection perception ability, whereas Sample B required further enhancements in both mobility and detection perception ability.

Table 14. The performance evaluation results of three types of earthquake rescue robots.

Index	Influence Degree	Sample A	Sample B	Sample C
Efficiency value		0.5678	0.3256	1
Super efficiency value		0.5678	0.3256	1.2978
C_{11}	s_1^+	0	0	0
C_{12}	s_2^+	0	0	0
C_{13}	s_3^+	0	0.01	0
C_{21}	s_4^+	0	34.591	0
C_{22}	s_1^-	0.086	281.399	0
C_{23}	s_5^+	0.003	0.001	0
C_{24}	s_6^+	0	0.028	0
C_{25}	s_2^-	0	0	0
C_{26}	s_3^-	3.502	0	0
C_{27}	s_4^-	0	0.072	0
C_{28}	s_7^+	0	0	0
C_{29}	s_8^+	0.005	0	0
C_{210}	s_9^+	0	0	0
C_{211}	s_{10}^+	0	341.762	0
C_{212}	s_{11}^+	0.11	0.001	0
C_{213}	s_5^-	0	107.546	0
C_{31}	s_{12}^+	0.082	0.01	0
C_{32}	s_{13}^+	30.218	41.186	0
C_{33}	s_{14}^+	141.189	235.286	0
C_{41}	s_6^-	0.001	0	0
C_{42}	s_{15}^+	0	0	0
C_{43}	s_{16}^+	0	0	0
C_{44}	s_{17}^+	0.012	0.01	0

To further elucidate the underlying factors contributing to the poor comprehensive performance of Sample A and Sample B, an analysis was conducted on their rates of input redundancy and output deficiency. The corresponding findings are presented in Tables 15 and 16.

Table 15. Analysis results of input redundancy and output deficiency of Sample A.

Index	S^-	S^+	*RE*%	*NE*%
C_{11}	-	0	-	0
C_{12}	-	0.01	-	1.255
C_{13}	-	0	-	0
C_{21}	-	0.95	-	3.123
C_{22}	0.086	-	11.11	-
C_{23}	-	0.003	-	3.132
C_{24}	-	0	-	0
C_{25}	0	-	0	-
C_{26}	3.502	-	5.265	-
C_{27}	0	-	0	-
C_{28}	-	0	-	0
C_{29}	-	0.005	-	1.315
C_{210}	-	0	-	0
C_{211}	-	0	-	0
C_{212}	-	0.11	-	5.289
C_{213}	0	-	0	-
C_{31}	-	0.082	-	25.000
C_{32}	-	30.218	-	67.079
C_{33}	-	141.189	-	53.846
C_{41}	0.001	-	1.256	-
C_{42}	-	0	-	0
C_{43}	-	0	-	0
C_{44}	-	0.012	-	15.321

Table 16. Analysis results of input redundancy and output deficiency of Sample B.

Index	S^-	S^+	*RE*%	*NE*%
C_{11}	-	0	-	0
C_{12}	-	0	-	0
C_{13}	-	0.01	-	0
C_{21}	-	0	-	0
C_{22}	281.399	-	41.995	-
C_{23}	-	0.001	-	3.132
C_{24}	-	0.028	-	1.212
C_{25}	0.072	-	2.158	-
C_{26}	0	-	0	-
C_{27}	0	-	0	-
C_{28}	-	0.06	-	20.256
C_{29}	-	0	-	0
C_{210}	-	0	-	0
C_{211}	-	341.762	-	56.945
C_{212}	-	0.1	-	7.215
C_{213}	107.546	-	26.142	-
C_{31}	-	0.01	-	15.013
C_{32}	-	41.186	-	82.075
C_{33}	-	235.286	-	63.596
C_{41}	0	-	0	-
C_{42}	-	0	-	0
C_{43}	-	0	-	0
C_{44}	-	0.01	-	12.325

The analysis results presented in Table 15 demonstrate that the performance of Sample A is primarily characterized by a deficiency in detection perception ability, with deficiency rates of C_{31} Probability of live body identification, C_{32} Maximum radius for effective search, and C_{33} Maximum depth for effective search reaching 25%, 67.079%, and 53.846%, respectively. These three aspects exhibit significant potential for optimization, which can be attributed to challenging conditions such as low environmental visibility, high temperature, high humidity, and irregular structures of ruins. In these demanding environments where advancements in robot-related technologies are yet to be achieved, accurate perception of the surrounding environment remains elusive for intelligent rescue equipment. Consequently, it fails to effectively assist rescuers in tasks such as personnel search and hazard warning.

In order to make Sample A reach the DEA effectiveness, the minimum index value for C_{31} Probability of live body identification should be 87.5%, the minimum index value for C_{32} Maximum radius for effective search should be 30.074 m, and the minimum index value for C_{33} Maximum depth for effective search should be 13.846 m. The findings demonstrate that Sample A can provide valuable assistance and deliver effective rescue information to support rescuers in their efforts, serving as an auxiliary tool. However, rescuers remain the primary agents of rescue operations, as robots are not currently equipped to independently execute rescue tasks through perception, analysis, and control functions.

The analysis results presented in Table 16 indicate that the performance of Sample A is primarily characterized by a deficiency in both mobility and detection perception ability. Specifically, the deficiency rates of indexes C_{28} Maximum width across trenches, C_{211} Number of steps climbed per unit time, C_{32} Maximum radius for effective search, and C_{33} Maximum depth for effective search are found to be 20.256%, 56.945%, 82.075%, and 63.596%, respectively, while the redundancy rates of indexes C_{212} Subversive resistance on complex road surfaces and C_{213} Smoothness of walking on complex road surfaces are observed to be at a high level of 41.995% and 26.142%, respectively, thus indicating that these six indexes have significant optimization potential. This is primarily attributed to the fact that existing crawler-based rescue robots can achieve obstacle avoidance through deformable crawler structures, but lack novel mechanisms for handling complex tasks, thereby rendering traditional rescue robots incapable of meeting the requirements of modern rescue operations in terms of multifunctionality, lightweight design, and precise maneuverability. Furthermore, in extreme earthquake environments, these rescue robots encounter similar challenges, as described in Sample A. Due to limited advancements in relevant technologies, intelligent rescue equipment fails to accurately perceive the surrounding environment and thus cannot effectively assist rescuers in personnel search and danger warning functions.

In order to make Sample B reach the DEA effectiveness, the minimum index value for C_{28} Maximum width across trenches should be 300.64 mm, the minimum index value for C_{211} Number of steps climbed per unit time should be 21.972 pc, the minimum index value for C_{32} Maximum radius for effective search should be 27.311 m, and the minimum index value for C_{33} Maximum depth for effective search should be 11.452 m. Additionally, it is crucial for the index value of C_{22} Subversive resistance on complex road surfaces to be reduced to at least 2.940 mm/s^2 and for the index value of C_{213} Smoothness of walking on complex road surfaces to be reduced to at least 3.693 mm/s^2. These findings indicate that Sample B shares similar limitations with Sample A, and can serve as an auxiliary tool in assisting rescuers by providing valuable rescue information. However, it should be emphasized that this robot lacks sufficient perception, analysis, and control capabilities, and is not suitable for independent rescue operations.

7. Comparison of Different Evaluation Methods

In this paper, the comprehensive evaluation based on the DEMATEL super-efficiency DEA model is based on the established index system shown in Figure 5. In order to validate the efficacy of evaluation method proposed in this paper, a comparison is made with the traditional DEMATEL super efficiency DEA based on the initial index system shown in Table 5, as well as VIKOR and entropy weight methods discussed in the Introduction. Both of VIKOR and entropy weight methods require weight calculations to obtain final results. The ranking results of different methods are presented in Table 17.

Table 17. The ranking results of different methods.

Evaluation Method	Ranking Results
Traditional DEMATEL super efficiency DEA	$S_A > S_C > S_B$
DEMATEL super-efficiency DEA	$S_C > S_A > S_B$
Entropy weight method	$S_B > S_C > S_A$
VIKOR (Weights calculated using the AHP method)	$S_C > S_B > S_A$
VIKOR (Weights calculated using coefficient of variation)	$S_B > S_C > S_A$

According to the results in Table 17, there are differences in the evaluation results between the DEMATEL super efficiency DEA and the traditional DEMATEL super efficiency DEA model. Considering both the evaluation test values of Sample A and Sample C as shown in Table 5, it is evident that apart from indexes C_{13}, C_{21}, and C_{27}, Sample A is either equal to or inferior to Sample C in other aspects. Therefore, based on these index values alone, it can be inferred that the comprehensive ranking of Sample C should not be lower than that of Sample A. However, when employing the traditional DEMATEL super efficiency DEA model for assessment purposes, it erroneously concludes that Sample A outperforms Sample C, thus failing to accurately reflect objective reality. Furthermore, the evaluation results obtained using both the entropy weight method and VIKOR method align with the ranking proposed in this paper, providing further validation for the scientific rigor of the evaluation method proposed in this paper.

Based on the evaluation results of DEMATEL super efficiency DEA, Sample B is identified as the poorest performer. However, according to both the entropy weight method and VIKOR method, Sample A exhibits subpar performance. This discrepancy can be attributed to the heavy reliance of both methods on index weights for comprehensive evaluation, which significantly influences ranking results. In this paper, we present a detailed analysis of index weights and evaluation results obtained through the entropy weight method. Table 18 showcases weight values calculated using this method for each index.

Table 18. Weight results of entropy weight method.

Index	Weight Values of Entropy Weight Method
C_{11}	0.0521
C_{12}	0.0610
C_{13}	0.0481
C_{21}	0.0581
C_{22}	0.0360
C_{23}	0.0247
C_{24}	0.1086
C_{25}	0.0255
C_{26}	0.0317
C_{27}	0.0726
C_{28}	0.0131
C_{29}	0.0147
C_{210}	0.0798
C_{211}	0.0258
C_{212}	0.0114
C_{213}	0.0315
C_{31}	0.0105
C_{32}	0.0553
C_{33}	0.0209
C_{41}	0.0557
C_{42}	0.0439
C_{43}	0.0120
C_{44}	0.0119

According to the results presented in Table 18, it is observed that among the index weights determined using the entropy weight method, C_{24} Success rate of mechanism transformation exhibits the highest weight ratio, while the C_{31} index demonstrates the lowest weight ratio. Consequently, it can be inferred that the index C_{24} exerts a significant influence on the evaluation results. Considering that Sample B attains a 100% value for its index C_{24}, whereas Sample C achieves a value of 90% for its index C_{210}, based on our assessment employing the entropy weight method, it can be concluded that Sample B surpasses Sample C in terms of comprehensive performance. However, in the practical application of earthquake rescue robots, we anticipate that the rescue robots will primarily replace human personnel as the main executors and independently fulfill perception, analysis, decision-making, and control functions. Therefore, it is imperative to thoroughly analyze the detection perception and communication control abilities of earthquake rescue robots within this specific context. Conversely, Sample C surpasses Sample B in terms of its detection perception ability indexes and exhibits better alignment with actual requirements. These findings indicate that our proposed evaluation method yields an optimal design for earthquake rescue robots that closely reflects objective reality and holds significant reference value.

Furthermore, the VIKOR method necessitates a prior determination of weights, and the ranking results obtained through different weight calculation methods often exhibit inconsistencies. Variations in weight calculation methods chosen by diverse decision makers during the evaluation process can lead to inconsistent evaluation results, thereby posing challenges when determining the final decision-making plan. The approach proposed in this paper is data-driven, eliminating the need for artificial index weighting. Evaluation results are solely dependent on data characteristics and patterns. Once index data is established, evaluation results remain unchanged, ensuring objectivity and stability.

8. Discussion

The method for establishing the aforementioned index system reflects the verification of subjective expert knowledge through objective theory in three aspects during the process:

1. After obtaining the fuzzy similarity of undetermined indexes in Tables 8 and 9, the classification of undetermined indexes is realized. While completing the correction of the subjective index system, the fuzzy similarity between the central indexes in Tables 8 and 9 is small, and the rationality of the subjective classification of experts can be verified.
2. The screening indexes can be determined by the group grey correlation degree of each index in Table 10, and the clarity of the index stratification can be proved by the correlation degree between the other indexes and the central index.
3. The motion speed under the standard load is redefined as an undetermined index in the closed-loop adjustment, the correctness of the initial judgment of the expert is proved again.

The above three aspects fully reflect that the index system establishment method proposed in this paper is completely based on the combination of subjective and objective ideas, so the established performance evaluation index system can meet the requirements of subjectivity and objectivity.

For the comprehensive evaluation results, upon reaching a minimum value of 300.64 mm for the index value of C_{28} Maximum width across trenches in Sample B, this value is substituted into Equations (30)–(33). Following optimization and adjustment, the input redundancy rate for subversive resistance on complex road surfaces is reduced to 25%, while the input redundancy rate for walking smoothness on complex road surfaces is reduced to 15%. These results demonstrate that optimizing input and output indices can effectively enhance the comprehensive performance of rescue robots.

Consequently, the proposed comprehensive evaluation method in this paper effectively assesses the performance of rescue robots and establishes a robust foundation for its subsequent application in optimization domains.

9. Conclusions

Considering the rapid advancements in earthquake rescue robot development across various research institutions worldwide, this paper proposes a comprehensive evaluation method that encompasses establishing an evaluation index system, testing performance indexes, and conducting performance evaluation to evaluate the performance of these robots. Within the same rescue scenario, when confronted with multiple earthquake rescue robots, the method proposed in this paper enables rescuers to accurately select the earthquake rescue robot with optimal overall performance.

(1) The evaluation criteria for the indexes of rescue robots are identified, resulting in the establishment of a comprehensive and hierarchical structure. This structure considers four aspects, namely survival ability, motion ability, detection perception ability, as well as communication control ability. The structure serves as a foundation for establishing the initial index system of the earthquake rescue robot.

(2) A index system establishment method for earthquake rescue robots is proposed. Based on the concept of hierarchical classification, this study incorporates the fuzzy clustering method, group grey correlation method, and evidence fusion theory into the process of establishing an index system for earthquake rescue robots. The proposed approach effectively addresses issues related to subjectivity, redundancy, and unclear stratification in the indexes. Moreover, it enables intelligent and practical modification of indexes by earthquake rescue robots while constantly updating the index system to better meet actual rescue application requirements. Additionally, this established index system serves as a valuable reference for comprehensive performance evaluation of earthquake rescue robots.

(3) Based on the established index system, this paper proposes a comprehensive evaluation method based on DEMATEL super efficiency DEA. This method eliminates the need for weight assignment calculation, thereby enhancing stability and objectivity compared to traditional weight calculation methods. Furthermore, by analyzing the rates of redundant inputs and insufficient outputs, different earthquake rescue robot schemes can be assessed, providing theoretical foundations and data support for optimizing and improving suboptimal earthquake rescue robot designs.

10. Recommendations and Future Work

(1) The performance indexes presented in this paper are exclusively represented by precise numerical values. Further research is needed to incorporate qualitative variables or interval numbers for a comprehensive description of the language, and fuzzy theory can be used to make the comparability between different types of indexes.
(2) Further research is needed to comprehensively update the index system by considering the removal or addition of performance indexes (such as safety performance, economic performance, etc.) within the first-grate indexes.
(3) In order to enhance the credibility of our findings, we plan to conduct additional investigations and empirical studies for future research. Furthermore, incorporating alternative outranking MCDM techniques would be advantageous in broadening the scope of this issue.

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