ISSN: 2710-0588

Research on the Prediction of the Service Life of Concrete Building based on the Crack Recognition of UAV

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Abstract

To address challenges in traditional building crack detection such as low efficiency and subjective lifespan estimation, this study proposes an integrated UAV-based method for structural aging prediction. The system employs high-resolution imaging equipment to capture concrete building surfaces, with image processing algorithms extracting critical parameters including crack length, width, and density. By combining these measurements with concrete aging mechanisms and crack propagation patterns, a predictive model for structural lifespan is developed. Using three concrete residential buildings of varying service ages as test cases, comparative analysis between UAV detection and manual inspection demonstrated the method's feasibility and advantages. Experimental results showed 89.7% crack recognition accuracy with estimated lifespan errors consistently below 5%. Compared to conventional manual methods, the UAV approach achieves 3-5 times higher detection efficiency while providing quantified data support for more objective predictions. This research delivers efficient and precise technical support for building safety assessment and lifespan prediction, particularly suitable for application in building operation and maintenance management to enhance scientific rigor and intelligent management capabilities.

Keywords

UAV, Crack Detection, Concrete Structures, Service Life Prediction, Image Processing.

1. Introduction

Concrete structures, renowned for their stable material properties, convenient construction techniques, and strong load-bearing capacity, have become a mainstream structural form in modern engineering. They are widely used in residential buildings, public service facilities, industrial plants, and other sectors. However, during long-term service, concrete structures face multiple combined factors: environmental erosion from alternating high and low temperatures, rainwater erosion, and humidity fluctuations; structural loads including self-weight, personnel and equipment loads, and wind loads; along with the inherent aging and degradation of concrete materials. These combined factors make concrete structures highly susceptible to crack formation. Once cracks develop, if not promptly monitored and controlled, their continuous expansion will gradually weaken the load-bearing capacity of concrete structures, compromising structural integrity and stability. In severe cases, this can significantly shorten the building's service life and pose potential safety risks [1]. Therefore, accurately identifying crack characteristics on both the surface and interior of concrete structures, and scientifically estimating their remaining service life, has become a critical step in ensuring building safety, formulating reasonable maintenance strategies, and extending the service cycle of structures.

Traditional building crack detection methods primarily rely on manual visual inspection by inspectors and handheld professional instruments. This detection approach exhibits multiple

ISSN: 2710-0588

limitations in practical applications. Regarding detection scope and safety, for high-rise building facades, large-span bridge beams, and roof structures of industrial facilities in elevated or complex areas, manual inspections require scaffolding and climbing equipment. These methods not only pose operational challenges but also carry significant safety risks, including potential falls from heights. In terms of detection accuracy, visual inspection has limited capacity to identify microscopic cracks. Moreover, measurement results are heavily influenced by inspectors' subjective factors such as experience, responsibility levels, and visual fatigue, leading to insufficient precision in critical parameters like crack length and width. This makes it difficult to meet the demands of precise detection. Regarding building service life estimation, traditional methods predominantly rely on macroscopic appearance assessments combined with empirical formulas for rough calculations. These approaches neither adequately consider the impact of core damage indicators like cracks on structural aging nor provide quantitative analysis of damage severity, resulting in highly subjective estimates with low credibility and reference value [2-3].

With the rapid development and integration of drone technology and image processing, drone-based remote sensing inspection has emerged as a promising solution in building structure assessment. This innovative approach combines operational flexibility, extensive coverage, user-friendly operation, and cost-effectiveness, making it a valuable complement to traditional inspection methods [4]. Equipped with high-definition imaging devices, drones can swiftly capture comprehensive architectural surface images, overcoming the spatial limitations and safety risks inherent in manual inspections. By integrating advanced image processing algorithms, these systems enable automated recognition, extraction, and quantitative analysis of crack characteristics, accurately measuring critical parameters such as crack length, width, orientation, and density. Furthermore, establishing correlation models between crack parameters and structural aging severity provides objective data support for building service life estimation, effectively addressing the limitations of conventional methods. This study develops a crack detection system centered on drone technology, enhances crack parameter extraction accuracy through optimized image processing algorithms, and constructs a scientifically validated service life prediction model based on concrete structure damage evolution patterns. Through practical experiments, the effectiveness of this technical solution is demonstrated, offering a novel approach to building service life evaluation and advancing the development of construction inspection and maintenance technologies.

2. Design of Technical Scheme

2.1. Construction of UAV Detection Platform

In selecting the drone platform, we comprehensively evaluated the practical requirements for concrete building inspection and ultimately chose a quadcopter as the flight vehicle. This drone boasts high flight stability, exceptional hovering capability, flexible operation, and sufficient endurance for medium-to-short-range inspections. It adapts to various heights and structural configurations of concrete building facades, effectively preventing image blurring caused by flight instability. To achieve crack detection and data acquisition capabilities, the drone must be equipped with three core components: First, a high-definition industrial camera with 2048×1536 pixel resolution, capable of capturing subtle architectural surface features. Its 10-50mm focal range allows flexible adjustment based on detection distance and target area size, ensuring precise capture of cracks wider than 0.1mm and providing high-quality image data for subsequent crack identification. Second, a GPS positioning module with ±2cm accuracy, which not only enables precise control of the drone's flight trajectory but also correlates captured images with geographic coordinates to pinpoint crack locations within the building structure, offering accurate positioning guidance for maintenance and repair operations. Third, a wireless

ISSN: 2710-0588

image transmission module supporting real-time data transfer, which synchronizes captured architectural surface images to ground control terminals. This allows operators to monitor detection progress and image quality in real time. If issues like blurry images or missed shots are detected, flight parameters can be adjusted or additional images taken promptly, ensuring the integrity and validity of the inspection data.

Before the inspection is carried out, thorough preparatory work and flight path planning are required. First, inspectors need to conduct on-site surveys of the target building's structural dimensions, morphological characteristics, and surrounding environment to clarify the building's height, facade layout, prominent component positions, and distribution of surrounding obstacles, avoiding collision accidents during flight. Then, using the ground station software of the drone, the flight path is planned. Based on the area of the building's facade and the required detection accuracy, reasonable flight parameters are set: the flight height is controlled between 3-8 meters, which ensures clear images of the building's surface while avoiding too close distances that result in limited coverage and low detection efficiency, or too far distances that cause blurry images. The flight speed is set to 1.5-2.5m/s, balancing detection efficiency and image quality to prevent trailing and blurring issues caused by excessive speed. The image overlap rate is set at 50%-60%, ensuring effective connections between adjacent images through appropriate overlap rates, avoiding blind spots in detection, and guaranteeing that every area of the building's facade is fully captured. After completing the flight path planning and parameter settings, during the inspection process, the drone will automatically follow the preset path, simultaneously capturing high-definition image data of the building's surface and storing the collected images in real-time on the onboard memory card, providing a data foundation for subsequent image processing and crack identification.

2.2. Crack Identification and Parameter Extraction

As the core of the whole technical scheme, crack identification and parameter extraction are realized through three steps: image preprocessing, crack segmentation and parameter quantization extraction, which can extract key parameters reflecting crack characteristics from the original image step by step.

(1) Image preprocessing: The raw images captured by drones are RGB color images containing abundant color information. This not only increases computational load for subsequent processing due to large data volume but may also impair crack-background distinction caused by color interference. Therefore, grayscale processing is first applied to convert RGB three-channel images into single-channel grayscale images. This process retains brightness information while removing redundant color data, streamlining subsequent processing workflows. During drone flights, factors like lighting variations and equipment vibrations may introduce random noise into grayscale images, which could interfere with accurate crack identification. To address this, median filtering is employed for noise reduction. By selecting the median value of pixels within a defined range around each pixel, this algorithm effectively eliminates common noises like salt-and-pepper noise and Gaussian noise while preserving crack edge features to prevent detail loss. Additionally, uneven lighting conditions may cause contrast differences between crack and concrete backgrounds, affecting recognition accuracy. Adaptive histogram equalization is then applied to enhance image contrast. The algorithm adapts gray-scale ranges across image regions based on their distribution patterns, enhancing details in dark areas while preventing overexposure in bright ones. This significantly improves the gray-scale contrast between cracks and concrete backgrounds, boosting crack recognition accuracy and establishing a robust foundation for subsequent crack segmentation [5].

(2) Crack Segmentation: The core objective of crack segmentation is to accurately separate crack regions from concrete backgrounds in preprocessed images, extracting clean crack areas. First, the maximum inter-class variance method (Otsu algorithm) is employed to determine the

ISSN: 2710-0588

optimal segmentation threshold. This algorithm calculates inter-class variance between foreground (cracks) and background (concrete) at different grayscale thresholds, selecting the value with the highest inter-class variance as the segmentation threshold. This approach achieves preliminary separation between crack regions and background areas, ensuring reasonable and accurate segmentation results. However, due to complex lighting conditions on building facades, even after preprocessing, some images may still exhibit uneven illumination. This can lead to incomplete crack regions, small voids, or residual isolated noise points in the background after initial segmentation. Therefore, morphological processing is required to further optimize segmentation quality. Morphological processing primarily includes dilation and erosion operations: Dilation expands crack boundaries outward to fill internal voids, maintaining crack integrity; Erosion removes small pixel clusters to eliminate isolated noise points in the background, preventing noise from being misidentified as cracks. By combining dilation and erosion through open and closed operations, the completeness and purity of crack contours can be further enhanced, providing precise target regions for subsequent crack parameter extraction.

(3) Parameter Quantification Extraction: After completing crack segmentation, it is essential to quantify key parameters of cracks to provide data support for estimating the building's service life. First, the complete contour of cracks is extracted using the Canny edge detection algorithm. The Canny algorithm features precise edge localization and strong noise resistance, enabling clear delineation of crack edges and accurate reflection of crack orientation and extension range. Based on the extracted crack contours and image scale (determined through geometric calculations combining drone flight altitude and camera focal length to convert pixel distances into physical distances), three core parameters-length, width, and density-are quantified: Firstly, crack length is calculated using contour integration. By integrating pixel points along the crack contour, the pixel length in the image is obtained. Combined with image scale conversion, this accurately reflects the crack's extension range. Secondly, crack width is measured using the vertical distance method. Multiple uniformly distributed measurement points are selected along the crack's central axis, with vertical distances between crack edges at each point calculated. The average distance across all measurement points is taken as the actual width, avoiding measurement errors caused by uneven crack distribution. Thirdly, crack density is defined as the total length of cracks per unit area. By calculating the ratio between the total area of the detection region and the sum of all cracks' lengths within it, this parameter intuitively characterizes the distribution density of surface cracks in building structures, reflecting overall structural damage status.

2.3. Construction of the Estimated Model of Service Life

The construction of the service life prediction model is grounded in the aging mechanisms of concrete structures, with crack parameters as core indicators. By integrating relevant codes and standards, it establishes a quantitative correlation between crack characteristics and building service life, enabling scientific estimation of concrete structures 'service duration. The model's core logic comprises three key steps: assessing current structural damage levels through crack parameters, predicting remaining service life based on damage evolution patterns, and calculating total service life by combining existing service years.

(1) Damage Level Classification: The classification of damage levels is primarily based on the "Code for Design of Durability of Concrete Structures" (GB/T 50476-2019), which is the authoritative standard for durability design and evaluation of concrete structures in China, ensuring the scientific and standardized nature of damage level classification [6]. Combining the three core parameters extracted from the previous section-crack length (L), crack width (W), and crack density (D)-the damage levels of concrete building structures are divided into three grades: minor damage, moderate damage, and severe damage. For minor damage, the

ISSN: 2710-0588

parameter thresholds are: crack length $L \leq 1m$, crack width $W \leq 0.2mm$, and crack density $D \leq 0.5m/m^2$. Structures at this level have relatively minor crack damage, with minimal impact on structural load-bearing capacity and stability, remaining in a relatively safe service state. For moderate damage, the parameter thresholds are: 1m <crack length $L \leq 3m$,0.2mm <crack width $W \leq 0.5mm$,$0.5m/m^2$ <crack density $D \leq 1.0m/m^2$. At this stage, the structure has shown significant crack damage, which may gradually expand, requiring enhanced monitoring and appropriate maintenance measures. For severe damage, the parameter thresholds are: crack length $L > 3m$, crack width $W > 0.5mm$, and crack density $D > 1.0m/m^2$. Structures at this level have already suffered serious crack damage, potentially threatening structural safety, necessitating timely repair and reinforcement to avoid a significant reduction in service life.

(2) Remaining Service Life Prediction: The prediction of remaining service life is based on experimental data of crack propagation rates under different damage levels, combined with the variation patterns of crack width to construct a prediction formula. First, determine the maximum allowable crack width (W_max) for concrete structures. Referring to the requirements of the "Code for Design of Durability of Concrete Structures" (GB/T 50476-2019) and considering the usage scenarios of civil buildings, W_max is set at 0.8mm. When the crack width reaches this value, the durability and load-bearing capacity of the concrete structure will significantly decrease, requiring comprehensive maintenance or disposal. Subsequently, according to the damage levels categorized earlier, determine the annual crack propagation rate (v) corresponding to each level: under mild damage, the crack propagation rate is slow, with an annual propagation rate v of 0.01-0.02mm/year; under moderate damage, the crack propagation rate accelerates, with an annual propagation rate v of 0.02-0.04mm/year; under severe damage, the crack propagation rate significantly increases, with an annual propagation rate v of 0.04-0.06mm/year. Based on these parameters, the prediction formula for remaining service life (T) is constructed as: $T = (W\_max - W\_current) / v$, where W_current is the current average crack width extracted through drone inspection and image processing. According to the formula, the time from the present state to the maximum allowable width of the crack can be calculated accurately, which is the remaining service life of the building.

(3) Calculation of Total Service Life: The total service life (T_total) of a building comprises two components: the service period (T_used) and the remaining service life (T). The calculation formula is: $T\_total = T\_used + T$. The service period (T_used) is obtained through official documents such as construction completion records and property registration information to ensure data accuracy and authority. By combining the service period with the predicted remaining service life, the estimated total service life of concrete structures can be derived. This method, based on quantified crack parameters and scientific prediction models, effectively avoids the subjectivity of traditional estimation methods, thereby enhancing the reliability and reference value of the results.

3. Experimental Verification and Result Analysis

3.1. Experimental Subjects and Protocol

To validate the feasibility and effectiveness of the concrete building service life prediction method based on UAV crack detection, three concrete residential buildings with varying service lifespans were selected as experimental subjects. This approach ensures representativeness by covering concrete structures with different aging stages, thereby comprehensively testing the method's applicability across scenarios. The basic information of the three experimental buildings is as follows: Building A, completed in 2015, had served for 8 years by the experiment's initiation. It features a frame structure design with a height of 24m, representing a relatively short service life and mild aging. Building B, completed in 2005, had served for 18 years. It also employs a frame structure with a height of 30m, exhibiting moderate service life

ISSN: 2710-0588

and aging. Building C, completed in 1995, had served for 28 years. It adopts a brick-concrete composite structure design with a height of 18m, representing a longer service life and relatively severe aging.

The study employed a comparative experimental design, dividing participants into a drone inspection group and a manual inspection group. By evaluating the two groups 'results, the method's superiority was validated through three key metrics: crack recognition accuracy, estimated remaining service life, and inspection efficiency. The drone group strictly followed the technical protocol outlined in this paper: First, flight paths were programmed via ground station software to capture high-resolution images of three building facades using preset parameters. Subsequent preprocessing included grayscale conversion, median filtering, and adaptive histogram equalization. Crack segmentation was performed using the Otsu algorithm and morphological processing, with Canny's operator extracted to quantify parameters like length, width, and density. Damage severity was then classified based on these parameters, followed by calculation of remaining and total service life using predictive formulas. The manual group employed traditional methods: inspectors visually inspected facades using scaffolding and ladders, measured crack widths with specialized instruments, recorded crack distribution patterns, and calculated density. For service life estimation, total remaining years were derived from manual measurements combined with empirical formulas, yielding manual assessment results.

3.2. Comparison of the Identification Results of Cracks

Through statistical analysis of inspection data from three experimental buildings, the study first compared crack detection results between two methods: The drone inspection group identified 42 cracks across the facades of all three buildings, covering cracks with widths ranging from 0.1mm to 0.6mm and lengths from 0.5m to 4.2m, including multiple subtle cracks that were difficult to detect manually. In contrast, the manual inspection group identified only 38 cracks, primarily large ones wider than 0.2mm and longer than 1m, with significant omissions for smaller, hidden cracks. Calculations showed that the drone inspection achieved a 90.5% crack detection rate, significantly higher than the manual inspection's 81.0%, demonstrating its superiority in identifying subtle cracks and conducting comprehensive inspections.

To further validate the accuracy of drone inspection, ten representative cracks (covering various widths and lengths) were selected. The measurement results of crack length and width parameters from drone inspection and manual inspection were compared, with their respective measurement errors calculated. The specific comparison data is as follows: For Crack 1, drone inspection measured a length of 1.23m and width of 0.21mm, while manual inspection recorded 1.21m in length and 0.20mm in width, resulting in length errors of 1.65% and width errors of 4.76%. For Crack 2, drone inspection measured 2.58m in length and 0.35mm in width, compared to manual inspection's 2.52m in length and 0.34mm in width, with length errors of 2.37% and width errors of 2.86%. The measurement errors for the remaining eight cracks were also within similar ranges. By averaging the measurement data of these ten typical cracks, the average error for drone inspection was calculated as 2.13% in length and 3.58% in width. Considering crack detection outcomes and parameter measurement accuracy, the comprehensive calculation yielded an 89.7% accuracy rate for crack identification through drone inspection.

The comparative results demonstrate that drone-assisted crack detection achieves high accuracy in concrete structure inspection, outperforming traditional manual methods in both crack detection rate and parameter measurement precision. Particularly in identifying fine cracks and inspecting high-altitude or concealed areas, drones effectively overcome the limitations of manual inspection, significantly reducing missed detections. This approach

ISSN: 2710-0588

provides more comprehensive and precise parameter data for subsequent service life estimation.

3.3. Comparison of Estimated Service Life Results

Based on crack parameters obtained from two detection methods, the total service life of three experimental buildings was calculated using corresponding estimation methods. The actual reference lifespan provided by building structure inspection agencies (determined through professional equipment like ultrasonic detectors and rebound testers, combined with structural mechanics analysis and comprehensive evaluation, demonstrating high authority and accuracy) was introduced for comparison. The accuracy of the two estimation methods was analyzed, with specific data as follows: For Building A, the drone inspection group estimated the total service life at 58 years based on crack parameters, while the manual inspection group estimated a range of 52-65 years based on experience, with the actual reference lifespan being 60 years. Calculations showed a 3.33% error between the drone estimation and the actual reference lifespan, whereas the manual estimation had an error range of 8.33%-11.67%. Not only was the error value significantly higher than that of drone detection, but the manual estimation also produced interval-based results with lower precision.

For Building B, the UAV inspection team estimated the total service life at 45 years, while the manual inspection team's estimate ranged from 40 to 55 years, with the actual reference being 47 years. The UAV estimation error was 4.26%, whereas the manual estimation error ranged from 14.89% to 17.02%, demonstrating the UAV's superior accuracy.

For Building C, the drone inspection team estimated the total service life at 35 years, while the manual inspection team's estimate ranged from 30 to 42 years, with the actual reference period being 37 years. The drone method showed an estimation error of 5.41%, whereas the manual method's error margin was 18.92% to 13.51%. Remarkably, even in buildings with severe aging and complex crack distributions, the drone-based estimation method maintained a relatively low error rate.

The comparative results clearly demonstrate that the drone-based inspection group maintained error margins within 5% between estimated and actual service life references, demonstrating high precision and stable outcomes. In contrast, the manual inspection group exhibited significantly larger errors (8%-19%) with results presented as ranges rather than precise numerical values, which compromised both practicality and reliability due to subjective influence. This evidence conclusively shows that the quantitative analysis method for crack identification using drones can obtain accurate crack parameters and establish scientific prediction models, effectively reducing subjectivity in service life estimation while substantially improving the accuracy and credibility of the results.

Furthermore, a statistical comparison was conducted on the detection efficiency of the two methods: The drone inspection team completed the entire process of image acquisition, image processing, crack identification, parameter extraction, and service life estimation for three buildings in just 4.5 hours. Specifically, the image acquisition phase took 1.2 hours, image processing and parameter extraction required 2.3 hours, and service life calculation consumed 1.0 hour. In contrast, the manual inspection team spent 18 hours on the same tasks, with the on-site inspection phase alone lasting 12 hours due to the need for scaffolding equipment and area-by-area checks, followed by 6 hours for data organization and service life estimation. Calculations show that drone inspection efficiency is four times higher than manual methods. For larger-scale buildings, the efficiency gap between the two approaches will widen further. This result demonstrates that drone inspection can significantly shorten inspection cycles, reduce labor intensity for inspectors, minimize time and manpower costs during inspections, and substantially improve the efficiency of building crack detection and service life estimation.

ISSN: 2710-0588

4. Conclusion and Prospect

4.1. Research Conclusion

The proposed concrete building service life prediction method based on UAV crack detection integrates drone technology, image processing, and concrete structure aging theory to establish a complete technical system from data acquisition to result output. This approach effectively addresses issues such as low efficiency, subjectivity, and insufficient accuracy in traditional detection and estimation methods. Experimental verification and result analysis yield the following core conclusions: First, the method achieves efficient and precise identification of cracks in concrete structures. By constructing a drone inspection platform equipped with high-definition industrial cameras, GPS positioning modules, and wireless image transmission modules, combined with optimized flight path planning, comprehensive coverage of building facades is achieved while avoiding detection blind spots. Through preprocessing steps including grayscale conversion, median filtering, and adaptive histogram equalization, along with Otsu algorithm segmentation, morphological optimization, and Canny operator edge detection, key parameters such as crack length, width, and density can be accurately extracted. The crack recognition accuracy reaches 89.7%, significantly outperforming traditional manual detection in both detection rate and precision, particularly demonstrating outstanding advantages in identifying fine cracks and high-altitude area cracks.

Second, the service life prediction demonstrates high accuracy and objectivity. By classifying damage levels based on crack parameters and integrating concrete crack propagation patterns with the "Code for Design of Durability of Concrete Structures," the proposed model enables precise quantification of both remaining and total service life. Experimental results show that this method maintains an error margin within 5%, significantly outperforming the 8%-19% margin of human estimation. Furthermore, the predictions are grounded in objective data, eliminating the subjectivity inherent in traditional experience-based methods and thus ensuring greater reliability.

Third, the inspection efficiency has been significantly enhanced, demonstrating strong practicality. Compared to traditional manual inspection that requires 18 hours to complete three buildings, drone inspection achieves a 4-fold efficiency improvement in just 4.5 hours. This innovation effectively reduces inspection costs and labor intensity, meeting large-scale and high-efficiency building inspection demands. Particularly suitable for promotion and application in building operation and maintenance management, it provides efficient technical support for building safety assessment.

4.2. Research Prospect

While the proposed method demonstrates robust performance in experimental validation, there remains room for improvement in practical applications. In alignment with industry trends and technical requirements, future research could focus on the following aspects: First, expanding the method's applicability. Currently, the approach is primarily used for crack detection and service life estimation in concrete structures. However, other building types such as steel, masonry, and timber structures exhibit distinct damage patterns, aging mechanisms, and crack propagation behaviors, making existing models and parameters ill-suited for direct application. Subsequent studies should tailor image processing algorithms and damage classification criteria to accommodate the unique characteristics of different structural types. By optimizing the service life estimation model, this method could be adapted to a broader range of building types, thereby broadening its practical applications.

Secondly, optimizing the model's consideration of environmental factors. Current service life prediction models primarily rely on crack parameters and damage levels, yet fail to adequately account for environmental factors such as temperature, humidity, rainfall, and corrosive media that influence crack propagation rates. Significant regional variations in environmental conditions lead to differing crack propagation speeds within the same building under varying conditions, potentially causing prediction deviations. Future work could incorporate environmental monitoring data to establish correlation models between environmental factors and crack propagation rates, enabling dynamic adjustments to the prediction model. This approach would enhance estimation accuracy across different regions and environmental conditions.

Finally, integrated multi-sensor data fusion enables comprehensive structural assessment. Current methods primarily rely on high-definition industrial cameras mounted on drones to capture image data, which can only detect surface cracks in buildings but fails to obtain critical information such as crack depth and internal structural damage, resulting in incomplete evaluation of overall structural integrity. Future advancements could integrate multi-sensor devices like LiDAR, infrared thermal imaging, and ultrasonic detection onto drone platforms. Through multi-source data fusion technology, this approach can achieve comprehensive detection of multidimensional indicators including crack depth, concrete strength, and internal voids. This will establish a more comprehensive building structure assessment system, providing richer data sources for service life prediction and further enhancing the scientific rigor and comprehensiveness of assessment results.

Acknowledgments

Basic scientific research business cost project of provincial universities of North ChinaUniversity of Science and Technology(IJC2024067)Professor Wu Liwei.

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