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Review

A Review of Detection Technologies for Underwater Cracks on Concrete Dam Surfaces

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Abstract: Cracks seriously endanger the safe and stable operation of dams. It is important to detect surface cracks in a timely and accurate manner to ensure the safety and serviceability of a dam. The above-water crack detection technology of dams has been widely studied, but due to the complex underwater environment, above-water crack detection technology on dam surfaces cannot be directly applied to underwater crack detection. To adapt to the underwater detection environment and improve the efficiency and accuracy of underwater crack detection, many methods have been proposed for underwater crack detection, including sensor detection and image detection. This paper presents a systematic overview of the development and application practices of existing underwater crack detection technologies for concrete dams, focusing on methods that use underwater robots as underwater mobile carriers to acquire images that are combined with digital image processing algorithms to identify, locate, and quantify underwater cracks in dams. This method has been widely used for underwater crack detection on dam surfaces with the advantages of being non-contact, non-destructive, having high efficiency, and wide applicability. Finally, this paper looks further forward to the development trends and research challenges of detection technologies for underwater cracks on concrete dam surfaces, which will help researchers to complete further studies on underwater crack detection.

Keywords: concrete dam cracks; underwater crack detection; underwater robot; underwater image processing

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1. Introduction

As one of the infrastructures of water conservancy and hydropower projects, dams play a huge role in flood control and disaster reduction, hydroelectric power generation, the irrigation of agricultural land, and water resource allocation [1–3]. At present, most dams are aging over a long period of use, increasing the risk of failure [3–5]. It is of great significance to carry out regular maintenance and inspection of dams to ensure their safe operation and reduce the overall repair and maintenance costs of dams.

During the long-term use of dams, there will be damages such as cracks, spalling, erosion, voids, and wear [6]. These defects seriously affect the safe and stable operation of the dam. Among these damages, cracks have attracted widespread attention because of their susceptibility, hazards, and inducing effects on other disasters. Most of the cracks originate on the surface of the structure, destroying the integrity of the structure and reducing its capacity for bearing [7–10]. Therefore, timely and accurate detection of cracks is an urgent problem to be solved in water conservancy and hydropower projects. At present, most of the crack detection for dams mainly focuses on the above-water part, and cracks are detected by technologies such as ultrasonic [11], electromagnetic wave [12], and sensing equipment [13,14]. In recent years, unmanned aerial vehicles (UAVs) combined with computer vision technology have been applied to dam damage detection. UAVs [15,16] are used to collect dam damage images, and computer vision methods [17,18] are used to identify the dam's damage through images.

Compared with the above-water concrete dam surface, the underwater concrete dam surface is more prone to cracks due to long-term immersion in water and the long-term coupling of temperature changes, water chemical corrosion, hydraulic fracturing, and other factors [19–22]. The underwater cracks of concrete dams not only exists on the surface, but also easily extend to the interior of the dam by the action of hydraulic fracturing, thus destroying the overall stability of the dam and causing immeasurable consequences. Therefore, it is necessary to regularly check the underwater cracks of concrete dams to reduce the impact of underwater dam surface cracks. However, due to the danger of underwater operation and the complexity of the underwater environment around dams, the detection is more difficult. When selecting the detection equipment, not only the applicability of the equipment, but also the water resistance should be considered. Existing detection methods mainly include sensor-based detection [23,24] and image-based detection [25,26]. However, long-term underwater operation greatly limits the practical application of embedded sensors. As an efficient detection technology for concrete dam surface cracks, the image detection method is widely used in crack detection of above-water dams. However, biofouling, insufficient light, etc., lead to complex underwater environments; thus, it is difficult for visual sensors to approach the underwater dam surface, which increases the difficulty of obtaining underwater images. Therefore, this method is also limited in use.

In recent years, some researchers have made review works of crack detection technologies and summarized the advanced technologies of crack detection. Hu et al. [27] introduced the surface crack detection method of transportation infrastructure based on machine vision. Yao et al. [28] summarized the crack detection technologies of civil infrastructures from the perspective of sensing approaches and data analysis approaches. Zakeri et al. [29] presented crack detection, classification, and quantification in asphalt pavement using image processing methods. Mohan et al. [30] reviewed concrete crack detection technics based on image processing techniques. Hsieh and Tsai [31] organized crack detection algorithms based on machine learning and compared the performance of different models. The above researches systematically reviewed the crack detection techniques for civil infrastructures. However, due to the complexity of the underwater environment of dams, underwater crack detection technology is different from traditional civil infrastructure crack detection methods. It is necessary to review the technologies for underwater cracks on concrete dam surface. Therefore, this paper takes underwater dam surface crack detection technology as the research object, summarizes various underwater dam surface crack detection methods, and focuses on the image acquisition and image processing of image-based underwater dam face crack detection methods. This paper is organized as follows: Section 2 presents existing methods for underwater crack detection on dam surfaces. Section 3 introduces the underwater crack detection of dam surfaces using an underwater robot. Section 4 details the underwater image processing method. Section 5 gives a summary and outlook.

2. Common Methods for Detecting Underwater Cracks in the Surface of Concrete Dams

2.1. Manual Visual Inspection

Manual visual inspection is the traditional method to detect cracks in dams. The cracks in the underwater concrete structure of the dam were mainly observed by professional technicians through visual inspection in the past [32]. The underwater cracks on the surface of concrete dams were mainly detected by building a cofferdam or emptying the reservoir water due to the backwardness of diving equipment in the early days [33–35]. However, emptying the reservoir is a waste of water resources, and the sudden change of engineering conditions easily causes engineering problems [36]. Additionally, most reservoir dams do not have emptying conditions as the reservoir capacity increases. With the development of diving technology, inspectors can use diving equipment to dive deep into the water and carry underwater detection equipment for artificial visual inspection of underwater dam cracks. This method, which does not require too high technical requirements, only inspects the underwater concrete by touch and observation. Therefore, it is widely used in the early underwater crack detection of dams. However, special underwater conditions (such as poor visibility, complex dam environment, strong current, and small operation area) make this method inefficient, time-consuming, and a serious threat to the safety of divers [37,38]. In addition, the results of underwater crack detection heavily depend on the subjective experience of the technician, and this method usually limits the operation of the hydropower station and affects its normal production [32].

2.2. Intelligent Monitoring Techniques

2.2.1. Acoustic and Vibration Methods

It was found that the acoustic signal (energy attenuation, travel time of diffracted wave, or the scattered wave field, etc.) and vibration characteristics (frequency, mode shape, modal damping, etc.) of the structure correspond to its mechanical properties [24,39–41], so acoustic and vibration methods can be used to detect underwater dam cracks. The acoustic and vibration methods mainly include ultrasonic detection, vibration-based technology, and impact-based technology. Ultrasonic waves are applied to underwater concrete crack detection because of their strong penetrating force, simple operation, and the absence of the need to consider water resistance [42–44]. The cracking of a structure implies a change in the mechanical properties of the structure, and the acoustic signal and vibration properties are closely related to the mechanical properties of the structure. Therefore, it is feasible to use impact-based and vibration-based techniques to detect underwater concrete cracks. All the above methods belong to non-destructive methods, which can ensure the normal operation of the structure while testing. However, the aforementioned methods are difficult to implement, the survey depth is shallow, and the localization error is large, which leads to the low efficiency of such methods in practice. Moreover, these methods are not suitable for large-scale control due to their high detection cost, low level of automation, susceptibility to interference from various factors, and the need to predict crack locations in advance [45,46].

2.2.2. Electromagnetic Methods

Electromagnetic methods mainly distinguish cracks based on differences in the electromagnetic properties of the medium. At present, the commonly used electromagnetic method for dam underwater crack detection is the ground penetrating radar test (GPR) method [33]. GPR is a non-destructive detection technique that uses high-frequency electromagnetic waves to detect underground objects. This method detects cracks based on the difference in dielectric constant and conductivity between the underwater crack of the dam and the surrounding solid medium, resulting in a change in the waveform of the electromagnetic wave as it crosses the crack. However, this method is usually used to identify cracks in concrete structures above water due to the influence of the complex underwater environment and the fact that the detection effect depends on parameters such as the propagation medium, wave absorption, and reflection coefficient. Among them, Xu et al. [33] used GPR to detect the cracks on the auxiliary buildings of the dam in the actual project. Besides GPR, electromagnetic methods include impedance tomography, the high-density resistivity method, transient current method, etc. However, these methods are rarely used for underwater dam concrete crack detection due to their high cost, limited survey depth, and the limitations of their own use conditions.

2.2.3. Temperature Tracing Method

The temperature tracing method is based on the theory of heat conduction and identifies the crack according to the difference in the cooling rate of the heat source between the crack and the surrounding medium. The schematic diagram of the temperature tracing method is shown in Figure 1. Chen et al. [47] measured the underwater concrete cracks according to the change of heat source cooling rate caused by the change of water content in the porous casing before and after the crack, but this method was less sensitive and could not measure the crack width. Zhu et al. [48] proposed a temperature tracing method and monitoring system for the detection of underwater concrete cracks in dams based on the theory of heat conduction. Zhang et al. [49] amplified the difference in the cooling rate of the heat source before and after crack emergence by using a hollow sleeve, and measured the crack width using an improved monitoring system. However, these methods require a large number of detection pipes to be pre-embedded in the underwater concrete structure, which will have some impact on the performance of the dam during its normal use.

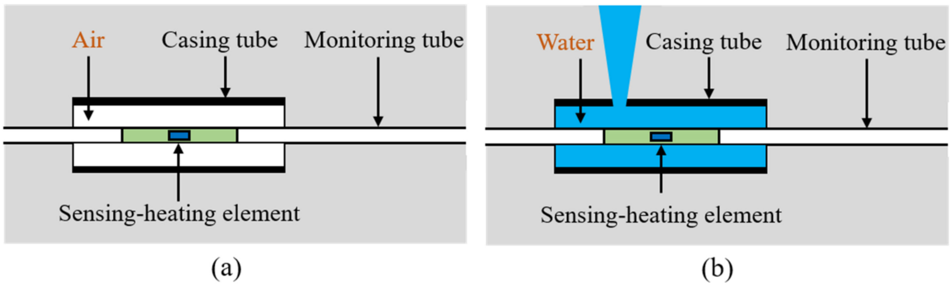

Figure 1. Change of medium around the measuring point before and after cracking: (**a**) before; (**b**) after.

2.3. Digital Image Detection Method

As a low-cost and high-efficiency detection method, digital image crack detection is widely used for underwater crack detection in concrete dams [25,50,51]. Digital image detection methods can be divided into optical image detection methods and sonar image detection methods based on different detection instruments and detection principles. Optical images and sonar images are shown in Figure 2. Optical image detection methods mainly use optical instruments such as cameras to obtain underwater images, and use artificial or computer techniques to identify and measure cracks in the acquired images. However, due to the presence of suspended particles in water, light is prone to refraction and scattering underwater. Water also has certain absorption and attenuation properties of light, and the quality of underwater image acquisition is often difficult to guarantee. Sonar image detection uses ultrasound to obtain high-resolution and wide-area images, which can make up for the shortcomings of optical images in muddy water environments and is an effective means to detect cracks in muddy water [52]. Digital image detection has gradually become the dominant method for underwater crack detection due to its high accuracy, low cost, wide applicability, and non-contact nature with the development of computer technology [20].

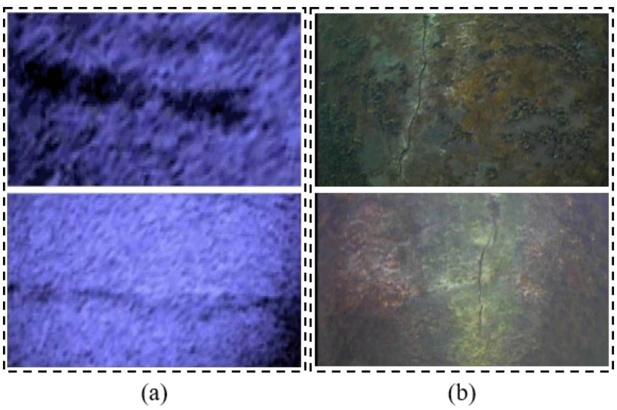

Figure 2. Digital image: (**a**) sonar image [53] and (**b**) optical image.

3. Dam Crack Detection Based on Underwater Robots

3.1. Underwater Robots

As the main tool for humans to explore the deep-sea environment, underwater robots have always been valued by various countries. In recent years, they have played an important role in the development of marine resources and deep-sea exploration [54]. At present, according to the operating space, control mode, and power characteristics, underwater robots can be divided into human-occupied vehicles (HOV) and unmanned underwater vehicles (UUV). In recent years, HOVs and UUVs have played an increasingly important role with the demands of deep and distant ocean surveys. Unmanned submersibles can be further divided into cable remote-operated underwater vehicles (ROV) and autonomous underwater vehicles (AUV) [35]. The classification of underwater robots is shown in Figure 3.

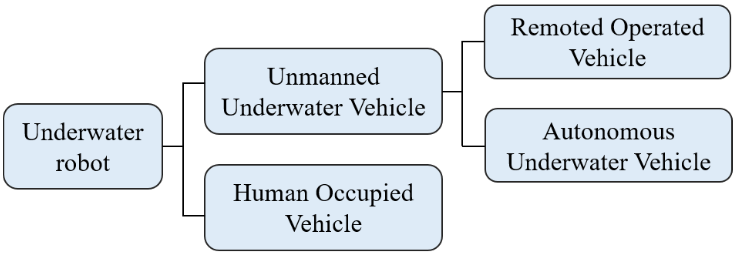

Figure 3. Classification of underwater robots.

HOVs can carry researchers into the deep sea for direct observation, analysis, and evaluation on the seabed, and can operate manipulators to carry out exploration tasks. Since HOVs involve personal safety issues and require a complete and complex life support system, HOVs have a large volume and weight and need to be equipped with complex carrying, lowering, and rescue systems; they are currently mainly used for scientific research and deep-sea investigations [55]. The symbol of the ROV is that it has an umbilical cable, which is the link of the signal and data transmission. The power, video, data, and control signals are connected to the control equipment through the umbilical cable, and are remotely operated by the inspectors to complete specific underwater tasks. ROVs have the characteristics of safety, economy, high efficiency, and large operating depth [56,57]. The AUVs do not need cables to control the underwater robot. The robot has a certain self-judgment ability and carries its own power energy. Since the AUV gets rid of the umbilical cable, the operation is more flexible and the operating range is larger [35]. Underwater robots are shown in Figure 4.

(a) (b) (c)

Figure 4. Underwater robot demonstration: (**a**) "Jiaolong" HOV [58]; (**b**) AUV; (**c**) ROV.

3.2. Application of Underwater Robots in Dam Crack Detection

In recent years, more and more underwater robots have been used in the underwater detection of hydraulic engineering. A variety of advanced underwater detection robots have been developed to provide economical, safe, and efficient solutions for the underwater inspection of large-scale hydraulic engineering facilities. Lan et al. [59] designed and built the "Yulong" dam maintenance submersible for underwater dam damage detection. The submersible can carry technicians to the site to identify defects and detect surface defects of the dam, grasp the underwater conditions of the dam in real time, and obtain comprehensive information on the dam surface in a timely manner. Ridao et al. [60] proposed an automated solution for the visual inspection of hydropower dams, which uses AUV to detect dam walls automatically, shoot images and collect navigation information at the same time, and generate high-quality geographic reference photos to realize systematic inspection. Neto et al. [61] demonstrated an AUV system for a dam underwater inspection task to detect and measure cracks in hydropower dams.

HOV and AUV have broad application prospects in underwater detection, but ROV power is supplied by the umbilical cable, and the working time is not limited. The ROV structure is mainly frame-based, and the portable equipment can be used in various occasions. Therefore, ROV meets the needs of most water conservancy and hydropower engineering inspections due to its advantages of good real-time performance, strong stability, and long battery life. In practical applications, ROV is the main model for the underwater detection of water conservancy and hydropower projects [32,57]. Venkatesh et al. [44] used ROV to carry cameras, sonar, laser, and other sensors for the non-destructive detection of underwater concrete structures, and verified the feasibility of non-destructive detection of underwater structures through experiments. Cruz et al. [62] developed a hybrid AUV/ROV called TriMARES for the inspection and regular monitoring of large dam reservoirs in Brazil. Yang et al. [63] proposed Anchor Driver 5.2 for dam detection, using an ROV with a camera for visual measurement of underwater concrete structures, and conducted a field experiment in the Amagase Dam of Japan. Shimono et al. [64] developed an underwater detection system consisting of an unmanned surface vehicle (USV) and an ROV suspended underwater to obtain the location of the measured point without using any high-cost equipment. Yu et al. [65] applied ROV, sonar, and GPS to track and detect the inclined dam wall with full coverage. Kohut et al. [66] designed an underwater hybrid robot detection system composed of a crawler robot and an underwater robot, which realized vision-based surface crack detection and the estimation of robot position and attitude. Hirai et al. [67] developed an underwater detection robot for the detection of underwater structures such as dams, which can perform video capturing, indirect measurement using a laser, depth and heading keeping, and other functions; it has been applied in actual dam detection, proving its effectiveness.

It is obvious that the development of underwater robots provides a safe, efficient, and economical platform for the detection of underwater structures such as dams. As an underwater mobile carrier, the underwater robot can be equipped with cameras or sonar to easily acquire a large number of underwater dam surface images and detect cracks on the underwater images based on digital image processing methods. However, the current research is still in the stage of data collection by various sensors installed on the underwater robot and detection by the above-water inspectors; the detection is not systematic enough and the degree of intelligence is not enough. In addition, the water environment near the dam is complex, and the underwater steel bars, rocks, etc., threaten the safety of underwater robots and increase the difficulty of underwater image acquisition. Therefore, it is necessary to carry out targeted research of underwater robots in combination with the actual needs in future work, and, at the same time, it is necessary to study more practical underwater robot detection systems and develop intelligent real-time detection technology of dam surface cracks with multivariate data, so as to improve the efficiency and accuracy of underwater crack detection.

4. Application of Image Processing Techniques to Underwater Crack Detection in Dams

Underwater crack image processing refers to the full extraction of underwater crack information through image preprocessing, image recognition, and image segmentation [30]. With the development of image processing technology, digital image detection has become the dominant method for surface crack detection in underwater dams due to its efficiency, low cost, high spatial resolution, and non-contact nature. Currently, the rapid development of underwater robotics has made underwater crack image acquisition more convenient, which has driven the development of digital image detection. The underwater crack detection method for a dam based on underwater robots combined with digital image processing is illustrated in Figure 5. However, the amount of underwater detection image data is huge, and identifying cracks by manual observation alone is time-consuming and inaccurate. Therefore, it is necessary to develop a method suitable for the automatic identification and extraction of underwater crack images on dam surfaces.

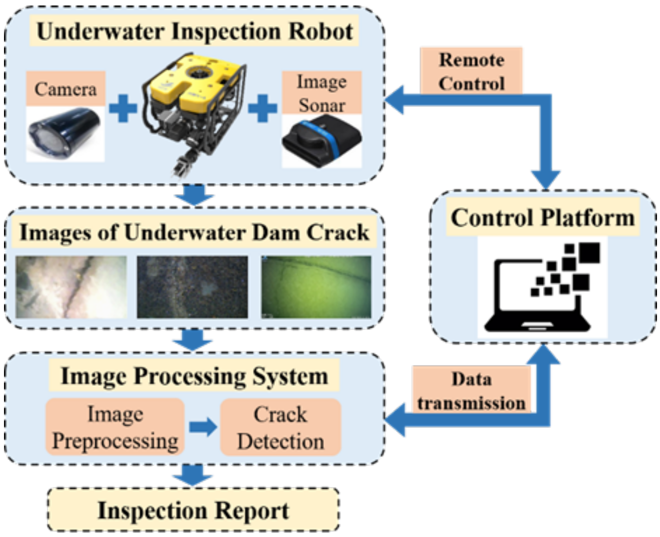

Figure 5. Methods for underwater crack detection based on underwater robots and digital image processing.

4.1. Problems in Underwater Image Processing

The complexity of the underwater environment and the specificity of the medium lead to certain degradations of underwater images, such as image blur, low contrast, color distortion, and other problems. Figure 6 is a comparison of crack images taken in the atmosphere and in water. The two images are quite different due to the different shooting scenarios. It can be seen that the recognition difficulty of underwater images is greatly increased due to the blurred edges of the cracks and the low signal-to-noise ratio by comparison. After years of development, significant progress has been made in the detection of cracks on the surface of concrete dams using image processing techniques, mainly including traditional methods and deep learning-based methods. However, the complex imaging environment of underwater images and the low quality of underwater images make it difficult for these methods to be directly applied to underwater crack detection on dam surfaces.

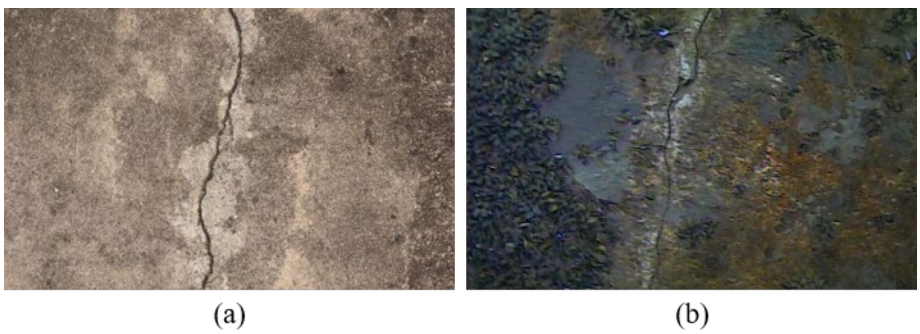

Figure 6. Crack image: (**a**) crack image taken in the air; (**b**) crack image taken underwater.

Traditional digital image processing methods have difficulty handling underwater images. Traditional methods for image crack detection mainly include threshold-based methods [68], edge detection methods [69], and methods based on local [25,70] or global features [71]. Figure 7 shows a comparison of the characteristics of above-water and underwater cracks on the surface of dams, with images of above-water cracks on the left and images of underwater cracks on the right. Threshold-based methods detect cracks by the difference between the gray value of the crack region and the surrounding region. However, in underwater images, inhomogeneous illumination, blurring noise, and shadows make the difference between the gray value of the crack and the background region not obvious, which leads to the difficulty of crack recognition. In the image of the above-water crack on the dam surface shown in Figure 7a, the gray values in the crack region A_{at} and in the background region are quite different, while the gray values in the regions C_{wt} and D_{wt}, far from the source, do not differ much from those in crack regions A_{wt} and B_{wt} in Figure 7b. Therefore, for underwater images, the crack region and the background region cannot be directly distinguished based on the gray value alone. Edge detection is performed by computing the first or second derivative to determine the edge position based on the principle that the gray value at the edge of the crack changes abruptly. However, for underwater images, there is no obvious edge feature at the crack location due to the low contrast of the image. As shown in Figure 7c,d, the edge feature of the crack area A_{ae} of the image in the atmosphere (Figure 7c) is obvious, while the gray value at the edge A_{we} of the crack area of the underwater image (Figure 7d) has no obvious change. It is obviously unreasonable to detect the edge of an underwater crack image directly through an edge detection algorithm. Methods based on global or local features are also no longer applicable due to many factors, such as underwater image noise and image distortion. As shown in Figure 7e,f, the noise of the background areas A_{ac} and B_{ac} of the atmospheric image (Figure 7e) is significantly different from the crack features, while the underwater image (Figure 7f) has areas similar to cracks at the background area A_{wc}, which leads to a misjudgment of the crack region and reduces the accuracy of crack detection.

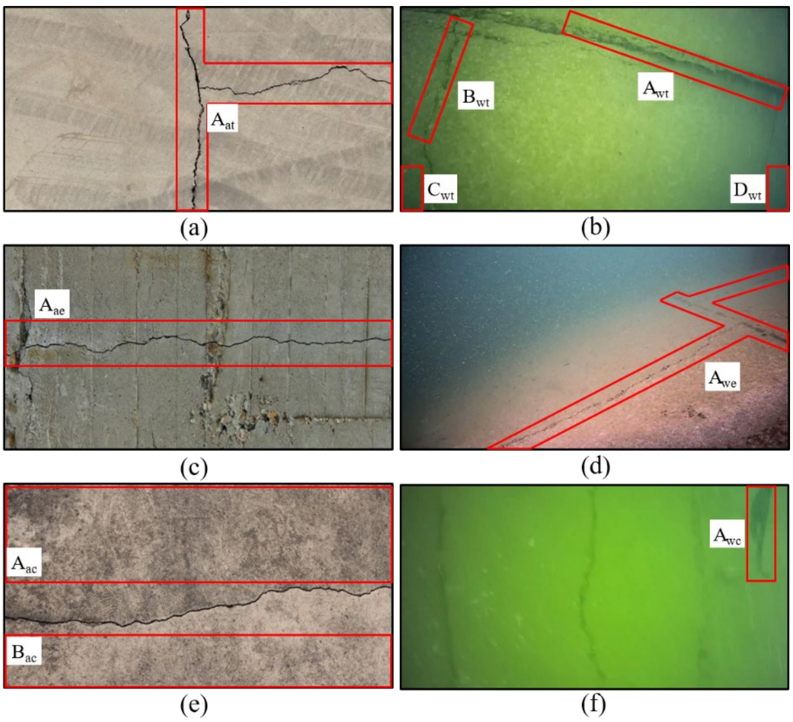

Figure 7. Comparison of above-water and underwater crack images on the dam surface: (**a**) the above-water crack image; (**b**) the under-water crack image; (**c**) the above-water crack image; (**d**) the under-water crack image; (**e**) the above-water crack image; (**f**) the under-water crack image.

Deep learning methods are based on massive crack data to analyze crack features and thus detect cracks in unknown images. Most deep learning-based crack detection methods are supervised learning methods, which require corresponding labels to extract crack features [72,73]. However, due to the peculiarities of the underwater environment, the images obtained by underwater devices are under-calibrated and the fracture images are uncertain and unstable. This leads to the transmission of ambiguous information in the crack images and labels. The crack detection effect of underwater images is uncertain. In addition, the images in different scenes are not similar due to the complex underwater environment, which further reduces the reliability of underwater crack detection.

In summary, the commonly used image processing methods for underwater cracks are difficult to apply directly to underwater crack image detection. Therefore, it is necessary to develop methods for underwater crack identification and feature extraction from dam surfaces.

4.2. Image Processing of Underwater Cracks

4.2.1. Underwater Crack Image Preprocessing

Under the influence of inhomogeneous illumination, absorption and scattering of light by water, nonlinear mapping of photodetectors, and other factors [68], underwater images suffer from problems such as color distortion, low contrast, low signal-to-noise ratio, and few details, which can affect the identification of cracks [74]. Therefore, it is necessary to pre-process underwater images with noise reduction and enhancement to improve image quality and enhance crack recognition accuracy. Among them, removing inhomogeneous illumination and enhancing image contrast are the main methods for underwater image preprocessing.

The cancellation of inhomogeneous illumination is mainly based on the statistical properties of the illumination in the normal regions, and the anomalous regions are pre-processed to obtain underwater cracks under uniform illumination. Currently, methods to eliminate inhomogeneous illumination in underwater crack images include affine shadow transform-based methods [25,32,46], coarse set-based methods [71], dark channel-based enhancement algorithms [75], and methods based on biological principles [74,76]. Although these methods eliminate the influence of inhomogeneous illumination in a certain way, they are slow in processing speed and do not have real-time features, requiring multiple human interventions. Increasing the contrast between cracks and background regions is another direction for underwater image preprocessing. Xin et al. [46] used adaptive histogram equalization to improve the contrast of underwater crack images; Zhang et al. [74] proposed an adaptive enhancement method based on the principles of biological vision, introducing a two-dimensional lateral inhibition network to highlight boundaries and designing a boundary highlight rule to enhance the gray contrast of faint object edges at different luminosities. Underwater image contrast is effectively enhanced by the above-mentioned methods, but there are issues such as slow speed and manual intervention. The methods and results used in the corresponding documents are shown in Table 1.

Table 1. Preprocessing methods and results for underwater crack images.

Author and Year	Approaches/Methods	Results
Xin et al. [46], 2023	Affine shadow transform-based methods and adaptive histogram equalization	The processed image gets uniform illumination.
Ma et al. [32], 2022	Affine shadow transform-based methods	The color deviation of the processed image is small and the definition of the processed image is improved.
Wan et al. [76], 2019	Methods based on biological principles	The image adaptively homogenizes the global brightness of the image according to its overall brightness distribution without human intervention.
Zhang et al. [74], 2018	Adaptive enhancement method based on the principle of biological vision	The proposed method enhances the grayscale contrast at the edges of faint objects at different brightness conditions.
Fan et al. [71], 2018	Coarse set-based methods	Obtained an image with balanced background lighting.
Shi et al. [25], 2016	Affine shadow transform-based methods	The proposed method eliminates the inhomogeneous illumination and well-preserves the crack texture in the image.
Ma et al. [75], 2016	Dark channel-based enhancement algorithms	The proposed method can effectively suppress the noise interference of underwater images and improve the clarity of underwater dam crack images.

4.2.2. Underwater Crack Image Recognition

Image pre-processing methods can significantly improve image quality and make images suitable for crack recognition. In order to assess the extent of the damage to the underwater portion of the concrete dam, it is necessary to identify cracks in pre-processed images of underwater cracks on the dam surface, so as to realize the accurate location and quantification of the underwater cracks on the dam surface. Existing optical image-based algorithms for underwater crack recognition fall into three main categories: traditional, deep learning, and hybrid algorithms. These image-based algorithms for underwater crack detection can be implemented programmatically using MATLAB or Python.

Traditional algorithms are mainly based on prior knowledge of cracks to identify underwater cracks [25]: (1) the gray value of the image region where the crack is located is smaller than the background region; (2) the crack has a slender shape; (3) the possibility of cracks increases with the information entropy. The improved edge detection algorithm is applied to the crack detection of underwater dam surfaces based on the above theory. Zhang et al. [74] proposed an artificial ant colony algorithm for edge detection based on biological principles to detect underwater cracks in dams. Chen et al. [77] proposed an adaptive underwater dam surface edge detection algorithm based on multi-structure and multi-scale elements. According to the differences between cracks and background regions in pre-processed images, crack detection algorithms based on local or global features have also been used to detect underwater cracks on dam surfaces. This approach typically divides the pre-processed image into several image blocks on average and uses the local features of each image block to identify crack and non-crack image blocks and further refine crack regions with global features. Mucoli et al. [20] extracted crack image patches based on local feature clustering. This method only localizes image patches that contain cracks and does not identify specific regions of the cracks. In order to achieve the extraction of fine cracks, Shi [25], Fan [71], and Xin [46], etc., selected crack image patches and fine remove of the non-crack information based on the local features of image patches and the global features of connected regions, respectively. Due to the difference between the gray scale and shape of the crack region and the background region in the pre-processed underwater images, the researchers segmented the surface cracks of the underwater dam based on a morphological approach. Chen et al. [78] distinguished cracks and background regions based on the curvature properties of the 3D spatial surface transformed from a 2D gray intensity map and achieved good results. Benefiting from the development of preprocessing techniques for underwater crack images on dam surfaces, most preprocessed underwater crack images conform to the prior knowledge of the crack. In addition, the improvement over the conventional method makes it possible to identify underwater cracks using the conventional method.

With the development of computer computing capabilities, deep learning algorithms have been used to extract underwater cracks on dam surfaces. Deep learning methods process unknown images based on the results of a large amount of statistical data [79]. However, due to the complexity of the underwater environment and the limitation of underwater photography technology, there are few effective underwater crack images of dam face, and the corresponding image label data are also lacking. Moreover, obtaining the best performing network model is based on repeated attempts with different network structures and repeated tuning of the parameters. Therefore, training a new network model from scratch significantly increases the computational burden [80]. Transfer learning [81] perfectly solves the aforementioned problems of a small amount of data and heavy computational burden by transferring the knowledge learned from the benchmark dataset to the new problem. Fan et al. [72] applied prior knowledge obtained from the source domain to underwater crack image segmentation by using a multi-level adversarial transfer network to reduce the data labeling effort, and integrated an attention mechanism into the segmentation network to achieve higher segmentation accuracy. Li et al. [37] overcame the problem of insufficiently labeled data by using a two-stage hybrid transfer learning approach and using a lightweight semantic segmentation network for real-time segmentation of underwater cracks on dam surfaces. Due to the reduction of the workload of underwater image acquisition and the calculation of network training, the application of the above methods further advances the development of deep learning for underwater crack detection on dam surfaces. Cao et al. [26] proposed a crack detection method to detect large-scale underwater cracks based on graph convolutional neural network. Li et al. [82] used a lightweight deep convolutional network to detect underwater cracks and achieved high performance. A hybrid algorithm, which uses a deep learning algorithm and a traditional algorithm to coarsely locate and accurately segment crack regions, not only overcomes the problem that local features are difficult to select when traditional algorithms are used to localize the fracture area, but also solves the time-consuming and labor-intensive problem of training image labeling when deep learning algorithms are used for accurate crack segmentation. Qi et al. [83] used convolutional neural networks and the Ostu algorithm to achieve accurate segmentation of underwater fracture images, but the segmentation accuracy was insufficient when the background was complex or the fracture was small. The deep learning method has been applied to crack detection in underwater images, which improves the accuracy and efficiency of the underwater crack detection technology.

Due to the low resolution and difficulty in extracting effective features from sonar images [84,85], sonar images are rarely used for underwater crack recognition and are generally used as a complement to visual images. However, the visual image detection of cracks in muddy water environments is limited. At this time, only sonar images can be used to detect cracks. Shi et al. [53] proposed an underwater dam crack detection and classification method based on two-frequency sonar images. The proposed method can be applied to low-resolution sonar images. This approach has been attempted for the detection of cracks using sonar images, providing a reference for the subsequent use of sonar images to detect underwater cracks. However, the detection speed of this method cannot achieve the real-time effect due to the complex computational procedure [37].

As the final result of underwater crack detection on the dam surface, the quantification of the cracks is another key point of the underwater crack detection on the dam surface. There are now related studies on the underwater image mosaic [26] and spatial information measurement of cracks [32,76]. However, the localization accuracy and processing speed of the aforementioned methods in the crack region still have problems. Therefore, the timely and accurate quantification of underwater cracks will be the focus of future research efforts. The methods and results used in the corresponding documents are shown in Table 2.

Table 2. Recognition methods and results for underwater crack images.

Author and Year	Approaches/Methods	Results
Xin et al. [46], 2023	Method of combining local features with global features	The proposed method can detect cracks well in low contrast, complex backgrounds, and uneven illumination conditions.
Ma et al. [32], 2022	Binocular vision method	The proposed method can quickly determine the crack width.
Cao and Li [26], 2022	An improved As-Projective-As-Possible algorithm and graph convolutional neural network	The proposed method achieves stitching of small images to obtain the full shape of underwater cracks. The image segmentation algorithm is highly accurate for cracks in different regions, different water depths, and different degrees of deformation.
Li et al. [37], 2022	Lightweight semantic segmentation network and two-stage hybrid transfer learning algorithm	The proposed method enables the construction of pixel-by-pixel segmentation models of underwater cracks in the presence of limited samples.
Fan et al. [72], 2022	Multilevel antagonism transfer network and improved U-net image segmentation network	The proposed method achieves accurate segmentation of underwater dam crack images, but its real-time performance is poor.
Qi et al. [83], 2022	Convolution neural network and Ostu algorithm	The proposed method can efficiently detect and localize cracks in underwater optical images at low illumination, low signal-to-noise ratio, and low contrast.
Mucolli et al. [20], 2019	Local features: Haralick texture features	The proposed method has high accuracy, robustness to illumination, and reasonable computational efficiency.
Wan et al. [76], 2019	Binocular vision method	The proposed method can obtain the spatial information of defects.
Fan et al. [71], 2018	Methods of combining local features with global features	The proposed method can effectively detect cracks in complex environments without supervision.
Zhang et al. [74], 2018	Edge detection model based on artificial bee colony algorithm	The proposed method can detect dam crack defects in complex underwater environments.
Shi et al. [53], 2017	Crack detection algorithm based on clustering analysis and tensor voting	The proposed method can accurately and efficiently detect and classify underwater dam cracks in complex underwater environments based on sonar images.
Shi et al. [25], 2016	Method of combining local features with global features	The proposed method can accurately and efficiently detect and classify underwater dam cracks in complex underwater environments.
Chen et al. [77], 2012	Adaptive underwater dam surface edge detection algorithm based on multi-structure and multi-scale elements	The proposed method can effectively remove noise and maintain image edge details.
Chen et al. [78], 2012	Morphology-based method	This method enables accurate and efficient detection and classification of underwater dam cracks in complex underwater environments.

5. Summary and Conclusions

During the long-term operation of dams, there will be cracks, erosion, spalling, leakage, and other defects, among which cracks will destroy the integrity of the structure, reduce the bearing capacity of the structure, and seriously threaten the safety of the dam. Therefore, in order to ensure the safe and stable operation of dams, it is necessary to regularly conduct comprehensive crack detection on the dam to observe the development of cracks. However, due to the particularity and complexity of the deep-water environment, the underwater crack detection of dam surfaces is more difficult to carry out. Research on dam crack detection for underwater environments is actively being carried out. Acoustic and vibration methods, electromagnetic methods, temperature tracing methods, and digital image detection methods have been studied for dam underwater crack detection. However, due to the large volume, the large detection area, and the high installation cost of the sensor of the underwater structure of the dam, acoustic and vibration methods, electromagnetic methods, and temperature tracing methods have great limitations and high detection difficulties, which are difficult to apply to the actual underwater crack detection of the dam. An underwater robot combined with the digital image detection method can conduct a comprehensive detection of the underwater dam surface through advanced photography and sonar technology, which greatly reduces the difficulty and cost of underwater crack detection and is more suitable for large-scale underwater dam surface detection. This paper summarizes and reviews the existing methods for underwater crack detection on dam surfaces, and emphatically introduces the underwater robot-based method for image data acquisition and the underwater crack detection method based on digital image processing techniques, aiming to provide a way for researchers to quickly and deeply understand the underwater crack detection on dam surface.

Although image acquisition methods based on underwater robots and underwater crack detection methods based on digital image processing techniques have greatly increased the efficiency of crack detection and reduced the work risk, there are also many factors that can adversely affect the results of underwater crack detection. Based on these, this paper discusses the main future research directions from the perspective of image acquisition and image processing, combined with the key challenges faced by underwater crack detection:

(1) The underwater environment near the dam is complex, and the underwater steel bars and rocks will restrict the operation of the underwater robot. In addition, due to the professionalism of detection requirements, it is necessary to carry out targeted research of underwater robots in combination with actual needs in future work to improve the portability and professionalism of the equipment.

(2) The existing above-water crack detection methods cannot be directly applied to underwater detection due to the specificities of the underwater environment. Preprocessing can enhance the quality of underwater images and achieve better detection results in specific situations, but is not universal. Traditional algorithms and deep learning algorithms cannot be widely used in engineering due to their own limitations. The image detection method of underwater cracks is the key technology for identifying underwater cracks on the dam surface. The technical problems that need to be solved in practical applications mainly include low crack detection efficiency, poor real-time recognition, and few quantitative methods. In follow-up study, the following work can be carried out: (a) the characteristics of optical images and sonar images can be combined to achieve the precise location of cracks; (b) the images of underwater cracks on dam surfaces should be collected to establish an image dataset of underwater dam cracks, which is necessary for training an underwater crack intelligent detection neural network; (c) more advanced algorithms are needed to improve the speed and efficiency of crack detection; (d) it is also important to develop a quantitative method of underwater cracks to establish a systematic analysis system of underwater dam cracks.

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