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Review

A Survey of Target Detection and Recognition Methods in Underwater Turbid Areas

Xin Yuan, Linxu Guo, Citong Luo, Xiaoteng Zhou and Changli Yu *

School of Ocean Engineering, Harbin Institute of Technology, Weihai 264209, China; xin.yuan@upm.es (X.Y.); linxuguo@gmail.com (L.G.); luocitong@gmail.com (C.L.); zhouxiaoteng@stu.hit.edu.cn (X.Z.)
* Correspondence: yuchangli@hitwh.edu.cn; Tel.: +86-138-6310-6670

Abstract: Based on analysis of state-of-the-art research investigating target detection and recognition in turbid waters, and aiming to solve the problems encountered during target detection and the unique influences of turbidity areas, in this review, the main problem is divided into two areas: image degradation caused by the unique conditions of turbid water, and target recognition. Existing target recognition methods are divided into three modules: target detection based on deep learning methods, underwater image restoration and enhancement approaches, and underwater image processing methods based on polarization imaging technology and scattering. The relevant research results are analyzed in detail, and methods regarding image processing, target detection, and recognition in turbid water, and relevant datasets are summarized. The main scenarios in which underwater target detection and recognition technology are applied are listed, and the key problems that exist in the current technology are identified. Solutions and development directions are discussed. This work provides a reference for engineering tasks in underwater turbid areas and an outlook on the development of underwater intelligent sensing technology in the future.

Keywords: turbid water; underwater operation; image processing; target detection and recognition; intelligent sensing

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1. Introduction

Nowadays, underwater intelligent sensing technology is widely used in seabed resource exploration, fishery monitoring, underwater archaeology, underwater warfare, pipeline maintenance, and other fields. It also benefits the economy, military, culture, and other aspects. The future in this field is immeasurable, and the demand for large-scale and long-term monitoring of the internal water body is increasing. Due to the unique underwater operation environment, it has significant benefits but is also accompanied by some challenges. Turbidity is often encountered in underwater development as the required targets always exist in complex water environments, and water contains a variety of organic and inorganic suspended particles. Thus, the direction of light transmission is changed by the scattering or absorption of water and particles, which results in significant interference in the reflected light received by the imaging system, resulting in a significant reduction in the clarity of underwater images. Compared with turbid water, intuitively, the quality and visibility of clear water is good. For example, in a small clean pond, the target characteristics obtained via visual sensing are easily recognized due to the small amount of biological impurities and sediment in the water. Shallow water has the advantage of good light transmittance. However, target detection in turbid water is a significantly challenging task. Turbid water can be divided into shallow turbid water and two kinds of deep turbid water. Shallow turbid water, such as turbid fish farms, has a significant impact on the transmission of light information due to the high density of aquatic organisms and suspended matters, such as fishes and sediments, in the water. This leads to significant image distortion, such as blurred target features, severe distortion, and color changes, which pose a significant challenge regarding visual technology and target recognition. Deep turbid water, such as some deep water areas, is challenged by the same problems as shallow turbid water and has low light conditions, resulting in the instrument receiving limited effective target light information. Due to these factors, traditional target detection and recognition methods cannot meet instruments' technical requirements. Therefore, the investigation of object detection and recognition in turbid areas is necessary. Currently, research on underwater vision is mainly focusing on scenarios with good water conditions, such as experimental pools, lakes, inland rivers, etc. Due to the complexity of underwater environments, significant differences between various types of water exist. As large-scale engineering operations are often carried out at sea, most research methods do not contain adequate robustness to overcome the significant difficulties encountered in practical engineering applications. Focusing on the common applications scenes of turbid areas, this paper systematically collates the relevant research methods and the latest achievements, analyzes key technical problems, and summarizes future development directions.

Since target detection in turbid water is more unique than that in clean water, this paper presents three perspectives: the first perspective is target feature extraction and detection based on deep learning methods, the second perspective is underwater image restoration and enhancement, and the last perspective is image processing based on the polarization imaging approach. The contents of this paper are summarized as follows: (1) the application of ConvNet and a typical network, such as Faster RCNN [1] and YOLOv3 [2], and a comparison of the Canny edge detection algorithm [3] and a track prediction algorithm combined with practical engineering are introduced, and the disadvantages of deep learning methods and their corresponding solutions are analyzed. (2) Some methods, including the migrating defogging algorithm and addition of the haze reduction module, for restoring and enhancing underwater images are summarized. (3) The polarization-based imaging technology [4] and scattering-based image processing methods are summarized and compared. (4) Some minor research methods (such as the use of an electric field) are introduced. (5) The commonly used visual research datasets in visual research carried out in turbid underwater environments are summarized to provide a reference for future study.

2. Research Field Analysis

In recent years, the emergence of deep learning has provided a new direction for target detection and recognition in turbid waters. The combination of this field with image processing, polarization imaging technology, and other areas has also obtained excellent experimental results as presented in the latest papers. However, little scientific research has been conducted on this aspect at present. In this field, scholars engaged in underwater vision have presented some research attempting to improve the scattering and enhancement of image contrast. In the exploration of new methods, researchers who were inspired by biology, such as marine organisms [5], have used electronic communication and sonar to broaden their understanding of solutions and promote the development of target detection and recognition in turbid waters.

Based on the Web of Science [6] database and the keyword turbid zone target recognition, the fields involved in research results presented over the last five years were identified. It was found that the application fields of these studies are very comprehensive, with strong generality and crossover. According to the identified applications of target detection and recognition in turbid waters, it can be concluded that this research field covers a wide range of disciplines. Moreover, it can be applied in, but not limited to, engineering, optics, instruments instrumentation, communication, computer science, oceanography, telecommunications, physics, chemistry and environmental ecology, chemical analysis, and biomedical engineering, such as the detection of targets in turbid solution samples. Figure 1 shows the general statistical results of the application of this study in various areas.

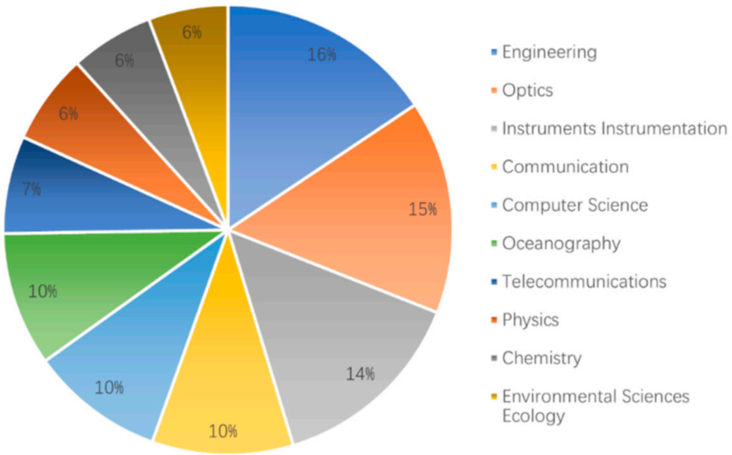


Figure 1. Percentages of different application areas.

Due to the unique environmental impacts of turbid waters, research on target detection in clear waters has progressed more significantly than target detection in turbid waters. At present, most advanced target detection and recognition approaches in water use deep learning, polarization imaging, and other techniques, and researchers have used these methods in turbid water to develop new improved methods, which is significant for promoting the development of underwater target detection technology.

3. Problems in Turbid Areas

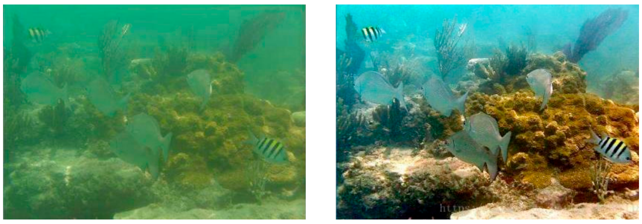
In engineering, common turbidity areas include aquaculture farms, shallow coastal areas, deep sea areas, etc. Aquatic aquaculture farms often result in severe blurring of water bodies due to the density of aquatic organisms and insufficient light transmittance in the water body. Most shallow water receives abundant light, but the turbidity of the water body is high due to coastal sediment, aquatic organisms, and human activities. Deep sea is characterized by weak light but clear water quality. Underwater images of specific turbid waters are demonstrated in Figure 2.

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

Figure 2. Underwater images of turbid water. (**a**) An underwater photo of a fish farm. (**b**) An underwater image of shallow water. (**c**) An underwater image of deep sea.

In general, turbid water cannot be purified, so the density of suspended particles in turbid water results in low contrast, with no inherent characteristics, blurring, and distortion. The most difficult problem encountered during the use of some detection approaches is the scattering effect of water on the light wave. Therefore, strong backscattered light, which carries impurity information, obscures the target data, and reduces the image contrast. Although typical optical image methods, such as the use of underwater cameras, offer an inherently high resolution capability, the unknown imaging conditions, including the optical water type, scene location, illumination [7], and absorption and scattering characteristics of the marine medium, severely limit the image performance. For example, the visible range in the Singapore coastline area is only 2–3 m [8]. Due to the attenuation of reflected light, blurring caused by tiny impurities, and abnormal changes in color, the accuracy of target recognition is reduced.

Considering the objective limitations of optical sensors in underwater scenes, most common detection methods in turbid areas are based on computer vision theory and utilize non-optical sensors, such as lidar, sonar, etc. However, as a result of the complexity and significant interference in turbid waters, these methods cannot provide satisfying results. Thus, the investigation of new approaches based on these methodologies is difficult. This work focuses on target detection methods based on deep learning, some underwater image restoration enhancement methods, and underwater image processing methods based on polarization imaging, which have demonstrated the most advanced target detection performances and meet the requirements of underwater intelligent sensing technology. The underwater image processing effect is depicted in Figure 3.



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

Figure 3. Comparison of images before and after underwater image processing. (**a**) Before analysis of the image. (**b**) After analysis of the image.

4. Research on Target Detection and Recognition in Turbid Waters

4.1. Target Detection Based on Deep Learning Methods

In recent years, deep learning technology has been widely used in underwater image defogging and target identification. Methods based on deep learning investigate image sets by training the neural network and seek to establish a logical relationship to improve the image clarity or extract target features for intelligent recognition. In turbid waters, such as typical fish farms, monitoring of fish in real-time is required. Therefore, accurate identification of targets and prediction of motion trajectories in turbid waters is important. Due to the typical problems, such as low contrast, a lack of inherent features, blurring, and distortion, caused by the turbidity of water or the presence of suspended particles in water in aquaculture farms, target detection of fish is difficult. This section discusses the applicability of deep learning networks for target recognition in turbid waters and methods to improve the deep learning defects.

Traditional target detection methods manually extract the features of target areas, which is time consuming and has poor robustness. With the appearance of the deep learning convolution neural network, the target detection algorithm entered a new stage. Existing target detection algorithms are mainly divided into two-stage algorithms and one-stage algorithms. Two-stage algorithms mainly include the RCNN series algorithms (RCNN [9], Fast RCNN [10], Faster RCNN [1]). These algorithms first generate regional proposals, and then perform classification and regression tasks on the regional proposals. Thus, detection is improved, but the processing time is increased accordingly. Such algorithms are more suitable for the detection of static underwater objects, such as seafloor rocks, corals, etc. Single-stage algorithms mainly include the SSD [11] algorithm and YOLO series algorithms (YOLO [12], YOLOv2 [13], YOLOv3 [2]). These algorithms improve the detection speed and maintain the detection effect as much as possible and use the direct regression method to forecast the category and location of targets. Therefore, such an algorithm is suitable for when the target detection required is frequent due to frequent aquatic activities, such as those of fish.

Effective target feature detectors and classifiers provide deep learning methods with an advantage in turbid water environments, which is why it is important for computers to adapt the fuzzy characteristic of turbid water and precisely identify target features. Lakshmi and Santhanam [14] proposed two types of classifiers: one is a two-classification convolution neural network for distinguishing between the target and background while the other is a multi-classification convolution neural network for predicting the background or one type of target, such as shoes and ropes. They trained a convolution neural network (CNN) to classify 64 × 64 inputs. The images were classified, and the classifier was used as the target feature detector. The accuracy rate of the 2-class convolution neural network was 93.9%, and the target detection accuracy rate of the multi-class convolution neural network was 90.1%, which is higher than existing multi-class detectors (88%).

Phooi et al. [15] focused on the selection and improvement of the basic network architecture in Faster RCNN. They preprocessed the acquired images and tested the basic network performance under different network architectures in Faster RCNN to select the best basic network for image training in turbid media. The experimental results showed that the accuracy of MobileNetV2 [16] on the basic network was 87.52%, which is better than other architectures. A comparison of the experimental results is shown in Table 1.

Table 1. Comparison of the experimental results of different basic networks. The networks were pretrained by the ImageNet.

Type	Number of Parameters	Number of Trainable Parameters	Training Model Storage	Accuracy (%)
ResNet50 [17]	34,386,842	34,356,164	137.8 MB	78.28%
MobileNet [18]	8,280,256	8,255,236	33.3 MB	82.19%
MobileNetV2 [16]	6,743,096	6,701,188	27.2 MB	84.57%
DenseNet [19]	42,726,388	42,672,772	171.4 MB	83.98%

To extract features from turbid areas with significant interference, Wei et al. [20] focused on a one-stage algorithm and proposed a target detection algorithm YOLOv3-brackish based on an improved scale and attention mechanism. In this algorithm, the extrusion excitation module is added behind the deep convolution layer, which enhances the feature extraction ability of the YOLOv3 model. To solve the problem of multiple small targets, the identification of which is difficult, shallow features with greater location information were combined with deep features to improve the detection performance of the small target model. The experimental results showed that the improved YOLOv3-brackish model performed better than SSD, Faster CNN, and YOLOv3, and the effect is demonstrated in Figure 4.

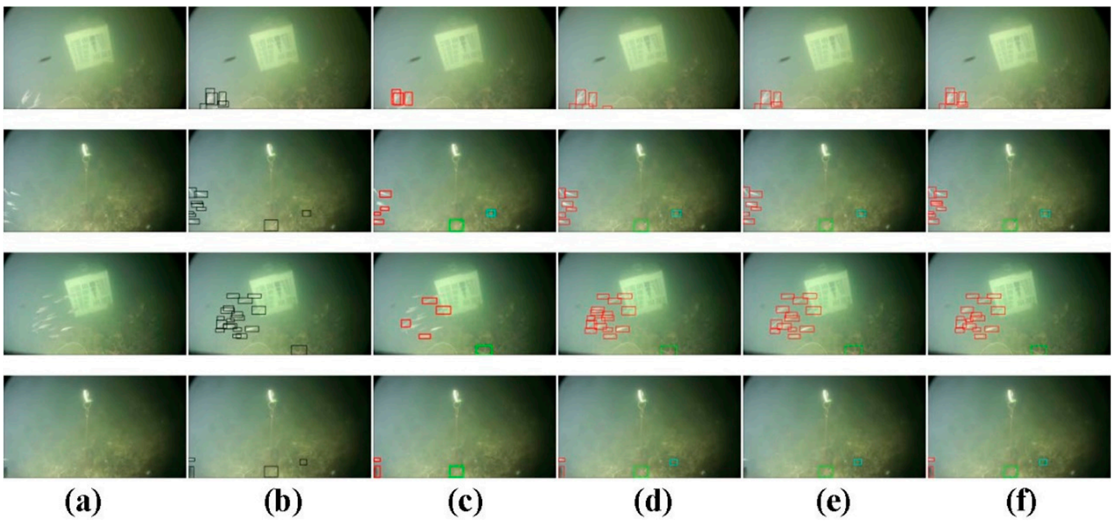


Figure 4. Comparison of target detection results. (**a**) Original picture. (**b**) Correct annotation. The target detection result of (**c**) SSD, (**d**) Faster RCNN, (**e**) YOLOv3, and (**f**) YOLOv3-brackish.

Liu et al. [21] combined image processing with deep learning to realize species identification and density calculation of marine organisms to monitor the invasion of marine organisms in real-time. An underwater camera was used to capture image data in real-time within the monitoring range and deep learning was used to achieve end-to-end recognition of jellyfish. First, the convolution neural network was designed and improved, and a convolution neural network composed of two convolution layers, two pooling layers, and a full connection layer was obtained. After training, the convolution neural network was predicted using test sample images. Under the non-uniform light field, the characteristics of the biological images taken in turbid water were investigated using image sharpening, edge detection, edge closure, hole filling, etc. A binary image separate from the target and background was obtained, demonstrating real-time estimation of the marine biological density. The results showed that this method can be effectively applied to calculate the marine biological density and detect marine biological species. This study provides a reference for the early warning of biological invasion in offshore waters.

Ahmed et al. [22] focused on the comparison of various existing edge detection methods, including Laplace, SobelX, SobelY, Combined Sobel, and the Canny detector. The results of these methods were obtained and analyzed, as shown in Table 2.

Table 2. Results of edge detection algorithms.

Type	Accuracy	Accuracy Evaluation
Laplacian [23]	68.9%	Normal
Sobel X [24]	79.26%	High
Sobel Y [24]	79%	High
Combined Sobel [25]	88.9%	Very high
Canny [3]	89.13%	Very high

When the Laplace method was used, the accuracy was 68%. The accuracy of SobelX was similar to that of SobelY. Canny showed higher accuracy than the other methods and has been widely used in edge detection. Therefore, the Canny edge detection method is the best algorithm for detecting the edge of the target contour in a turbid area.

In practical engineering applications, an algorithm that can identify the underwater bios trajectory of fisheries to enable easier localization and capture has also been investigated. As an optimization tool, the genetic algorithm has been widely used in various fields, but it has not been fully studied in terms of the trajectory prediction of moving targets. However, in a recent study, the concept of the dynamic traveler problem based on the genetic algorithm and Newton equation of motion was used to obtain excellent results in predicting the minimum distance traveled by a moving fishing boat in the future. Since use of the genetic algorithm (GA) in this field has not been fully realized, Palconit et al. [26] further discussed its application potential in fish tracking based on GA. On the other hand, the deep learning algorithms recurrent neural network (RNN) and long short-term memory (LSTM) have been used in several visual track prediction methods to predict targets, including pedestrians, vehicles, mobile robots, fish, etc. The results from these methods were shown to be better than most tracking methods, and thereby underwater video fish tracking research has been carried out based on RNN-LSTM. The results showed that trajectory prediction using LSTM is more accurate than the use of a genetic algorithm, but both showed an acceptable accuracy and the average absolute percentage errors of GA and LSTM were 2.8~30.5% and 3.33~17.74%, respectively. LSTM has been widely used in trajectory prediction in many fields while the genetic algorithm has seldom been used as a trajectory prediction method. The results of GA can be improved through the use of additional variables or fitness functions, such as Newton's equation of motion and quadratic regression. Three-dimensional coordinates have been shown to provide more accurate prediction results for GA and LSTM, so it can be further extended for two-dimensional and three-dimensional path prediction in the future, such as the use of GA and LSTM in fish tracking and marking or investigation of its combination with other tracking algorithms.

Intelligent target recognition and positioning using deep learning methods is powerful. However, the accuracy of underwater target recognition is affected by the image clarity, and deep learning methods are only applicable in waters that are similar to the training set image, so this method has some limitations. Therefore, the combination of good image restoration methods and deep learning methods can make target detection and recognition in turbid waters more effective.

4.2. Underwater Image Restoration and Enhancement Methods

Deep learning has been widely used in underwater image restoration and enhancement to improve the quality of underwater images to a certain extent. Methods based on deep learning can be used to study the relationship between the features of an image set by training the neural network, and reduce the error caused by prior invalidity. Some characteristics of turbid water are similar to those of foggy weather, including problems regarding the attenuation of reflected light, blur caused by tiny impurities, and abnormal changes in color. These factors result in severe color distortion and low visibility [27] in the captured image, so suitable light models and algorithms need to be developed to eliminate any negative impacts. Because underwater image processing and defogging have certain similarities, various defogging algorithms have been gradually improved for application to the enhancement of underwater images.

Thomas et al. [28] developed a fully connected convolution neural network for underwater image defogging. The integration of low-level and high-level features through the depth frame of the encoder-decoder helped to restore blurred images, showing better results than existing methods, such as the structural similarity index (SSIM) [29], peak signal to noise ratio (PSNR), and mean square error (MSE). It was also able to retain details during the removal of fog. Dudhane et al. [30] proposed an end-to-end trainable image defogging network called LIGHT-Net, which includes a color constancy module and a haze reduction module. The color constancy module was used to remove color differences in the image caused by the weather conditions, and the haze reduction module used an initial residual module to reduce the haze effect. Feature sharing was also proposed in this module, which means the features learned at the initial level are effectively shared through the network. The experimental results of this method are promising. Yin and Ma [31] proposed a migration learning method for several types of naturally degraded image enhancement, including underwater image enhancement. They used transfer learning for each specific natural degradation. By repeatedly applying the general enhancement model, they overcame existing problems regarding the shortage of training datasets for in-depth learning methods and the computational burden of the training process. The enhanced model was finetuned, and its performance surpassed several of the most advanced methods designed for specific tasks, such as uwcnn [32] and funie-gan [33].

Martin et al. [34] proposed a combination of image enhancement, image recovery, and the convolution neural network, resulting in a method for target detection of recovered images. Due to the maximum number of green pixels in underwater images, under dark channel prior method (UDCP)-based energy transmission restoration (UD-ETR) was proposed to process green channel images and obtain the recovered images. The image processing results are displayed in Table 3.

On this basis, a method for fish detection in restored images using CNN was proposed, and a PC-based automatic target detection recognition visual system was developed. The training results of CNN were also shown to be significantly better than that of the traditional model, which solves the problem of inaccurate target detection caused by blurred images.

Table 3. Comparison of the parameters from transmission map estimation and UD-ETR.

Parameters	Existing Approach (Transmission Map Estimation) [35]	Proposed Approach (UD-ETR-Based Restoration)
Contract luminance	39	89
UCIQE	12	26
Saturation	0.1	0.5
Chroma	2.5	5.5
PSNR	5	14
RMSE	140	50
MSE	1.7	0.3

Cecilia et al. [36] proposed an effective edge perception restoration and enhancement model for severely blurred shallow coastal images with low contrast. Restoration methods, which are based on the dark channel and rolling guidance filter, were used to restore and denoise such images, resulting in clearer edge perception. This method introduced a rolling guidance filter in dark channel prior (DCP) restoration, which effectively restored images and decreased the noise in the images. This experiment showed that the rolling filter based on the recovery model has better denoising effects.

Regarding the enhancement of the quality of underwater images taken in different water body types, the image forming model used in earlier methods is imprecise and its restoration effect is poor. Zhou et al. [37] developed a defogging method using a modified model. They first designed an underwater image depth estimation method to create depth maps and estimate backscattering based on the depth values of each pixel, and then removed backscattering based on a more accurate underwater imaging model. To address the color distortion characteristics of the turbid area, they proposed a color correction method to automatically adjust the global color distribution of an image. This method used a single underwater image as the input, eliminating the effects of light wave absorption and scattering. Experiments have demonstrated that this approach has better applicability compared with previous research methods.

Considering that scattering attenuation and color correction of high-turbidity underwater images affects the classification results of target recognition based on machine learning (ML), Li et al. [38] proposed a contrast-enhanced method to remove scattering. This enhancement method considers the illumination and camera spectral characteristics, eliminates scattering, and correctly restores the scene color. They also used different ML approaches for classification in their research to confirm that this method can be applied to classification and recognition architecture preprocessing based on deep learning, which showed a better image classification effect. However, for practical applications, use of the scattering removal algorithm does not provide the accuracy required by practical engineering.

Yang [39] proposed an underwater polarized imaging target enhancement technique based on non-polarized illumination to overcome the disadvantages of the current underwater polarized scattering algorithm, such as its low accuracy and limited application range. The use of unpolarized light ensures that any polarization difference between the target reflected light and stray light can be detected. At the same time, the characteristic parameter of the polarization angle ensures accurate estimation of the stray light intensity. Compared with current underwater polarized imaging technology based on linear polarized light illumination, it has a wider application range and higher image restoration accuracy. The results showed that the visibility of underwater restored images is improved effectively, and the contrast is improved by at least 100%. Meanwhile, this technique can be applied to water environments with various material targets, imaging distances, diverse impurities, and turbidity levels, and has potential application value in many underwater imaging fields.

Drews-Jr et al. [40] proposed a new underwater restoration method based on monocular image sequences, which utilizes the time relationship and geometric and environmental information to improve the quality of visual features in underwater images. It can also robustly estimate the depth map and attenuation coefficient. The attenuation coefficient is used to evaluate the loss of light in the medium, so the accuracy of its estimation affects image restoration. Depth estimation is realized using adaptive optical flow and structure motion technology, and the attenuation coefficient is estimated by introducing an underwater optical attenuation model into the RANSAC frame [41]. Meanwhile, a depth map is estimated from the combination of motion structure technology and model-based restoration. The simulation and real image test results showed that the method restores the image, thus improving the ability of target recognition and feature matching.

Cheng et al. [42] proposed a method for image fusion based on the Mueller matrix to enhance the quality of underwater degradation images. Each Mueller matrix element image is given a weight and fused to generate a new image. The optimal weights are obtained by searching for values that maximize the image quality. The validity of this method was proved by comparison with the Mueller matrix image and the latest method using objective and subjective analysis. Moreover, the image was enhanced using analog weights. Due to the nature of the Mueller matrix, this method improves the underwater observation distance and image quality, and provides the enhanced images with information that is unavailable when conventional methods are used.

Due to the absorption and scattering of light in water, color projection and poor contrast are often present in underwater images. Zhou et al. [43] proposed an underwater image restoration method based on a priori underwater features. They first established a powerful model to estimate the background light based on the characteristics of flatness, hue, and brightness, thus effectively mitigating color distortion. The red channel of the color-corrected image was then compensated to correct its transmission map. The rough transmission diagram was refined by combining it with a structure-guided filter.

4.3. Underwater Image Processing Based on Polarization Imaging and Scattering

The most difficult problem encountered during optical detection in turbid areas is the scattering effect of water on the light wave, which mainly results in low image contrast, a reduction in resolution, and image blurring. Scattering includes forward and backward scattering processes. When forward scattering occurs, light deviates from the original transmission path, resulting in a reduced image resolution and blurred image. Backscattered light, which carries suspended particulate information, produces a ‘curtain effect’ on the target image and reduces the image contrast. Therefore, it is necessary to overcome the scattering and reflection problems in underwater imaging to improve the imaging distance and quality.

Polarized imaging technology has obvious advantages in removing background scattered light and achieving clear underwater images by deeply mining the uniqueness and differences in polarization information in a scattered light field. Currently, accurate estimation of the polarization characteristics and relationship between target information light and background scattered light, inverting the intensity distribution of target information light and background scattered light, are key research areas of underwater imaging technology. Research has shown that the polarization characteristics of incident polarized light can be used to separate these two kinds of light in a scene, effectively restoring a clear scene, improving the contrast and clarity of imaging results, and aiding underwater target detection and recognition. Because underwater search and rescue operations often face target detection problems in high-turbidity water, exploration of polarization imaging technology that is suitable for turbid water is necessary. An overview of this method is depicted in Figure 5.

With a long research history and significant basic experience, polarization imaging technology is suitable for more in-depth research in this direction. Currently, polarization imaging methods are being developed for the unique environment of turbid waters.

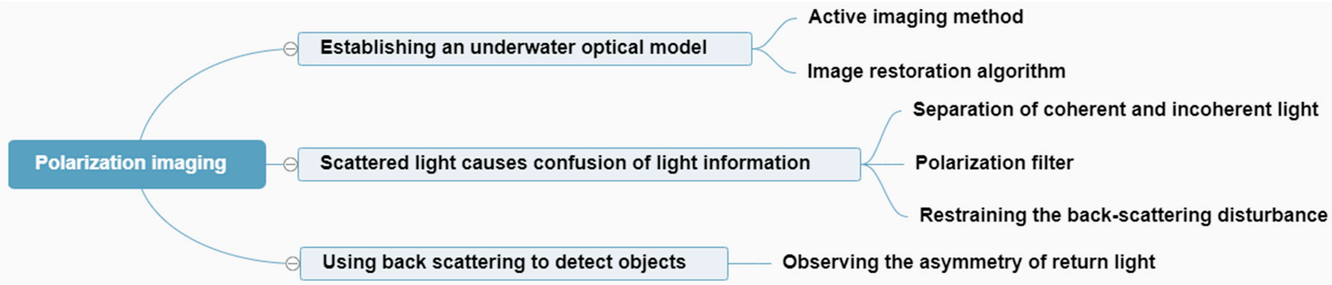


Figure 5. An overview of underwater data processing methods based on polarization imaging.

Underwater models for studying turbidity and illumination have been established, which is helpful for optical research of target detection and recognition in turbid waters. Bailey et al. [44] proposed a model based on the spatial variation in underwater environments and coherent light and used it for low-contrast target detection in turbid water. This model was used to theoretically study the effects of turbidity, projection space-frequency variation, and three-dimensional target shapes on unstructured scattered light components and the target structured return signal. The results showed that the model's accuracy is adequate for the modeling of noise reduction technology. This result indicates that the received three-dimensional target image can be modeled with backscattering and structured illumination, and noise reduction and target identification can be achieved in the model environment. Based on the image degradation model, Han [45] considered image degradation due to the joint effects of forward and backward scattered light, estimated the degradation function of forward scattered light using the edge method, and further restored clear scene images. He constructed a turbid water polarization imaging model, and then obtained the polarization degree of target information light and background scattered light using the optical correlation principle to restore the clear scene.

On the premise of establishing an optical model, Han [45] proposed an active underwater polarization imaging method, which is based on the imaging noise analysis model, and studied the effect of noise that is introduced during the polarization imaging process on the final imaging quality. This method resulted in the best polarization azimuth image for active underwater polarization imaging, and the relationship between different polarizer images and the final imaging quality was established. This method can effectively realize the imaging distance in a high-turbidity water body, improve the imaging quality and detection effect, and providing support for underwater search and rescue work in rivers and offshore areas.

Huang [46] proposed a polarization image restoration algorithm and a new curve fitting-based method to estimate the target signal of polarization difference images. Based on the polarization effect of reflected light in underwater imaging, the former was used to restore underwater blurred images with polarization imaging, and study the imaging model of underwater active illumination imaging systems and the transmission behavior of polarization information in an underwater turbid medium. The latter considers the polarization effect of the reflected light from the object in the scene to derive the true transmission coefficient image and underwater restored image. Both can overcome the invalid detection problem in the area corresponding to objects with a low degree of deflection and effectively enhance the underwater imaging quality.

As backscattered light occurs due to the presence of high concentrations of impurities in turbid water, the reflected light from an object is easily confused, which makes it difficult to distinguish the object from the environment. Therefore, the division of reflected light from interfering light, such as backscattered light, which reflects the characteristic of the object, is a core issue for underwater image processing using polarized imaging. At present, several methods, such as optical sensing technology, the polarization filter method, and the backscattering interference suppression method, that can separate coherent light from incoherent light exist. Cochenour et al. [47] proposed new optical sensing technology based on the orbital angular momentum (OAM). The target is illuminated by a Gauss beam. By setting a diffraction spiral phase plate at the receiving end, the reflected and backscattered light of the object passes through the phase plate to form vortex light, thus spatial separation of coherent and incoherent light is achieved. Experiments have shown that the echo of a ballistic target can achieve detection that is two to three orders of magnitude the level of backscattered clutter. The detection of this coherent element is realized using a complex optical heterodyne scheme. In addition, the detection of this small coherent signal is completed without the use of any complex optical heterodyne scheme, which indicates that the unique characteristics of OAM can be used to distinguish between objects and the environment. Amer et al. [48] used a polarized imaging optical system to reduce the influence of underwater beam diffusion on image acquisition and optimized the DCP method. They used a low-pass polarization Gauss filter to calculate the illumination from the input image and enhance underwater optical imaging, which reduced the long running time and ameliorated the efficiency reduction of traditional algorithms with the increase in turbidity. Moreover, the visibility of this method was significantly higher than that of the traditional DCP method and the processing time was reduced by nearly 50-fold. Zhao et al. [49] proposed an underwater image restoration method based on transmission correction for when the object polarization effect cannot be ignored. Without sacrificing the quality of image restoration, this method showed a better performance, has a simpler algorithm, and used less computational time than previous methods. This approach converts the transmittance of a low depolarized object from a negative value to a positive value and uses a simple polynomial fitting algorithm to optimize the image quality. The results showed that it can effectively improve the quality of underwater images regardless of the degree of depolarization of the target. The suppression of background backscattering interference also combines polarization imaging technology with image processing technology, which has greater engineering application value. Zhao [50] proposed a target detection algorithm based on guided filtering combined with ViBe and a secondary target detection algorithm based on polarization difference image and intensity image fusion combining image processing and polarization imaging technology. To eliminate the influence of the backscattering of scattered particles in turbid media, enrich the detailed information of the detection target, and improve the effectiveness and practicability of the target detection algorithm, the author established a database containing the light polarization characteristics of different turbid media and typical targets to provide prior knowledge for information analysis and target detection of polarization imaging in certain circumstances. The former has certain advantages for target detection in turbid liquids but has certain requirements regarding the turbidity range of the media. The latter has a greater experimental effect, improving the image quality and significantly suppressing the interference that occurs due to background backscattering.

Hunt et al. [51] thought that the prediction of the correct target return value using ML would also produce a better backscattering interference suppression effect. This method is suitable for 3-D underwater imaging of signals reflected from targets using lidar in turbid waters. When the receiver encounters backscattering of scattered particles from turbid media, it produces false peaks (both from scattering reflections and from scatter-introduced shot noise), which makes it difficult to determine which peaks correspond to the object. Underwater lidar systems have been used in turbid waters and an ML model has been used to detect target signals. The experimental results showed that the accuracy of the ML classifier was significantly better than that of the baseline detector under high turbidity conditions, which indicates that this method could improve the performance of underwater lidar systems, especially for systems with a realized frequency domain and other scattering suppression techniques. The classifier worked well under low turbidity conditions, thus having good application prospects for high turbidity conditions.

However, Hu et al. [52] identified the limitations of previous polarization-based underwater image restoration methods and proposed a method for estimating the spatial distribution of the degree of polarization (DOP) and backscattering radiation based on extrapolation fitting. Past limitations include the assumption that DOP of backscattering and the irradiance of backscattering at infinite distances are constant. They believed that the assumption that the identification of the inherent parameters of underwater imaging conditions, including the degree of polarization of backscattering and the backscattering intensity at the various positions of an image, as spatial constants is inappropriate in many cases for polarized imaging in turbid mediums. For example, in inhomogeneous light fields, the intrinsic parameters of underwater imaging conditions may vary with the shooting position, and if these parameters are considered as constants, in some areas of the scene, the image quality may deteriorate. The experiment results of the new estimation method showed that the quality of underwater images can be significantly improved under the conditions of a non-uniform light field, and the quality of the restored images at various locations can be maintained at a high level.

Regarding the significant light scattering effect evident in mixed water, a new method for target detection by backscattering was proposed. Wu et al. [53] proposed a method for target detection and geometric contour analysis based on backscattering asymmetry. The asymmetry of the returned beam was observed by using different propagation depths, transverse coherence lengths, and propagation angles of the beam. This asymmetric model was converted into a surface inclination angle and different surface gradients were obtained by collecting two-beam scans to reconstruct the basic surface contours of the target. The experimental results showed that the asymmetric method is capable of target detection and contour analysis using the differential parts of the backscattered signal when the backscattered light interference is strong. This method is also compatible with continuous-wave and pulsed lasers, which can provide a low-cost platform using a continuous wave laser or can be combined with the time-of-flight concept, using a pulsed laser to enhance the effect. Compared with the traditional visual limit of high-scattering underwater environments, this method can extend the detection range of these features by three to five times under certain turbidity conditions.

4.4. Other Methods

Other methods for target detection and recognition in turbid waters also exist, which are not restricted to inertial thinking. It is necessary to explore other methods. For example, for subsea pipelines and underwater pipelines, sonar can effectively identify targets, and electronic communications can also be used for target detection and positioning.

Liu [54] found that forward-looking sonar is prone to interference when imaging linear targets in water. The geometric, grayscale, and statistical features of such interferences are similar to real targets, which easily leads to misjudgment and omission of the visual system. Therefore, underwater linear target detection technology combining the Hough transform and threshold segmentation has been proposed. This method combines the Hough transform and threshold segmentation and uses the Hough transform to restrict the orientation of threshold segmentation. Meanwhile, threshold segmentation provides a detection basis for the Hough transform, and the two interact. When the statistical characteristics of the change in the segmentation area with the attitude are used as the objective evaluation conditions, this method can effectively extract linear objects, such as pipes, and the straight-line part of the target area is neat, with less external noise. For sonar images from other angles that are not displayed, the segmentation effect of this method is still better than some other segmentation methods.

In nature, weak-current fish generate electric fields, which are used for navigation and target detection, and the recognition of terrain and prey. Inspired by this biology, Chen et al. [5] studied the effect of obstacles on electronic communication in quasi-two-dimensional water environments with bionic electronic communication systems. They first applied the Fresnel zone theory to theoretically analyze the influence of obstacles on electronic communication, simplified the marine terrain obstacles, and used ANSYS Maxwell to simulate the impact of these obstacles on electronic communication. The simulation and experiment results showed that the material, relative position, geometry, and size of the obstacles have different effects on electronic communication. This work illustrated the possibility of underwater target recognition based on the obstacle effect, which indicates that electronic communication could represent a new and feasible underwater target detection method, and further proves that a robot integrated with an electronic communication system can detect underwater targets using the obstacle effect.

4.5. Engineering Technology Summary

In terms of the division of technical application fields, underwater operation in various turbid areas requires different technical support. The deep-sea engineering detection area is a typical 'deep and clear' water area, for which the main difficulty is the shortage of light, which leads to low-contrast and blurred images. Therefore, the construction of a model for the optical environment of the seafloor in necessary or an artificial light source or polarization imaging should be used for image processing. 'Shallow and turbid' waters often have plenty of light and do not required an artificial light source, but the turbidity of the water is high, and the background scattered light intensity is strong, so an image restoration model should be established, and target features extracted by removing background scattered light interference. Deep-water aquaculture farms represent a typical 'deep and turbid' area, with a turbid water body, poor light transmittance, and high aquatic biological density. Moreover, compared with deep-sea engineering work areas, it is more likely that the engineering requirements include identification of the quantity, type, health status, and movement tracking of aquatic organisms. These projects vary according to the actual conditions. Therefore, deep learning and ML should be flexibly used to achieve engineering automation. This combines underwater image restoration and enhancement techniques to improve the accuracy of depth learning methods.

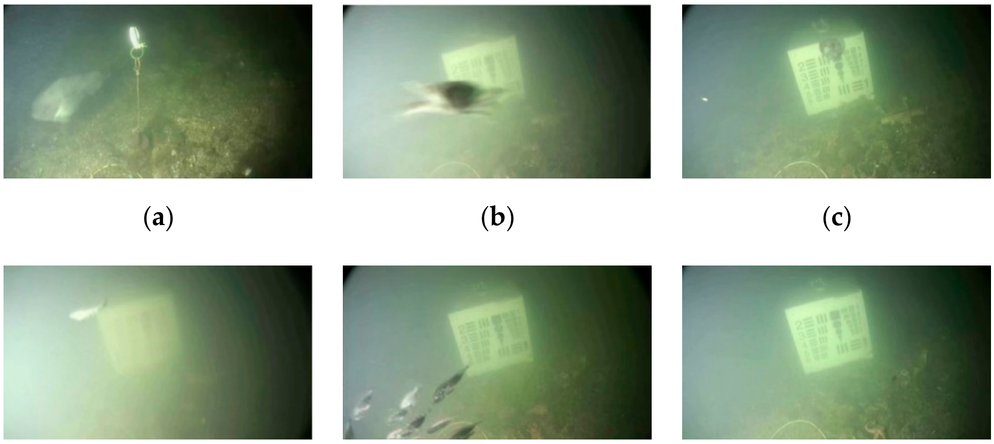
4.6. Datasets for Target Detection and Recognition in Turbid Water

Due to the uniqueness of turbid waters, underwater image datasets are scarce, and have high acquisition costs. Rich and open-source datasets support deep learning theory and effective application, so greater attention should be given to the collection of underwater image datasets in the future. The Open Image Dataset [55], as a composite dataset, contains about 9 million images spanning about 6000 categories and contains more real-life entities than ImageNet. It contains a significant number of aquatic images and underwater image data, which provide sufficient training data for training depth learning network models.

Mja et al. [56] introduced an extended underwater image database for salient target detection or salient detection. This dataset is called the Marine Underwater Environment Database (MUED), and contains 8600 underwater images with 430 sets of significant targets. These images have complex backgrounds, many targets, and complex changes in attitude, space position, light, water turbidity, etc. This database also includes manual annotation of truthful information to study more robust underwater image processing and underwater computer vision methods. It can be used to evaluate the performance of target detection and recognition technology in turbid waters, and benefits the development of underwater vision technology, thereby providing unprecedented opportunities for underwater vision and other researchers. Some examples of MUED are displayed in Figure 6.

Figure 6. Example of MUED.

The Brackish dataset [57] is a real underwater biological video dataset, captured 9 m from the water surface at the bottom of Limfjorden, Denmark. This dataset divides videos by frame into more than 14,000 images with a size of 960 × 540. It contains more than 11,000 images, including targets to be detected, and more than 3000 images with undetected targets. The entire dataset consists of six categories: big fish, small fish, crab, shrimp, and jellyfish, as depicted in Figure 7.



(a) (b) (c)

(d) (e) (f)

Figure 7. Example of the Brackish dataset. (**a**) Big fish. (**b**) Crab. (**c**) Jellyfish. (**d**) Shrimp. (**e**) Small fish. (**f**) Star fish.

The uniqueness of the dataset is that it contains many small aquatic organisms, especially small fish and crabs. The distribution of small fish is centralized, and the dataset also contains some incomplete images of detected targets.

The Underwater Image Enhancement Benchmark (UIEB) [58] includes 950 real underwater images, of which 890 have corresponding reference images, and the other 60 underwater images that do not have better reference images are used as challenging data. Using this dataset, the most advanced underwater image enhancement algorithms can be comprehensively studied, which is suitable for training CNN.

The Stereo Quantitative Underwater Image Dataset (SQUID) [59] is an image dataset that contains images taken at various locations, with different water properties, and displays color charts in the scene. This dataset can quantitatively evaluate the restoration algorithm of natural images.

The Heron Island Coral Reef Dataset (HICRD) [60] is a large real underwater image dataset for underwater image restoration. It contains 2000 reference restored images and 6003 original underwater images in the unpaired training set. A summery of the datasets described in this section is provided in Table 4.

Table 4. Dataset summary.

Dataset	Main Content	Analysis
Open Images Dataset [55] https://github.com/openimages/dataset (accessed on 30 January 2022)	Comprehensive dataset	Open source, diversity, wide extending, suitable for multi-class classifiers.
MUED Dataset [56] https://zenodo.org/record/2542305#.Ynd05YxBxEZ (accessed on 30 January 2022)	aquatic organisms image set	Complex background with large number of targets, which is suitable for the high-order training and the verification of a deep learning network.

Table 4. *Cont.*

Dataset	Main Content	Analysis
Galdran A et al. [61] https://github.com/agaldran/UnderWater (accessed on 3 February 2022)	underwater biological image set	Includes some species of underwater organisms.
SQUID Dataset [59] https://paperswithcode.com/dataset/squid (accessed on 3 February 2022)	Underwater stereo quantitative image dataset	Contains different water properties, which is suitable for image enhancement and restoration.
Brackish dataset [57] https://www.kaggle.com/aalborguniversity/brackish-dataset (accessed on 2 February 2022)	Underwater bios video (including many small aquatic creatures)	Includes small aquatic organisms, which is suitable for verifying the ability of high-precision recognition.
HICRD Dataset [60] https://paperswithcode.com/dataset/hicrd (accessed on 3 February 2022)	Underwater image dataset	Large dataset for underwater image restoration.
UIEB Dataset [58] https://li-chongyi.github.io/proj_benchmark.html (accessed on 2 February 2022)	Underwater enhanced image dataset	Contains reference images and non-reference images, which is conducive to the verification of results.

5. Applications of Underwater Target Detection and Recognition Technology

Underwater turbid area target detection and identification technologies are used in a wide range of applications, including the detection of underwater organisms and underwater equipment. The need for productivity and automation in the aquaculture industry has given rise to technologies for the detection of underwater organisms, including fishes and sea cucumbers and shrimps, crabs, and scallops. This technology's aim is to achieve automated identification of the species, numbers, health status, and behavior patterns of underwater organisms. The detection of coral reefs has also been extensively studied due to the need for ecological monitoring. In addition, some underwater environments require habitat mapping and mineral identification. The inspection of underwater equipment includes many aspects, such as cables, pipes, hull corrosion, cracks, and welds.

5.1. Target Detection and Recognition of Underwater Organisms

Target detection technology is used to monitor fish and sea cucumbers in aquaculture, most of which use deep learning methods for detection. Kandimalla [62] developed a fish channel observation platform, which combines the convolutional neural network and Kalman filter to realize automatic detection of fish species and quantities using sonar and optical cameras. Yu [63] proposed a method for identifying the unique behaviors of fish schools based on simulated feature point selection (SFPS). By combining feature point extraction with special behavior recognition, the detection accuracy of feeding behaviors was 96.02%.

Li [64] proposed an underwater sea cucumber image enhancement method based on the fusion of the Retinex algorithm and dark channel prior algorithm. Using the evaluation indicators of the MSE, equivalent numbers of looks (ENL), information entropy (IE), and signal to noise ratio (SNR) values, this method has shown an advantageous effect regarding defogging and the enhancement of underwater sea cucumber images. Zhang [65] performed sea cucumber detection based on a stochastic gradient descent algorithm, and the developed recognition model performed well on various forms of obstacles and natural sites. Li [66] proposed a sea cucumber detection method based on Faster R-CNN and plotted the motion trajectories of sea cucumbers. The experimental results showed that this method enabled accurate identification and localization of sea cucumbers. Analysis of the behavioral patterns of sea cucumbers through deep learning provides valuable information for the health status assessment and early identification of diseases in sea cucumber farming.

Cao [67] proposed a real-time lightweight multi-scale object detection algorithm called Faster MSSDLite, which was used to detect live crabs in underwater images. Its noise reduction and detection effects were found to be very efficient, and it is suitable for low-performance embedded equipment, such as automatic feeding boats. Lu [68] used image dehazing technology and the YOLO algorithm to identify and track marine life, including sharks, crabs, etc. Rasmussen [69] proposed a deep convolutional neural network architecture for scallop detection, using the YOLOv2 algorithm to make the system run faster and achieve high accuracy. This network can be used on autonomous underwater vehicles (AUVs) for real-time scallop population counting and health monitoring.

5.2. Target Detection and Recognition in Underwater Environments

Coral reefs represent an important part of marine ecology, and their long-term monitoring is necessary because they directly reflect the health of the ecological environment. González-Rivero [70] used the deep learning convolutional neural network to automatically analyze coral reef images. After comparison, the unbiased agreement rate between expert observation and automatic observation was 97%. This approach enabled data analysis and reporting to be at least 200 times faster and cost only 1%, which significantly improved the processing speed of the coral reef monitoring data. Oladi [71] used different image enhancement methods to process coral images in turbid environments and conducted reliability tests, and the results showed that the Retinex algorithm performed the best in terms of the image quality and reliability.

Many minerals are located at the bottom of the ocean, but the costs and difficulty associated with their detection are high. Sture [72] used an AUV equipped with an underwater hyperspectral imager (UHI) to detect sulfide minerals in the mid-Atlantic ridge for the first time at a depth of 2350 m. Dumke [73] used a novel underwater hyperspectral imager (UHI) on a remote operating vehicle (ROV) to detect manganese nodule fields in the Peruvian Basin to a water depth of 4200 m. Two supervised classification methods were used to detect nodule surfaces, and the results showed that the support vector machine (SVM) method outperformed the spectral angle mapper (SAM) method.

Deterioration of the Earth's environment has increased the risk of underwater habitat destruction, and monitoring helps to identify such environmental changes. Typically, underwater habitats are surveyed by divers or large hydrographic vessels, which is costly and risky. Diegues [74] used an AUV-mounted visible-light camera to capture habitat images, and then performed image enhancement and used a convolutional neural network to classify the habitats present in the images, which significantly reduced the cost of mapping. Wasserman [75] used ROVs to map estuarine habitats, recording multiple sets of videos along the width of the estuary to identify, classify, and map habitats. This study also revealed the distribution of previously unknown invasive red seaweeds.

5.3. Underwater Equipment of Target Detection and Recognition

Fatan [76] proposed a method for underwater cable detection and tracking using autonomous underwater vehicles. The edges of the image were first extracted, and then classified using texture information identified with a multilayer perceptron (MLP) neural network and SVM. Finally, the filtered edge was repaired using the morphological operator, and the cable was detected using the Hough transform with high accuracy. Thum [77] compared the classification effects of 5 deep learning models on underwater cable images and found that MobileNetV2 performed the best, with the highest accuracy rate of 93.5% for underwater cable image classification.

In the offshore oil and gas industry, pipeline corrosion problems can lead to cracks and leaks in pipelines. The use of human divers to monitor pipelines is increasingly dangerous as mining platforms travel deeper into the ocean. Khan [78] proposed a new method for subsea pipeline corrosion estimation using the corroded pipeline color. The images were first segmented, then the color-corrected and contrast-enhanced images were fused using a wavelet-based fusion algorithm, and the corroded surface area of the pipeline was estimated using a clustering algorithm, with an accuracy of over 90%. Hull corrosion is a major problem that affects the safety and health of ships. Soares [79] used a deep neural network to identify ship corrosion levels, and classified underwater images into four corrosion levels of high, medium, low, and no corrosion stages. This network could be embedded in ROVs to monitor ship corrosion conditions.

Shi [80] proposed a crack detection and classification method for underwater dams, which uses a dodging algorithm to eliminate uneven light brightness in underwater visible light images and has a good detection effect on smaller cracks. Liu [81] used a laser vision sensor to detect welds. After a series of processing, such as the Hough transform, the effects of image enhancement and denoising were achieved. Duan [82] proposed a robotic system scheme for weld seam recognition based on edge computing. After the weld image was filtered and preprocessed by edge detection, it was input into the CNN model for identification, which satisfies the requirements of maintaining a balance between high accuracy and the real-time performance requirements of underwater welding robots.

6. Conclusions

In this manuscript, target detection methods in turbid waters were divided into two areas. One focused on alleviating the problems in image degradation caused by the special conditions of turbid water. The establishment of a model, application of image restoration algorithms, or the use of polarized images can pertinently process images. The other area focused on some approaches regarding underwater target detection and recognition that consider the features of underwater images, target feature extraction, and actual engineering requirements. Appropriate deep learning and ML networks can be used to diversify this research, and it can also be flexibly used in future engineering.

This paper analyzed the target detection and recognition methods used in turbid waters and classified them into three categories: target detection based on depth learning approaches, underwater image restoration and enhancement methods, and underwater image processing methods based on polarization imaging technology and scattering. It also introduced other methods, such as the use of sonar to identify pipes and the use of electronic fields for target detection, and summarized relevant datasets. However, some problems still need to be analyzed. For example, there is no uniform evaluation system for image processing in turbid waters, the robustness of target detection algorithms is inadequate, and the target detection distance of polarization imaging technology in turbid waters is lacking. Comprehensive target detection and recognition technology in turbid water can be effectively integrated with an information management system to meet the requirements of clear imaging in turbid water, and to solve the problems of biological observation, pipeline inspection, exploration detection, and evaluation in high-turbidity water. This technique can be combined with advanced information processing technologies, such as large data, to analyze and evaluate underwater engineering structures and to prevent catastrophic accidents. Thus, it reduces adverse consequences and economic losses caused by structural damage, provides more accurate statistical data and breeding and fishing methods for fishing grounds, offers efficient tools for underwater ecological environment monitoring, and devises innovative technologies for underwater exploration.

In the future, with the development of deep learning and image approaches, more algorithms that are suitable for turbid areas need to be developed; an underwater light model library covering a variety of water environments needs to be established; and a more unified, objective, and comprehensive underwater image evaluation system needs to be proposed. Relevant breakthroughs in this technology will certainly drive the progress and development of related fields and help to realize industrialization and automation. This will result in broad application prospects and have significant social benefits.

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Abbreviations

The following abbreviations are used in this manuscript:

AUV	Autonomous Underwater Vehicle
CNN	Convolution Neural Network
DCP	Dark Channel Prior
DOP	Degree Of Polarization
ENL	Equivalent Numbers of Looks
GA	Genetic Algorithm
HICRD	Heron Island Coral Reef Dataset
IE	Information Entropy
LSTM	Long Short-Term Memory
MLP	MultiLayer Perceptron
MSE	Mean Square Error
MUED	Marine Underwater Environment Database
OAM	Orbital Angular Momentum
PSNR	Peak Signal to Noise Ratio
RCNN	Region Convolution Neural Network
RNN	Recurrent Neural Network
ROV	Remote Operating Vehicle
SAM	Spectral Angle Mapper
SFPS	Simulated Feature Point Selection
SNR	Signal to Noise Ratio
SQUID	Stereo Quantitative Underwater Image Dataset
SSD	Single Shot multi-box Detector
SSIM	Structural Similarity Index Method
SVM	Support Vector Machine
UDCP	Under Dark Channel Prior method
UDCP	Under Dark Channel Prior method
UD-ETR	Under Dark Channel Prior based Energy Transmission Restoration
UHI	Underwater Hyperspectral Imager
UIEB	Underwater Image Enhancement Benchmark
YOLO	You Only Live Once

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