Applications of Underwater Target Detection and Recognition Technology

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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.

Underwater Detection Recognition

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.

2. 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.

3. 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.

4. 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.