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Review

Underwater robot sensing technology: A survey

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ABSTRACT

Underwater robot technologies are crucial for marine resource exploration and autonomous manipulation, and many breakthroughs have been achieved with key indicators (e.g., dive depth and navigation range). However, due to the complicated underwater environment, the state-of-the-art sensing technologies cannot handle all the needs of underwater observations. To improve the autonomous operating capacity of underwater robots, there is an urgent need to develop underwater sensing technology. Therefore, in this paper, we first introduce the development of underwater robot platforms. We then review some key sensing technologies such as underwater acoustic sensing, underwater optical sensing, underwater magnetic sensing, and underwater bionic sensing. Finally, we point out the challenges of underwater sensing technology and future directions in addressing these challenges, *e.g.*, underwater bionic sensing, new underwater material development, multisource information fusion, and the construction of general test platforms.

1. Introduction

Recently, underwater robot sensing technologies have drawn remarkable attention for marine engineering and resource exploration. On the one hand, underwater robots need to perceive the environment and perform autonomous navigation and obstacle avoidance. On the other hand, underwater robots also depend on the ability of sensing technology to perform a variety of practical application tasks (*e.g.*, object detection, underwater robot grasp, and underwater high-precision 3D measurement). In summary, underwater robot sensing technology is playing an increasingly important role in robots.

Most underwater sensing technologies rely on acoustic signals (*e.g.*, sonar), light signals, electromagnetic signals, and bionic sensors. Specifically, sonar estimates the position of a submerged object by measuring the travel time and phase difference of acoustic pulses, which can work at a much longer range and cannot be affected by water turbidity. Although underwater acoustic sensing methods have a large sensing range, their resolution is low, which limits the practical applications of underwater sonar. Optical sensors capture the light rays of their surroundings to acquire environmental information, which can achieve higher resolution and refresh rate. However, due to the complicated underwater light conditions (absorption and scattering), optical sensors can only achieve short-range sensing [1]. An electromagnetic-based sensor could be applied in an underwater environment to estimate the distance precisely as well [2]. However, environmental electromagnetic fields may interfere with the precision. Additionally, researchers begin to study underwater bionics sensing technologies (*e.g.*, whisker and lateral lines [3]). However, these technologies are not mature enough and need to be improved in practice [3]. Each of the above mentioned technologies has their own advantages and drawbacks, and researchers have to combine multiple sensing methods to carry out various underwater exploration tasks in practice.

2. Underwater Robots

Many countries have performed long-term research on underwater robots. For instance, the U.S. military designed the "bluefin" autonomous underwater vehicle (AUV), as shown in Fig. 1(a), which can perform autonomous underwater navigation and object detection and played a significant role in the search for missing Malaysia Airlines MH370 data in 2014. Russia designed the "Peace 1" and "Peace 2" underwater robots, which are the only pair of manned submersibles in the world that can perform collaborative underwater exploration [4]. Germany developed an AUV called "Deep C", which is an undersea vehicle of 4000 meters and can work 60 hours in the deep sea. France develops the "VICTOR 6000", as shown in Fig. 1(b), which is a cable-operated underwater robot that can acquire a high-quality underwater optical image [5]. Britain developed the fully automatic "Autosub6000" submarine, as shown in Fig. 1(c), which installed batteries and sensors enabling them to navigate independently [6]. Japan developed a deep ocean underwater robot, named the "Kaiko" ROV as shown in Fig. 1(d), which is mounted with

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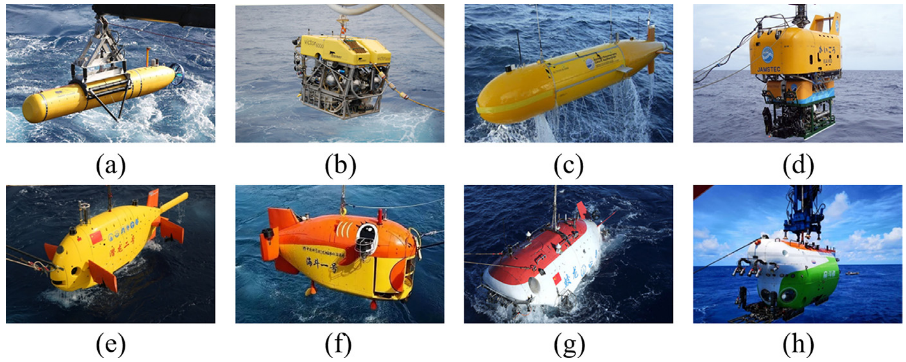

Fig. 1. Underwater robots: (a) Bluefin AUV [7], (b) Victor6000 ROV [5], (c) Autosub6000 AUV [6], (d) Kaiko ROV, (e) Qianlong, (f) Haidou, (g) Jiaolong [8] , (h) Fendouzhe.

various underwater sensors and has dived 296 times. China has also performed extensive research on submarine robots. For instance, the Shenyang Institute of Automation (SIA) developed the "Qianlong" and "Haidou" underwater robots, as shown in Fig. 1(e) and Fig. 1(f), which are equipped with sonar, cameras and lights and have performed a large variety of manipulation tasks at different depths from the sea surface to the seabed. The China Ship Scientific Research Center, SIA and other institutions developed the Jiaolong- and Fendouzhe-manned underwater submarines, as shown in Fig. 1(g) and Fig. 1(h), respectively, which have been used for deep sea exploration. Additionally, Harbin Engineering University developed underwater robots such as "Orange Shark" and "Hai Ling," which can perform underwater environment exploration by installing a variety of underwater sensors. The Institute of Automation, CAS China designed the "Bionic Dolphin" underwater robot that operates at a depth of up to 800 meters.

Although there are many robot platforms for underwater environment exploration, they often require a variety of sensors to achieve environmental information. Therefore, the development of sensor sensing technologies has an important influence on underwater exploration.

3. Underwater acoustic sensing

The acoustic sensing technique is widely applied in underwater environments (*e.g.*, in underwater robot localization and navigation, marine engineering, ship maintenance and pipeline measurement). In addition, in military applications, based on sonar data, warships can promptly identify threats (*e.g.*, torpedoes, submarines and anti-submarine aircraft). In this section, we introduce underwater acoustic sensors and underwater acoustic sensing applications.

3.1. Underwater Acoustic Sensors

Underwater acoustic sensors are the most favorable sensing technology in underwater robot applications. Generally, underwater acoustic sensors can be roughly categorized into the following two classes: acoustic ranging/imaging sensors and acoustic positioning sensors.

3.1.1. Underwater Acoustic Ranging/Imaging Sensor

Underwater acoustic ranging/imaging sensors mainly include single-beam sonar, side-scan sonar, and multibeam sonar.

Single-Beam Sonar: As shown in Fig. 2(a), the single-beam sonar receives a beam of the short-pulse acoustic signal emitted by a transducer and computes the depth of a submerged object by travel time accordingly. Due to its low cost and easy to use, single-beam sonar is widely used in marine engineering and resource exploration. However, it cannot obtain high-precision measurement results and a wide range of coverage.

Side-Scan Sonar: The side-scan sonar is composed of submodules such as the control unit, towed body, cable, and recorder, which aims at detailed study of topography, geology, and minerals and further performs object search and tracking. As shown in Fig. 2(b), the side-scan sonar emits directional pulse acoustic signals, where the horizontal beam angle is extremely small (less than 2 degrees) and the vertical beam angle is large (approximately 32 degrees). By analyzing the received acoustic image data, an object on the sea floor can be identified. However, side-scan sonar can only roughly estimate the direction of the object and cannot accurately measure the depth of the submarine.

Multibeam Sonar: Multibeam sonar is the combination of multiple single-beam sonars, as shown in Fig. 2(c), which can obtain the high-precision direction and depth value of the submarine object by travel time. Compared with single-beam sonar, the multibeam system can provide larger coverage of the seabed area with faster speed and higher accuracy, which greatly improves the efficiency of ocean exploration.

3.1.2. Underwater acoustic positioning sensors

Underwater acoustic positioning sensors can estimate the position of a measured object (*e.g.*, underwater robot). Depending on the length of the baseline, underwater acoustic positioning systems can be divided into the following three categories: the ultrashort baseline (USBL), the short baseline (SBL), and the long baseline (LBL) positioning systems, as shown in Fig. 3.

USBL and SBL: Both methods combine an array of acoustic transducers installed on a ship and a submarine transponder placed on an underwater robot. By providing the space transformation matrix between the array of acoustic transducers and the hull, we can estimate the relative pose by travel time and phase difference. The major difference between USBL and SBL is the space distances among the transceivers. For the USBL, the distance among transceivers is less than one meter. The SBL system generally contains more than three transducers with a distance of 20–50 m. By increasing the space distances, the measurement accuracy can be improved. However, the main drawback of these sensors is that they are difficult to calibrate.

LBL: Different from the USBL, as shown in Figs. 3(b) and 3(c), LBL uses a set of acoustic transponders placed on the sea floor with a known relative position. Based on at least three acoustic beacons with a baseline length of 100 m to 20 km, we can compute the localization of robots within the coverage area of the acoustic signal. The LBL sensor can obtain high measurement accuracy and is not affected by the water depth, but the system is costly to establish and maintain because an underwater acoustic network needs to be deployed and recovered regularly.

3.2. Underwater Acoustic Sensing Application

Applications based on sonar images mainly include underwater acoustic image detection/tracking and 3D reconstruction.

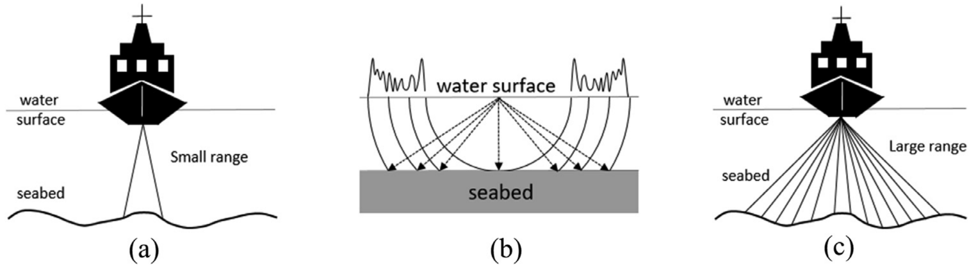

Fig. 2. Typical sonar: (a) single-beam sonar; (b) side-scan sonar; (c) multibeam sonar.

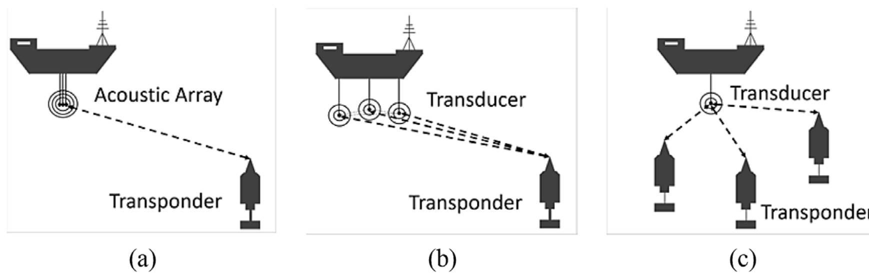

Fig. 3. Underwater acoustic positioning sensor: (a) ultrashort baseline; (b) short baseline; (c) long baseline.

3.2.1. Underwater Acoustics Image Detection/Tracking

Since sonar can acquire medium- and long-distance underwater acoustic image data, it is widely used in underwater object detection and tracking, as shown in Figs. 4(a) and 4(b). In the early period, object detection and tracking based on sonar were performed through expert processing (*e.g.*, handcrafted selection). However, this method is time-consuming and affects the performance of sonar sensors. Then, researchers began to explore acoustic features (*e.g.*, time, frequency, and time-frequency features). Among the above features, the time-frequency feature is suitable for nonstationary object detection and can obtain better results. For example, depending on the wavelet analysis and the relative Hilbert-Huang transform, Wang *et al.* [9] performed frequency decomposition and reconstruction of acoustic signals for underwater object detection.

Recently, machine learning has achieved many progresses in object detection and classification. For example, Zhang *et al.* [10] summarized 19 conventional classifiers for underwater acoustic object detection (*e.g.*, support vector machines (SVMs), K nearest neighbors (KNNs), and decision trees (DTs)). Ke *et al.* [11] proposed a supervised feature extraction algorithm to perform the object classification of underwater sonar images. In addition, deep learning is widely used in underwater acoustic signal analysis. Wang *et al.* [12] adopt deep neural networks (DNNs) to learn and fuse features and further utilize the Gaussian mixture model (GMM) to improve the performance. Phung *et al.* [13] proposed an unsupervised image statistics algorithm that combines deep semantic features to localize sonar targets.

3.2.2. Underwater Acoustics Image 3D Reconstruction

Acoustic images also obtain significant developments in underwater acoustic 3D reconstruction (*e.g.*, sparse reconstruction, dense reconstruction, and acoustic and optical fusion reconstruction), as shown in Figs. 4(c) and 4(d) [14,15].

Sparse Reconstruction: Approaches to perform sparse reconstruction typically detect the corner points on the sonar image and further solve the elevation angle and relative attitude transformation based on the sampling method. However, these methods are susceptible to the degradation of the sonar sensor model and the initial value of the algorithm [16]. An alternative method is structure from motion, which tracks and matches the scene's sparse features and further performs sparse scene reconstruction. Huang *et al.* [17] designed an acoustic based structure from motion model named as ASFM, which adopts handcrafted features to recover the 3D location of landmarks. Subsequently, Yonghoon *et al.* [18] optimized the ASFM algorithm to improve feature extraction and data association modules for acoustic sparse reconstruction.

Dense Reconstruction: Acoustic dense reconstruction is a challenging problem because of the low signal-noise ratio of acoustic images. To address this problem, Zerr *et al.* [19] propose a two-step algorithm for dense reconstruction of the sea floor, which can generate a 3D target model by combining a height map and reflection map. Cho *et al.* [20] propose to estimate the pitch angle and assume that the top of the submarine target generates acoustic backscatter, which can obtain more details in the reconstructed results.

Acoustic and Optical Fusion Reconstruction: Methods based on acoustic and optical fusion reconstruction can combine the advantages of both sonar and visual images to improve underwater reconstruction performance. For example, Sharmin *et al.* [21] designed a navigation algorithm using sonar, vision and inertial information for underwater scene reconstruction. Since acoustic data provide robust information about underwater obstacles, the proposed method combines visual features with sonar features to optimize the robot position and 3D scene points. Subsequently, they also achieved high-precision 3D reconstruction results of underwater caves by combining sonar with vision sensors [22].

4. Underwater Optical Sensing

Underwater acoustic sensing methods have a large sensing range, but their resolution is low, which limits the practical applications of underwater sonar. Underwater optical images can achieve high resolution and accuracy at short distances (*e.g.*, underwater small object detection, underwater biological observation [8], underwater robot grasping, and underwater archaeology [23,24]), as shown in Fig. 5. In this section, we mainly review the underwater 2D visual sensing and underwater 3D visual sensing technology.

4.1. 2D Visual Sensing

Underwater 2D visual sensing is crucial for underwater environment observation and object recognition in underwater robots due to its simplicity. In this subsection, we mainly introduce underwater image quality restoration and underwater object detection and tracking.

4.1.1. Underwater Image Enhancement

Due to the complex underwater scenario with light absorption and scattering, capturing a clear underwater images is still a challenging problem. Furthermore, these effects can reduce visibility and contrast [25]. As shown in Fig. 6(a), the image captured in the marine environment obtains low-quality results. By enhancing the image quality, we can achieve a high-quality image, as shown in Fig. 6(b). Generally, the methods of underwater image enhancement can be roughly subdivided into three categories (*i.e.*, nonphysical model-based methods, physical model-based methods, and data-driven methods).

Nonphysical model-based methods: These methods often enhance the image quality by changing the contrast and color space of the image. Iqbal *et al.* [26] adjusted the pixel range in HSV and RGB color space to enhance the underwater image quality. Based on the multiscale fusion strategy, Ancuti *et al.* [27] combined contrast enhancement with color correction methods to improve the image quality. However, since these methods do not build a real-world physical model for underwater image enhancement, they cannot obtain high-quality image results.

Physical Model-Based Methods: Methods based on physical models improve image quality by building a physical model of degradation. (*e.g.*, Jaffe-McGlamery equation), which can be denoted as:

$$I_c = J_c \cdot e^{-\beta_c^D \cdot z} + B_c^{\infty} \cdot \left(1 - e^{-\beta_c^B \cdot z}\right)$$

where I_c denotes the pixel value, z is the distance from the object to the camera, B_c^{∞} denotes the veiling light, and J_c is the true but unknown color of the 3D point. β_c^D and β_c^B represent the light attenuation coefficient.

Based on the Jaffe-McGlamery equation, Galdran *et al.* [28,29] considered that the absorption rate of red light is greater than both blue and green light and proposed a model based on the color channel of the image, which achieves image color restoration by establishing the relationship between the color value of the image and the medium parameters of the underwater environment. However, these methods require an accurate physical model of light degradation and a uniform distribution of the absorption coefficient. Therefore, these methods easily lead to unstable image restoration results. Recently, Akkaynak *et al.* [24] assumed that the absorption coefficient is not uniformly distributed in an underwater scenario and depends on the distance and reflection of the object. Based on this finding, they built an accurate underwater attenuation model to enhance the quality of the underwater image, which improves the robustness of image quality restoration.

Data-Driven Methods: These methods can be roughly subdivided into two categories (*i.e.*, methods based on synthetic data and methods based on real data). More specifically, methods based on synthetic data are trained through artificially synthesized data pairs. However, underwater image models depend on special scenes, light conditions, temperature, and turbidity. Therefore, this method cannot be used conveniently

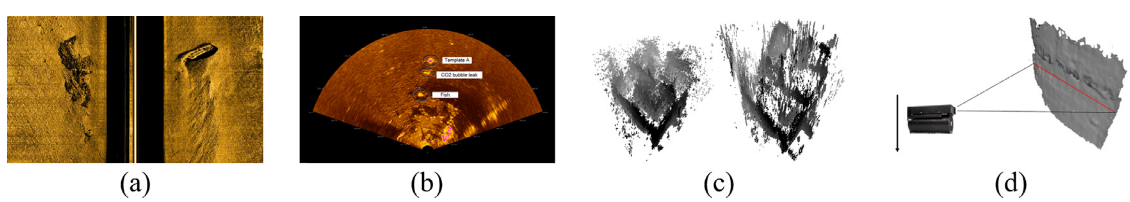

Fig. 4. Underwater acoustic object detection and scene reconstruction: (a) side-scan sonar object detection; (b) multibeam sonar object detection; (c) sparse reconstruction [10]; (d) dense reconstruction [11].

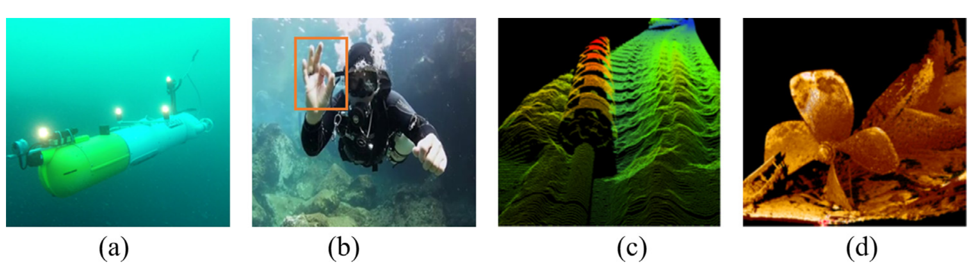

Fig. 5. Underwater visual sensing applications: (a) underwater robot docking; (b) underwater human-machine interaction; (c) underwater pipeline measurement; (d) underwater ship wreck reconstruction.

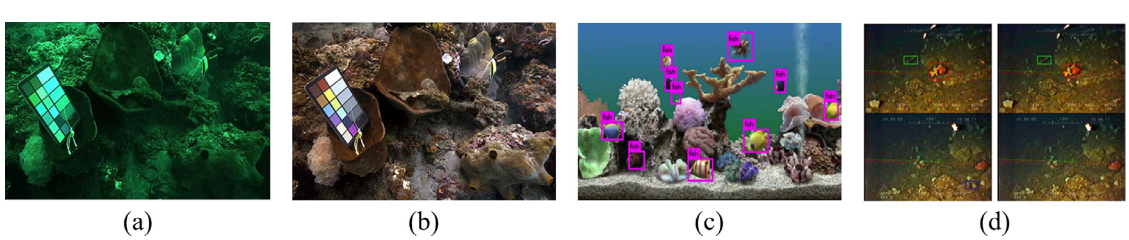

Fig. 6. Underwater 2D visual sensing: (a) low-quality underwater images; (b) underwater image quality restoration results [24]; (c) underwater object detection; (d) underwater object tracking.

in a practical environment. An alternative strategy is to train the model through real underwater data. Li *et al.* [30] propose an underwater image restoration model (*i.e.*, WaterGAN), which combines the RGBD data in the air with the scene parameters to synthesize underwater images. Based on the synthetic data, they trained the deep learning model and enhanced the underwater image quality with a two-stage network. Li *et al.* [31] proposed a cycle-consistent weakly supervised underwater color restoration model, which trains the model with an adversarial network and can be used in an unknown water domain. However, due to the nature of multiple potential outputs [32], it tends to produce inauthentic results in some instances . Li *et al.* [33] built an underwater image enhancement dataset including low-quality underwater images and reference high-quality images and evaluated related underwater image enhancement algorithms. However, the performance of deep learning based methods are worse than physical model based models in terms of robustness and generalization.

4.1.2. Underwater Object Detection and Tracking

Underwater object detection aims to find the objects of interest in an image, as shown in Fig. 6(c). Generally, underwater object detection can be roughly divided into two categories (*i.e.*, methods based on traditional features and methods based on deep learning).

Methods Based on Traditional Features: These methods use handcrafted features (*e.g.*, local binary patterns (LBP), histogram of oriented gradient (HOG), and Haar features (Haar)). The method includes the following three steps: 1) generating the multilevel image pyramid by down-sampling the original image in both the horizontal and vertical directions and 2) extracting the image features by sliding on the image pyramid with a fixed-size window and sending the extracted features to the extractor and classifier (*e.g.*, SVM and AdaBoost).

Methods Based on Deep Learning: These methods can be categorized into single-stage object detection methods and two-stage object detection methods. More specifically, the first method directly localizes objects by estimate the score of the bounding box directly that can be obtained by dense sampling on the input image (*e.g.*, YOLO [34] and SSD [35]), which has fast detection speed but low accuracy. In contrast, the second method can obtain higher precision by generating object proposals and obtain more accurate results through region proposal networks (RPNs) (*e.g.*, Faster RCNN [36]).

Underwater object tracking involves continuously predicting and updating the statuses (scale, position, and rotation) of a specified object in the subsequent images, as shown in Fig. 6(d), which often encounters some problems (*e.g.*, object deformation, object occlusion, similar object characteristics in the object and background, shadow and illumination changes). Classical methods can be divided into the following three categories: optical flow, mean shift, and convolutional network tracking (CNT). More specifically, the method based on the optical flow requires robust features in the image, which is not effective for motion blur; the method based on mean shift also requires features, which can track nonrigid objects efficiently and is robust to distance changes; CNTs can directly learn features from raw image data, which can extract the internal structure and local geometric information of the image and obtain better performance in this task.

4.2. 3D Visual Sensing

Underwater 3D visual sensing has attracted much attention due to its significance in robot environment exploration, which can not only recover underwater 3D structures but also accurately localize object positions. In this subsection, the underwater camera calibration methods are demonstrated. We then introduce underwater structured light 3D reconstruction and underwater multiview 3D reconstruction.

4.2.1. Underwater Camera Calibration

Underwater camera calibration that relates image pixels and 3D world points is a prerequisite for many tasks (*e.g.*, 3D reconstruction and localization). Most studies ignore the influence of medium refraction and directly use the pinhole camera model in underwater scenarios. However, these methods often lead to inaccurate 3D reconstruction results [37]. To improve the accuracy of underwater camera calibration, many studies focus on exploring the impact of refraction on the underwater camera model. The Woods Hole Oceanographic Institute studies the ray-based underwater camera model and found that the backprojection rays do not intersect at one point, so the underwater camera model cannot be represented by a single-view pinhole camera model [37]. Agrawal *et al.* [38] proposed a refractive camera model, which can simplify the underwater camera model as an axis camera model. Furthermore, based on the axis camera model, the forward and backward projection equations can be well formulated. Chen *et al.* [39] proposed a three-wavelength dispersion method to calibrate an underwater camera. Tomasz *et al.* [40] built a precomputed lookup table to quickly correct refraction distortion, but they assumed that refraction distortion is not related with the depth of the scene and rectified all images through the same look-up table.

4.2.2. Underwater 3D Data Acquisition

Some studies achieve 3D reconstruction using structured light, laser imaging (*e.g.*, TOF), and multiview reconstruction. Among the above techniques, the structured light with high precision has been used for underwater 3D data acquisition. Therefore, we mainly introduce underwater structured light 3D reconstruction in this subsection.

Underwater structured light sensors acquire the 3D point cloud by computing the intersection point between the laser light plane and the camera beam. Bodenmann *et al.* [41] designed an underwater laser scanner, as shown in Fig. 7(a), which can simultaneously capture the gray image and laser stripe image. Furthermore, they transform the collected color image data into 3D point clouds, which can obtain accurate shape and color information. Bleier *et al.* [42] designed a cross-line laser scanner, as shown in Fig. 7(b), where the camera captures the cross-line projected by the laser and computes the 3D point clouds by ray-plane triangulation. However, these methods ignore the influence of medium refraction in underwater environments. Palomer *et al* [43] developed an underwater scene scanning sensor with only laser rotation, which uses a stepper motor to quickly rotate the laser in the field of view and can perform 3D scene reconstruction in the field of view in a short time. Subsequently, Palomer *et al* [43,44] found that the laser plane entering the underwater scenario is refracted twice and cannot be described by a plane equation. Therefore, they denote the light plane as an elliptic cone and obtain higher 3D reconstruction accuracy with ray-cone triangulation. They also install the designed laser scanner on the underwater robot to perform underwater robot grasping, as shown in Fig. 7(c). Recently, the Shenyang Institute of Automation designed an underwater structured light sensor, as shown in Fig. 7(d). By explicitly considering medium refraction, the sensor can achieve high-precision reconstruction performance [45].

4.2.3. Underwater Multi-View 3D Reconstruction

Underwater multiview 3D reconstruction can simultaneously estimate the camera pose and reconstruct the 3D scene structure based on the 2D re-projection error, where the minimization function can be denoted as:

$$T_{k,k-1} = \underset{T_{kk-1}}{\operatorname{argmin}} \sum_{i=1}^{N} \| q_k^i - \pi\left(T_{k,k-1}, Q_{K-1}^i\right) \|^2$$

where q_k^i is the captured i^{th} feature that occurs in the k^{th} image. $T_{k,k-1}$ is the spatial transformation matrix from the $k-1^{th}$ image to the k^{th} image. Q_{K-1}^i denotes the 3D point. $\pi(T_{k,k-1}, Q_{K-1}^i)$ denotes the projection function. Classical multiview 3D reconstruction can be classified into the following two classes: simultaneous localization and mapping (SLAM) [[46] and structure from motion (SFM) [47]].

Underwater SLAM: SLAM can estimate the robot's pose and reconstruct the 3D scene structure simultaneously. Due to the complicated underwater environment (*e.g.*, scattering, absorption, turbidity, and refraction), underwater SLAM is a challenging problem [48]. Ferrera *et al* [49] collected multiple underwater datasets for the underwater SLAM task, where the trajectories computed by the structure-from-motion (SfM) library Colmap were used as reference trajectories. Bharat *et al.* [46] also collected an underwater SLAM dataset with an underwater robot, where they performed underwater trajectory estimation and evaluated the performance of the most recent open-source packages (*e.g.*, LSD-SLAM, DSO, SVO, ORB-SLAM2, ROVIO, OKVIS, VINS-Mono) on the collected datasets, as shown in Fig. 8(a). Table 1 summarizes the characteristics of the open-source SLAM method. From the evaluated results, OKVIS and ROVIO can achieve good results in terms of robustness and accuracy; ORB-SLAM2, SVO, and VINS-Mono achieve good results in terms of the absolute scale; based on minimizing a photometric error, DSO can obtain dense 3D reconstruction results.

Underwater SFM: SFM recovers the 3D scene structure from unordered images. Most existing methods ignore the influence of medium variation and adopt the pinhole camera model for underwater SFM directly, as shown in Fig. 8(b) [50]. However, if we adopt the pinhole camera model for underwater SFM, the systematic geometric bias will interfere with the precision of the 3D reconstruction because of the multirefraction between different media. Recently, some methods have begun to consider the influence of medium refraction for 3D reconstruction in underwater scenarios. To perform underwater refractive pose estimation, Jordt *et al.* [51] formulate a cost function by combining a real camera (refractive camera model) and a virtual camera (pinhole camera model). Along with refractive pose estimation, they perform underwater 3D reconstruction based on minimizing the 2D reprojection error. Chadebecq *et al.* [52] introduced Plucker coordinates and constructed a refractive fundamental matrix for underwater object and fluid-immersed organ reconstruction. However, these methods of underwater SFM often require a complex computation process and cannot perform underwater SFM efficiently.

5. Other Underwater Sensing Methods

Although underwater acoustic and optical sensing technologies have been widely used in many tasks, there still exist many challenging problems (*e.g.*, acoustic multipath effects, acoustic reverberation and optical attenuation). To improve the sensing ability of underwater robots, there is an urgent need to explore diversified underwater sensing technology. Recently, underwater electromagnetic sensing [53] and underwater bionic sensing [54] have drawn considerable attention in marine engineering.

5.1. Underwater Electromagnetic Sensing

In this section, we introduce both underwater electric field sensing and underwater magnetic sensing.

Underwater Electric Field Sensing: Underwater electric field sensing can enable robot communication in complicated underwater environments and effectively avoid acoustic multipath effects. For example, inspired by the South American electric eel and African pipe fish, Xie *et al.* [55] developed a communication system based on the bionic electric field that can perform effective communication in a complex underwater environment.

Table 1
Compare the SLAM methods [46].

Method	Camera	IMU	Loop Closure
LSD-SLAM	mono	×	√
DSO	mono	×	×
SVO	multi	Optional	×
ORB-SLAM2	Mono, stereo	×	√
ROVIO	multi	√	×
OKVIS	multi	√	×
VINS-Mono	mono	√	√

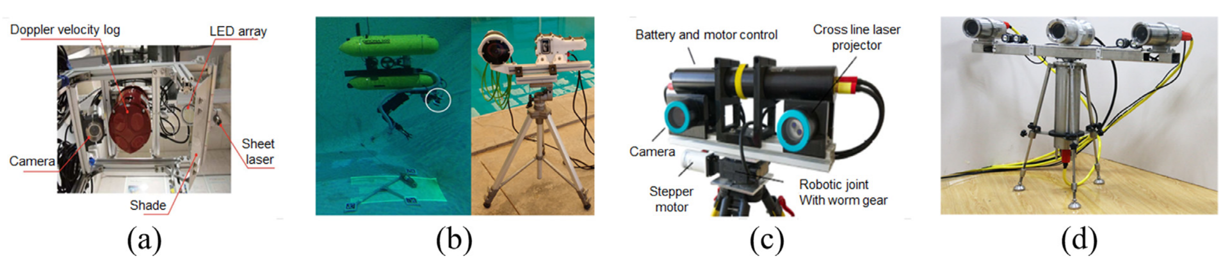

Fig. 7. Underwater laser scanner sensor: (a) underwater structured light measurement sensor designed by University of Tokyo [41]; (b) underwater cross-laser scanning sensor designed by Julius-Maximilians-University Wurzburg [42]; (c) underwater rotation laser scanner designed by University of Girona [43]; (d) underwater laser scanner sensor designed by Shenyang Institute of Automation, Chinese Academy of Sciences [45].

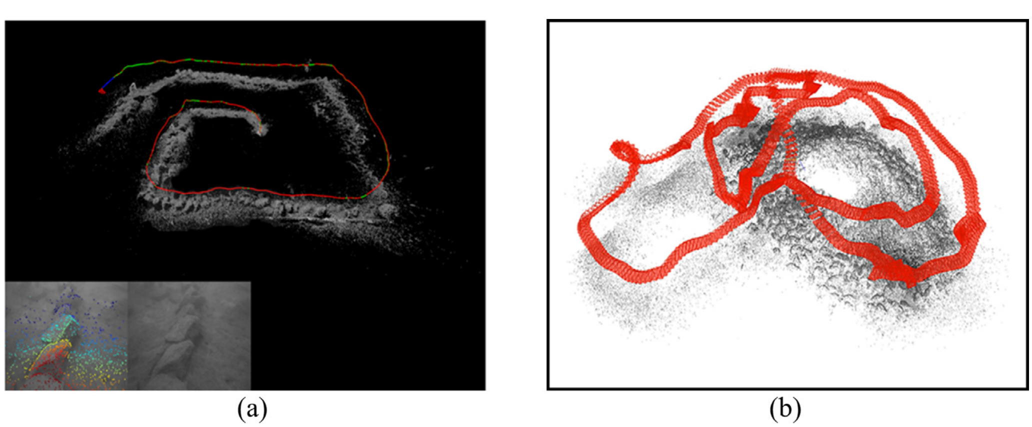

Fig. 8. Underwater multiview 3D reconstruction: (a) underwater SLAM [46]; (b) underwater SFM [49].

Underwater Magnetic Sensing: Underwater magnetic sensing has many advantages (*e.g.*, high concealment, robust detection performance and high positioning accuracy); therefore, this technique can work in complicated conditions (*e.g.*, turbid water and turbulent water flow) [53]. For example, American and Canadian navies deployed electromagnetic induction electrodes on icebergs around the Bering Straitand cooperated with the satellite positioning system to successfully detect the former Soviet Union's "Tresala" nuclear submarine [53]. The Russian VNI-IOFI research institute developed an ultralong-range, long-range (100 km, resolution 250 m) underwater electromagneticearly warning system called Anagram, which has been successfully used for the detection and tracking of signals from submarines andships. Chinese research on underwater magnetic sensing technologyalso makes significant strides in electromagnetic feld generationmechanisms and marine electromagnetic exploration technology. For example, the Naval University of Engineering developed low-noise, high-precision silver electrode sensors (e.g., fluxgate sensors and optical pump magnetometers) for underwater electromagnetic feld measurements [53].

5.2. Underwater Bionic Sensing

To improve the sensing ability of underwater robots, especially in the case of ultraclose distances (less than 1 meter), researchers have gradually paid attention to underwater sensing technology based on bionic principles (*e.g.*, lateral lines [54] and whiskers [56,57]).

Lateral Line: The lateral line is a sensing organ of the fish, which could perceive changes in the flow of the surrounding water and further help the fish perceive the surrounding environment in darkness, as shown in Fig. 9(a). Inspired by bionics, artificial lateral lines mainly focus on sensor and system design, which is summarized in [54]. In Fig. 10, representative artificial lateral line sensors are given. Additionally, researchers have begun to apply sensors to practical environments. For example, Dervries *et al.* [58] explore the application of distributed lateral line sensing systems in the closed-loop control strategy of a robotic fish.

Whiskers: Whiskers are important sensing organs for underwater creatures that are used to identify, locate and track prey [64]. Inspired by the seal's whiskers, as shown in Fig. 9(b), researchers have developed many artificial whisker sensors. For example, Wolf *et al.* [56] developed an artificial whisker based on the cantilever beam structure, which can sense a change in hydrological information of 5 microns/second. Gui *et al.* [65] designed a fully 3D printed artificial whisker by graphene 3D printing technology, which can perform qualitative analysis of the underwater vortex, velocity and flow direction. Leporade et al. [11] developed an active whisker that uses a motor to control its movement. Experiments show that active whiskers can achieve higher sensing precision.

6. Challenges and Future Directions

Although many progresses have been achieved for underwater sensing technology, there are still some problems (*e.g.*, sensing distance, accuracy, efficiency, robustness) that affect the underwater information acquisition and further limit the efficiency of the underwater robot exploration. Inspired by the recent works on the underwater sensing technology, we have the following suggestions.

Underwater Bionic Sensing: Compared with underwater creatures, current artificial underwater sensors exist a large gap not only in detection accuracy, distance, sensitivity and other technical indicators, but also in the sensor power consumption and volume. Aiming at this challenge, the first strategy is to learn how the underwater creatures sense the environmental information. For instance, by observing animals to avoid obstacle through acoustics, we design the sonar sensor. The second one is to learn the perceptual structure of animal organs, by learning

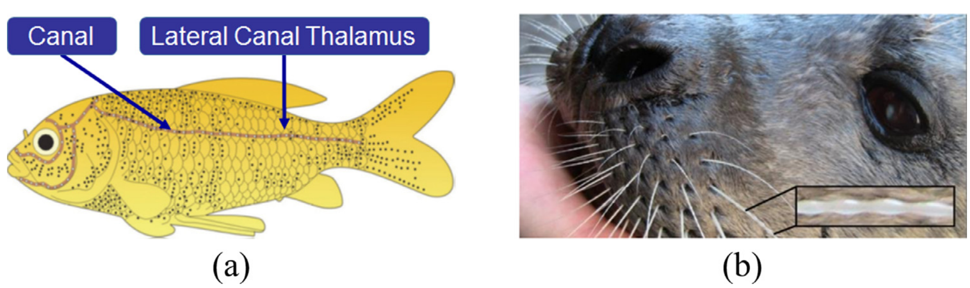

Fig. 9. Underwater bionic sensing: (a) The diagram of fish lateral line organs [54]; (b) illustration the whiskers of the seal [56].

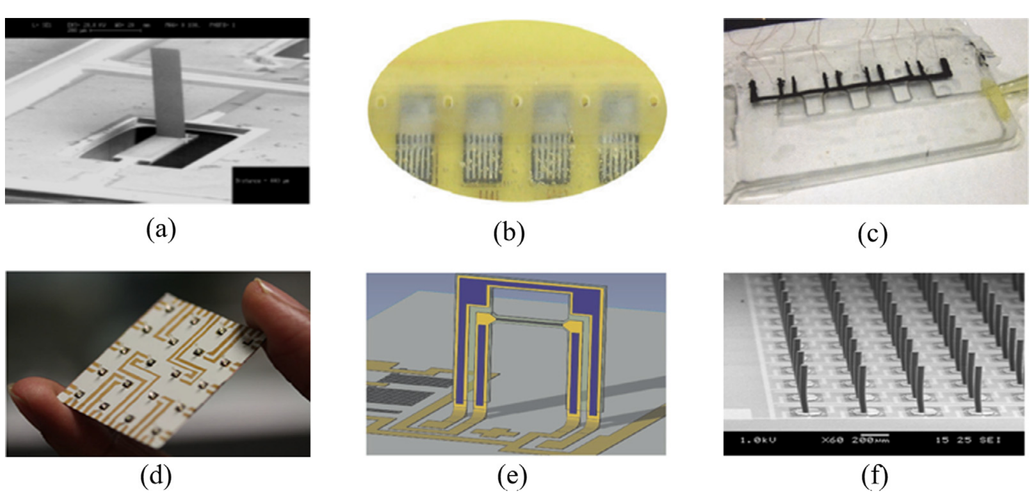

Fig. 10. Representative artificial lateral line sensors: (a) the first artificial lateral line [59], (b,c) high precision piezo resistive lateral line [60], (d) self-powered lateral line [61], (e) piezo resistive lateral line [62], and (f) low power consumption lateral line [63].

Table 2
Representative underwater robot competitions.

Name	Competition content	URL
URPC	Underwater target recognition and grasp	http://www.cnurpc.org/index.html
URC	Underwater robot manipulation and racing	http://www.ilur.org/comp
RoboSub	Autonomous driving, grasp, positioning	https://robosub.org/programs

its benefits, the sensing abilities of underwater robots can be improved effectively.

New Underwater Materials R&D: How to convert various environmental information into electric signals to obtain the environmental information, and perform autonomous processing are the core of underwater sensors, some strategies could be adopted. The first strategy is to enhance the data conversion capabilities of the existing materials. For instance, we can continue to develop the underwater sonar transducer systems to improve the measurement accuracy. The second strategy is to design a new material to achieve the underwater information. Relying on the new material, the underwater robot can achieve more valuable information.

Multi-Source Information Fusion: As we known, each sensing mechanism exists its limitations. Moreover, underwater creatures usually rely on multiple sensing organs to percept the environments. Therefore, how to fuse multiple sensors, learn from each other's strengths and obtain complementary benefits is still a challenge. In order to overcome these, the first strategy to fuse multiple data source together, where the data from one sensor is considered as an independent source to other sensors. The second one is to integrate multiple data source into a tightly coupled algorithms by optimizing them simultaneously.

Underwater Data Sets and Robot Competitions: In recent years, many underwater robot competitions have been held, which acquire various underwater datasets. Representative competitions include the Underwater Robot Target Grasping Competition (URPC) organized by the National Natural Science Foundation of China, and the Underwater Robot Competition (URC) organized by the International Underwater Robot Federation, the International Underwater Robot Competition (RoboSub) jointly organized by the International Federation of Unmanned Systems (AUVSI) and the US Naval Equipment Research Institute (ONR) as shown in Table 2. In the future, for the typical applications of underwater robots, the construction of common and general test platforms and offline dataset is a trend in underwater sensing technologies.

7. Conclusion

In this review, we intend to contribute to this growing area of research in underwater robot sensing. Therefore, we survey the related works of underwater robot sensing technologies including underwater acoustic sensing, underwater optical sensing, underwater magnetic sensing, as well as underwater bionic sensing. Finally, we also propose some valuable suggestions and future challenges and directions for future researches.

Declaration of Competing Interest

The authors declare no conflict of interest.

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