https://doi.org/10.1016/j.asoc.2019.04.025

The Extended Marine Underwater Environment Database and Baseline Evaluations

Muwei Jian[1,*], *Qiang Qi*[2], *Junyu Dong*[2], *Chaoran Cui*[1], *Xiushan Nie*[1], *Huaxiang Zhang*[3], *Kin-Man Lam*[4,*], *Yilong Yin*[5,*]

[1]School of Computer Science and Technology, Shandong University of Finance and Economics, Jinan, China.

[2]Department of Computer Science and Technology, Ocean University of China, Qingdao, China.

[3]School of Information Science and Engineering, Shandong Normal University, Jinan, China.

[4]Centre for Signal Processing, Department of Electronic and Information Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

[5]School of Software Engineering, Shandong University, Jinan, China.

* (Corresponding author) E-mail: jianmuweihk@163.com; kin.man.lam@polyu.edu.hk; ylyin@sdu.edu.cn

ABSTRACT

In the underwater environments, the captured underwater images are usually confronted with complex illuminations, severe turbidity of water, objects with large varieties in pose and spatial location, etc., which all present challenges to underwater vision research, in practice. In this paper, an extended large-scale underwater image database for salient-object detection or saliency detection is introduced. This database is called the Marine Underwater Environment Database (MUED), which contains 8600 underwater images of 430 individual groups of conspicuous objects, with complex backgrounds, multiple salient objects, and complicated variations in pose, spatial location, illumination, turbidity of water, etc. Specifically, this publicly available MUED provides researchers in relevant industrial and academic fields with underwater images under different types of variations. Manually labeled ground-truth information is also included in the database, so as to facilitate the research on more applicable and robust methods for both underwater image processing and underwater computer vision. The scale, accuracy, diversity, and background structure of MUED can not only be widely used to assess and evaluate the performances of the state-of-the-art salient-object detection and saliency-detection algorithms for general images, but will also particularly benefit the development of underwater vision technology, and offer unparalleled opportunities to researchers in the underwater vision community, and beyond.

Keywords: underwater vision; underwater turbidity; underwater image; saliency detection.

1. Introduction

Recently, autonomous underwater navigation has been a hot area of research with broad commercial and military applications, and underwater image/video processing has drawn wide attention. On the one hand, with the development of underwater imaging systems, such as North-East Pacific Undersea Networked Experiments (NEPTUNE) sub-sea observatories, it becomes difficult and time-consuming to obtain useful information from massive amount of underwater video/image data. On the other hand, the exploration and development of marine resources take place all over the world. Thus, precise detection of underwater fatalness and salient objects is one of the primary and essential issues in underwater navigation research nowadays. Underwater saliency detection, serving as a pre-processing step like conventional visual saliency detection, aims to identify the most informative location of objects in underwater images and greatly benefits many practical computer-vision applications in image segmentation [1, 2], object retargeting [3, 4], automatic image cropping [5], scene classification [6], moving object detection [43], and motion detection [44, 45]. This detection can not only efficiently focus on the interesting underwater image regions or objects, but also particularly benefits the development of underwater vision technology in the future.

Although significant progress has been made in the last two decades, visual saliency detection [9, 11, 15, 19, 24, 34, 37, 40] remains a challenging issue, due to the interrelated and mutually influenced interaction in the underwater scenarios, such as complicated illumination conditions, low-contrast objects under complex background, light absorbing and scattering, severe turbidity of water, etc. Therefore, modeling the saliency-detection mechanism in underwater scenes is a tough and challenging task in the underwater vision domain. In particular, although there exists a data set of turbid underwater images for evaluating image-restoration methods [42], publicly available underwater databases can seldom be used for underwater saliency detection, and only limited research has been carried out to investigate how to tackle underwater salient-object detection [28, 29].

In this paper, for extending saliency detection into the underwater vision domain, an extended underwater image database based on the OUC-VISION database [33], which is called the Marine Underwater Environment Database (MUED), is constructed and presented. This database contains underwater images with pose variations (including the frontal, the opposite, the left, and the right views of each individual underwater object), changes of different spatial location (underwater object located at the top-left corner, the top-right corner, the center, the bottom-left corner, and the bottom-right corner), complicated illumination conditions, varying degrees of turbidity, complex background and multiple-salient objects, in a single uniform database. The currently released underwater image data set contains 8600 images, which were captured for 430 groups of underwater subjects, under different conditions. Furthermore, we will also describe the design, collection, labeling, and categorization of the samples for the database in detail. The advantages of the designed underwater image database are that there are a large number of images for each distinct subject, and the images are categorized according to the controlled variations of the different situations. In our experiments, we also compare and evaluate the performances of several state-of-the-art saliency-detection methods on this publicly available underwater database.

The main contributions of this paper are summarized, as follows:

- To the best of our knowledge, no large-scale underwater database for saliency detection and assessment is publicly available. For extending saliency detection to the underwater vision domain, a large-scale and diverse underwater image database is constructed and presented.
- This released underwater image database can identify the strengths and weaknesses of the existing state-of-the-art saliency-detection algorithms for underwater images. The experiments with the algorithms on the underwater image database provide reference-evaluation results for researchers working on underwater computer vision.
- This database can not only offer unparalleled opportunities to researchers in the underwater vision community and beyond, but also will particularly benefit the development of underwater vision technology in the future.

A preliminary conference version of the released database was published in [33]. In contrast to the previous work in [33], which contained 4400 underwater images of 220 individual objects, the new MUED includes 4200 more underwater images of 210 conspicuous underwater objects. Furthermore, this database also considers the complex underwater background variations, underwater floating debris, and multiple salient objects, so as to construct a larger and more comprehensive data set. We also provide the baseline evaluations to researchers in the underwater vision community, to facilitate the research on more applicable and robust methods for both underwater image processing and underwater computer vision.

The remainder of this paper is organized as follows. In Section 2, we will introduce the related work on saliency detection and underwater salient-object detection. In Section 3, we introduce the imaging set-up and the lighting system for capturing underwater images. Then, the design and the consents of the MUED are presented in Section 4. In Section 5, the designed database is described in detail. The performances of several state-of-the-art saliency-detection methods on the MUED are evaluated in Section 6. Section 7 describes how to obtain the MUED. Finally, the paper closes with a conclusion and discussion in Section 8.

2. Related Work

Visual saliency detection, aiming at locating salient regions or conspicuous objects in an image, has recently drawn extensive attention, and has also been extensively studied in both the fields of image processing and computer vision [7]. Practical applications of saliency detection include image segmentation, automatic image retargeting, visual tracking, object recognition, etc. Generally, saliency-detection computational models fit into two categories: those based on the bottom-up model and those based on the top-down model, according to the design and the technology route of modeling. The bottom-up approaches [1, 12-29] consider low-level stimuli, such as color, contrast, location and texture, and are usually data-driven. The top-down approaches [30, 31], which use supervised methods with high-level cues, are often task-dependent and goal-driven.

Over the past decades, most of the bottom-up computational schemes, which simulate primate perceptual abilities, use low-level visual features to estimate image saliency. The pioneering model, which simulates the Human Visual System (HVS) for visual saliency detection, by Itti et al. [7] utilized a center-surround operator to compute saliency across three low-level cues. Later, lots of bottom-up salient-object detection methods were developed, which are based on low-level handcrafted features, such as image contrast [8], pattern distinctness [9], texture [10], etc. In [11], a novel graph-based method was proposed to estimate saliency map in order to make salient-object detection more precise. However, the graph-based method usually generates low-resolution saliency maps. Thus, a spectral residual-based saliency-detection method was proposed by Hou and Zhang in [12]. These early methods found it hard to handle the cases with complex image scenes or backgrounds. To soften this problem and acquire accurate salient regions, Ma et al. [13] presented a local contrast-based method for saliency detection, which increases the accuracy of saliency detection for the images with complicated background. In [14], a special color-appearance method, based on a non-parametric low-level vision model, was proposed for saliency detection. In [15], a visual-attention-aware model was proposed to mimic the HVS for salient-object detection. Song et al. [16] proposed a RGBD co-saliency method, which uses bagging-based clustering to detect salient objects. In [17, 18], a saliency-detection method was devised, which utilizes both visual-directional stimuli and two low-level object cues. In order to take object boundary information into account, a novel hierarchical model incorporating probabilistic object boundaries was presented for salient-object detection in [19]. Recently, deep learning has delivered superior performance in the saliency-detection task. Wang et al. [24] proposed a deep neural network, which integrates local estimation and global search, for saliency detection. In [25], an end-to-end deep contrast network was proposed to predict the saliency degree of each superpixel. However, these deep-learning-based saliency-detection models contain fully connected layers, which are computationally expensive. In addition, the fully connected layers drop the spatial information of input images. To alleviate these issues, Li et al. [26] proposed a multi-task deep model based on a fully convolutional neural network with global input and global output for saliency detection. Later, in order to improve the accuracy of the saliency results and address the problem that salient objects may appear in a low-contrast background, Hou et al. [27] proposed a novel saliency-detection approach by integrating short connections and the skip-layer structures within the Holistically-Nested Edge Detector (HED) architecture. Zhang et al. [28] designed a novel deep fully convolutional network model, which learns deep uncertain convolutional features (UCF), for accurate salient-object detection. Pang et al. [45] presented a CiC (convolution in convolution) method, which has a stronger capability for feature representation and hence can be used to extract the image’s saliency.

Compared to the bottom-up saliency-detection models, which utilize low-level visual features in images, another saliency-detection mechanism is the top-down model, which is a learning-based framework, and relies on high-level cues and prior knowledge. In [20], an efficient top-down saliency-detection model based on a Bayesian framework, which incorporates the object-appearance cues and scene context, was proposed to estimate saliency maps of input images. Later, a top-down visual saliency model, which combines dictionary learning and the Conditional Random Field (CRF), was proposed in [21]. Murabito et al. [22] presented an approach for top-down saliency detection guided by visual classification. In [23], a novel locate-by exemplar top-down framework, which incorporates deep association and background discrimination, was proposed to detect the saliency of images.

Although many saliency-detection models have made great progress, their performances are still unsatisfactory when the images considered contain complex backgrounds or low-contrast objects, such as images captured underwater. In particular, modeling the saliency-detection mechanism in underwater scenes is a difficult and challenging task, owing mainly to the following reasons. Images captured with underwater objects are usually confronted with variations of complicated illumination conditions, low-contrast object appearances, turbidity of water, light absorbing and scattering, lack of color information, etc., which are all challenges to the state-of-the-art saliency-detection models. Currently, only limited research has been carried out to investigate how to tackle underwater salient-object detection. In [29], a vision-based system for underwater object detection was presented to detect objects on the sea bed. Zhang et al. [30] proposed a method for underwater image detection based on the discrete fractional Brownian random field. In [31], an underwater target detection method was proposed, which combines active polarization imaging and optical correlation-based approaches. Wang et al. [32] presented a saliency-based adaptive object-extraction algorithm for underwater images.

However, to the best of our knowledge, no public underwater database is available for underwater saliency detection, which is perhaps the primary reason for attaining little improvement in the area of underwater saliency detection. To address this problem, in this paper, we introduce a large-scale and diverse underwater image database, which can not only be widely used to assess and evaluate the performances of the state-of-the-art saliency-detection algorithms for general images, but also will particularly benefit the development of underwater image processing [46-48], underwater image enhancement/restoration algorithms [49-52], and underwater vision technology in the future.

3. Underwater Imaging Set-Up

In order to mimic the environment of the ocean floor and capture underwater images with different variations in pose, spatial location, illumination, turbidity, background and the number of salient objects, we set up a special cube pool, whose dimension is 1.5×1.5×1.5 m^3. The cube pool is full of water, with sand and weed put on its bottom, so as to simulate the ocean floor. The necessary facilities are installed in the underwater photographic room in the OUC-VISION laboratory, including a camera system and a lighting system. Fig. 1 illustrates the imaging set-up of the camera and the lighting system for capturing underwater images. The details are described in the following sections.

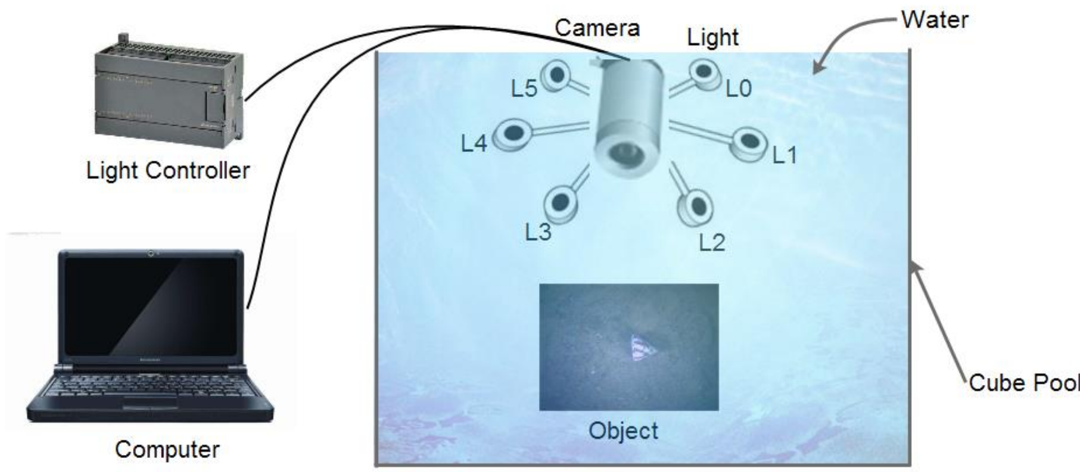


Fig. 1. The sketch map of the imaging set-up for the camera and lighting system.

3.1. Camera system

In our underwater photographic room, a camera system is made up of an MV-GE500C camera and a computer. The underwater camera, MV-GE500C, with resolution 2592×1944 pixels, is used to capture underwater images, and the computer is elaborately designed for collecting and storing the images. The camera is connected to the computer through a USB interface. In order to control the camera and capture the images in a shot, we developed a software system to implement this function. When we click on the capture button, the software will direct the camera to collect the underwater images of an object and store the images in its memory device.

To capture the images of a whole object, the seabed surface and camera are fixed, and the object is placed completely within the field of view of the camera. Furthermore, the object is moved to different positions, i.e. the center and the four corners of the images, when images are being captured.

3.2. Lighting System

A special lighting system, with six high-power LED (Light Emitting Diode) lights, is used to simulate the underwater ambient illumination, which can be controlled to obtain underwater images under various lighting conditions. The six LED lights are mounted on a hexagon with the same distance apart, as shown in Fig. 1. They are labeled as L0–L5, in their clockwise direction, with 60° separation between adjacent lights. Each light has its own switch, so we can control them separately. Fig. 1 shows a sketch map of the lights' set-up, arranged in a hexagon.

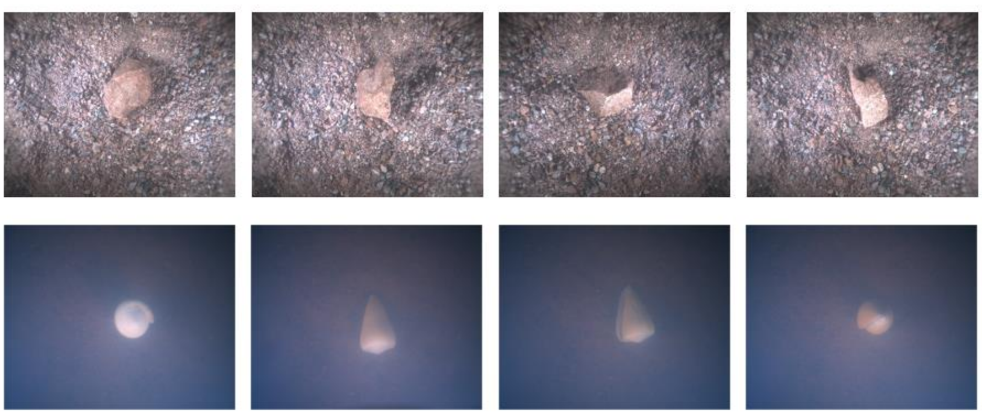
In our photographic room, we used the symmetrical lights of L0, L2, L4 to capture underwater images to mimic different illuminations. By combining the three LED lights, different lighting conditions can be simulated. In our implementation, the illumination variations are not strictly controlled, but these lighting variations can be easily distinguished.

4. Design of the Marine Underwater Environment Database

Six variations, namely pose, spatial location, illumination, turbidity, background, and the number of salient objects, are considered simultaneously in the construction of the MUED. The salient objects in the images were also labelled by different people, so as to provide ground truths for evaluation and assessment purposes. The following sections will describe the six variations and the labeling process in detail.

4.1. Pose Variations

To capture underwater images with various poses of an object, we consider four sides (the frontal, the opposite, the left, and the right) of each underwater object. In each side, an underwater image is collected from the camera in one shot. Thus, a total of four underwater images for each subject will be captured. Fig. 2 shows an example of the four sides of an underwater object, namely, the frontal image, the opposite image, the left image, and the right image of an underwater object.

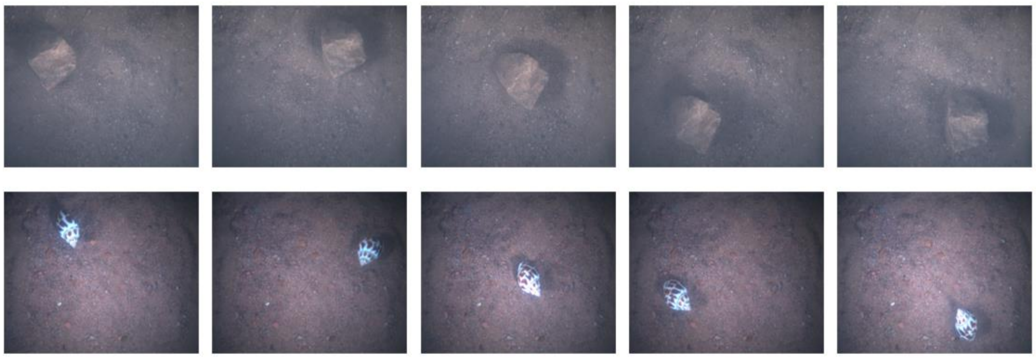


(a) (b) (c) (d)

Fig. 2. An underwater object at different poses: (a) frontal-, (b) opposite-, (c) left-, and (d) right-side, of an underwater object.

4.2. Spatial Location Variations

In order to reflect the variations in terms of spatial locations in our presented underwater database, each underwater object is placed at five different locations, including the top-left corner, the top-right corner, the center, the bottom-left corner, and the bottom-right corner of the image. Therefore, for each of the poses, five underwater images, with the object at different spatial locations, are captured. Fig. 3 shows the five images of an underwater object with the same pose.



(a) (b) (c) (d) (e)

Fig. 3. The spatial-location variations of an underwater object. The object is placed at (a) the top-left corner, (b) the top-right corner, (c) the center, (d) the bottom-left corner, and (e) the bottom-right corner, of the respective images.

Each object is captured with four different poses (the frontal, the opposite, the left, and the right views of each underwater object) and at five different locations (the underwater object is located at the top-left corner, the top-right corner, the center, the bottom-left corner, and the bottom-right corner). Therefore, each underwater object is captured with twenty images when both the pose and spatial-location variations are considered. Twenty example images of an underwater object, with four poses and five spatial locations, are illustrated in Fig. 4.

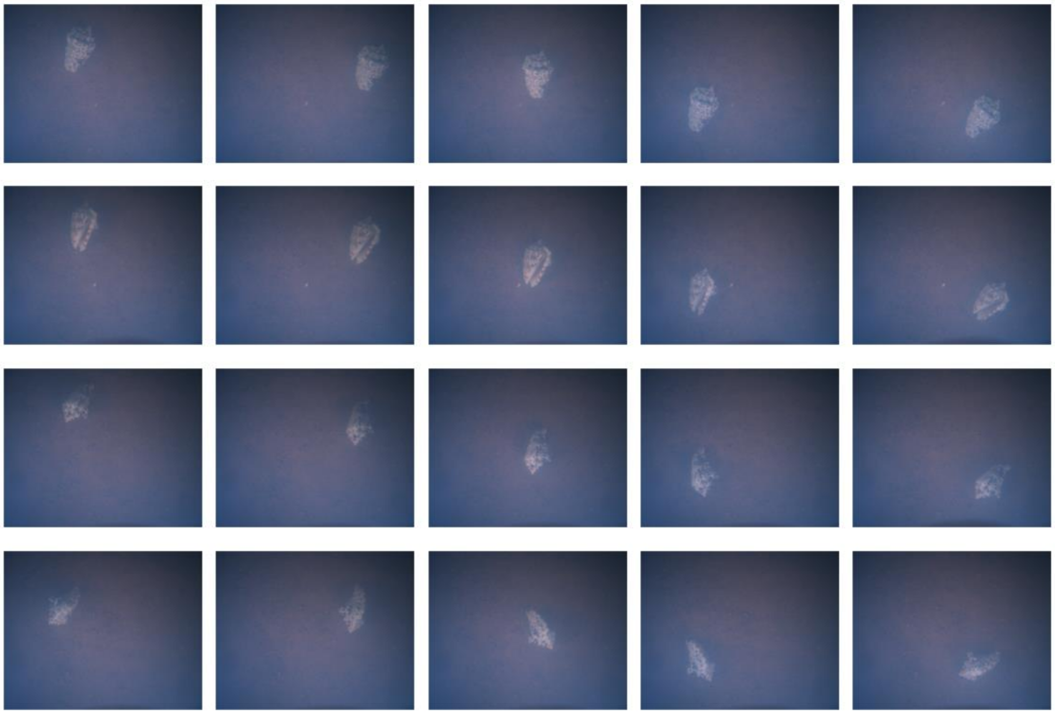


Fig. 4. An underwater object in four poses and five spatial locations.

4.3. Lighting Variations

As described in Section 3.2, the L0, L2 and L4 LED lights (per 60°) in the lighting system are controlled to simulate different underwater lighting conditions. During the capture of an underwater image, four different illumination conditions are generated, by turning on all the three LED lights, two of the LED lights, one LED light, and turning off all the three LED lights, respectively. Fig. 5 shows some sample underwater images under the four different lighting conditions.

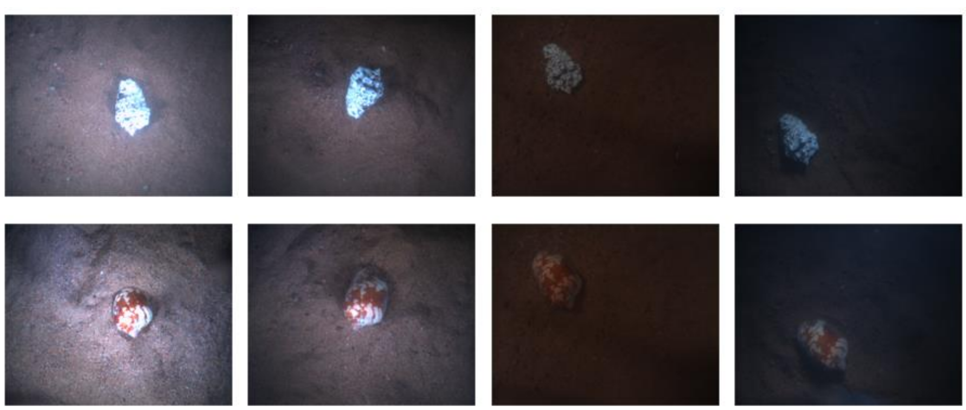


Fig. 5. The underwater images captured with four different lighting variations.

4.4. Turbidity Variations

The variations in water turbidity are an important factor influencing saliency detection of underwater images. The turbidity is subject to change in the ocean in real applications. In order to evaluate its effect on underwater-image saliency detection, three degrees of variations in water-turbidity, i.e. limpidity, medium, and turbidity, are considered, as illustrated in Fig. 6. We change the water turbidity by adding soil and milk to the cube pool. From Fig. 6, it can be seen that the appearances of the underwater images are highly dependent on the turbidity of the water. When the turbidity of the water is stronger, the images become more blurred and unclear in the complex underwater environment.

(a) Limpidity (b) Medium (c) Turbidity

Fig. 6. Underwater images captured with different degrees of water turbidity.

4.5. Background Variations

Although many saliency-detection algorithms have achieved great progress, their performances are still unsatisfactory when the images contain complex backgrounds, especially for those images captured from a complex and adverse underwater environment. Thus, background variations are essential for the database to assess and evaluate the performances of the underwater saliency-detection methods.

Six background variations, including coarse sand, medium sand, silver sand, and three degrees of variations in weed quantity (morsel, medium, and mickle), are considered in our underwater database. Fig. 7 shows some sample underwater images, under the six different backgrounds.

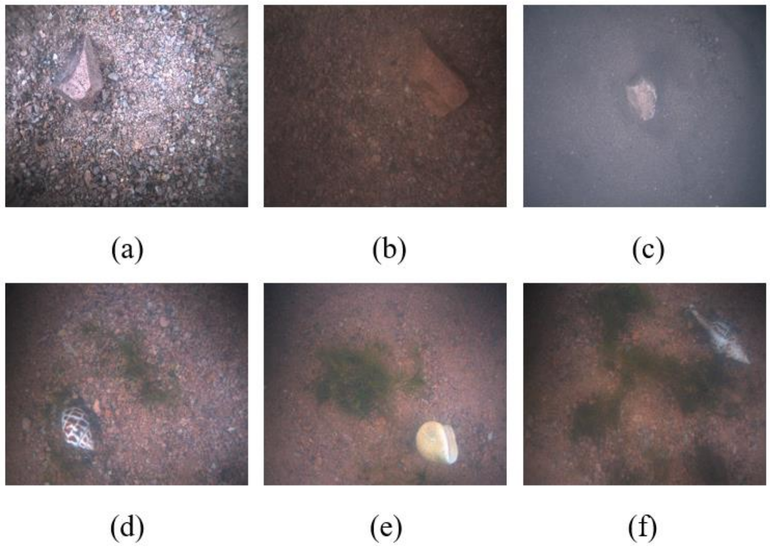


Fig. 7. An underwater object at different background variations: (a) coarse sand, (b) medium sand, (c) silver sand, (d) a morsel of weed, (e) a medium amount of weed, and (f) a mickle of weed.

To reflect the real environments where an underwater object usually resides, we also take the floating debris into consideration in the construction of the underwater database. This will benefit the research on developing robust underwater saliency-detection algorithms for real applications, under real underwater circumstances. Fig. 8 illustrates some examples of underwater salient objects, partly enveloped by some weed.

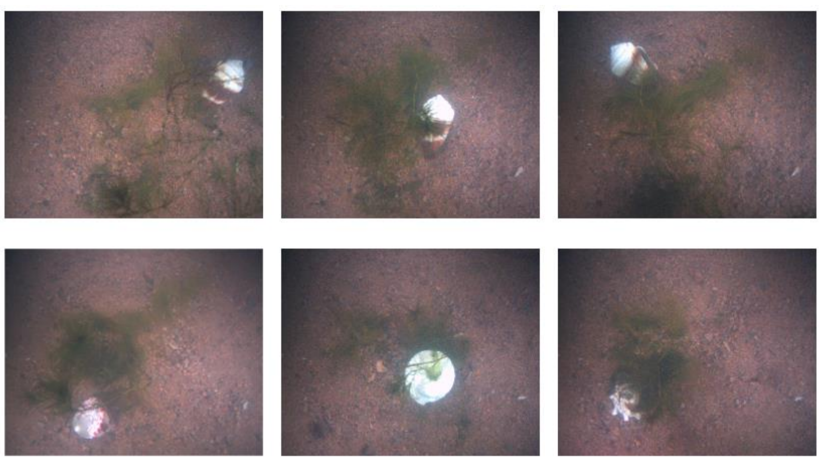


Fig. 8. Examples of underwater images, where the salient objects are partly enveloped by some weed.

4.6. Multiple Salient Objects

The number of salient objects in an image has an important influence on the saliency-detection results. In reality, multiple salient-object detection is a more challenging issue than the single salient-object detection. In order to evaluate the performance of an algorithm on multiple salient-object detection for underwater images, three different scenarios, namely a single salient object, two adjacent salient objects, and two detached salient objects, are included in the MUED. Fig. 9 shows some of the underwater images captured with a single salient object, two adjacent salient objects, and two detached salient objects.

(a) (b) (c)

Fig. 9. Underwater images captured with (a) a single salient object, (b) two adjacent salient objects, and (c) two detached salient objects.

4.7. Image Labeling

The salient objects in the captured underwater images were manually labeled to form the ground-truth set. We have five participants for labeling the ground-truth set. They are postgraduate students with knowledge of object detection and saliency detection.

We cropped all the images to the size of 486×648 pixels (one quarter of the original size), retaining most of the important information in order to increase the speed of labeling. Each of the students was asked to draw a rectangle to specify the most salient object in each image, in the process of manually labeling the images. Each student spent about 30 seconds drawing a rectangle on an image, and entered the coordinates of the rectangle in a text file. In order to obtain accurate results, each person was asked to label one fifth of all the images independently, and check the labeling results done by the other four students. The whole labeling process took about two weeks for the five students. Fig. 10 shows some images with the labeled ground-truth information.

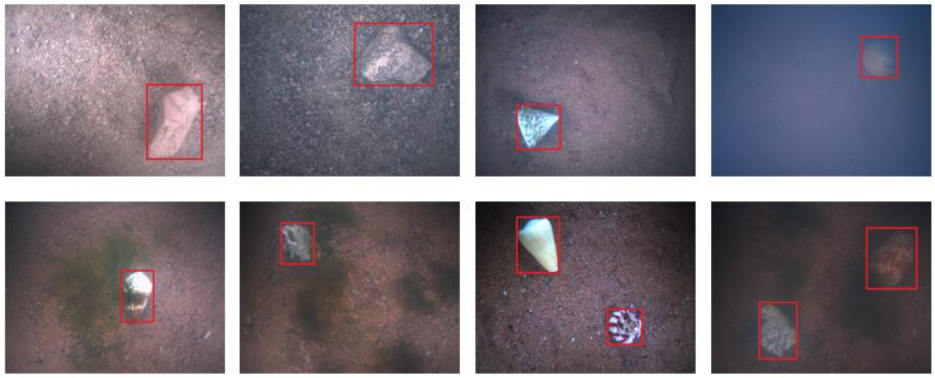


Fig. 10. Some example images with labeled ground-truth information, where each salient object is surrounded by a red rectangle.

5. Publicly Released Marine Underwater Environment Database

The MUED is now publicly accessible, and it is useful for researchers who are working on underwater salient-object detection or saliency detection. This database provides researchers and the industry, working on underwater computer vision, with underwater images under different types of variations, especially pose, spatial location, illumination, turbidity of water, background, and multiple number of salient objects, in a uniform database. Manually labeled ground-truth information is also provided in this large-scale underwater database. We will introduce this publicly released MUED in detail in this section.

5.1. Contents of the Marine Underwater Environment Database

The MUED contains 8600 underwater images of 430 underwater distinct objects, which have one or more salient objects, relatively complex background and complicated variations in pose, location, illumination, and turbidity. Each object was captured by considering four poses (described in Section 4.1) and five spatial locations (described in Section 4.2), so that 20 images are available. To represent the environments that underwater images generally fall into, three degrees of water turbidity, four illumination variations, and seven background variations are also considered in the database. In addition, multiple salient objects and ground-truth information are included in this database for the research of more applicable and robust methods for both underwater salient-object detection and underwater computer vision. Thus, the released database has the advantages of containing large quantity of underwater subjects, captured under different controlled variations.

5.2. Image Format

The original 8600 underwater images are in RGB color format, with resolution 2592×1944 pixels, captured by the camera MV-GE500C. The storage capacity required for the whole database is about 134.7 GB, which is too large to download and store. To alleviate this issue, we cropped all the images to the size of 486×648 pixels (one quarter of the original image), while retaining most of the important information.

6. Evaluation on the Marine Underwater Environment Database

The main purposes of evaluating baseline algorithms on the Marine Underwater Environment Database are as follows:

- ✓ First, we want to assess the difficulty of saliency-detection algorithms on underwater images;
- ✓ Second, we want to provide reference evaluation results for researchers working on underwater object detection and computer vision; and
- ✓ Third, we want to identify the strengths and weaknesses of existing state-of-the-art saliency-detection algorithms for underwater images.

In the experiments, we compare our method with nine state-of-the-art methods, which were published in the past five years and achieved promising performances on normal images, including the Graph-Regularization (GR) [34], Patch-Distinctness (PD) [35], Dense and Sparse Reconstruction (DSR) [36], Nonlinearly Covariance (NC) [37], Multi-Scale Superpixel (MSS) [38], Cellular Automata (CA) [39], Quaternionic Distance Based Weber Descriptor (QDWD) [19], Multiple Instance Learning (MIL) [40], and Pattern distinctness and Local contrast (PL) [41].

6.1. Qualitative evaluation

In order to qualitatively compare the nine state-of-the-art saliency-detection methods, Fig. 11 shows their saliency-detection results on the MUED. We can see that hardly any of these state-of-the-art saliency-detection algorithms can produce promising and satisfactory performances. The results, based on the PD [35], DSR [36] and MSS [38] methods, are lacking in some aspects, as some background regions are not suppressed completely, and are falsely recognized as salient regions, which lead to the final saliency map containing many noisy results. These three methods mainly rely on low-level priors, which cannot achieve satisfactory performances when applied to underwater images with complicated illumination conditions, low contrast, turbidity of water, and lack of color information. Some methods, such as GR [34], NC [37] and QDWD [19], produce inconspicuous boundaries, miss homogeneous regions of the underwater salient objects, and cannot even detect the salient objects completely, as illustrated in Fig. 3. The CA [39] method, which detects salient objects based on cellular automata, is easily affected by illumination variations. This method erroneously detects the bright area and some backgrounds as salient regions. In addition, the turbidity of water has significant influence on the performance of the MIL [40] method. This approach hardly distinguishes salient objects from the background when the underwater images are captured under the condition of severe turbidity of water. The PL [41] method, which integrates directional stimuli, pattern distinctness, and local contrast to obtain the final saliency maps, can detect almost the entire salient objects, with obvious boundaries and less background pixels. Consequently, the PL method produces slightly superior performance to other state-of-the-art saliency-detection algorithms. However, the background is not suppressed completely when the underwater images contains complicated lighting conditions, serious turbidity of water, and complex background.

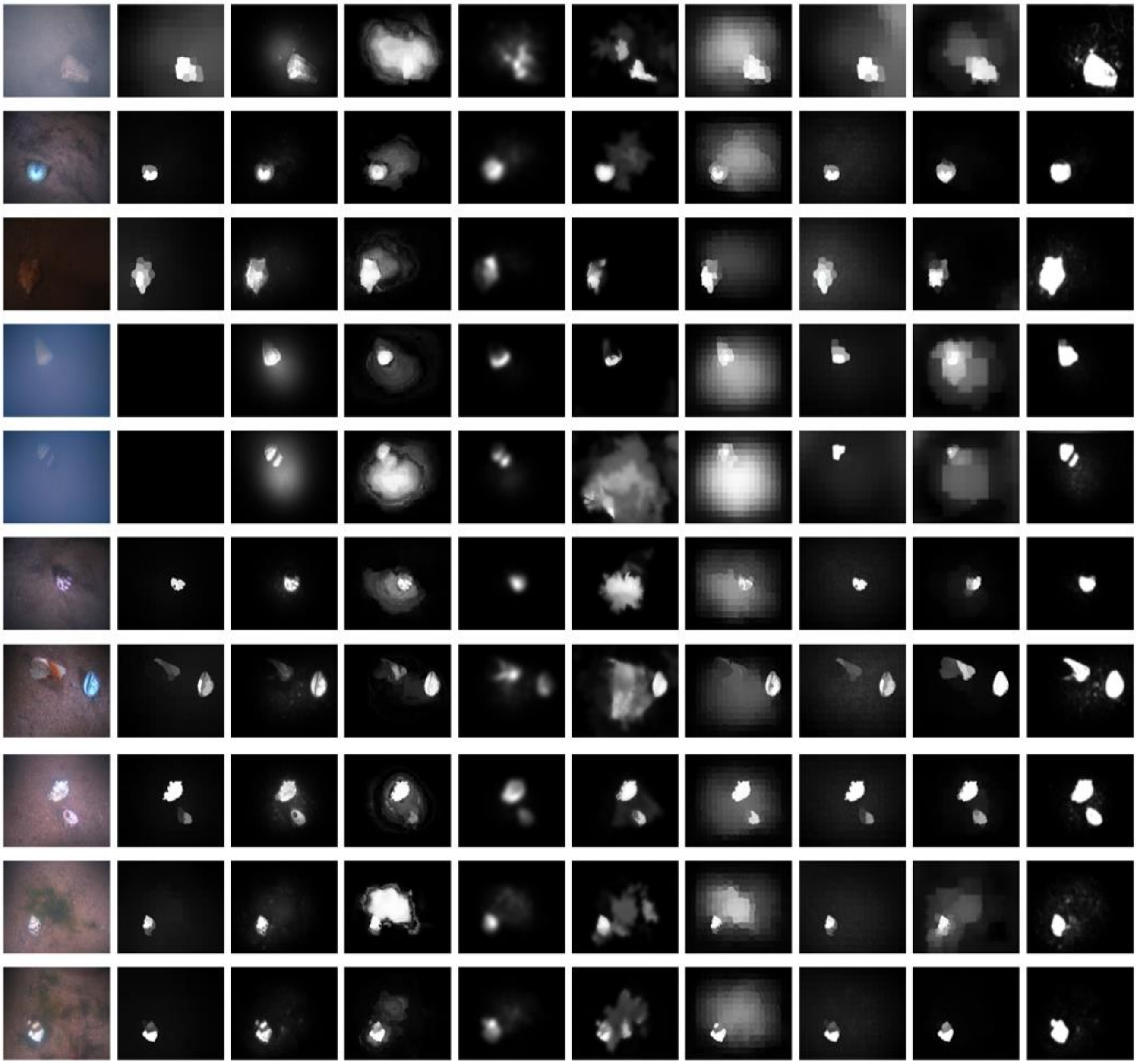


Fig. 11. Some visual results based on the nine state-of-the-art saliency-detection algorithms.

6.2. Quantitative evaluation

To quantitatively assess the nine state-of-the-art saliency-detection models, the average precision, recall, and F_β measure are utilized. Precision measures the proportion of the detected salient-object rectangle overlapped with the ground-truth rectangle, over the detected salient-object rectangle, while recall is defined as the ratio of the detected salient-object rectangle overlapped with the ground-truth rectangle, over the ground-truth rectangle. The F_β measure is an overall evaluation, which provides a comprehensive measurement to weigh precision more than recall, and is defined as follows:

$$F_\beta = \frac{(1+\beta)\times \text{Precision} \times \text{Recall}}{\beta \times \text{Precision+Recall}}, \tag{1}$$

where β is a real positive value and is set at 0.3.

Fig. 12 shows the experimental results of the nine state-of-the-art methods, in terms of the average precision, recall, and F_β measure. For these three measures, we can see that all of the methods, except PL [41], have their values lower than 50%, which indicates that underwater image saliency detection is still a very challenging issue for existing methods. In underwater environments, the recall rates of most methods are lower than 45%, except for QDWD [19], MIL [40], and PL [41]. For the precision rate, only PD [35], QDWD [40], and PL [41] exceed 45%. For the overall F_β measure, only PD [35], QDWD [40], and PL [41] achieve higher than 45%, but lower than 50% except PL [41]. These performances are much lower than when the methods are applied to simple conditions, i.e. not under an underwater environment. The experimental results also show the difficulty of saliency detection in the underwater vision domain.

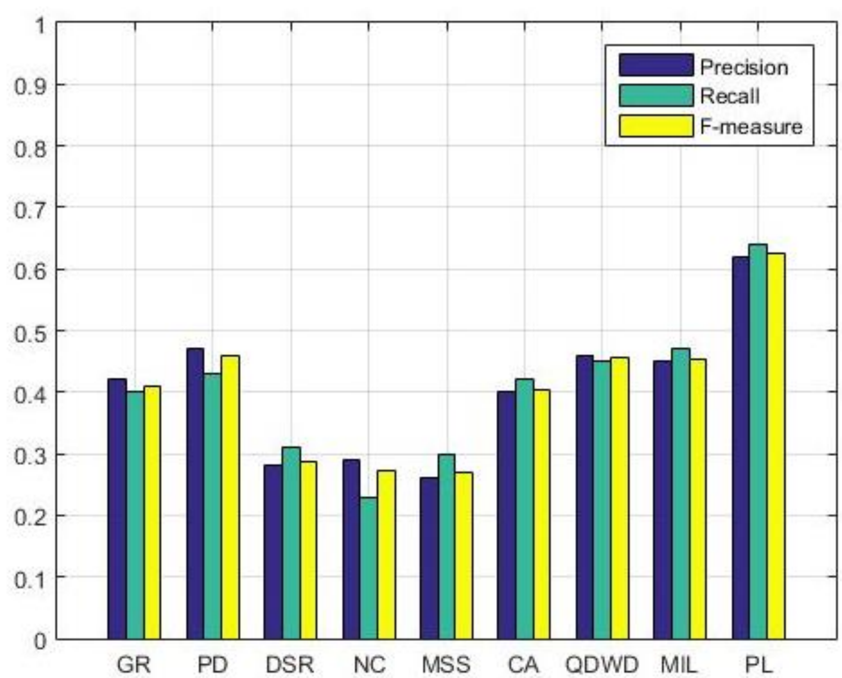


Fig. 12. Comparison of the nine saliency-detection methods, in terms of average precision, recall, and F_β measure on the MUED.

Objects captured underwater are always blurred, like being surrounded by fog. Therefore, in this experiment, a defogging algorithm [53] is applied to preprocess the underwater images, and then the nine saliency-detection models are evaluated. From the saliency-detection results, we found that the saliency maps are similar to those presented in Fig. 11, and the distinction between with or without preprocessing by the defogging algorithm is not obvious or conspicuous. Besides that, to compare the performances more precisely, we also compute the average precision, recall and F_β measure of each saliency-detection methods, with and without using defogging. Fig. 13 shows the experimental results of the nine state-of-the-art methods, in terms of the average precision, recall, and F_β measure. A comprehensive comparison, as shown in Figs. 12 and 13, indicates that the variations, as well as the effect of applying the defogging algorithm, are very small, ranging from -0.0024 to 0.0217. Experimental results show that applying a defogging algorithm cannot improve saliency detection in underwater images.

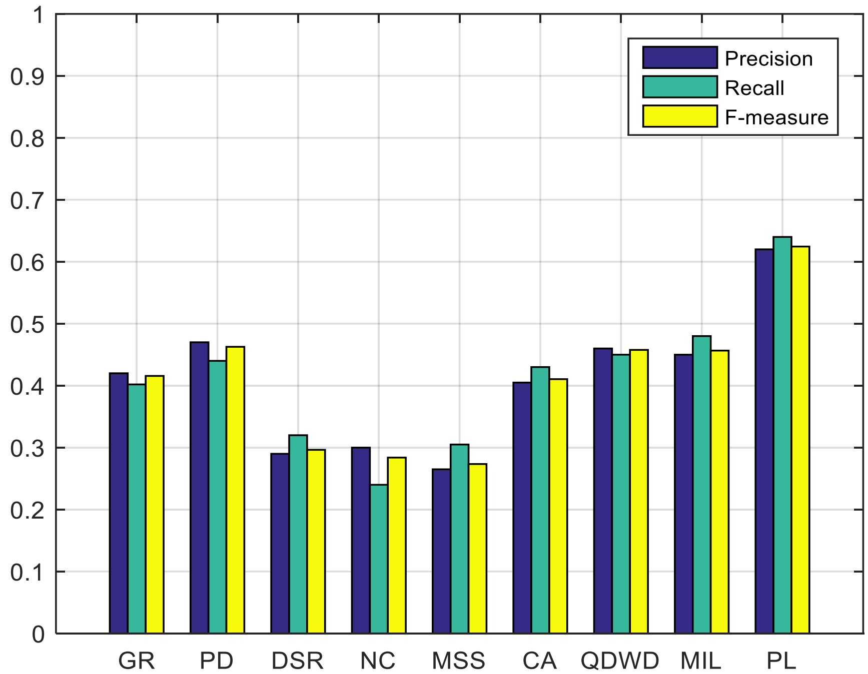


Fig. 13. Performances of the proposed model, compared with state-of-the-art methods, based on the results of defogging preprocessing [53], in terms of average precision, recall, and F_β measure.

6.3. Generalization analysis on the Marine Underwater Environment Database

In recent years, some state-of-the-art methods have been proposed to improve the performance for saliency detection, and have achieved excellent performance on simple images. However, modelling the saliency-detection mechanism in underwater scenes is a new research direction and still a challenging task. Most of the state-of-the-art saliency-detection models scarcely adapt to the complex and severe underwater environments. The primary causes of the failure of existing saliency-detection algorithms are that the complex underwater environment makes the captured underwater images suffer, due to:

- variations of complicated lighting conditions,
- low-contrast objects with the background,
- light absorbing and scattering in water,
- complex seabed environments, with influence of water plants,
- severe turbidity of water, and
- lack of color information of underwater objects.

All of these effects are combined and interacted mutually, which form an open and challenging problem to be solved by the state-of-the-art underwater saliency-detection algorithms. In other words, further efforts for underwater saliency detection must be made for the future development of underwater computer vision.

7. Obtain the Marine Underwater Environment Database

The information on how to obtain a copy of the MUED can be found on the website http://cs.sdufe.edu.cn/info/1162/2389.htm.

8. Conclusion and Discussion

In this paper, we have described the set-up and the contents of the Marine Underwater Environment Database (MUED). We have also presented the detailed description of the released MUED, which contains 8600 underwater images of 430 underwater objects, with different types of variations, especially pose, spatial location, illumination, turbidity of water, multiple salient objects, and the diverse background. Manually labeled ground-truth information is also included in the underwater database for the research of more applicable and robust methods in both underwater salient-object detection and underwater computer vision. The large-scale and diverse underwater database, which contains a large quantity of distinct objects captured under different underwater environments, offers unparalleled opportunities to researchers working on underwater computer vision. A number of the state-of-the-art saliency-detection algorithms have also been evaluated on the database. Experimental results show that existing algorithms achieve unsatisfactory performances on underwater images.

Acknowledgments

This work was supported by National Natural Science Foundation of China (NSFC) (61601427, 61602229, 61771230); Natural Science Foundation of Shandong Province (ZR2016FM40); Shandong Provincial Key Research and Development Program of China (NO. 2017CXGC0701); Fostering Project of Dominant Discipline and Talent Team of Shandong Province Higher Education Institutions.

9. REFERENCES

[1] T. Huang, Y. Tian, J. Li, H. Yu, Salient region detection and segmentation for general object recognition and image understanding, Science China Information Sciences, Vol. 54, Issue 12, pp, 2461–2470, 2011.

[2] J. Feng, L. Ma, F. Bi, X. Zhang, H. Chen, A coarse-to-fine image registration method based on visual attention model, Science China Information Sciences, Vol. 57, Issue 12, pp, 1–10, 2014.

[3] Y. Ding, J. Xiao, and J. Yu, "Importance filtering for image retargeting," In: Computer Vision and Pattern Recognition, pp. 89–96, 2011.

[4] Y. Liu, X. Li, L. Wang, Y. Niu, Interpolation-tuned salient region detection, Science China Information Sciences, Vol. 57, Issue 1, pp, 1–9, 2014.

[5] A. Santella, M. Agrawala, D. Decarlo, et al, "Gaze-based interaction for semi-automatic photo cropping," SIGCHI, pp. 771–780, 2006.

[6] C. Siagian, L. Itti, "Rapid biologically-inspired scene classification using features shared with visual attention," IEEE transactions on pattern analysis and machine intelligence, vol. 29, no. 2, pp. 300–312, 2007.

[7] L. Itti, C. Koch, E. Niebur, "A model of saliency based visual attention for rapid scene analysis," IEEE Transactions on pattern analysis and machine intelligence, vol. 20, no. 11, pp. 1254-1259, 1998.

[8] F Perazzi, P Krähenbühl, Y Pritch, et al, "Saliency filters: Contrast based filtering for salient region detection". In Computer Vision and Pattern Recognition, pp. 733–740, 2012.

[9] A. Borji, "What is a salient object? a dataset and a baseline model for salient object detection," IEEE Transactions on Image Processing, vol. 24, no. 2, pp. 742–756, 2015.

[10] C. Yang, L. Zhang, H. Lu, X. Ruan, et al, “Saliency detection via graph-based manifold ranking,” IEEE conference on computer vision and pattern recognition, pp. 3166–3173, 2013.

[11] J. Harel, C. Koch, P. Perona, “Graph-based visual saliency,” Advances in neural information processing systems, pp. 545-552, 2006.

[12] X. Hou, L. Zhang, “Saliency detection: a spectral residual approach,” IEEE conference on computer vision and pattern recognition, pp. 1-8, 2007.

[13] Y. F. Ma, H. J. Zhang, “Contrast-based image attention analysis by using fuzzy growing,” ACM conference on Multimedia, pp. 374-381, 2003.

[14] N. Murray, M. Vanrell, X. Otazu, et al, “Saliency estimation using a non-parametric low-level vision model,” IEEE conference on computer vision and pattern recognition, pp. 433-440, 2011.

[15] M. Jian, K. M. Lam, J. Dong, et al, “Visual-patch-attention-aware Saliency Detection,” IEEE transactions on cybernetics, vol. 45, no. 8, pp. 1575-1586, 2015.

[16] H. Song, Z. Liu, Y. Xie, et al, “RGBD Co-saliency Detection via Bagging-Based Clustering,” IEEE Signal Processing Letters, vol. 23, no. 12, pp. 1707-1711, 2016.

[17] M. Jian, Q. Qi, Y. Sun, K-M Lam, “Saliency Detection Using Quaternionic Distance Based Weber Descriptor and Object Cues,” Signal and Information Processing Association Annual Summit and Conference, pp. 1-4, 2016.

[18] M. Jian, Q. Qi, J. Dong, K-M Lam, “Saliency detection using quaternionic distance based weber local descriptor and level priors,” Multimedia Tools and Applications, pp. 1-18, 2017.

[19]H. Lei, H. Xie, W. Zou, et al, “Hierarchical Saliency Detection via Probabilistic Object Boundaries,” International Journal of Pattern Recognition and Artificial Intelligence, vol. 31, no. 06, 2017.

[20] C. Kanan, M. H. Tong, L. Zhang, et al, “SUN: Top-down saliency using natural statistics,” Visual Cognition, vol. 17, no.6-7, pp. 979–1003, 2009.

[21] J. Yang, M. H. Yang, “Top-down visual saliency via joint CRF and dictionary learning,” IEEE conference on computer vision and pattern recognition, pp. 2293-2303, 2012.

[22] F. Murabito, C. Spampinato, S. Palazzo, et al, “Top-Down Saliency Detection Driven by Visual Classification” arXiv preprint arXiv:1709.05307, 2017.

[23] S. He, R. W. Lau, Q. Yang, “Exemplar-driven top-down saliency detection via deep association,” Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 5723-5732, 2016.

[24] L. Wang, H. Lu, X. Ruan, M.-H. Yang, “Deep networks for saliency detection via local estimation and global search,” IEEE conference on computer vision and pattern recognition, pp. 3183–3192, 2015.
[25] G. Li, Y. Yu, “Deep contrast learning for salient object detection,” IEEE conference on computer vision and pattern recognition, pp. 478–487, 2016.
[26] X. Li, L. Zhao, L. Wei, et al, “Deep saliency: Multi-task deep neural network model for salient object detection,” IEEE Transactions on Image Processing, vol. 25, no. 8, pp. 3919–3930, 2016.
[27] Q. Hou, M. M. Cheng, X. W. Hu, et al, “Deeply supervised salient object detection with short connections,” arXiv preprint arXiv:1611.04849, 2016.
[28] P. Zhang, D. Wang, H. Lu, et al, “Learning Uncertain Convolutional Features for Accurate Saliency Detection,” arXiv preprint arXiv:1708.02031, 2017.
[29] G. L. Foresti, S. Gentili, “A vision based system for object detection in underwater images,” International Journal of Pattern Recognition and Artificial Intelligence, vol. 14, no. 02, pp. 167-188, 2000.
[30] T. D. Zhang, L. Wan, et al, “Underwater image detection based on the discrete fractional Brownian random field,” Opto-Electronic Engineering, vol. 35, no. 8, pp. 41-46, 2008.
[31] M. Dubreuil, P. Delrot, et al, “Exploring underwater target detection by imaging polarimetry and correlation techniques,” Applied optics, vol. 52, no. 5, pp. 997-1005, 2013.
[32] H. B. Wang, X. Dong, J. Shen, et al, “Salieney based adaptive object extraction for color underwater images,” Applied Mechanics and Materials, pp. 2651-2655, 2013.
[33] M. Jian, Q. Qi, J. Dong, et al, “The OUC-vision large-scale underwater image database,” 2017 IEEE International Conference on Multimedia and Expo (ICME), pp. 1297-1302, 2017.
[34] C. Yang, L. Zhang, H. Lu, “Graph-regularized saliency detection with convex-hull-based center prior,” IEEE Signal Processing Letters, vol. 20, no. 7, pp. 637-640, 2013.
[35] R. Margolin, A. Tal, and L. Zelnik-Manor, “What makes a patch distinct?” IEEE conference on computer vision and pattern recognition, pp. 1139–1146, 2013.
[36] X. Li, H. Lu, L. Zhang, X. Ruan, et al, “Saliency detection via dense and sparse reconstruction,” Proceedings of the IEEE International Conference on Computer Vision, pp. 2976-2983, 2013.
[37] E. Erdem and A. Erdem, “Visual saliency estimation by nonlinearly integrating features using region covariances,” Journal of vision, vol. 13, no. 4, pp. 11, 2013.
[38] N. Tong, H. Lu, L. Zhang, et al, “Saliency detection with multi-scale superpixels,” IEEE Signal Processing Letters, vol. 21, no. 9, pp. 1035-1039, 2014.

[39] Y. Qin, H. Lu, Y. Xu, et al, “Saliency detection via cellular automata,” Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 110-119, 2015.

[40] F. Huang, J. Qi, H. Lu, et al, “Salient Object Detection via Multiple Instance Learning,” IEEE Transactions on Image Processing, vol. 26, no. 4, pp. 1911-1922, 2017.

[41] M. Jian, Q. Qi, J. Dong, et al, “Integrating QDWD with pattern distinctness and local contrast for underwater saliency detection,” Journal of Visual Communication and Image Representation, vol. 53, pp. 31-41, 2018.

[42] Amanda Duarte, Felipe Codevilla, et. Al. A dataset to evaluate underwater image restoration methods, Conference: OCEANS 2016-Shanghai, DOI: 10.1109/OCEANSAP.2016.7485524.

[43] Y. Pang, L. Ye, X. Li, et al, “Incremental learning with saliency map for moving object detection,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 28, no. 3, pp. 640-651, 2018.

[44] Y. Pang, H. Zhu, X. Li, et al, “Motion blur detection with an indicator function for surveillance machines,” IEEE Transactions on Industrial Electronics, vol. 63, no. 9, pp. 5592-5601, 2016.

[45] Y. Pang, M. Sun, X. Jiang, et al, “Convolution in convolution for network in network,” IEEE Transactions on Neural Networks and Learning Systems, vol. 29, no. 5, pp. 1587-1597, 2018.

[46] J. Jaffe, K. Moore, J. McLean, et al, “Underwater optical imaging: status and prospects,” Oceanography, vol. 14, no. 3, pp. 66-76, 2001.

[47] Y. Schechner, N. Karpel, “Clear underwater vision,” Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on. IEEE, vol. 1, pp. I-I, 2003.

[48] R. Schettini, S. Corchs, “Underwater image processing: state of the art of restoration and image enhancement methods,” EURASIP Journal on Advances in Signal Processing, 2010(1): 746052.

[49] J. Chiang, Y. Chen, “Underwater image enhancement by wavelength compensation and dehazing,” IEEE Transactions on Image Processing, vol. 21, no. 4, pp. 1756-1769, 2012.

[50] C. Li, J. Guo, R. Cong, et al, “Underwater image enhancement by dehazing with minimum information loss and histogram distribution prior,” IEEE Transactions on Image Processing, vol. 25, no. 12, pp. 5664-5677, 2016.

[51] Y. Peng, P. Cosman, “Underwater image restoration based on image blurriness and light absorption,” IEEE Transactions on Image Processing, vol. 26, no, 4, pp. 1579-1594, 2017.

[52] M. Mangeruga, M. Cozza, F. Bruno, "Evaluation of Underwater Image Enhancement Algorithms under Different Environmental Conditions," Journal of Marine Science and Engineering, vol. 6, no. 1, pp. 10, 2018.
[53] K. He, J. Sun, X. Tang, "Single image haze removal using dark channel prior," IEEE transactions on pattern analysis and machine intelligence, vol. 33, no. 12, pp. 2341-2353, 2011.