A Survey on Underwater Image Segmentation and Image quality Enhancements using Deep Learning Models

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Abstract

Due to their crucial role in ensuring the continuity of life on Earth, marine ecosystems including their habitats are growing in significant amount. Marine ecosystems are frequently observed utilising underwater cameras to take films and photographs for analysing that ecosystem and for environmental preservation due to their distant and challenging to the access to nature. Unfortunately, it is challenging to train deep improvised models due to the lack of underwater photos with undistorted images data as references. It is so essential to establish more efficient learning techniques that harvest better supervised information from restricted training samples. Modern Artificial Intelligence (AI) subset known as Deep Learning (DL) has achieved better outcomes in the analysis of visual data. Despite having a wide range of applications, its usage in underwater picture segmentation is still being researched. In this survey, several works of literature related to underwater image segmentation are taken based on machine learning and deep learning models from IEEE explore, Research Gate, PubMed, Google Scholar, Scopus, and Web of Science search engines. Most of the literature is recently published between 2016-2023. This literature survey identifies some important shortcomings of the state-of-art-underwater image segmentation models considering various methodologies and datasets. Finally, a precise underwater image segmentation model based on deep learning-based algorithms can become a genuine option for underwater photos quality enhancement.

Keywords

Image processing, underwater, Deep learning, marine ecosystem, machine learning, computer vision

1. Introduction

Several applications underwater image segmentation can be found in fields like biological research and underwater inspection. It can play a significant role in more difficult tasks like image restoration, animal counting, and for robot obstacle avoidance. For that reason, the segmentation approach needs to be able to separate underwater photos that are captured in the extreme scenarios [1]. Without appropriate instruments to investigate and learn about our world's largest ecosystem as well as the marine environment, a complete understanding of the planet and its ecosystems cannot be achieved. Through the use of its underwater cameras, Computer Vision (CV) techniques can assist us in better understanding and managing remote marine item ecosystems [2]. The use of unmanned underwater robots with high-performance

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surveillance [3] modules as a primary instrument for ocean exploration is on the rise. Unfortunately, the environment for underwater photography is highly complex and is constantly altered by factors including plankton, underwater drifting sand, illumination variations, and local disturbances. In addition, underwater light attenuation frequently results in low contrast and fuzzy detail information, which presents significant difficulties for vision-based underwater activities. In order to enhance the image quality of underwater photos, underwater image enhancement thus has recently attracted a lot of attention and rigorous research [4]. Because of the absence of survival endurance, marine environment investigation has surely been more challenging over time than terrestrial ecosystem exploration. Oceanography, maritime defence, information navigation, and marine life analysis are all areas that require exploration. Underwater exploration has drawn a lot of interest in recent years from the research perspective. In contrast to outdoor photography, underwater photography involves complex lighting, atmosphere, and color casts, makes the restoration process a bit difficult operation. The wavelength-dependent non-uniform attenuation of light is one of the primary causes of such visual distortions. Moreover, marine snow, which enhances the effect of light scattering, has a significant impact on how visible the undersea biosphere is via the lens [5]. Semantic segmentation is now being handled by Deep Neural Network (DNN) that have been trained via supervised learning. The so-called label-space, which is used for this training, consists of datasets of images that have been labelled with a set of specified labels. These datasets are particularly expensive to produce since they must be manually labelled at the pixel level, unlike datasets enabling object detection, which merely need to be bounding box labelled. But because of the magnitude of their visual data, human processing is time- and cost-inefficient, necessitating a fundamental change in data analysis through cutting-edge technologies like Deep Learning (DL). This paper is arranged in the following style. Section 2 discusses several available techniques for underwater image segmentation. Section 3 discusses the details of available datasets. Section 4 discusses the related work regarding the underwater image segmentation and image enhancement. Section 5 describes the generalized methodology for the underwater image segmentation. Section 6 discusses the simulation metrics and tools, and section 7 concludes the paper.

2. Underwater image segmentation techniques

Several techniques have been applied for the underwater image segmentation and image enhancements. Few are discussed here:

2.1. Machine Learning

Machine Learning is a kind of automation process built on machine intelligence to link with the physical world. Artificial intelligence (AI) is subdivided into two important subsets namely Machine learning and Deep Learning algorithms. These algorithms are mainly focused on building a model for prediction and data analysis for generating important insights. Thus, both ML and DL algorithms are stronger and praiseworthy methods to generate meaningful information from raw data, especially in the case of image data analytics. In another word, ML algorithms can be defined as the scientific discipline with the objective of learning data using an automation process through computers. The main base of machine learning is a statistical analysis to discover insights from data using computing methods. This technique is capable of handling billions or trillions of data by designing a computational statistical model.

2.2. Deep Learning

Computer vision is one of the subsets of deep learning. DL has been effectively implemented to a variety of difficult computer vision problems [6, 7, 8], including semantic picture segmentation, since its deep neural network topologies can learn complicated mappings from the high-dimensional data for performing feature extraction. The primary benefit of DL is its capacity to learn features within various data formats, including images of underwater objects [2]. Deep Learning algorithms have gained high praise in the last few years in terms of designing complex deeper architectures and networks and have shown their worth in numerous applications like research, medicine, science, and technology. Different types of deep learning techniques can be adopted for learning behaviour and the patterns of underwater images such as ANN, CNN, KNN, and GAN so that the underwater image regions can be identified easily.

3. Datasets involved in underwater Segmentation

A data set seems to be a grouping of connected, discrete pieces of connected data that can be viewed separately, together, or handled as a single unit. An image dataset consists of digitised images that have been carefully selected for use in training, testing, and assessing the performance of computer vision and machine learning algorithms. Here they have discussed few popular datasets involved in underwater image segmentation as well as image enhancement.

NAUTEC UWI Real, 700 real underwater photos from the internet were used to create this Real Underwater dataset. Foreground as well as background pixels were manually separated from the photos. For testing and training, they choose 300 photos at random each. In Fig. 1, three samples from the dataset are shown together with the corresponding ground truth. The collection includes photos that were taken in a variety of locations, with varying amounts of light and water, and without distinguishing between benthic and pelagic zones. Both naturally and artificially illuminated photos exist. These photographs were captured in the wild, therefore divers, marine life, and several underwater items are visible [1].

UIEB, This dataset includes 950 actual underwater photographs, 890 of which include comparable reference photographs. The remaining 60 undersea photographs, for which they can find no appropriate reference images, are viewed as difficult data. They are able to do in-depth study using datasets [9].

NYU Depth V2, This dataset offers segmentation-labeled pictures and excellent depth maps. By classifying pixels labelled as floor, wall, roof etc. as background as well as pixels labelled as objects as foreground, they altered the initial segmentation labels. **NAUTEC UWI Sim1000**, In comparison to the Sim200, this dataset has four extra stages of rising simulated underwater turbidity, totaling 1000 simulated underwater photos.

4. Literature Survey

As DL approach has made significant progress in a variety of low-level vision tasks, this results in use of deep learning approach by researchers are the beginning to use deep learning to the improvement of underwater images. Moreover, learning techniques using paired samples from the actual world have drawn a lot of interest. Researchers have worked hard in recent years to develop novel methods for creating samples, improved learning techniques, and network structures. Here, a few recent studies are highlighted.

In order to determine whether these photographs were taken in the same location, this study suggests a cross-domain as well as cross-view image matching method employing a colour aerial image and an underwater sound image. The technique is made to compare photos taken in partially organised environments that have common features, including harbours and marinas. Our processing system combines deep neural network and conventional image processing methods [10].

For low-energy as well as real-time image analysis at the undersea edge, they suggest an optimal deep learning approach. This results in merely transmitting the low-volume outcomes that can be delivered through wireless sensor networks instead of the big image data that is required. They segment fish in underwater films and make comparisons with traditional methods to show the advantages of our ideas in practical applications. They demonstrate that processing underwater-captured photos at the collecting edge can be done 4 times faster than using a land-based server [11].

In this research, the authors first construct an underwater image synthesis algorithm (UISA), which allows them to create a synthetic underwater image from an outdoor ground-truth image dependent on the real-world underwater image. Based on this approach, they create the synthetic underwater picture dataset, a newly designed benchmark that includes both real-world and artificial underwater photos of the same scene (SUID). Our SUID, which has strong reliability and viability, is built using the underwater IFM (image formation model) and features of the underwater optical propagation [12].

They suggest using a technique called MLLE, which is effective and reliable, to enhance underwater images. To be more precise, they begin by locally modifying an input image's colour and features in accordance with a minimum colour loss concept and a maximum attenuation map-guided fusion technique. The average and variance from local picture blocks are then computed using the integral as well as squared integral maps, which are then utilised to adaptable change the contrast of such input image. In the meanwhile, another colour balance approach is presented to balance the CIELAB colour space's channel both a channel b channel colour discrepancies [13].

They suggest using our local spatial mixture (LSM) technique in this study to segment images from any kind of deployed side-scan sonar system. This innovative technique improves segmentation by taking into account the potential spatial connection between nearby pixels while estimating pixel labels within sonar pictures. By including an additional step (I-step) between both the expectation (E-step) and maximisation (M-step) processes, LSM alters the expectation-maximization algorithm. They use a new initialization approach, whose thresholds are automatically determined to attain and sustain robustness in varied underwater conditions, to battle intensity in homogeneity [14].

In order to address the issue of image segmentation, this research suggests a whale optimization algorithm (WOA) built on Kapur's entropy approach. Exploration and exploitation can be balanced well by the WOA in order to avoid early convergence and achieve the world's best solution. A number of studies on underwater photos from the Harbin Engineering University experimental pool are carried out [15] to confirm the segmentation accuracy of the WOA.

They suggest a multiscale feature fusion network as a technique for improving underwater sensing scene images (MFFN). The measure combining the feature extraction, feature fusion, and attention reconstruction modules is created for extracting the multi-scale feature. This action can improve the scene's flexibility and aesthetic impact. To fit the nonlinear mapping, they also suggest a number of goal functions during supervised training [16].

They present a powerful method to improve underwater photography that has suffered from medium scattering as well as absorption degradation. Our solution uses a single image and doesn't call for any specialist equipment or expertise in underwater situations or scene organisation. It is based on the merging of two images which were produced by taking the original deteriorated image and applying colour correction and white-balancing. The two images being fused, along with the maps that go with them, are designed to encourage smooth transfer of edges as well as colour contrast towards the final image. They also adopt a multiscale fusion technique [17] to prevent artefacts from being produced by the sharp map transitions in the low frequency components of the reconstructed image.

To provide visual-friendly and task-oriented enhancement, they suggest an object-guided twin adversarial contrastive learning-based strategy for underwater enhancement. They specifically create a bilateral limited closed-loop adversarial enhancement mechanism first, which reduces the need for paired data when using an unsupervised approach and maintains more informative features by linking with twin inverse mapping. They also use contrastive signals throughout the training phase to give the reconstructed images a more appropriate appearance [18].

In this paper, a deep residual model is proposed as a technique for underwater image improvement. First, convolution neural network models are trained using synthetic underwater images produced by cycle-consistent adversarial networks (CycleGAN). The second development is the introduction of the very-deep super-resolution reconstruction model (VDSR) to underwater resolution applications, along with the Underwater Resnet model, a residual learning model for underwater picture enhancement tasks [19].

To quickly extract complete & clean areas of interest (ROIs) out the images having significantly changing content and quality, a dynamic down-scaling algorithm was developed in the current study. To guarantee the integrity of weak targets based on local two-dimensional (2D) entropy parameters, the original image was downscaled and dynamic segmentation was carried out in a scale pyramid space. Then, iteratively examining a number of local thresholds as well as clustering gradients was done for ROI selection [20].

For the Polaris, a non-governmental Taiwanese oceanic research vessel, the researchers in this project created holographic image software. It is a survey vessel that was jointly built by Dragon Prince Hydro-Survey Enterprise Co. and the National Kaohsiung University of Science and Technology. The ship's dimensions are 260 tonnes, 36.98 metres in length, and 6.80 metres in width, and its top speed is 11 knots. It has experience with such missions because it has participated in underwater rescue & exploration operations. Survey vessels frequently encounter interference during underwater exploration operations that are brought on by elements like current velocity, water temperature, spectral conditions, refraction, and climate, ocean current, the presence of algae, and light reflection by schools of fish [21].

This study focuses on classifying sonar images into multiple categories, including drowning victim, wreck, aeroplane, mine, and seafloor. Initially, they created a real side-scan sonar picture dataset called Seabed Objects-KLSG over an extended period of time, which at present contains 385 wrecks, 36 drowning victims, 62 aeroplanes, 129 mines, and 578 seabed photographs. Second, they proposed a semi-synthetic data generation technique to generate sonar images of aeroplanes and drowning victims that utilises optical images as input and manages to combine image segmentation along with intensity distribution modelling of different regions [22], taking into account that the real dataset is unbalanced.

To train two of the top deep learning segmentation models, they create a dataset of genuine underwater photographs as well as various combinations utilizing simulated data, with the goal of handling the segmentation of underwater images within wild ecosystem. In additional to models developed using these datasets, methodologies for picture restoration and fine-tuning are also investigated. All the models of segmentation are compared with in testing set of actual underwater photographs in order to conduct a more thorough evaluation [23].

During the past few years, academics from all around the world have already been studying underwater photography and the capacity to take clear pictures. The entire process of recovering the collected photos is also time-consuming. Due to the scientific processes of absorption and scattering, several faults can be seen in the produced underwater photographs. The main problems with these photographs are colour distortions, blurriness, and poor contrast effects. To get over this, the proposed study work utilizes a deep learning algorithm to enhance the underwater photographs [24].

4.1. Survey table of few existing research

Table 1
A comparative Analysis of existing deepfake image detection approaches

Year	Author	Methodology	Advantage	Research Gap
2023	K Sun, Yobo Yubo Tian [25]	A dual-branch fusion network known as the DBFNet to stop underwater image deterioration.	DBFNet outperforms the compared approaches and considerably enhances the visual quality.	enhance the study of the fusion module for better visual results.
2023	B Sun, Y Mei, Ni Yan, Y Chen [26]	an underwater multiscene generative adversarial network (UMGAN)	On a variety of data types, UMGAN operates satisfactorily.	The performance of the algorithm has to be improved with regard to the retention of picture detail information and training speed.
2023	G Chen, Z Mao, K Wang, J Shen [27]	new hybrid transformer network-based architecture for underwater object recognition	compares favourably to the most recent advanced detectors in terms of both characteristics	Lightweight detectors are not researched for object detection within open underwater situations.
2023	J Wang, H Li, G Huo, C Li, Y Wei [28]	Using image style transfer and content picture feature extraction, Side-Scan Sonar (SSS)-type objects were created.	approach is more stable	performs only better with artificial data.
2022	Y Li, S Yang, Y Gong, J Cao, G Ho [29]	a fresh approach to dataset construction that uses MSRCR and selects the top photos using the well-known UIQM strategy.	enhancing images from cold seeps.	Improved evaluation techniques should be used.
2023	E Chen, Q Chen, B Huang [30]	Adaptive colour correction is created to deftly select between two colour correcting techniques.	attains the best results in terms of full-reference image quality evaluation.	If the white balance is off, the augmentation will be subpar.
2023	Q Zhao, L Zhang, L Liu [31]	this paper improves the original YOLOx algorithm	demonstrated the method's viability and examined the outcomes.	neighbor's motion poses not investigated
2023	U A Manavadu, M D Zoysa, C Premachabdra [32]	swarm pattern detection implemented with a Convolutional Neural Network (CNN)	Enhanced image segmentation	It should contain a larger sea environment.
2023	X Yang, Y Yuan, Y Wang [33]	CNN is used to categorise the target underwater photos.	give sensible guidance for the shrewd advancement of outdoor diving instruction	Complex architecture

5. Methodology

The goal of the systematic literature study in the preceding section was to identify and classify the top methods for applying deep learning to obtain underwater images. Systematic reviews of the literature is compiled and evaluates previously published studies using predetermined assessment criteria. Such analyses assist in determining the current information known in the relevant field of research. The identification of underwater images benefits greatly from the use of deep learning models. They are made up of a collection of connected nodes. Their interconnected neural structure is comparable to that of the human brain. Its nodes collaborate to find solutions to issues. Deep learning algorithms are trained for specific tasks, after which the networks function as subject-matter experts in certain fields. In our study, deep learning models they are trained to segment underwater images and to recreate those images with better quality. The efficient segmentation and feature extraction can be achieved using deep learning model by obtaining region of interest (ROIs) in the image and by extracting shape, color and texture features. At last, image quality enhancement of recreated images is an additional step to evaluate performance of proposed deep learning model.

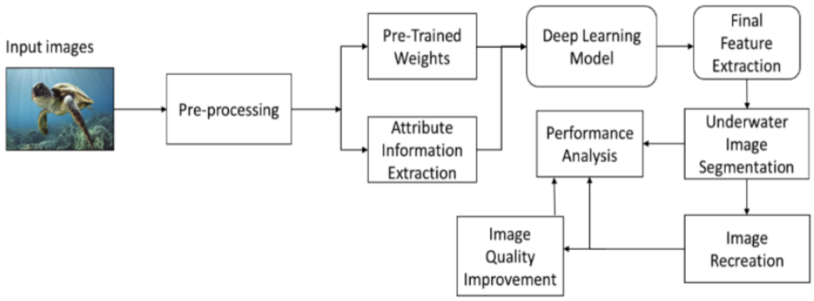

Figure 1: Proposed Underwater Image Segmentation and Recreation Process

6. Results & Discussion

The tools, programming languages, and performance metrics required to get high-performance results using deep learning algorithms to design an underwater image segmentation model are discussed in the next section. Tools that are massively used in Deep Learning model implementation with python and MATLAB programming are.

- Python
- Matlab
- Pytorch
- OpenCV
- Tensorflow

The performance of the designed machine learning models using these mentioned tools is obtained in a statistical manner. For example, the performance of the underwater image segmentation model is evaluated in terms of classification accuracy, precision, recall, F1-measure, recall, and sensitivity based on the obtained confusion matrix (true positive, true negative, false positive, false negative values).

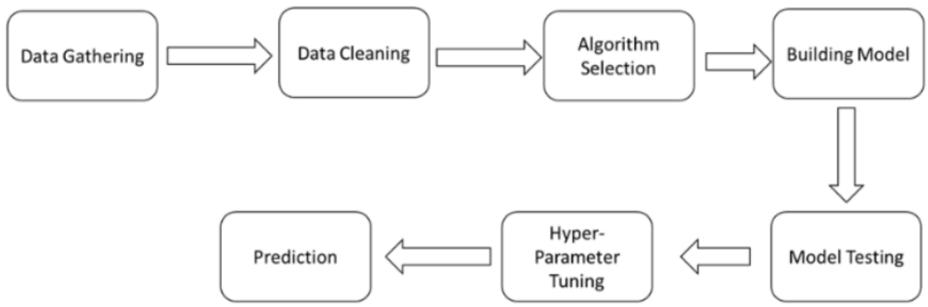

Figure 2: Deep Learning algorithm workflow

7. Limitations

DL which has been the subject of numerous research efforts, faces a number of difficulties when it comes to underwater image monitoring. We first discuss the main difficulties encountered when creating models for segmenting underwater images in this part.

1. Monitoring models need to be capable of identifying items and scenarios in intricate, challenging backdrops in order to function in aquatic environments. This is a problem for both the development as well as training of these algorithms along with their thorough testing.
2. Underwater scenes are incredibly dynamic, meaning that the scene's objects and content are always changing. The background can switch between being entirely obscured and being viewable.
3. Refraction can lead to inaccurate depth and distance perception. For shorter distances, this is more severe.
4. There is a lot of ambient noise, including a wide range of illumination. A faraway object appears significantly less light than one that is near up. When the background is uneven, these issues exacerbate.

8. Conclusion & Future Work

In the current survey paper, a comprehensive discussion and review are conducted on the state-of-art underwater image segmentation model. In this survey report, different underwater image segmentation datasets, different Deep Learning algorithms, their working process, implementation tools, performance metrics, several prediction methods, and varied research limitations are discussed. Numerous authors have emphasized that understanding of research limitations and benefits is useful for analysing any prediction model. The most used machine learning implementation interfaces are Python, MATLAB, OpenCV and TensorFlow. The goal of this research survey is to provide details of current underwater image segmentation techniques, and their working model and highlight their limitations so that an effective underwater image segmentation model can be built in near future. This survey can help researchers to design a reliable and accurate underwater image segmentation model in the early stages. It can be concluded that to design an enhanced underwater image segmentation model, proper pre-processing of data, exploratory data analysis, data cleansing, proper model selection, feature selection, and efficient classification model selection are the mandatory requirements. In future work, designing an effective predictive mechanism related to underwater image segmentation is the cardinal interest in minimizing most of the limitations of existing works.

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