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Underwater image enhancement: a comprehensive review, recent trends, challenges and applications

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Abstract
The mysteries of deep-sea ecosystems can be unlocked to reveal new sources, for developing medical drugs, food and energy resources, and products of renewable energy. Research in the area of underwater image processing has increased significantly in the last decade. This is primarily due to the dependence of human beings on the valuable resources existing underwater. Effective work of exploring the underwater environment is achievable by having excellent methods for underwater image enhancement. The work presented in this article highlights the survey of underwater image enhancement algorithms. This work presents an overview of various underwater image enhancement techniques and their broad classifications. The methods under each classification are briefly discussed. Underwater datasets required for performing experiments are summarized from the available literature. Attention is also drawn towards various evaluation metrics required for the quantitative assessment of underwater images and recent areas of application in the domain.

Keywords Underwater image enhancement · Colour correction · Image quality metrics · Contrast enhancement · Image dehazing · Fish identification

1 Introduction

Exploration of the mysterious world of underwater has caught the attention of researchers in recent years. Analysis of underwater imaging is extremely important for ocean resource exploration, marine ecological research, monitoring of deep-sea installations and naval military applications (Lu et al. 2017; Yang et al. 2019). The utilization of

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resources available underwater is of significant importance to human beings. This has led to the need for remotely operated underwater vehicles (ROVs) and autonomous underwater vehicles (AUVs) modelled with high-quality imaging system for effectively investigating the underwater environment (Ahn et al. 2017; Johnsen et al. 2016). Low quality of underwater images leads to the failure of computer systems which are used for visual inspection of images. Hence, it is extremely vital to develop the underwater enhancement techniques for use in sophisticated underwater imaging tasks. Last few decades have attracted much research in the domains of underwater image restoration and enhancement. This work tries to provide an in-depth review of various methods explored in the area of underwater image enhancement.

Underwater image processing deals with refinement of pictorial information essential for interpretation and processing by humans as well as machines (Zhang et al. 2019). Underwater research in the areas of sub-sea pipeline crack detection, the study of flora and fauna and marine archaeology depends largely on unambiguous and lucid underwater images (Khan et al. 2018).

The complete study on underwater applications relies on the quality of captured underwater images. Generally, the quality of underwater photos is dependent on numerous aspects, such as limited range of visibility, non-uniform lighting, an unwanted signal like noise and diminishing colour (Azmi et al. 2019; Ancuti et al. 2012). Underwater image processing can be broadly classified into two categories, namely image restoration and image enhancement (Lu et al. 2017). Underwater image enhancement does not make use of any physical model for enhancement task. It utilizes qualitative, subjective criteria to produce a visually pleasing image. Enhancement based approaches are simpler and faster than model-based approaches (Anwar and Li 2020).

In today's world, underwater images have to capture the most important information for use in myriad applications. Although numerous techniques for image enhancement are accessible, they are mainly limited to regular images, and very few methods have been explicitly established for underwater images. Quality of underwater image is poor due to the environment of the water medium. With the development in the areas of artificial intelligence and research in the area of machine learning algorithms, it has been observed that there have been significant improvements in the underwater image enhancement and restoration processes (Anwar and Li 2020).

The organization shown in Fig. 1 elaborates the basic structure of the survey presented in this paper. This article focuses on an in-depth survey of various attributes involved in the process of underwater image enhancement. This work consists of a brief introduction to the domain and elaborates the characteristics of underwater environment which covers the underwater imaging model, degradation of light and the challenges faced by the underwater medium. A broad classification of the underwater image enhancement techniques based on hardware and software methods is described. The evaluation metrics used for assessing the performance of the enhancement algorithms are also elaborated in detail. Datasets available for research are enumerated along with their source. The applications where the role of underwater image enhancement is significant are explored.

Figure 2 illustrates the number of publications in conferences and journals per year during 2011 to 2020. As can be seen from Fig. 2, there has been a significant increase in the area of underwater image enhancement in the last seven to eight years. This is mainly due to the need to utilize the resources in deep-sea for technological development and to unravel the new source of food (Li et al. 2018b; Ahn et al. 2017; Boom et al. 2012).

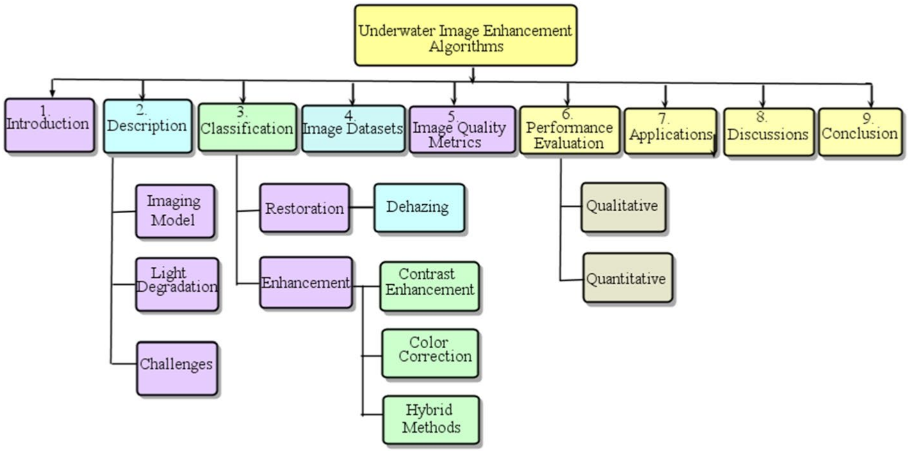
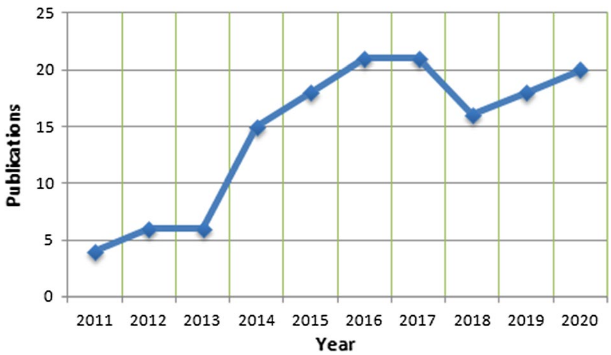


Fig. 1 Structure of this survey

Fig. 2 Journal and conference publications during 2011–2020



1.1 Motivation

Underwater image processing applications require clear images which is achieved by enhancement and restoration techniques. Image restoration processes requires physical models of degradation, which is dependent upon parameters like turbidity, time, attenuation coefficient. Image enhancement methods are faster and does not necessitate any calculation of parameters. The research area of image enhancement is in need of adaptive approaches and faster techniques of enhancement. In this article we have done the broad classification of the primary algorithms, presented by researchers in last two decades. This article presents state-of-the-art techniques in underwater image enhancement by prominently emphasising the contributions made by researchers in over 115 technical papers. A synopsis of underwater image enhancement methods based on the imaging types is presented in 2017 (Lu et al. 2017). The authors illustrated the basic concepts and the classification methods primarily focused on physical models. Whereas, this article targets the work done in non-physical based methods. Various underwater image restoration and enhancement techniques are evaluated and analysed using five image quality metrics in Zhang et al. (2019).

All the image quality metrics and major datasets are compiled that can be used for evaluating the efficiency of the designed algorithms in this article. The work presented in Yang et al. (2019) has focused on the analysis of different underwater scenarios, which helps to select the methods based on different types of underwater conditions. The evaluation carried out in Anwar and Li (2020) emphasises only on the deep learning-based approaches from CNNs to GANs that can be employed for underwater enhancement. In this work, we have tried to include the extensive research carried out in the field of underwater image enhancement from the year 2006. To the best of our knowledge, all major datasets and image quality metrics are included with their sources, which were used by researchers to carry out experiments. All the tabulated details in this article will enable future researchers to make accurate decisions in selecting appropriate methods for their works. Experiments have been done on images from two well known datasets using state of the art enhancement techniques, and their performance have been evaluated using qualitative and quantitative underwater image quality metrics.

The following are the contributions of this paper:

- This study covers more than 110 related works to determine the various approaches used by researchers to implement underwater image enhancement techniques.
- A detailed explanation of underwater imaging and the light degradation model is presented covering the challenges.
- All the image quality assessment metrics used for evaluating the performance of the algorithm is discussed and the major datasets which are currently used in the field of underwater image processing are summarized in the paper.
- Performance evaluation is carried on images from underwater image datasets.
- Different application areas like sea-cucumber image enhancement and fish detection are also explored.

The paper is organised as follows. Section 2 presents the description of underwater environment. Classification of underwater image enhancement methods is discussed in Sect. 3. Underwater image datasets and Image quality metrics are mentioned in Sects. 4 and 5 respectively. Performance evaluation is detailed in Sect. 5. The applications in the field of underwater image enhancement are elaborated in Sect. 7. Discussions are presented in Sects. 8 and 9 concludes the work.

2 Description of underwater environment

The underwater environment is the region immersed in water, in a natural or artificial body of water, such as an ocean, sea, reservoir, river or aquifer. The underwater environment is considered to be the origin of life on earth, and it is the environmental region most vital to the sustenance of life, and natural habitat for most of the living organisms. A large number of human activities are carried out in the accessible regions of the underwater environment. Hence it is important to understand the characteristics of the underwater imaging model in order to do carry out research in various domains.

2.1 Underwater imaging model

Literature indicate approaches to enhance underwater images based on physical models. Jaffe-McGlamery underwater image model is a well- known imaging model proposed by Jaffe-McGlamery (Vasamsetti et al. 2017; Schettini and Corchs 2010). The model is based on facts of linear superposition and modelling of water medium. The irradiance which enters the camera consists of linear combination of three different components namely the direct component E_d, forward-scattered component E_f, and backscatter component E_b. The total irradiance E_T is given as:

$$E_T = E_d + E_f + E_b \tag{1}$$

where E_d is the light that is reflected by the object and reaches the camera without getting scattered.

Forward scatter E_f occurs when the light reflected from the object scatters in its direction on the way, before reaching the camera. Backscatter occurs when the reflected light directly reaches the camera before reaching the scene to be illuminated. These models are widely used for image restoration purposes and require high-speed computations and longer times for execution (Chen et al. 2014; Berman et al. 2020).

2.2 Scattering

The presence of dust particles leads to the phenomenon of scattering in underwater medium. The reflected light from the outside of the object reaches the camera, and a scattering effect is formed when the light interacts with the floating particles present in the imaging medium. The two types of scattering that affect underwater images are forward scattering and backward scattering (Yang et al. 2019).

Deviation of light from the object to the camera leads to forward scattering, which in turn results in a blurred image. Backward scattering is due to the reflection of a fraction of light to the camera by water or floating particles, before it reaches the object. This leads to a low contrast and haze like effect on the image (Yang et al. 2019; Lu et al. 2017; Anwar and Li 2020).

2.3 Underwater light degradation

According to the Lambert-Beer empirical law, decay in the intensity of light depends on the properties of the medium through which the light travels (Schettini and Corchs 2010). The intensity decays in an exponential manner when it travels via water. This loss in intensity is called attenuation. It emerges from the effects of absorption, which causes loss of light energy, and scattering that causes a change in the direction of electromagnetic energy.

The phenomenon of absorption and scattering leads to the attenuation of light (Ancuti et al. 2017). Attenuation of light is of great concern while dealing with underwater images as it leads to the hazy effect that hinders image processing applications in the marine environment. Attenuation of light limits the visibility at about 20m in clear water, and 5m in turbid water (Chiang et al. 2011).

The absorption of light in water varies with wavelength. The diverse colours of light vanish with an increase in the depth of water. The red light is absorbed first due to its longest wavelength. The blue colour penetrates the longest distance in water medium because of its shortest wavelength hence the presence of bluish tint in underwater images (Zhang et al. 2019; Schettini and Corchs 2010).

2.4 Challenges of underwater imaging

Underwater imaging system primarily consists of optical camera, underwater RoVs or specialised hardware for capturing underwater images (Kumar et al. 2018). Except for optical cameras, all the other methods have their own limitations, like a constricted field of view, depth restrictions and complex operations etc. Control system of ROVs is complex because of the unfamiliar non-linear hydrodynamic effects, lack of a precise model of ROV dynamics and parameter uncertainties.

The requirement of highly skilled divers for underwater exploration makes it a costly affair. Each investigation may require stand-by divers and supervisors for a single mission. Moreover, only a restricted amount of time can be spent in an underwater medium, particularly when inspections are carried out by a diver. This leads to an increase in time duration needed for the purpose of exploration. This drawback can be overcome to a great extent by utilising underwater image enhancement techniques.

During the propagation of light through water, the optical property of water cause adverse affects to underwater imaging. The effect of refraction in an underwater medium makes it extremely difficult to focus on the subject of interest and leads to a blurry effect in images. Absorption of light and colours significantly affect the visual quality of underwater images. In order to overcome this limitation it is important that research is carried out to develop efficient and high-performing enhancement techniques.

Water medium is a natural light filter which absorbs a considerable amount of light traveling through it. For every 10 m of depth underwater, half of the light is lost. This means at a depth of 10 m, we just have 50 percent of the light that we had at the surface, and only 25 percent at a depth of 20 m (Zhang et al. 2019).

The availability of light will not be the same always; it depends on the time of the day. The water's surface reflects the least amount of its light when the sun is directly overhead. Weather plays a crucial role in the availability of light. If the weather conditions are stormy, uneven water will impact the light conditions significantly. Colour absorption is another major challenge faced due to absorption of wavelengths of light. Blue and green colours have longer wavelengths due to which they reach further deep, and that is the reason why underwater images have hues of blue and green colour.

Absorption and scattering lead to effects of blurriness, decreased contrast, and overall loss of image quality. This problem is further exacerbated in high turbidity underwater conditions or when powerful sources of artificial light are employed. Artificial light sources cause non-uniform lighting in the scene, which cause reflections that mask image details and generate bright spot (Schettini and Corchs 2010) as shown in Fig. 3. This may lead to misinterpretation of data. Fluorescence of biological objects and the presence of macroscopical particles in water lead to degradation of underwater images. Underwater image-processing provide measures of overcoming some of these challenges, as shown in Fig. 4, by making visual information a part of quantitative assessment. Adopting efficient image-based methods will provide precise quantitative information with minimum human supervision to append to visual inspection techniques and improve reliability.

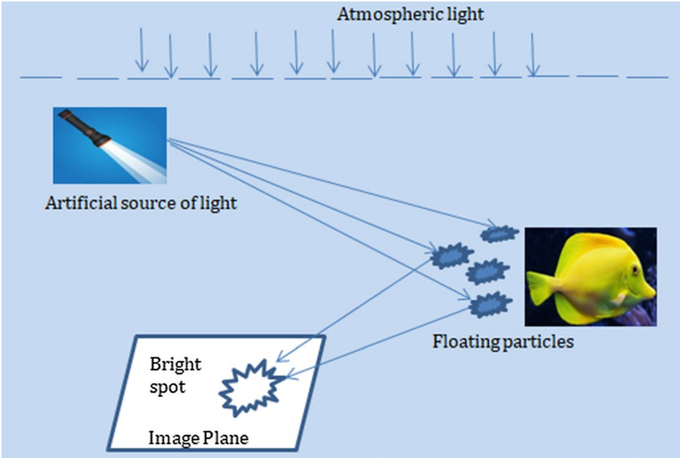
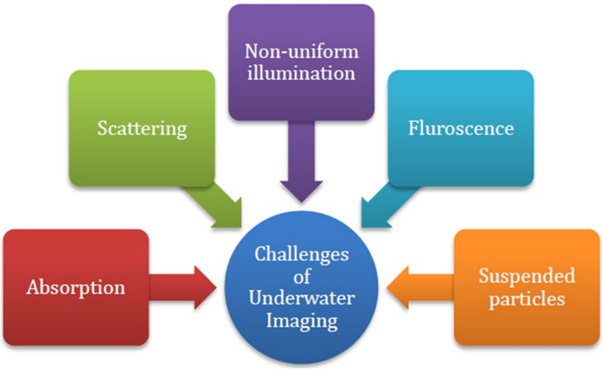


Fig. 3 Effects of non-uniform illumination (Schettini and Corchs 2010)

Fig. 4 Challenges faced by underwater imaging



3 Classification of underwater image enhancement and restoration methods

Underwater image enhancement is significant for obtaining clear images which are vital for understanding the real-life underwater scenario. Research in the areas of marine life exploration is possible only if we are able to attain good quality images. As can be noted from Zhang et al. (2019), the degraded image is concentrated towards green colour. This results in an image with less visual clarity. The enhanced image, on the other hand, exhibits more information with superior visual quality. This is also evident from the histogram distribution that shows homogeneous distribution of red, blue and green colours. This explains the need for enhancement and restoration methods for obtaining good quality images in the field of research and real-life applications.

Underwater image enhancement methods are not based on image formation model (IFM) whereas underwater image restoration methods depend on image formation models. Dehazing techniques are based on image formation models and are considered as restoration method. Methods not dependent on IFM can be further categorized into two main approaches: hardware-based and software-based. Software-based approaches can further be classified into contrast enhancement, colour correction and hybrid methods. The classification chart is, as shown in Fig. 5.

3.1 Underwater image restoration methods

Underwater image restoration techniques are dependent on physical models for their implementation. The physical model based methods entail the process of building the degradation model, calculating the parameters of the model and tackling the inverse problem. The model-based methods are dependent on prior knowledge and various assumptions of environmental conditions. Mathematical models which are built on apriori knowledge are complex, and the methods required for the estimation of the model parameters are computationally complex. Algorithms based on dehazing can be categorised under underwater image restoration.

3.1.1 Dehazing techniques

Dehazing has captured the interest in the research field as many application domains are using technologies based on digital imaging and computer vision. The images obtained underwater are difficult to interpret and are hazy in nature because of the presence of floating particles present in the water medium. The haziness is mainly caused by the absorption and scattering of rays of light when they travel from air to water.

Dehazing plays an important role in applications where the scenes are significantly deteriorated by environment factors. In images that are affected by fog, or haze, the dehazing techniques try to restore the visual quality of images in order to make them worthy for further processing.

An adaptive underwater image restoration technique is presented in Lu et al. (2019) using multi-scale cycle generative adversarial networks (MCycleGAN) and dark channel prior (DCP). In this deep learning approach, multi-Scale structural similarity index measure (SSIM) loss is utilized to improve the image restoration performance in terms of contrast enhancement and colour correction.

Underwater light field image restoration and enhancement technique are developed in Cui et al. (2018) by converting input image into the four-dimensional data. The approach

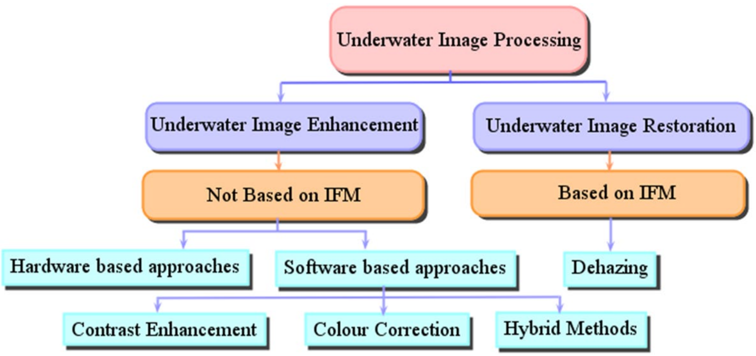


Fig. 5 Classification of underwater image enhancement and restoration methods

is based on the image haze removal using dark channel prior and pyramid image fusion. A light field imaging method is introduced for spectral characteristic-based colour correction for a low-intensity underwater image in Lu et al. (2018). Additionally, underwater image depth estimation method is presented based on light field camera and deep convolutional neural network.

Single-shot image restoration technique is developed by fusing a physics-based model for light propagation and a set of quality metrics (Barros et al. 2018). The model reduces the artefacts and degradation imposed by the attenuation, forward scattering, and backscattering effects. Multi-scale fusion strategy for underwater image restoration is explored to enhance colour correction, and contrast (Zhang et al. 2018a). Initially using the optical underwater model, the restored image is obtained. Then, the white balance and the contrast enhanced image of the restored version is acquired and fused together.

Underwater image restoration approach is proposed in Li and Li (2019) using four methods. Seawater properties are determined using the deep-sea optical imaging model, and later a dual dark channel model is utilized to remove the haze. Laplacian pyramid based image fusion method is illustrated to enhance turbid scene visibility under artificial illumination (Treibitz and Schechner 2012). The method preserves shadow contrast and reduces backscatter in each frame with uniform illumination.

Underwater image restoration framework is proposed based on wavelength compensation and image dehazing (WCID) in Chiang and Chen (2012). The method extracts depth map, presence of artificial light source and the residual energy ratio to eliminate distortions due to the presence of light scattering and colour change. A restoration method using a variant of dark channel prior for red channel correction is presented by Galdran et al. (2015). The method requires fewer parameters and efficiently enhances underwater images, even in the presence of an artificial light source.

The relation between the background colour of underwater images and the inherent optical properties of water medium is derived for underwater image enhancement (Zhao et al. 2015). Authors found that global background light is independent of object-camera geometry. The ratios of attenuation coefficients are used to estimate the transmission map of individual channels in Han and Chen (2016). The colour cast issue after restoration is sorted by applying a colour correction method based on averaging of colour channels.

A pipeline corrosion estimation using an enhancement and restoration algorithm is illustrated in Khan et al. (2018). The algorithm reduces the effects of blurring and improves the contrast of images. The imaging data with enhanced colours helps in the estimation process. A robust retinex model is developed in Li et al. (2018a), which enhances low light images degraded by excessive noise. An alternating direction minimisation (ADM) based algorithm is used for solving the optimization problem. This method can also be used for remote sensing applications as well as in hazy and dusty environmental conditions.

A prior based on adaptive attenuation curve, which can model the attenuation function of light in various environments is proposed in Wang et al. (2017b). The saturation constraints are exploited in order to reduce the overall effects of over-saturation and to eliminate the effects of noise from the images which are restored. A restoration process is proposed in Liu and Chau (2016) which utilises a systematic method of enhancement by considering water light and transmission map. A cost function is formulated and minimized for the precise calculation of the transmission map. Based on the degradation model, the distortion and backscattering effects are corrected. The degraded images are enhanced effectively with prior knowledge of point spread function (PSF) in Chen et al. (2012). Authors have reviewed numerous empirical PSF models and have used blind restoration process to recover degraded images.

In Emberton et al. (2018), entropy-based segmentation is employed to localise pure haze regions to enhance visibility for underwater image and video dehazing. A Gaussian normalisation is also used to ensure temporally stable pure haze segmentation in underwater videos. Image dehazing method using a joint trilateral filter is presented in Serikawa and Lu (2014) by Serikawa and Lu to enhance underwater images. Using difference based prior to colour channels, the transmission depth map is estimated, which improves global contrast and reduces noise level. During the estimation process, the influence of an artificial lighting source is not considered.

A two-stage dust removal approach is proposed in Li et al. (2019b). In the first stage, fine dust is removed from underwater images using red-green channel prior to de-scattering. The second stage employs a deep convolutional neural network to further remove the dust. DCP based underwater image enhancement is attempted in Sathya et al. (2015). The thickness of haze is estimated with knowledge of prior and imaging colour model, which leads to a haze-free image of superior quality. The DCP method mainly depends on underwater image statistics.

Table 1 summarizes the techniques utilized by researchers for dehazing underwater images, thereby leading to image enhancement.

3.2 Underwater image enhancement methods

Underwater image enhancement methods do not depend on physical models for implementation. They extract information of the images without prior knowledge of environmental conditions. Enhancement methods can be classified into hardware and software based approaches.

3.2.1 Hardware based methods

There are four main hardware approaches that are used for underwater imaging, namely polarization, range-gated imaging, fluorescence imaging and stereo imaging (Lu et al. 2017). Polarization, which is a passive method of imaging enables to capture the images very quickly and also leads to a significant reduction of noise. Range-gated imaging is an active method of imaging and is utilized for systems in turbid water. The device settings in these systems are complex and are susceptible to environmental conditions. Fluorescence imaging is used to detect microorganisms present in coral reefs. Stereo imaging is mainly used in AUVs and is designed with the aid of real-time algorithms. They help to recover underwater images by estimating the coefficients of visibility.

Polarization-Difference Imaging (PDI) obtained using Strokes vector approach is investigated for underwater image enhancement (Tian et al. 2018). Image with consistent contrast is obtained using the approach and is suitable for moving object detection when combined with the imaging polarimetry. Underwater image reconstruction technique based on maximum a posteriori scheme and point spread function regularization using range-gated imaging is proposed by Chen and Yang (2013). It is observed that point spread function (PSF) of underwater range-gated imaging enhances image resolution compared to the hardware limit. A restoration approach using region segmentation and depth estimation is described in Chen et al. (2014) for underwater images captured in inhomogeneous environment. Initially, using a bright and dark channel prior, the depth map and haze concentration are estimated. With these parameters, dehazing and colour compensation of the imaging light are computed.

Table 1 Summary of dehazing algorithms

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Chiang and Chen (2012)	2012	WCID	Compensates attenuation along the path of propagation by considering artificial light	Highest SNR value indicate robustness of the method	Handles light scattering and color distortions simultaneously
Galdran et al. (2015)	2015	Red channel method	Colors with shorter wavelengths are recovered leading to contrast recovery	High Values of e, r and low σ values indicate good visibility	Locates artificially illuminated regions and handles them by avoiding color artifacts
Zhao et al. (2015)	2015	Underwater imaging model	Derives inherent optical properties of water from background color	High SNR values indicate good contrast enhancement	Performs colour correction and removes haze
Sathya et al. (2015)	2015	DCP	Prior knowledge of local patches helps in estimating the thickness of haze	PSNR values indicate better performance	Superior haze removal ability and color balancing capability
Li et al. (2018a)	2018	Robust Retinex model	Optimization function include novel regularization terms for illumination and reflectance	Low values of NFERM, BTMQI, and higher values of NIQMC, and CPCQI, indicate good improvement of visual content	Image enhancement in hazy or dusty conditions, also used for remote sensing
Cui et al. (2018)	2018	Dark channel prior and pyramid image fusion	Converting light field image into four-dimensional data	Larger variance indicate good restoration of light field image	Image restoration and enhancement of light field image
Zhang et al. (2018a)	2018	White balance and contrast enhancement+ blending by multi-scale fusion	Dynamic threshold white balance method deals with colour fading	Reduces the execution time, better visual quality	Effectively enhance underwater image
Li and Li (2019)	2019	Optical imaging+Dual dark channel model	Halo-estimation devignetting removes artificial light	Method is suitable for ocean observations	Removes unwanted particles, corrects non-uniform illumination, recover real scene color, and super-resolve the images
Lu et al. (2019)	2019	MCycleGAN+DCP	Deep learning	Large values of UIConM , UICM and UISM indicate good performance	Improve performance of image restoration

Table 1 (continued)

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Li et al. (2019b)	2019	Red-green minimum channel prior descattering	Deep convolutional neural-network-based dust removal method	High SNR show improved performance	Forward scattering, backward scattering, absorption, and artificial lighting issues are solved

3.2.2 Software-based methods

Non-physical based models deal with the manipulation of pixel values of the image leading to the visual enhancement of the images. These techniques use software algorithms for enhancement of underwater images. Underwater image enhancement techniques can broadly be classified into three categories, namely, contrast enhancement, colour correction and hybrid methods. Hybrid methods are implemented by combining the methods of contrast enhancement, dehazing and colour correction.

3.2.2.1 Contrast enhancement techniques Contrast is an essential criterion in any subjective evaluation of image quality. Contrast is formed by the disparity in luminance reflected from two adjacent planes. Contrast is the deviation in visual properties that makes an object distinguishable from other entities and the backdrop scene (Ueki and Ikehara 2019).

The sensitivity of our vision is more towards contrast than the absolute luminance; hence, we can perceive the world in spite of significant variation in illumination conditions. If the contrast of an image is highly concentrated on a particular range, e.g. an image is found to be very dark; the information may be completely lost in those areas (Liu and Chau 2016). The contrast has to be optimized for representing all the details in the input image. Numerous algorithms for achieving contrast enhancement have been developed to address the issues in underwater image processing.

Stationary wavelet transform (SWT) based contrast enhancement approach for acoustic images captured by side-scan sonar is proposed in Priyadharsini et al. (2018). Low-frequency sub-band is modified using a Laplacian filter and the masking technique, resulting in higher peak signal to noise ratio (PSNR) and SSIM values. Guraksin et al. (2019) designed underwater image enhancement technique using discrete wavelet transform (DWT) and the differential evolution algorithm. Contrast enhancement and homomorphic filtering are applied as the first step in order to enhance contrast and brightness. After decomposing the image using DWT, differential evolution algorithm was utilized to detect the optimum parameters for different performance evaluation factors.

Contrast enhancement algorithm based on rayleigh stretching of an individual colour channel is developed in Sankpal and Deshpande (2019) using maximum-likelihood estimation of scale parameter for degraded underwater images. Furthermore, energy correction is applied to estimate information loss and to enhance the entropy of the contrast-enhanced image. In order to equalise contrast and address issues related to lighting in underwater images two stretching algorithms are applied on the RGB and HSI colour models (Iqbal et al. 2007). The work of Iqbal et al. (2007) is further extended by applying histogram stretching in a manner which differs from that used for integrated colour model (ICM) and unsupervised colour correction method (UCM) (Sankpal and Deshpande 2019). The noise content is reduced to a great extent, along with a significant increase in image details.

Contrast enhancement method based on Rayleigh histogram stretching and by averaging RGB and HSV colour spaces is suggested in Ghani and Isa (2014b, 2015b). Qualitative and quantitative analysis confirms improvement over the histogram equalization approach. High turbidity underwater enhancement approach is proposed in Li et al. (2016b) using image de-scattering and physical spectral characteristics. Additionally, authors presented a new underwater image quality assessment metric and deep neural network-based framework for classification.

The CIELAB color scheme is much similar to the human visual system (HVS) consisting of three different channels: a luminance channel and two chromatic channels. In

Zhang et al. (2017a), retinex and LAB based approach called *LAB-MSR* is proposed for contrast enhancement of underwater images. Bilateral and trilateral filter are combined on three CIELAB color channels leading to an extended multi-scale retinex (MSR) approach. In Zhang et al. (2017a), the original retinex algorithm is modified to achieve competitive performance by reducing the halo artefacts.

Although there are still some issues about deep networks (Goceri 2019b), deep CNN network where convolution layers are employed for encoding and deconvolution layers for decoding is modelled in Sun et al. (2017) and applied widely with different types of images including colored photographs in recent works (Goceri 2019c). Enhancement is obtained in an adaptive way without considering the physical environment. The model can also handle images with varying levels of noise. Linear image interpolation and limited image enhancer is used in Bindhu and Maheswari (2017) to remove distortion, improve the contrast and increase the resolution. The mean squared error (MSE), PSNR and entropy values indicate good performance compared to other state-of-art methods.

A guided filter with a low-cost architecture is designed in Chang et al. (2017). The architecture reduces the computational complexity associated with transmission estimation. DCP based underwater image enhancement method along with luminance adjustment is proposed in Li et al. (2016a). The edges and image details are well preserved, and there is a significant improvement in the global contrast of the image.

Adaptively clipped contrast limited histogram equalisation (ACCLAHE) used along with DCP is used in Dixit et al. (2016) for estimating the blur regions present in the image and removing them. Homomorphic filtering technique is used to preserve the edges, and median filtering is employed to eliminate noise. The disadvantage of extensive computations required for real-time enhancement is solved by using regional histogram equalization in Alex et al. (2016). The design is implemented on field programmable gate array (FPGA), which is useful for parallel processing.

A differential evolution (DE) algorithm is used for contrast enhancement in Güraksin et al. (2016). The underwater images are separated to R, G, B channels and contrast stretched by applying the parameters obtained from the DE algorithm. A fusion of contrast-limited adaptive histogram equalisation (CLAHE) transformed image and unsharp masking (USM) transformed image using weighted blending is done in Zheng et al. (2016). The results of linear fusion approach are found to be promising than the state-of-the-art methods.

An enhancement method by improving the auto levels for each channel, thereby increasing the contrast of each of the RGB channels is presented in Basuki and Ramadijanti (2016). The method is useful when good equipment is not available for capturing underwater images. A virtual retina model is used to attain underwater image enhancement in Wang et al. (2016). Contrast enhancement is achieved, and the original object colours are also retrieved. An image quality assessment (IQA) based on patch discrete cosine transform (PDCT) approach is used as an adaptive enhancement strategy.

A distance factor estimation is used for enhancing underwater hazy images in Dwivedi et al. (2015). The author uses the object distance from the point in a scene based on the intensity of the pixel along with an optimization method to attain substantial results.

An enhancement model making use of the blurriness of the image for estimating the depth map for image enhancement is implemented in Peng et al. (2015). The image formation model, combined with the information about image blurriness, is used to estimate the distance covered between the camera and the scene points, thereby leading to enhanced visual images.

For increasing the interpretability and visibility of underwater images, an empirical mode decomposition (EMD) is presented in Çelebi and Ertürk (2012). The RGB image is decomposed into intrinsic mode functions (IMFs), and the enhanced image is obtained by adding the IMFs of the individual colour channels with different weights. The weight set is calculated with the help of a genetic algorithm. This method displays better-quality results than the conventional methods of histogram equalization and contrast stretching.

Enhancement of colour images using HVS is implemented in Au et al. (2012). The algorithm is used to lead to colour enhancement in the compressed domain, mainly focusing on chromatic components. Weber-Fechner law is utilized to implement a simple method for eliminating the blocking artefacts. The distinguishing feature in this algorithm is that, it has a modified approach with a focus on chromatic components rather than the luminance components as in other algorithms.

Underwater image enhancement is done using particle swarm optimization in AbuNaser et al. (2015) where the adjustment of RGB is made using the optimization algorithm. The method used led to an improvement in the illumination and true colours of underwater images. A local intensity distribution equalization (LIDE) based on the parametric model is implemented in Marukatat (2015), which lead to a major reduction in memory requirements and computational requirements. LIDE with Laplacian mixture model is also proposed in Marukatat (2015), and it was found that it produces images with better visual details and low speckle noise than adaptive histogram equalisation (AHE). A natural-based underwater image colour enhancement (NUCE) method which significantly reduces colour cast is implemented in Azmi et al. (2019). A swarm intelligence based algorithm is also included to improve the naturalness of the image. The overall sharpness of the image is improved by using unsharp masking.

Various algorithms developed for accomplishing contrast enhancement have been tabulated in Table 2.

3.2.2.2 Color correction techniques The images obtained underwater are dominated by blue and green colour as they travel deeper in water because of their shorter wavelengths. As can be observed from Zhang et al. (2017b) the underwater image captured at a particular depth appears greenish. The histogram distributions of the three channels indicate that the mean of the red channel is insignificant than that of the green channel. Also, the histogram distribution ranges of RGB channels does not cover the range from [0,255]. To address the issue of colour cast, a colour correction technique has to be applied to underwater images for improving the content of visual information.

Automatic and manual colour correction technique is evaluated to obtain the mean value of the stretched histogram in Shamsuddin et al. (2012) to enhance colour diminishing in underwater images. It is observed that the manual correction approach is better as compared to auto enhancement technique because of the significance level. An enhancement method which uses fuzzy logic to determine colour cast and utilizes bacterial foraging optimization (BFO) to remove the colour cast is presented in Sethi et al. (2015). The adaptive nature of the approach enhances the visual quality of the images. The proposed work gives better results than UCM and gray world algorithms. Performance evaluation shows that bacterial foraging leads to the most favourable balance of colour and also improves the contrast of the images.

A method for non-uniform illumination correction is proposed in Sankpal (2016). A maximum-likelihood estimation is used in this work in order to map the image to Rayleigh distribution. The input image is separated into three colour channels, and the scale

Table 2 Comparison of contrast enhancement based underwater image enhancement algorithms

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Çelebi and Ertürk (2012)	2012	EMD	Spectral component of images decomposed into IMFs +Genetic Algorithm for weight calculation	Entropy and average gradient values indicates best performance	Best visual performance and the method displays interpretability, in terms of colour and clarity
Au et al. (2012)	2012	HVS	Weber–Fechner law	CEF, WBQM, MASDS values shows improved colour image enhancement	Eliminating the blocking artifacts
Ghani and Isa (2014b, 2015b)	2014	Integration of modifications of image histogram in RGB and HSV color models	Histograms are remapped to follow rayleigh distribution	Acceptable values of entropy, MSE and PSNR, makes it second to PDSCC	Contrast and visibility is improved and better object recognition in images
AbuNaser et al. (2015)	2015	Particle swarm optimization	Adjustment of RGB done using optimization algorithm	PSNR, entropy and standard deviation values indicate good performance	Improvement in illumination and true colors
Marukatat (2015)	2015	LIDE	LIDE with laplacian mixture model	Images are produced with better visual details and low speckle noise than AHE	Major reduction in memory requirements and computational requirements
Li et al. (2016b)	2016	Joint guidance image filter	Image de-scattering and physical spectral characteristics-based color correction	CNR, SSIM,color distance values shows that method works good for scatter removal	Useful for pre-processing of deep learning based classification and recognition architecture
Li et al. (2016a)	2016	DCP based enhancement	Luminance adjustment	Naturalness image quality evaluator (NIQE) low value shows good visual quality	Improvement in the global contrast of the image
Dixit et al. (2016)	2016	ACCLAHE used alongwith dark channel prior	Homomorphic filtering and median filtering	High PSNR show increase in data substance of image	Elimination of noise and preservation of edges
Alex et al. (2016)	2016	Regional histogram equalization	Implementation using FPGA	Resource utilization show successful implementation on ALTIUM nanoboard	Can be used in AUVs
Güraksin et al. (2016)	2016	Differential evolution	Separation to R G and B channels	Entropy and average gradient values indicate good levels of enhancement	Contrast enhancement

Table 2 (continued)

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Wang et al. (2016)	2016	Virtual retina model+ IQA	Adaptive enhancement strategy with no-reference IQA based on PDCT	Information entropy, contrast ratio, PDCT values show improvement in contrast and good recovery of object colors	Improved precision and vision effects in images
Zhang et al. (2017a)	2017	LAB-MSR,	Blending of bilateral filter and trilateral filter on three channels of the image in CIELAB color space	Comparative results MSE values	Underwater robot control and manipulation, underwater scene analysis
Sun et al. (2017)	2017	Encoding-Decoding deep CNN networks	Convolution layers are employed for encoding and deconvolution layers are used for decoding	Values of SSIM, PSNR, MSE display better performance of conv3-deconv3 than conv5-deconv5	Achieves image enhancement in an end-to-end adaptive way without considering physical environment
Bindhu and Maheswari (2017)	2017	Interpolation + limited image enhancer	Resolution of image increased first and later contrast	MSE ,PSNR and entropy values indicate good performance	Noise is reduced by increasing resolution and contrast of the image
Chang et al. (2017)	2017	Guided image filter	A low-cost architecture is developed to achieve real-time full-HD enhancement	Design utilizes 11.3 percent of gate counts and 42.2 percent of on-chip memory	Full-HD enhancement of image with less gate counts
Priyadharsini et al. (2018)	2018	Stationary Wavelet transform	Low frequency sub-band modified using Laplacian filter and masking technique	High PSNR and SSIM values	Contrast is improved by retaining crucial details of image at each level of decomposition
Guraksin et al. (2019)	2019	Wavelet transform and differential evolution algorithm (DEA)	Contrast enhancement and homomorphic filtering is used to enhance contrast and brightness. DEA is utilized to detect optimum parameters	Entropy and PSNR based approaches are found to be efficient	Visual information is more distinguishable
Sankpal and Deshpande (2019)	2019	Rayleigh stretching	Maximum-likelihood estimation+ Energy correction	Best results for the parameters MSE and SSIM	Better recovery of original image and the structural components

Table 2 (continued)

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Azmi et al. (2019)	2019	NUCE	Integration of four steps also involving swarm-intelligence algorithm for equalizing mean values of histograms	Entropy, average gradient, sobel count, and PCQI have highest average score showing improved contrast	Also reduces color cast and improved image details

parameter is estimated. Histogram stretching is done on the three channels and later concatenated to obtain a corrected image. Image quality metrics like average contrast (AC), average information entropy (AIE), normalised neighborhood function (NNF) and comprehensive assessment function (CAF) indicate better performance when compared with other methods.

The adaptive linear stretch method, which is better than linear stretching, is proposed in Ao and Ma (2018). This method is found to improve the subjective quality by keeping low computational complexity. The regions with low light distributions are adjusted with threshold depending on the histogram. The values of entropy, MSE, PSNR, SSIM and the processing time indicate that the results are suitable for real-time applications.

Retinex model for illumination adjustment by extraction of illumination map and successive implementation of gamma correction is developed in Zhang et al. (2017b). Adopting special normalization method, the colour cast of the images can be corrected. The structure of edges are preserved, and the textures are smoothened at the time of illumination adjustment. Experiment results indicate that the method is superior in terms of colour, and appearance when compared with state of-art methods. Processing time is the shortest when compared with other methods, and the underwater image quality measurement (UIQM) values indicate the best results.

A wavelet-based approach is used for colour correction in Singh et al. (2015). The approximation and detailed coefficients are obtained by application of DWT to the input image. For the purpose of colour correction, approximation coefficients are utilized, and the detailed coefficients are utilized to preserve the structure. PSNR and SSIM quality metrics exhibit superior values.

Enhancement of underwater images by a deep residual framework is presented in Liu et al. (2019). Cycle consistent adversarial networks (CycleGAN) and a reconstruction model very-deep super-resolution reconstrustion model (VDSR) is employed in Liu et al. (2019) for the purpose of enhancement. An underwater Resnet model is used for the enhancement task. The method shows that batch normalisation (BN) layers accelerate the rate of convergence and is very useful in enhancement. Highest score of UIQM further shows the significant improvement in visual effects.

Table 3 encapsulates the approaches and the performance evaluation measures used by researchers in their work.

3.2.2.3 Hybrid methods A combination of the above-mentioned methods like contrast enhancement and colour correction or colour correction and dehazing or dehazing and contrast enhancement lead to hybrid methods. Hybrid methods lead to greater levels of image enhancement.

(i) *Color correction and contrast enhancement techniques* In Vasamsetti et al. (2017), approximation and detailed coefficients generated by applying discrete Wavelet transform are modified separately for colour correction and contrast enhancement of underwater images. Colour casting factor (CCF) is computed for individual RGB components to adjust the pixels values. The proposed method is evaluated qualitatively and quantitatively using three different databases. Contrast-limited adaptive histogram equalization (CLAHE) for contrast enhancement and percentile methodology for colour correction are combined for underwater image enhancement in Garg et al. (2018).

Table 3 Colour correction algorithms

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Sethi et al. (2015)	2015	Fuzzy logic	BFO removes colour cast	Better results than UCM and gray world algorithms	Balance of color and improves contrast ofthe images
Singh et al. (2015)	2015	DWT	Approximation coefficients used for colour correction and detailed coefficients are used to preserve the structure	PSNR and SSIM quality metrics exhibit superior values	Human-computer interaction and realization of underwater environment
Sankpal (2016)	2016	Maximum-likelihood estimation	Input image is separated into three colour channels and scale parameter is estimated	AC, AIE, NNF and CAF indicate better performance	Improvement in contrast values in comparison to traditional methods
Zhang et al. (2017b)	2017	Normalization method	Retinex model	Edges are preserved and the textures are maintained	Effective and robust
Ao and Ma (2018)	2018	Adaptive linear stretch method	Low light distributions are adjusted with threshold	Entropy, MSE, PSNR ,SSIM and PT indicate results are suitable for real-time applications	Improve subjective quality, low computational complexity
Liu et al. (2019)	2019	Cycle GAN+ VDSR	Deep residual framework	High UIQM value indicate significant visual improvement	Can be utilized for vision based tasks

The method presented in Honnutagi et al. (2019) employs luminance, chromatic, salient weight map, and Laplacian pyramid fusion techniques to enhance the contrast and colour of an underwater image. The method is evaluated using MSE, PSNR and entropy. A fusion-based enhancement/restoration method is described using colour correction, and contrast enhancement versions of input underwater image or video in Ancuti et al. (2012). Four different weight maps are used to enhance the distant object visibility, and this method is suitable for segmentation, image matching and dehazing of underwater images and videos.

By combining global and local contrast correction, dual-image Rayleigh-stretched contrast-limited adaptive histogram specification approach is proposed in Ghani and Isa (2015a) for low-quality underwater image enhancement. Contrast and color correction steps are employed, resulting in significant improvement in image contrast.

Huimin et al. (2016) developed an approach for underwater turbid image enhancement and color correction using three steps: (a) removal of a footprint effect present due to artificial light for imaging using a de-vignetting technique (b) estimation of transmission map of red and blue channels using descattering based on dual-channel prior and (c) a weighted guided trigonometric filter for color correction and noise removal preserving edges. Authors showed 1 dB average PSNR improvement over other image enhancement approaches.

Recursive adaptive histogram modification (RAHIM) algorithm for color correction and contrast enhancement is proposed in Ghani and Isa (2017). The image histogram is modified with Rayleigh distribution in HSV color space in order to enhance underwater image contrast. A two-stage enhancement method is described in Ghani and Isa (2014a), where contrast enhancement and colour correction are applied to an image which is converted to HSV model. Rayleigh stretching is used in this work to improve the visual details of the image and to eliminate noise.

A residual CNN that aggregates data information and prior knowledge for the estimation of transmission map is discussed in Hou et al. (2018). Also, four residual based network models have been analyzed with colored images in a different study (Goceri 2019a). The underwater residual CNN (URCNN) model with very good learning capabilities, also aids in illumination balance. The method is effective in removing the hazy effect present in the images and improves the overall contrast. A single image approach for underwater image enhancement using rayleigh stretching is proposed in Mathur and Goel (2018). White balancing followed by gamma correction is used to compensate for the colour cast issues caused due to underwater medium. The results obtained from qualitative and quantitative analysis prove that the effects of over and underexposed areas from the image are minimised significantly.

Multiscale fusion strategy which blends the images derived from a white balanced single input image, is used by Ancuti et al. (2017) for improving the global contrast and sharpness of edges. The algorithm works reasonably well without depending on the camera settings. An algorithm based on empirical mode decomposition, to eliminate the effects of scattering and blurring due to poor illumination is implemented in Mallik et al. (2017). A white balance approach which uses gray world technique is used, for refining the contrast and colour cast issues.

A structure texture decomposition model which enhances the underwater images without magnifying the artefacts is proposed in Yang et al. (2017). The proposed approach uses histogram equalisation for colour correction and later uses total-variation and L1 norm minimisation (TV-L1) on the image for decomposition into two layers, structure layer and decomposition layer, respectively. These layers are denoised and enhanced separately and later are combined to obtain the texture mask. Colour distortion is addressed using piecewise linear transformation in Fu et al. (2017). An optimal contrast technique is used in Fu et al. (2017) for removing the artefacts and enhancing the underwater image visually. The computational time indicates the effectiveness of the method for real-time applications.

A fusion-based method operating on frequency domain is found to improve the visual content of the underwater images (Wang et al. 2017a). The method makes use of wavelet decomposition and employs principles of weighted average method and local variance method for the fusion process.

The algorithm proposed in Erat et al. (2017) employs colour correction based on histogram equalisation methods and contrast enhancement in the frequency domain. DCT based approach is used for improving the contrast feature in colour images. UIQM measures show that the algorithm plays a crucial role in extracting features of importance from underwater images used for maritime border protection.

An approach proposed in Singh and Biswas (2017) uses a hazy underwater image to generate a contrast enhanced input and white balanced input image. The weight maps of chrominance, saliency and luminance are imposed on the two input images. A multi-scale fusion of all the input images and the weight maps enables in obtaining the final dehazed image. A hybrid method based on DCT-DHE is implemented in Dubey et al. (2017). Dynamic histogram equalization filter is used before the block splitting algorithm for achieving the required levels of enhancement.

Images that are colour corrected and contrast-enhanced are decomposed to obtain wavelet coefficients in Khan et al. (2016). Later, fusion of coefficients with maximum values from the decomposed images is carried out using fusion techniques. Inverse decomposition leads to an enhanced image, and the results of RMSE, PSNR and SSIM indicate good levels of enhancement.

Non-linear filtering techniques are used in Rodrigues et al. (2016) for achieving enhancement of images obtained from turbid waters. The method uses an automatic enhancement technique which involves the computation of saturation map, lightning correction, contrast enhancement and colour correction. The values of absolute mean brightness error (AMBE) and measure of enhancement (EME) establish that the method is powerful than the traditional methods.

A fractional filter is implemented in Shourya et al. (2016) to achieve contrast enhancement. The order of the filter can be selected adaptively depending on the strong and weak edges. Fractional differential function with adaptive orders is used in order to maintain the weak textures while the stronger edges are enhanced.

An red channel correction based on green and blue channels (RCCGB) and mean pixel enhancement is used in Mohd Azmi et al. (2019) for enhancing images from deep underwater by improving color cast and contrast. RCCGB minimizes the illumination effects, and particle swarm optimization (PSO) algorithm is utilized to improve the contrast. Quantitative evaluation of NIQE, entropy and average gradient indicate superior performance.

Conditional generative adversarial network is used to solve the issue of image enhancement with a multi-scale generator in Yang et al. (2020). A dual discriminator captures the local and global information and provides naturalness to the image. The PSNR and SSIM values display favourable results with respect to other state-of-the-art methods.

Hybrid methods that consider color correction and contrast enhancement techniques are revealed in Table 4. The table also enlists the advantages and performance evaluation of the methods.

(ii) *Dehazing and color correction methods* A two-step underwater image enhancement algorithm is illustrated in Ding et al. (2018) using super-resolution convolutional network. In the first step, an adaptive colour correction algorithm is used to balance colour casts and generate natural colour corrected images. Later, a super-resolution convolutional neural network is applied to images which are colour corrected so as to remove the effects of blurring.

Dehazing and colour correction methods are exploited for enhancing underwater images in Zhang et al. (2018b). Several subjective and objective experiments are conducted to test the proposed algorithm. Underwater image dehazing and colour correction approach is illustrated using a stacked conditional generative adversarial networks (GAN) framework in Ye et al. (2018). The framework is organized in two components, a haze detection and a colour correction sub-network, both having a generator and a discriminator.

Estimating a medium transmission and a global background light detection is useful in dehazing and color correction of underwater images. In Li et al. (2017a), image dehazing and color correction technique is proposed by fusing characteristics of light in underwater medium and background light estimation using a regression model. Various subjective metrics including UCIM and underwater colour image quality evaluation metric (UCIQE), and objective performance metric are demonstrated for performance evaluation of the proposed method. Table 5 summarizes the technique, approach, evaluation details and the advantages of the methods used by researchers combining dehazing and colour correction algorithms.

(iii) *Dehazing and contrast enhancement methods* Fog removal and contrast enhancement technique for underwater images is illustrated using an improved segmentation dark channel prior (ISDCP) in Guo et al. (2017). Dehazing is present due to the refraction of light and contrast degradation is because of the variation of attenuation with different wavelengths. Initially, ISDCP is employed for fog removal and later contrast enhancement is done by using histogram stretching in RGB channels with low complexity and improved visibility.

A dehazing algorithm based on the minimum information loss principle is proposed in Li et al. (2016a). Histogram distribution prior is used for improving the contrast of underwater images. The method is found to reduce the artefacts as well as noise to a great extent. Corrosion estimation for pipelines is achieved in Khan et al. (2016) by a dehazing and enhancement process. Fusion techniques based on wavelet is applied to colour corrected as well as contrast-enhanced image for obtaining a dehazed synthesized image. Accuracy of estimation is maintained by defining region of interest for separating other objects from the pipeline in the image.

A multi-scale fusion method which blends the input images and their weight maps to get a dehazed image is proposed in Singh and Biswas (2016). The efficiency of this method is proved with high values of entropy, and low values of AMBE. An efficient underwater enhancement method independent of the scene information is implemented in Farhadifard et al. (2015). A colour correction strategy based on guided colour mapping scheme is used to compensate for the colour cast. To tackle the effects of forward scattering, a singular value decomposition (k-SVD) based deblurring algorithm is used. The results show that natural colormap is highly preserved.

Table 4 Colour correction and contrast enhancement algorithms

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Ancuti et al. (2012)	2012	Multi-scale fusion	Single image approach	IQM metric shows amplification of contrast	Robust to artifacts, restores global contrast and local features
Ghani and Isa (2014a)	2014	Image histogram is modified in RGB and HSV color model	Modification of RGB colour model followed by conversion to HSV color model	Entropy, MSE, and PSNR values indicate increase in valuable information of image	Improvement in image color leads to improvement in the visibility of the objects and hence improves object recognition
Ghani and Isa (2015a)	2015	DIRS CLAHS dual-image Rayleigh-stretched contrast-limited adaptive histogram	Integration of global and local contrast	High EME and entropy values indicate ability to enhance image details	Weakens effect of under-enhanced and over-enhanced areas, reduces noise
Lu et al. (2016)	2016	Weighted guided trigonometric filter	Attenuation discrepancy is compensated along the propagation path	PSNR and SSIM values show that the method removes scatter	Noise level reduction, exposure of dark regions, improvement in global contrast, edge details are significantly enhanced
Vasamsetti et al. (2017)	2017	Wavelet based perspective on variational enhancement	Method applied on approximation and detailed coefficients of an image followed by color correction	PSNR, entropy and SSIM index values indicate improved contrast and preservation of structure of the objects	Removes color cast, improves contrast of underwater images, preserves detailed structural features
Ghani and Isa (2017)	2017	Recursive adaptive histogram modification (RAHIM)	Enhancement by Modification of image histograms column wise in accordance with rayleigh distribution	High values of EME, EMEE, NIQE, entropy exhibit best visual quality	Significant improvement in image color through stretching process
Mallik et al. (2017)		Empirical Mode Decomposition (EMD)	Gray world approach	Low MSE and high PSNR shows improvement in visual performance	Reduce noise and artifacts in image, enhance contrast
Hou et al. (2018)	2018	Underwater residual convolutional neural network (URCNN)	Data-driven residual architecture for estimation of transmission along with a knowledge driven residual formulation used for illumination balance	Low scores of blur metric (BM), SSEQ and NIQE represents good image quality	Haze effect is removed, increase in contrast and restoration of natural appearance
Garg et al. (2018)	2018	CLAHE+ percentile methodology	Blending	RMSE and entropy values indicate good results	Good interpretability, visibility , colour and clarity

Table 4 (continued)

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Mathur and Goel (2018)	2018	Integration of white balancing and rayleigh streching	Histogram stretching is done based on dominant and weaker channels to improve varied levels of degradation in the channels	NIQE and UICM values indicate good performance	Improvement in terms of contrast and colour
Mathur and Goel (2018)	2018	Single image approach without specialised hardware	Blending of colour compensated and white balanced image	PCQI, UCIQE and UIQM metrics indicate good perceptual quality, global contrast enhancement, and improved image structure details	Not dependent on camera settings, improves accuracy of image segmentation and keypoint matching
Honnutagi et al. (2019)	2019	Fusion	Laplacian pyramid fusion	MSE, PSNR and entropy values are indicative of good quality of fused image	Improves sight difference and color appearance
Mohd Azmi et al. (2019)	2019	RCCGB+SCSMPE	Red channel correction, contrast stretching and mean pixel enhancement with PSO and unsharp masking	NIQE, entropy and MSSIM values indicate visual improvement	Improves contrast and reduces effect of color cast

Table 5 Dehazing and colour correction based underwater image enhancement algorithms

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Li et al. (2017a)	2017	Global background light estimation algorithm	Fusing characteristics of light in underwater medium and background light estimation using a regression model	Higher UCIQE indicate better balance of chroma, saturation, and contrast, high UICM value indicates improvement in color	Improves contrast and brightness, restores color, produces natural appearance
Ding et al. (2018)	2018	Super-resolution convolutional network	Adaptive color correction algorithm + super-resolution convolutional network	High values of PCQI and entropy, and low blur metric values indicate good enhancement	Removes blurring, sharpens the images
Zhang et al. (2018b)	2018	DCP based	Building the relation between the transmission rates of three color channels	Highest NIQE and CNI scores indicate effective restoration, High values of UIQM and UCIQE indicate robustness	Remove haze-like effect and correct color cast, preserve the natural appearance
Ye et al. (2018)	2018	GAN framework	Generator produce a hazing detection mask, which goes through the second generator to correct the color	High values of PSNR and SSIM demonstrate superior performance	Clear vision, stretched contrast balanced color, and most similar results to the groundtruth images

The various techniques used for underwater image enhancement by considering dehazing and contrast enhancement methods along with their advantages are summarized in table 6.

4 Underwater image datasets

Underwater image datasets play a very significant role in the development of image processing techniques. The underwater image datasets, utilized by researchers in the underwater image enhancement processes, is as shown in Fig. 6.

MBARI underwater image dataset (Yang et al. 2019) consists of 666 images of fishes obtained from Monterey Bay Aquarium Research Institute. The dataset is available at https://www.mbari.org. Real-world Underwater Image Enhancement (RUIE) data set (Liu et al. 2020) is segregated into three different subsets. These subsets targets issues like the visibility of image, quality, color casts, and high-level detection and classification. RUIE dataset consists of about 4000 images of scallops, sea cucumbers and sea urchins is available at: https://arxiv.org/abs/1901.05320.

The AFSC data is obtained from a remotely operated vehicle (ROV) placed underwater and equipped with an RGB video camera. This dataset consists of a large number of videos from different ROV missions. There are about 571 images in the AFSC dataset (Yang et al. 2019). These images are of fishes and other related species. The image resolution of the images is 2112 by 2816.

The NWFSC data is collected from a remotely operated vehicle, by looking downward at the ocean floor. There are 123 images of fishes and other related species near the seabed in the initial release of the dataset. The resolution of images in the dataset is 2448 by 2050 (Yang et al. 2019). The annotations in this dataset are actually keypoints instead of bounding boxes.

MOUSS data (Yang et al. 2019) is collected from a stationary camera, about one to two meters above the ocean floor, with sufficient ambient illumination. The dataset has 159 images of fish with labels on all species. The test data without released annotations include images from the training as well as novel collections. The resolution of images is 968 by 728.

The AFSC, NWFSC and MOUSS datasets are integrated and provided by the CVPR AAMVEM workshop. The SUN database provides a wide-ranging collection of annotated images which covers a large variety of underwater scenes, places and the objects (Xiao et al. 2010). Raw underwater images used in Li et al. (2017a) are extracted from the dataset obtained from the internet. It consists of 45 underwater images which are degraded. The entire dataset can be downloaded from the link given in Li et al. (2017a).

A real underwater dataset by, Marine Hydrodynamics Laboratory of the University of Michigan, is used in Li et al. (2017c). It consists of over 15000 underwater images. The SQUID (Stereo Quantitative Underwater Image dataset), consists of 57 stereo pairs from four different sites in Israel, two in the Red Sea which represents tropical water and two in the mediterranean sea which represents temperate water. The sites in Red sea are of coral reef and a shipwreck. Both sites in the Mediterranean sea are of rocky reef environments, separated by 30km, Nachsholim which is at a depth of 3-6 meters, and Mikhmoret at a depth of 10-12 metres (Berman et al. 2020).

In Li et al. (2019a), an Underwater Image Enhancement Benchmark (UIEB) was constructed which consists of 950 underwater images. Eight hundred ninety of these real-world

Table 6 Dehazing and contrast enhancement based underwater image enhancement algorithms

Ref	Year	Technique	Approach used	Performance evaluation	Advantages
Farhadifard et al. (2015)	2015	Guided colour mapping scheme	Forward scattering solved by k-SVD based deblurring algorithm	Sharpens the images and yields accurate contrast and colors, visual comparison indicate good results	Natural colormap is highly preserved
Singh and Biswas (2016)	2016	Multi-scale Fusion	Blends the input images and weight maps to get a dehazed image	High values of entropy and low values of AMBE	Improved visibility of dehazed image, enhanced quality and appearance
Li et al. (2016a)	2016	Minimum information loss principle	Histogram distribution prior is used for improving the contrast	NIQE values indicate the results are more natural, global contrast improved	Reduce the artifacts as well as noise to a great extent
Khan et al. (2016)	2016	Wavelet based fusion	Enhancement and dehazing	Corrosion detection has been improved by 60%and 55% of ROI.	Helps in detection of corrosion in underwater pipelines
Guo et al. (2017)	2017	ISDCP	Contrast enhancement by using histogram stretching in RGB channels	Low MSE value and high PSNR indicate good results	Low complexity, improved visibility

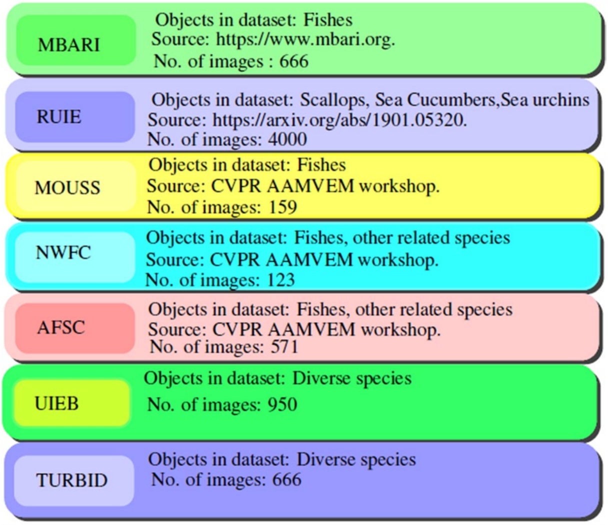


Fig. 6 Datasets used by researchers for experiments

underwater images have corresponding reference labels. The rest 60 underwater images are termed as challenging data as their suitable reference images were not obtained. This dataset can be used for qualitative and quantitative analysis of algorithms used for underwater image enhancement.

Enhancement of Underwater Visual Perception (EUVP) dataset is presented in Islam et al. (2020), that contains a paired and an unpaired compilation of underwater images. These images are captured using seven diverse cameras during deep-sea explorations and human-robot experiments under different visibility conditions. This dataset can be used for the purpose of adversarial training. The dataset is accessible at http://irvlab.cs.umn.edu/resources/euvp-dataset.

An open image dataset known as the TURBID dataset (Duarte et al. 2016), has been developed to contribute in the research work of underwater image processing. The dataset contains a collection of five different partitions of corrupted images along with its relevant ground-truth. Fish4knowledge dataset consists of fish data which is acquired from a live video dataset. It has 27370 verified fish images, and the complete dataset is segregated into 23 clusters with every individual cluster representative of a particular species (Boom et al. 2012). A few sample images from the datasets are shown in Fig. 7.

5 Underwater image quality evaluation metrics

Underwater image quality assessment is a challenging task that is used to evaluate the quality of the image accurately and automatically. Image quality assessment (IQA) methods are employed to automatically evaluate the quality of images. IQA approaches are broadly classified into: (a) objective and (b) subjective image quality assessment (Mohammadi et al. 2014; Shigwan and Birajdar 2015). Subjective image quality assessments are expensive and time-consuming and hence not suitable for real-time applications. Objective assessment techniques use statistical and mathematical models based on human visual system (HVS) to automatically estimate image quality.

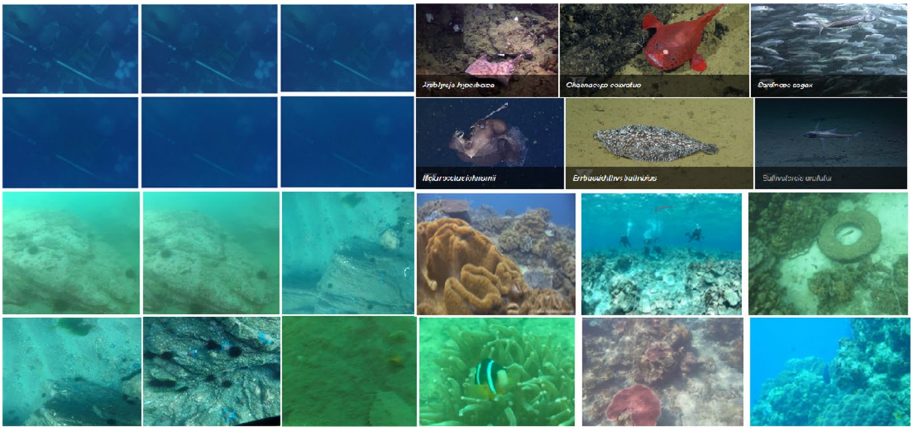


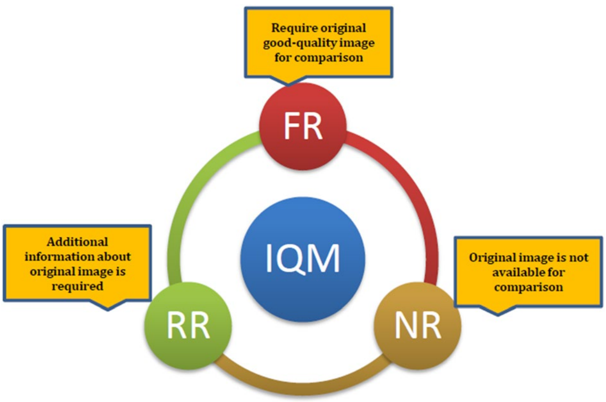
Fig. 7 Sample images from available datasets

Based on the availability of original image, objective IQA methods can be classified into three categories as shown in Fig. 8: (1) full reference IQA (FR) where the reference image is available, (2) reduced reference IQA (RR) where partial information of reference image is available and (3) no reference IQA (NR) in which reference image is not available. In addition to the standard performance evaluation parameters, to assess underwater image quality effectively, specialized metrics are proposed in the literature. The list is as shown in Fig. 9.

The performance of various underwater image enhancement and restoration techniques are analyzed using different qualitative and quantitative parameters. The qualitative evaluation involves the visual enhancement of the image by comparing histogram. The quantitative performance framework deals with various quality metric parameters which include:

- *Mean square error (MSE):* MSE computes the cumulative squared error between the enhanced and the original image. Lower the MSE, better is the quality (low error) and is given as,

Fig. 8 Objective image quality assessment methods



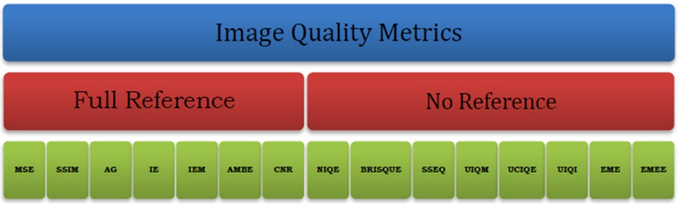


Fig. 9 Image quality metrics

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[F(i,j) - E(i,j)\right]^2 \tag{2}$$

where $F(i, j)$ is the original image, $E(i, j)$ is the enhanced image, and $M \times N$ is image size.

- *Peak-signal-to-noise ratio (PSNR)*: It is the measure of the peak error and computed as

$$PSNR = 20\ \log_{10}\left(\frac{MAX_F}{\sqrt{MSE}}\right) \tag{3}$$

where, maximum pixel value of the image is represented by MAX_F and is 255 for gray level image.

- *Entropy*: Entropy is a measure of information content present in the image and is given as:

$$H(F) = -\sum_{i=0}^{255} p_i\ \log_2\ p_i \tag{4}$$

where p_i is the probability of occurrence of intensity i at a pixel in image F.

- *Structure similarity index measure (SSIM)*: SSIM measures the similarity between original image patches and enhanced patches at locations x and y from three aspects: brightness, contrast and structure (Wang et al. 2004),

$$SSIM(F,E) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2\mu_y^2 + C_1)(\sigma_x^2\sigma_y^2 + C_2)} \tag{5}$$

where μ_x, μ_y are the mean values and σ_x, σ_y are the standard deviation values of the pixels in patch x and y respectively. σ_{xy} is the covariance of patches x and y and $C_1 = (k_1L)^2$ and $C_2 = (k_2L)^2$ are small constant to avoid instability while the denominator is close to zero. L is the dynamic range of pixel values, $k_1 = 0.01$ and $k_2 = 0.03$. The higher the SSIM value, the smaller the distortion and better the enhancement.

- *Colour enhancement factor (CEF)*: t helps in the representation of the effect of enhancement and is given as

$$CEF = \frac{CM(\tilde{I})}{CM(I)} \tag{6}$$

where $CM(I) = \sqrt{\sigma_\alpha^2 + \sigma_\beta^2} + 0.3\sqrt{\mu_\alpha^2 + \mu_\beta^2}$ where σ_α^2 and σ_β^2, represent the standard deviations and μ_α^2 and μ_β^2 are the average values of α and β respectively. $CM(\tilde{I})$ is used to denote enhanced image and $CM(I)$ the original image.

- *Contrast to noise ratio (CNR)*: This metric describes the amplitude of the signal relative to the surrounding noise in an image. CNR is computed by using

$$CNR(I, I') = \frac{\left(\mu_i - \mu_n\right)}{\sigma_n} \tag{7}$$

μ_i represents the mean value of original image and μ_n is mean value of enhanced image and σ_n denotes the standard deviation.

- *Image enhancement metric (IEM)*: This metric gives information about the sharpness and the improvement in the contrast after the process of enhancement. It is computed as follows

$$IEM = \frac{\sum_{l=1}^{k1}\sum_{m=1}^{k2}\sum_{n=1}^{8}\left|I_{e,c}^{m,l} - I_{e,n}^{m,l}\right|}{\sum_{l=1}^{k1}\sum_{m=1}^{k2}\sum_{n=1}^{8}\left|I_{o,c}^{m,l} - I_{o,n}^{m,l}\right|} \tag{8}$$

k1 and k2 denote the non overlapping blocks. o and e represent the original and enhanced images respectively. The intensities of the centre pixel is denoted by $I_{o,c}^{m,l}$ and $I_{e,c}^{m,l}$. $I_{o,n}$ and $I_{e,n}^{m,l}$ are the intensities of the neighbours from the centre pixel.

- *Absolute mean brightness error(AMBE)*: AMBE helps to compute the brightness content that is preserved after the process of image enhancement. It is given as

$$AMBE(o, e) = \left|\mu_o - \mu_e\right| \tag{9}$$

the equation represents the absolute difference between the mean of original and enhanced images. Median values of AMBE metric indicates good preservation of brightness.

- *Spatial spectral entropy based quality index (SSEQ)*: SSEQ is a highly efficient no-reference (NR) IQA model proposed by (Liu et al. 2014). SSEQ can assess the quality of a image which is distorted across various distortion categories. SSEQ can be calculated by

$$E = -\sum_i \sum_j P(i,j) \log_2 P(i,j) \tag{10}$$

where $P(i,j)$ is the spectral probability map given as

$$P(i,j) = \frac{C(i,j)^2}{\sum_i \sum_j C(i,j)^2} \tag{11}$$

- *Measure of enhancement (EME)*: EME calculates the contrast of the images and aids in the optimum selection of processing parameters. It is computed as:

$$EME_{m_1 m_2} = max\left(\frac{1}{m_1 m_2}\sum_{l=1}^{m_1}\sum_{n=1}^{m_2} 20 \log \frac{X^{\omega}_{max;n,l}}{X^{\omega}_{min;n,l}}\right) \tag{12}$$

where $X^{\omega}_{max;n,l}$ and $X^{\omega}_{min;n,l}$ represent the maximum value and minimum value of the image within the block $\omega_{n,l}$.

- *Root mean square error (RMSE)*: *R*MSE is computed by calculating the square root of MSE. It is given as

$$RMSE = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[F(i,j) - E(i,j)\right]^2} \tag{13}$$

- *Measure of enhancement by entropy (EMEE)*: *E*MEE is computed by

$$EMEE_{m_1 m_2} = max\left(\frac{1}{m_1 m_2}\sum_{l=1}^{m_1}\sum_{n=1}^{m_2}\alpha\frac{X_{max;n,l}(\theta)}{X_{min;n,l}(\theta)}^{\alpha}\log\frac{X_{max;n,l}(\theta)}{X_{min;n,l}(\theta)}\right) \tag{14}$$

Good image quality is indicated by high value of EMEE. $m1$ and $m2$ represent the blocks in which the image is divided.

- *Underwater colour image quality evaluation metric (UCIQE)*: *U*CIQE was specifically designed to quantify the effects of non-uniform color cast, low contrast and issues of blurring that effect underwater images. UCIQE for an image X in CIELab space is calculated as:

$$UCIQE = c_1 \times \sigma_{chroma} + c_2 \times contrast_l + c_3 \times \mu_{saturation} \tag{15}$$

where c_1 c_2 c_3 represent the weighted coefficients, σ_{chroma} denotes the standard deviation, $contrast_l$ is the contrast and the average value of saturation is denoted by $mu_{saturation}$ (Yang and Sowmya 2015). Higher values of UCIQE signify that the image has good equilibrium among chroma, contrast and saturation.

- *Underwater image quality measure (UIQM)*: *U*IQM is based on the human visual system model and works without a reference image (Panetta et al. 2015). UIQM comprises of three main measures, UICM the underwater image colorfulness measure, UISM the underwater image sharpness measure, and UIConM the underwater image contrast measure. UIQM is calculated as follows:

$$\begin{aligned} UIQM = {} & Coeff_1 \times UICM + COeff_2 \times UISM + Coeff_3 \\ & \times UIConM \end{aligned} \tag{16}$$

Higher values of UIQM indicate good levels of enhancement.

- *Colourfulness contrast fog density index (CCF)*: *N*o-reference IQA method is proposed to predict underwater color image quality in Wang et al. (2018) using CCF metric. CCF metric is a weighted combination of colorfulness index, contrast index and fog density index which is computed as,

$$CCF = \omega_1 \times \text{Colorfulness} + \omega_2 \times \text{Contrast} + \omega_3 \times \text{Fogdensity} \tag{17}$$

Colorfulness index due to absorption, blurring because of forward scattering and fog density due to backward scattering are examined in the CCF computation.

- *Average gradient (AG)*: *A*verage gradient is a full reference metric which is used to define the sharpness of the given image. It represents the change in rate of minute details present in the image. It is computed as,

$$AG = \frac{1}{(L-1)(M-1)} \sum_{i=1}^{L-1} \sum_{j=1}^{M-1} \sqrt{\left(\nabla_x I(i,j)\right)^2 + \sqrt{\left(\nabla_y I(i,j)\right)^2}} \tag{18}$$

where L and M denote the width and height of the image and ∇_x and ∇_y represent the gradient in x and y directions respectively.

- *Patch based contrast quality index (PCQI)*: *P*CQI is defined as,

$$PCQI(i,j) = \frac{1}{P} \sum_{k=1}^{P} l_r(i_k, j_k) l_s(i_k, j_k) l_t(i_k, j_k) \tag{19}$$

where P is the number of patches present in the image and l_r, l_s and l_t represent the comparison functions. Higher values of PCQI indicate good contrast.

It is important to evaluate an algorithm in order to understand its functioning with various category of underwater images. Such evaluations also aid in the best estimation of parameters which can be used for different applications. The evaluation parameters are tabulated in table 7. The underwater image quality metrics immensely helps in assessing the efficacy of underwater image enhancement algorithms.

6 Performance evaluation

In this section we have performed experiments on two datasets UIEB (Li et al. 2019a) and EUVP (Islam et al. 2020) for qualitative and quantitative evaluation of under water image enhancement methods. UIEB dataset consists of 890 real water underwater images. EUVP dataset consists of paired and unpaired compilation of underwater images. We have used five images from each dataset for the purpose of evaluation. Typical methods of underwater image image enhancement like AHE, CLAHE (Zuiderveld 1994), ICM (Iqbal et al. 2007), UCM (Iqbal et al. 2010), Gray World (GW), (Wong et al. 2018), Wavelet fusion (Khan et al. 2016) and Recursive adaptive histogram modification (RAHIM) (Ghani and Isa 2017) method have been used for the experiments.

6.1 Qualitative evaluation of underwater image datasets

Subjective evaluation help to understand the effects of enhancement. Figures 10 and 11 present the results obtained by applying the underwater image enhancement methods mentioned above. For the purpose of representation we have shown a single image from UIEB dataset and EUVP dataset, along with the histograms for the analysing the effect of enhancement. As can be seen from Fig. 10 and 11, AHE method lends a bluish tone to the images. The equal distribution of red, green and blue pixels in CLAHE enhanced image indicates that the method provides much better clarity than AHE method. There is no over-enhancement. In ICM method it is observed that the enhanced image displays equalization in the colour contrast.

UCM shows better performance in terms of enhancement than ICM. The colour correction step in UCM decreases the blue colour cast in the enhanced image. The histogram plot also confirms this as the blue values stretch towards the minimum value. There is a rich effect in terms of colors. Both these methods does the redistribution of saturation and

Table 7 Underwater image enhancement performance evaluation parameters

Parameter	Equation	Details	Comments	References
Mean squared error	$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[F(i,j) - E(i,j)\right]^2$	$F(i,j)$ = original image, $E(i,j)$ = enhanced image, and $M \times N$ = size of image	Lower the MSE, better is the quality	(Priyadharsini et al. 2018)
Peak-signal-to-noise ratio	$PSNR = 20\log_{10}\left(\frac{MAX_F}{\sqrt{MSE}}\right)$	$MAX_F$is maximum pixel value of the image	Higher the PSNR, better is the quality	(Khan et al. 2018)
Entropy	$H(F) = -\sum_{i=0}^{255} p_i \log_2 p_i$	p_i is the probability of occurrence of intensity i at a pixel in image F	High value of entropy means good information content	(Güraksin et al. 2016; Rodrigues et al. 2016)
Structure similarity index measure (SSIM)	$SSIM(F,E) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2\mu_y^2+C_1)(\sigma_x^2\sigma_y^2+C_2)}$	μ_x, μ_y are the mean values and σ_x, σ_y are the standard deviation values of the pixels in the patch x and y	Higher the SSIM value, smaller the distortion and better the enhancement	(Khan et al. 2018; Priyadharsini et al. 2018)
Colour enhancement factor (CEF)	$CEF = \frac{CM(\tilde{I})}{CM(I)}$ where $CM(I) = \sqrt{\sigma_\alpha^2 + \sigma_\beta^2} + 0.3\sqrt{\mu_\alpha^2 + \mu_\beta^2}$	σ_α^2 and σ_β^2, represent the standard deviations, μ_α^2 and μ_β^2 are the average values of α and β	High CEF indicates improved image quality	(Shourya et al. 2016; Au et al. 2012)
Contrast to noise ratio (CNR)	$CNR(I,I') = \frac{(\mu_i-\mu_n)}{\sigma_n}$	μ_i = mean value of original image, μ_n = mean value of enhanced image, σ_n = standard deviation	Higher the CNR value, better the enhancement	(Rodrigues et al. 2016)
Image enhancement metric (IEM)	$IEM_{8p} = \frac{\sum_{l=1}^{k1}\sum_{m=1}^{k2}\sum_{n=1}^{8}\left\lvert I_{e,c}^{m,l} - I_{e,n}^{m,l}\right\rvert}{\sum_{l=1}^{k1}\sum_{m=1}^{k2}\sum_{n=1}^{8}\left\lvert I_{o,c}^{m,l} - I_{o,n}^{m,l}\right\rvert}$	The intensities of the centre pixel is denoted by $I_{o,c}^{m,l}$ and$I_{e,c}^{m,l}$.$I_{o,n}$ and $I_{e,n}^{m,l}$ are the intensities of the neighbours from the centre pixel	Higher the CNR value, better the enhancement	(Priyadharsini et al. 2018)
Absolute mean brightness error (AMBE)	$AMBE(o,e) = \lvert\mu_o - \mu_e\rvert$	μ_o represents mean value of original image , μ_e is mean value of enhanced image	Median values of AMBE indicate good preservation of brightness values	(Priyadharsini et al. 2018)

Table 7 (continued)

Parameter	Equation	Details	Comments	References
Spatial spectral entropy based quality index (SSEQ)	$E = -\sum_i \sum_j P(i,j)\log_2 P(i,j)$	$P(i,j)$ is the spectral probability map given as $P(i,j) = \frac{C(i,j)^2}{\sum_i \sum_j C(i,j)^2}$	Highly efficient no-reference(NR) IQA model	(Qing et al. 2015)
Measure of enhancement (EME)	$EME_{m_1 m_2} = max(\frac{1}{m_1 m_2} \sum_{l=1}^{m_1} \sum_{n=1}^{m_2} 20\log \frac{X^{\omega}_{max;n,l}}{X^{\omega}_{min;n,l}})$	$X^{\omega}_{max;n,l}$ represent maximum value and $X^{\omega}_{min;n,l}$ represent minimum value of the image within the block $\omega_{n,l}$	Aids in optimum selection of processing parameters	(Rodrigues et al. 2016)
Underwater colour image quality evaluation metric (UCIQE)	$UCIQE = c_1 \times \sigma_{chroma} + c_2 \times contrast_l + c_3 \times \mu_{saturation}$	$c_1\, c_2\, c_3$ represent the weighted coefficients, σ_{chroma} denotes standard deviation, $contrast_l$ is the contrast and the average value of saturation	High values of UCIQE indicate the image good equilibrium among chroma, contrast and saturation in the image	(Khan et al. 2018)(Zhang et al. 2019)
Underwater image quality measure (UIQM)	$UIQM = Coeff_1 \times UICM + COeff_2 \times UISM + Coeff_3 \times UIConM$	UIQM comprises of UICM the underwater image colorfulness measure, UISM the underwater image sharpness measure, and UIConM the underwater image contrast measure	Higher values of UIQM displays good degree of enhancement	(Zhang et al. 2019; Deng et al. 2017)
Colourfulness contrast fog density index (CCF)	$CCF = \omega_1 \times \text{Colorfulness} + \omega_2 \times \text{Contrast} + \omega_3 \times \text{Fogdensity}$	CCF includes the colorfulness index, contrast index and the fog density index along with three weighted coefficients	Efficient performance is signified by elevated value of CCF	(Wang et al. 2018)
Average gradient (AG)	$AG = \frac{1}{(L-1)(M-1)} \sum_{i=1}^{L-1} \sum_{j=1}^{M-1} \sqrt{\left(\nabla_x I(i,j)\right)^2 + \sqrt{\left(\nabla_y I(i,j)\right)^2}}$	L and M denote width and height of the image and ∇_x and ∇_y represent gradient in x and y directions	Low values of average gradient indicate good image quality	(Li et al. 2016a)
Patch based contrast quality index (PCQI)	$PCQI(i,j) = \frac{1}{P} \sum_{k=1}^{P} l_r(i_k,j_k) l_s(i_k,j_k) l_t(i_k,j_k)$	P is the number of patches present in the image, l_r, l_s and l_t represent the comparison functions	Good contrast performance is identified by high values of PCQI metric	(Khan et al. 2018; Zhang et al. 2019)

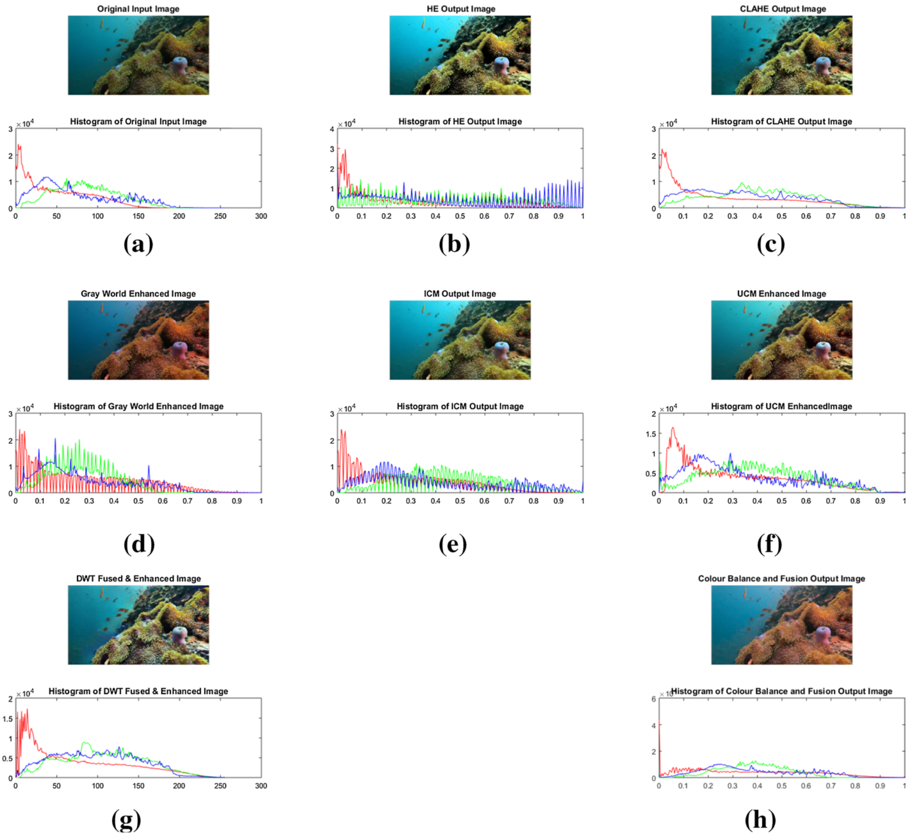


Fig. 10 Enhanced images and Histograms of **a** Original image, **b** HE, **c** CLAHE, **d** GW, **e** ICM, **f** UCM, **g** WAVELET FUSION, **h** COLOUR BALANCE and FUSION methods: Sample images from UIEB dataset

intensity values from the HSI colour space. As can be observed from the GW method the effect of red colour is dominant in the enhanced image. The brightness of the image is not improved. This method works well only if all the pixels of red, green and blue components are properly balanced. The wavelet fusion based approach provides better enhancement in terms of colour and also the clarity of surrounding objects is improved. The method shows improved global contrast. The method of RAHIM improves the brightness, which lends a natural effect of image colour.

6.2 Quantitative evaluation of underwater image datasets

Objective analysis is carried out with image quality metrics like MSE, PSNR, SSIM, CEF, AMBE, Entropy, UIQM, AG, SSEQ, PCQI, UIQI and PIQE. These metrics were used to quantitatively analyse the enhancement methods. Tables 8 and 9 show the IQM values for five images from UIEB and EUVP dataset. Lower values of MSE represent less error or noise content in the image. The values of PSNR are indicative of ability to suppress the levels of noise in the enhanced images. Higher the PSNR, less is the noise present in the image. Images with

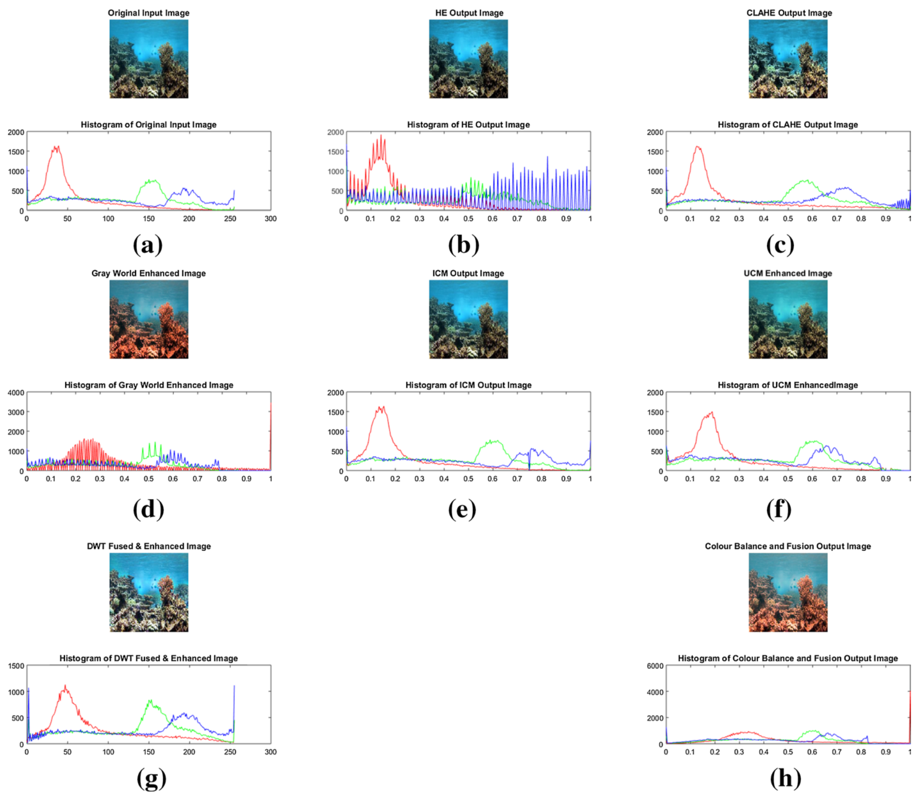


Fig. 11 Enhanced images and Histograms of **a** Original image, **b** HE, **c** CLAHE, **d** GW, **e** ICM, **f** UCM, **g** WAVELET FUSION, **h** COLOUR BALANCE and FUSION methods: Sample image from EUVP dataset

low MSE and high PSNR value is indicative of a good resultant image. SSIM or the structural similarity index quantifies the similarity between the original and enhanced images.

The values of SSIM nearer to the value of 1 indicate good degree of similarity. The low values of AG indicate that UCM and GW method does not enhance the images with proper contrast. High values of PSNR, CEF and SSIM displays better performance of RAHIM (Ghani) method. High values of UIQM shows the proper balance of saturation and contrast, and good colourfulness and sharpness in the enhanced image. The spatial-spectral entropy based quality (SSEQ) metric helps to assess the distortion present in the image. Universal image quality index (UIQI) utilizes luminance, contrast and structure details for comparison between the images. The full-reference metric PCQI indicates the change in contrast levels of the image. High PCQI values refers to improved clarity in images. The perception based image quality evaluator (PIQE) is a no-reference quality metric score which varies inversely with respect to image quality. Lower the score higher is the image quality.

Table 8 Quantitative evaluation of images from UIEB dataset

Image	Algorithm	MSE	PSNR	SSIM	CEF	AMBE	Entropy	UIQM	AG	SSEQ	PCQI	UIQI	PIQE
Image 1	AHE	2177	14.751	0.67613	0.87225	8.8259	7.6315	2.2511	1.4878	35.327	1.1471	0.44912	29.297
	CLAHE	169.26	25.845	0.92261	0.87284	3.3798	6.8387	2.2511	1.4878	35.327	1.1768	0.73316	24.043
	ICM	2292.7	14.527	0.81967	0.87293	46.817	6.8364	2.2511	1.4878	35.327	0.94341	0.74021	27.386
	UCM	1076.8	17.808	0.99762	0.87279	17.732	7.4681	3.345	1.4878	34.613	0.99966	0.63718	33.516
	GW	167.66	25.874	0.99963	0.87323	0.050232	6.0843	3.345	1.4878	34.613	0.9998	0.98116	34.414
	WavFusion	871.25	18.729	0.90873	0.8727	28.014	6.7403	2.2511	1.4878	35.327	1.0532	0.77852	26.223
	Ghani	928.1538	18.454	0.777	0.8715	13.685	7.366	2.25105	1.4878	35.326	1.2266	0.5318	25.8710
Image 2	AHE	1424.2	16.595	0.76391	0.95825	25.965	7.2213	2.6483	1.3843	33.833	1.049	0.59651	31.395
	CLAHE	187.91	25.391	0.93527	0.95945	7.2979	6.6139	2.6483	1.3843	33.833	1.1302	0.78151	26.639
	ICM	2825.2	13.62	0.88322	0.95857	52.342	6.073	2.6483	1.3843	33.833	0.8399	0.69263	29.129
	UCM	1219.2	17.27	0.99754	0.95855	19.405	7.4048	7.989	1.3843	37.74	0.99965	0.28662	32.533
	GW	739.52	19.443	0.99925	0.95847	0.0039065	7.0939	7.989	1.3843	37.74	0.99984	0.16556	35.852
	WavFusion	83.538	28.912	0.96255	0.95909	5.0327	6.5858	2.6483	1.3843	33.833	1.127	0.85289	26.295
	Ghani	1027.33	18.0136	0.7152	0.9587	16.649	7.3529	2.648	1.3842	33.832	1.2266	0.4683	24.290
Image 3	AHE	2519	14.119	0.75899	0.6991	38.541	7.5031	3.3333	1.2228	38.49	1.0418	0.56536	38.423
	CLAHE	75.755	29.337	0.94634	0.69514	6.0193	6.4981	3.3333	1.2228	38.49	1.1384	0.79166	34.984
	ICM	1840.8	15.481	0.85119	0.69951	33.647	7.3328	3.3333	1.2228	38.49	1.0606	0.69851	38.488
	UCM	1335.8	16.879	0.99703	0.69947	22.226	7.3156	3.7421	1.2228	34.247	0.9996	0.6472	42.745
	GW	20.232	35.089	0.99995	0.69751	0.014154	6.4257	3.7421	1.2228	34.247	0.99995	0.97547	39.047
	WavFusion	2387.2	14.352	0.7828	0.69709	40.102	7.4395	3.3333	1.2228	38.49	1.0842	0.56941	36.357
	Ghani	2125.20	14.856	0.625	0.696	35.729	7.503	3.333	1.222	38.489	0.445	0.0734	39.299

Table 8 (continued)

Image	Algorithm	MSE	PSNR	SSIM	CEF	AMBE	Entropy	UIQM	AG	SSEQ	PCQI	UIQI	PIQE
Image 4	AHE	1342.6	16.851	0.83846	0.94073	25.746	7.6273	1.8949	2.518	42.733	1.036	0.66575	49.608
	CLAHE	773.81	19.244	0.88717	0.93992	17.877	7.4601	1.8949	2.518	42.733	1.1003	0.68938	47.595
	ICM	691.96	19.73	0.9455	0.94015	24.155	7.3679	1.8949	2.518	42.733	0.99718	0.87274	52.09
	UCM	545.15	20.766	0.99881	0.94064	19.881	7.4101	9.2623	2.518	41.879	0.99977	0.90169	55.875
	GW	51.258	31.038	0.99988	0.94034	0.015164	6.8904	9.2623	2.518	41.879	0.99992	0.95917	58.418
	WavFusion	276.15	23.719	0.95419	0.94067	12.093	7.246	1.8949	2.518	42.733	1.0735	0.82627	49.33
	Ghani	1386.963	16.710	0.8719	0.9408	30.641	7.538	1.894	2.518	42.733	1.0317	0.662	49.006
Image 5	AHE	1302.4	16.983	0.78379	0.80521	16.862	7.7348	2.9986	4.6166	40.616	1.0012	0.60578	53.352
	CLAHE	356.37	22.612	0.91914	0.80766	7.2685	7.4178	2.9986	4.6166	40.616	1.0814	0.73827	48.496
	ICM	11.097	37.679	0.99527	0.80732	2.1254	7.0221	2.9986	4.6166	40.616	1.0106	0.94697	50.124
	UCM	128.46	27.045	0.99972	0.80711	8.668	7.1623	9.796	4.6166	39.044	0.99998	0.92574	51.333
	GW	9.5248	38.417	0.99998	0.80588	0.010925	6.8741	9.796	4.6166	39.044	0.99994	0.99383	51.34
	WavFusion	196.63	25.194	0.96643	0.80757	8.5786	7.2615	2.9986	4.6166	40.616	1.0672	0.84912	50.072
	Ghani	383.690	22.290	0.9388	0.8054	10.3246	7.447	2.998	4.6165	40.615	1.061	0.7620	48.911

Table 9 Quantitative evaluation of images from EUVP dataset

Image	Algorithm	MSE	PSNR	SSIM	CEF	AMBE	Entropy	UIQM	AG	SSEQ	PCQI	UIQI	PIQE
Image 1	AHE	704.06	19.655	0.81049	0.93594	13.747	7.6488	2.1083	3.2583	33.245	0.94306	0.63114	27.198
	CLAHE	315.91	23.135	0.92871	0.93601	5.4716	6.8729	2.1083	3.2583	33.245	1.0995	0.75602	21.976
	ICM	331.96	22.92	0.94333	0.93314	15.074	7.4	2.1083	3.2583	33.245	1.0116	0.89373	27.846
	UCM	1019.8	18.042	0.99765	0.93837	30.805	7.2995	4.0405	3.2583	38.349	0.99959	0.8431	24.495
	GW	48.817	31.258	0.99991	0.93832	0.010933	7.1205	4.0405	3.2583	38.349	0.99998	0.94089	25.45
	WavFusion	340.94	22.804	0.9212	0.93527	15.726	7.2296	2.1083	3.2583	33.245	1.0887	0.7936	21.994
	Ghani	1320.111	16.9246	0.8462	0.934	21.362	7.1549	2.1082	3.258	33.2453	1.0645	0.65419	20.3588
Image 2	AHE	1275.4	17.074	0.73299	0.90191	8.6297	7.7279	3.2855	7.8684	26.884	1.1894	0.6786	31.293
	CLAHE	269.55	23.824	0.87541	0.89833	0.52452	7.1913	3.2855	7.8684	26.884	1.2476	0.82619	29.595
	ICM	139.22	26.694	0.97661	0.89806	10.796	7.0142	3.2855	7.8684	26.884	1.0424	0.97017	28.402
	UCM	423.9	21.849	0.9992	0.89942	15.367	7.294	5.1742	7.8684	26.203	1.0002	0.88096	24.086
	GW	33.539	32.883	0.99993	0.89944	0.010183	6.8401	5.1742	7.8684	26.203	1.0001	0.98023	25.015
	WavFusion	198.11	25.162	0.91574	0.89699	8.4668	7.1522	3.2855	7.8684	26.884	1.1913	0.88192	26.968
	Ghani	563.5369	20.6215	0.8235	0.895	6.7852	7.5824	3.2855	7.8684	26.883	1.2552	0.7692	30.641
Image 3	AHE	806.46	19.065	0.76348	0.98693	23.955	7.2243	3.5709	3.9729	36.222	0.93808	0.65941	27.634
	CLAHE	132.61	26.905	0.90461	0.98802	3.1407	7.0255	3.5709	3.9729	36.222	1.121	0.83283	19.258
	ICM	121.86	27.272	0.96778	0.9873	7.2095	7.201	3.5709	3.9729	36.222	1.0657	0.94982	18.791
	UCM	435.37	21.737	0.99905	0.98841	17.098	7.3003	5.1742	3.9729	26.203	0.99983	0.8630	16.236
	GW	1019.5	18.05	0.99801	0.98764	0.029584	7.2234	6.1791	3.9729	37.486	0.99981	0.7224	20.617
	WavFusion	75.454	29.354	0.95324	0.98719	4.8768	6.9552	3.5709	3.9729	36.222	1.1492	0.90424	18.418
	Ghani	389.3729	22.227	0.8206	0.987	5.1376	7.3660	3.5709	3.972	36.221	1.1810	0.6800	20.196

Table 9 (continued)

Image	Algorithm	MSE	PSNR	SSIM	CEF	AMBE	Entropy	UIQM	AG	SSEQ	PCQI	UIQI	PIQE
Image 4	AHE	49.338	31.199	0.97019	0.97671	4.6001	7.4516	2.8203	10.736	26.936	0.98803	0.93968	30.061
	CLAHE	648.67	20.011	0.89128	0.97715	9.3952	7.5598	2.8203	10.736	26.936	1.12	0.84007	29.927
	ICM	40.296	32.078	0.98304	0.94599	2.8756	6.9334	97.108	5.1768	31.385	1.051	0.97109	34.834
	UCM	302.59	23.329	0.99949	0.94483	9.6222	7.1993	98.768	5.1768	32.041	1.0001	0.81967	42.832
	GW	599.66	20.352	0.99956	0.94493	0.0051159	6.896	98.768	5.1768	32.041	1.0002	0.52785	55.475
	WavFusion	248.88	24.171	0.94828	0.97614	10.02	7.477	2.8203	10.736	26.936	1.1129	0.91925	29.939
	Ghani	858.700	18.792	0.873	0.978	1.7980	7.5184	2.820	10.736	26.9361	1.0620	0.81534	30.9229
Image 5	AHE	1068.4	17.843	0.71219	0.93831	14.17	17.357	1.4738	3.7033	41.865	1.1853	0.63832	28.632
	CLAHE	222.17	24.664	0.86464	0.9393	7.3209	6.7283	1.4738	3.7033	41.865	1.2295	0.78154	24.561
	ICM	535.24	20.845	0.91162	0.94077	19.21	7.0966	1.4738	3.7033	41.865	1.1366	0.87208	27.307
	UCM	356.01	22.62	0.99952	0.93687	9.1365	7.1183	4.0526	3.7033	42.934	1.0001	0.63117	32.54
	GW	571.5	20.562	0.9994	0.93442	0.015632	6.8412	4.0526	3.7033	42.934	1.0001	0.47448	37.403
	WavFusion	72.765	29.512	0.9524	0.94176	4.1191	6.9497	97.108	5.1768	31.385	1.1386	0.91515	36.802
	Ghani	1034.841	17.982	0.6419	0.939	18.1806	7.2078	1.473	3.7032	41.8649	1.3199	0.534	26.882

7 Applications of underwater image enhancement

7.1 Fish identification

Convolutional neural network (CNN) for identifying and counting coral reef fish species on underwater images is presented in Villon et al. (2018). Authors reported correct identification accuracy of 94.9%, which is greater than the human identification rate of 89.3%. An Autonomous Underwater Vehicle (AUV) for automatic fish tracking using computer vision is developed in Kumar et al. (2018). This compact and low-cost AUV can also be used as a platform for photo-mapping of the seafloor using the onboard camera and light arrangement.

In Boudhane and Nsiri (2016), underwater image preprocessing, fish localization and detection algorithm is proposed using three steps: (a) noise removal using estimation of Poisson–Gaussian mixture distribution and image enhancement (b) use of mean shift algorithm for image splitting into different regions and (c) finally combining regions into objects using statistical estimation based on log-likelihood test.

A detection approach for uneaten fish food in underwater images using adaptive threshold approach is proposed (Li et al. 2017b) in order to minimize the waste and financial loss with the highest accuracy of 95.6%. The expectation-maximization based Gaussian mixture model is employed for histogram fitting and identifying the type of histogram and to further compute the adaptive threshold.

CNN based fish detection presented in Cui et al. (2020) makes use of three optimization approaches in order to augment the number of learning samples and simplify the network for holding the artificial neural network. The process of training is made more efficient by training process speed up. The training time and loss were reduced dramatically by using the dropout algorithm and refining the loss function. The decrease in processing time and improvement in accuracy has shown the potential for the method to be used for AUV implementation.

7.2 Sea cucumber image enhancement

Sea-cucumber products are rich sources of high-quality proteins and vitamins with low-fat content. These products are an important source of nourishment for people who rely on animal proteins for their nutrition.

Blurred and colour distorted underwater sea cucumber image is enhanced based on the fusion of retinex and dark channel prior in Li et al. (2018b). After pre-processing using the dark channel prior, the input image and a Gaussian template are convolved to produce an enhanced image. The saturation and brightness levels are enhanced in the HSV colour space.

Further, the next step in sea cucumber automation is proposed for automatic segmentation of sea cucumber in the underwater environment in Qiao et al. (2017a). First, image contrast enhancement is performed using a fusion of RGB colour model and CLAHE approach. Later, edges of sea cucumber for thorns and rectangular edges for the body are extracted using active contour segmentation and is considered it as an initial contour. Finally, thorn and body segmentation are combined to obtain final sea cucumber automatically.

Sea cucumber pre-processing is important to enhance image quality. Use of CLAHE and wavelet transform is presented in Qiao et al. (2017b) where CLAHE is employed for contrast enhancement, and wavelet transform is used for denoising of underwater images (Qiao et al. 2017b). The algorithm is assessed using peak signal to noise ratio (PSNR), mean square error (MSE) and entropy to show its effectiveness.

7.3 Subsea pipeline corrosion estimation

Offshore oil and gas industry deal with severe problems of pipeline corrosion. Presence of corrosion leads to cracks and leakages in the pipeline. Infrastructures are moving into deep waters in search of fossil fuels. Hence it becomes difficult for human divers to monitor the pipelines due to unfavourable conditions underwater. A wavelet-based corrosion estimation by using segmentation of region of interest and image restoration and enhancement process is implemented in Khan et al. (2018). Finally, unsupervised clustering is used to determine the percentage of pixels present in the corroded regions of the pipeline, thereby aiding in the estimation of corrosion. The results show very high accuracy for different blurring conditions.

7.4 Coral-reef monitoring

A robust method of coral–reef monitoring using deep learning is demonstrated in González-Rivero et al. (2020). Monitoring of coral reefs is a very costly affair and requires specialized knowledge in the domain. Artificial intelligence is used in González-Rivero et al. (2020) for data processing and simulating learning and decision making. The automated approach used in this work has shown an acceleration of 200x in terms of reporting and data analysis. In this work, the image is passed through a CNN network for the abstraction of features. Various layers of CNN are used for the purpose of learning by extraction of transform features. Probabilistic inference is used for interpreting the output of the network. In comparison to other machine learning methods, the result shows the unbiased agreement of 97%.

7.5 Other applications

Underwater hyperspectral imaging (UHI) deployed on the remotely operated vehicle for seafloor mapping, coral reef identification and underwater pipeline monitoring is illustrated in Johnsen et al. (2016). A method for underwater cable detection and tracking using an autonomous underwater vehicle is proposed in Fatan et al. (2016). After extracting edges of the image, texture features are employed for the classification using the multilayer perceptron (MLP) neural network and support vector machine (SVM) (Kumar et al. 2020). Finally, the Hough transform is used for cable detection.

Deep-sea region exploration AUV is developed in Ahn et al. (2017) to capture and store images of marine ecological life. Further, crab recognition using retinex based deep underwater image enhancement algorithm is employed for the performance evaluation.

Underwater moving target detection is a challenging task because of the interference and scene dynamics. Moreover, light scattering and attenuation reduce the target and background contrast. Contrast enhancement technique based on MSR, which uses nonsubsampled contourlet transform (NSCT) to eliminate non-uniform illumination is presented in

Zhou et al. (2017). A nonlinear mapping and a gain function to automatically regulate the HVS-based NSCT contrast and lowpass subband coefficients is developed in Zhou et al. (2017). The technique suppresses noise, enhances edges and improves non-uniform illumination from the underwater environment to increase the target detection. Figure 12 lists the important application areas of underwater image processing.

8 Discussions

The study demonstrates the vital need for research in the domain of underwater image enhancement. The problems arising due to the underwater environment like absorption, scattering and attenuation are all inherent to the water medium and will lead to degraded images. Various techniques for enhancing the visual quality of the images were studied in this survey and categorized on the basis of physical model-based and non-physical based approaches.

As can be seen from the review, physical model-based methods depend on prior knowledge and knowledge of environmental conditions. Techniques like WCID (Chiang and Chen 2012), and DCP (Sathya et al. 2015) are found to handle scattering of light and removes haze along with maintaining the colour balance in underwater images. The values of SNR and PSNR in these methods exhibit their robustness. The red channel method (Galdran et al. 2015), dual dark channel method (Li and Li 2019), and deep convolution neural network-based approaches (Li et al. 2019b), aids in locating artificially illuminated regions and facilitate the correction of issues due to non-uniform illumination and artificial lighting. Problems due to forward and backward scattering are also solved in Li et al. (2019b). Robust retinex method (Li et al. 2018a), dark channel prior method with pyramid fusion (Cui et al. 2018), and MyCycle GAN with DCP method (Lu et al. 2019) which use deep learning techniques improves restoration of underwater images in hazy conditions.

Non-physical model-based techniques deal with the manipulation of pixel values for visual enhancement of underwater images. Enhancement techniques based on non-physical model can be categorized into three categories, namely contrast enhancement, colour correction and hybrid methods.

Empirical mode decomposition (Çelebi and Ertürk 2012), which utilizes a genetic algorithm for weight calculation was found to demonstrate good visual performance. Adaptive enhancement strategy incorporated by (Wang et al. 2016) by using a virtual retina model showed improved precision and visual effects. The guided filter-based approach in Chang

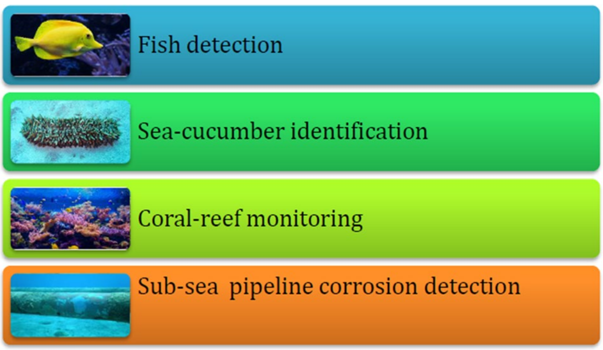


Fig. 12 Application areas of underwater image processing

et al. (2017) provides full HD enhancement with fewer gate counts by opting for a low-cost architecture. Differential evolution (Güraksin et al. 2016), SWT (Priyadharsini et al. 2018), and Wavelet Transform based technique (Guraksin et al. 2019), lead to significant contrast improvement by preserving the crucial image details. NUCE (Azmi et al. 2019) using swarm intelligence based algorithm and unsharp masking has found to retain the naturalness and improve the sharpness of underwater images.

The performance of bacterial foraging optimization (Sethi et al. 2015) technique is good in terms of improving the balance of colours. The results are better than UCM and gray world algorithms. The adaptive linear stretch method in Ao and Ma (2018) has found to reduce the computational complexity. A deep residual framework in Liu et al. (2019) which employs CycleGAN and VDSR makes it suitable for vision-based tasks.

Methods in Ghani and Isa (2015a), Lu et al. (2016), Mallik et al. (2017) are found to remove noise artifacts. Rayleigh stretched contrast limited adaptive histogram method; weighted guided trigonometric filter and EMD using gray world approach are used in these works. The evaluation parameters display the ability to enhance the image details and assists in the removal of scattering thereby leading to good visual enhancement. The recursive adaptive histogram modification in Ghani and Isa (2017) makes use of the process of stretching for considerable improvement in colour. URCNN (Hou et al. 2018) with a knowledge-driven residual formulation removes the haze effect leading to increased contrast in images. The PSNR, MSE and entropy value in Laplacian pyramid fusion (Honnutagi et al. 2019) based method displays a good quality of the fused image. Red channel based correction with PSO in Mohd Azmi et al. (2019) improves the contrast and reduces the effect of colour cast.

A global background light estimation algorithm (Li et al. 2017a) and a DCP based approach is used to restore and correct the colour cast issues. It also facilitates in providing natural appearance to images. The natural colour map is highly preserved in Farhadifard et al. (2015) by means of a guided colour mapping scheme. A multi-scale fusion approach in Singh and Biswas (2016) improves the quality of dehazed images by blending input underwater images and weight maps. A wavelet-based fusion in Khan et al. (2016) helps in improvement of corrosion detection in underwater pipelines.

Recovering the visual quality of an underwater image can be very subjective. A technique which provides a superior quality of image might vary from individual to individual. Hence, it is important to establish quantitative measures to evaluate the effects of enhancement algorithms based on image quality.

Objective and subjective quality assessment plays a very crucial role in gauging the performance of underwater image enhancement algorithms. The value of entropy (Güraksin et al. 2016; Rodrigues et al. 2016) signify the detailed information present in the images. Higher the value of entropy greater is the number of details available. PSNR (Khan et al. 2018) values illustrate the quality of enhanced images. Higher the value of PSNR better is the enhancement. As a wide dynamic range is associated with the signals, the metric is expressed in logarithmic scale. Local contrast present in images can be suitably measured by using EME (Rodrigues et al. 2016). It is found to be range dependent. High values of EMEE are representative of good quality images. This metric is an extension of EME and also relies on the idea of entropy. CNR (Srividhya and Ramya 2015) performance is a very useful metric for describing the amplitude of the signal relative to the surrounding noise in an underwater image. Low values of CNR indicate good performance in terms of visual quality.

The sharpness of the enhanced image and improvement, in contrast, can be assessed by higher values of IEM (Srividhya and Ramya 2015). The brightness content present in the underwater images can be evaluated by the metric AMBE (Rodrigues et al. 2016; Srividhya and Ramya 2015). Lower values of AMBE indicates better preservation of brightness. PCQI (Wang et al. 2015; Khan et al. 2018) the patch based contrast quality index is used for accurately predicting the human perception of variations in contrast and can be used for the assessment of contrast. SSEQ (Qing et al. 2015) a no-reference quality assessment metric that utilizes spatial and spectral entropy features of distorted images. Less score of SSEQ is indicative of good performance. High values of UCIQE (Khan et al. 2018) shows good equilibrium of chroma, contrast and saturation.

The dataset in image processing is a set of digital images that researchers use to test, train and assess the performance of their proposed algorithms. TURBID (Duarte et al. 2016) and Fish 4Knowledge (Boom et al. 2012) datasets were commonly used by researchers until recent years. MOUSS, AFSC, MBARI, NWFC (Yang et al. 2019), and RUIE (Liu et al. 2020) dataset were developed recently.

Some experiments were performed on sample images from UIEB and EUVP datasets. Typical underwater image enhancement methods were utilized to analyse the effects of enhancement. Qualitative and quantitative results were obtained and tabulated.

We have tried to catalogue some of the important applications of underwater image enhancement in recent years. Fish identification and detection, coral-reef monitoring (González-Rivero et al. 2020) were found to be a critical research area as observed from the literature studies. Researchers have used CNN based methods for the identification of fish species (Villon et al. 2018). Various optimization-based approaches were used to increase the learning samples for simplifying the network (Cui et al. 2020) for the purpose of detection. Use of CNN helps to improve on the task of the human eye, and the process of identification and detection can be completed with better precision and accuracy. CLAHE, Retinex and DCP (Li et al. 2018b) based methods are found to improve brightness and saturation levels in sea-cucumber image enhancement. CLAHE and transform domain-based approaches were used for denoising and contrast enhancement in Qiao et al. (2017b).

There has to be a well established method for the quantitative evaluation of systems required for improvement of quality of underwater images. Reference datasets used for image enhancement is less explored area. Hence underwater image enhancement benchmark dataset can be the focus of future research. In research related to deep learning methods using Generative Adversarial Networks (GAN), there is strong dependency on the datasets that consist of large number of original and referenced images. Hence, it becomes imperative to build a public underwater image dataset with diverse pairs of original and enhanced images (Zhang et al. 2019; Wang et al. 2019)

In studies related to deep learning, the powerful ability of representation by deep learning networks and prior knowledge of the physical models can be exploited together for boosting the performance of the system (Fu and Cao 2020).

Numerous image quality metrics for objective evaluation of underwater image quality are proposed in literature but only very few are suited appropriately for underwater images. Work should be carried out to establish an effective assessment metric. Also researchers can devote to a smart combination of objective and subjective evaluation (Wang et al. 2019).

In the current scenario the enhancement methods focus mainly on the quality of images but does not delve deeper if the enhanced underwater images can effectively increase the accurateness of high-level image processing tasks like tracking applications and classification. The improvement in the visual quality of underwater images can ease the stress of high-level underwater tasks. Future work can concentrate on tasks like target detection and utilize the computational time as a criterion for evaluation of the enhancement method (Wang et al. 2019).

Also from literature studies it is observed that very few enhancement algorithms are realized and implemented using hardware. Studies show that in order to facilitate parallel processing hardware implementations have been done on field programmable gate arrays (FPGAs) (Alex et al. 2016). Few articles portrays VLSI architectures with less dependence on computational resources have also been employed for creating systems for underwater image enhancement. But due to the cost and need for complex architectures with requirement of soaring memory bandwidth for frequently loading and storing image data and intermediate coefficients the overhead associated with the on-chip memory becomes high. However due to the availability of low cost GPUs nowadays it is practically possible to implement real-time underwater image enhancement algorithms. We can anticipate that in the next couple of years more researchers will focus in this area of work (Chang et al. 2017).

Deep learning is an efficient and cost effective approach from the domain of machine learning. Significant breakthroughs have been made in the field of deep learning. The methods employed display appreciable performance in various applications. Deep learning is widely used in the field of business, science, biological image classification, cancer detection, computer vision, natural language processing, object detection, speech recognition, smart city, stock market analysis and a lot of more (Dargan et al. 2019). In recent years, the success of deep learning has led to its application in underwater image enhancement and has paved direction for researchers in the field of image processing. The rapid use of deep learning algorithms displays its flexibility and versatility. The enhanced accuracy rates associated with the deep learning algorithms exhibits the significance of this technology, clearly emphasizing the tendency for research. Encouraged by the latest success of deep learning in visual understanding and pattern recognition researchers are working on novel underwater image synthesis algorithms, and designing of robust, data-driven solution for underwater image and video enhancement (Li et al. 2020; Zhang et al. 2020).

9 Conclusion

This review constitutes an extensive survey of works carried out in the areas of underwater image enhancement. The underwater imaging model and the effect of diminishing colours that lead to degradation of underwater images are discussed. The broad categories of enhancement techniques are identified, and the techniques used by researchers are classified and presented in the survey. The datasets available for researchers for carrying out experimental work and research are reported in this work. Various image quality metrics required for quantitative evaluation of underwater image quality are described and tabulated in detail. Evaluations were done on two datasets to understand the effects of enhancement on the images by using state-of-the-art methods. Recent applications of underwater image enhancement techniques are discussed in this work to make aware of the need and requirement of underwater image processing and also to enable future researchers in their work.

In the recent years there has been tremendous growth in the algorithms for single underwater image enhancement methods but no algorithm has been developed that can be used to enhance the images that are captured under varied underwater environments with different depths. There is scope for improvement in terms of flexibility and robustness of traditional underwater enhancement algorithms. The complexity of the techniques can be reduced so that work can be scaled up for practical studies and applications in the domain. An improvement in the enhancement algorithms can be achieved by strategically combining image enhancement and restoration methods.

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