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Review of underwater image restoration algorithms

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Abstract: Underwater images are susceptible to various distortions compared to images taken on land, due to the nature of the water environment. These images often suffer from diffraction, polarisation, absorption, scattering, colour loss and attenuation of light. Each part of the ocean will have its own sources of distortions, due to flickers caused by direct sunlight, marine snow, the fluorescence of biological objects, the presence of macroscopical organisms, loss of stability in divers, loss of light, artificial lighting and floating dust particles present in the water. There are numerous techniques and algorithms that may be used to restore these underwater images. This study reviews different algorithms and methods, developed in the past two decades, to give clearer ideas on the techniques present in the image restoration process, specifically for underwater images.

1 Introduction

Underwater images are in many ways different from the images that are taken on air. The images taken underwater suffer from scattering, diffraction and colour absorption, as well as many other distortions. Sea water may be divided into three parts: the Euphotic, Disphotic and Aphotic zones, depending on its depth and light penetration levels. The Euphotic zone is the upper part of the ocean that receives bright and clear sunlight. This zone may extend to a depth of 80 m in clear tropical waters, but near the poles, it may just be 10 m deep due to sunlight not penetrating much. Beneath this zone is the Disphotic zone, which may extend to 800 m in clear water. The lowest layer beneath the Disphotic zone is the Aphotic zone where no sunlight enters. Images taken in the Euphotic zone are affected by flickers due to direct sunlight on suspended particles and absorption by floating microorganisms. In the Disphotic zone, backscattering, Rayleigh scattering and diffraction due to marine larval ecology are possible whilst in the deep Aphotic zone, loss of colours is a common issue along with strong visual cues from benthic features. Fig. 1 shows the different distortions in underwater images [1]. When a camera focuses on a target, its lens focuses on the target texture and sends out veiling light, which may be disturbed by particles and marine snow, as well as experiencing Rayleigh, Mie, Back, forward and multiple scatterings. Swimming macroscopical particles also lead to diffraction of the veiling light. Artificial light, normally used for taking images in dark underwater areas also undergoes Rayleigh and Mie scattering, as well as producing noise. Rayleigh scattering results in hazy images whilst Mie scattering results in blurry, murky and faded images.

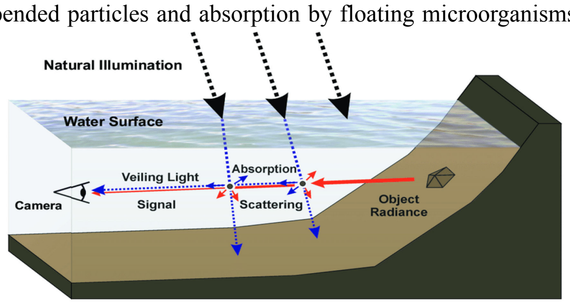


Fig. 1 *Types of distortions in underwater images, as of Rafael et al. [1]*

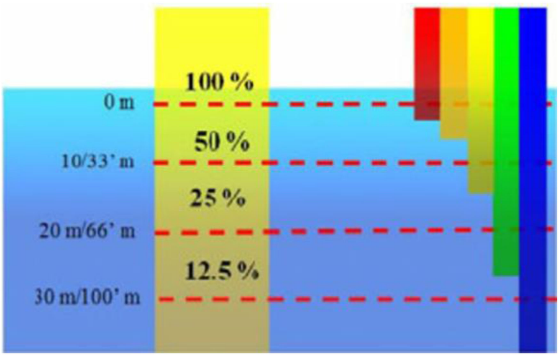


Fig. 2 *Light absorption in water and penetrating levels of different colours, as of Chiang and Chen [2]*

Differing colour absorption poses another threat to underwater images. The main reason behind this is that each colour has its own wavelength and frequency. Red light loses its strength after 5 m deep; which is why red fishes appear nearly black at 20 m. The green travels up to 30 m whilst blue light travels >50 m. Fig. 2 shows the light absorptions in water and their penetrating levels. In deep water, different penetrating levels of different colours result in underwater images to have a bluish green tint.

Apart from these, underwater images also suffer from other problems such as focus, magnification and motion. Underwater, it is very difficult to point the lens exactly at the centre of focus of the target. Magnification is also a problem because the target is always 25% magnified when seen through the perspective of the snorkelers' goggles.

This paper reviews some of the algorithms from the past two decades, which were developed for the restoration of underwater images.

2 Image restoration algorithms

Distortions in the underwater environment lead to the development of restoration methods to allow recovery of images taken underwater. The restoration process involves the removal of blur and noise from an image. Blurring is the overall bandwidth reduction, which leads to an imperfect image formation model. On the other hand, noise is due to scattering effects and sometimes from the recording medium. The restoration process is based on a general Image Formation Model (IFM)

$$I(x) = J(x)t(x) + B(x)(1 - t(x)) \quad (1)$$

where $I(x)$ is the observed intensity at pixel x. $J(x)$, $B(x)$ and $t(x)$ are scene radiance, background light and transmission map at pixel x, respectively.

Lu *et al.* [3] review a total of 34 papers from the literature on restoration methods for underwater images, by broadly classifying them into two approaches: hardware and software-based approaches. In contrast, three approaches have been reviewed in this paper: hardware, software and network-based approaches, and as such, provide a more comprehensive review on restoration methods for underwater images. Tables 1–3 show summaries of methods under hardware based, software based and network-based approaches, respectively.

2.1 Hardware-based approaches

As its name implies, hardware-based methods use hardware components to directly restore underwater images. This includes the use of sensors, lasers, polarisers, polaricams, aqua tripods, Remotely Operated Vehicles (ROVs), laser-based methods and stereo imaging. Polarisation process can reduce backscattering to a certain extent and may be done, either by using polarisation cameras or by using a polarised light source to take pictures. To eliminate backscattering, laser imaging system uses a camera that can precisely close the flash gate at a specific point in time. Waterproof sensors may be used to sense macroparticles, marine snow, swimming biological organisms to allow rejection of reflections due to the particles. On the other hand, aqua tripods are placed on the seafloor to capture images more effectively.

2.1.1 Polarisers: Schechner and Karpel [4] propose an image inversion model, based on images taken at different angles through a polariser. After analysis of the physical effects of visibility degradation, it has been concluded that the main degradation from underwater images is due to partial polarisation of light. To counter this, polarisers at different polarising angles are used to take pictures of the targets, which are then processed using an algorithm to invert the image formation process to improve visibility of the images. Dataset, from multiple images from the polarisers at different angles and orientations, is used to derive a distance map of the scene. Noise sensitivity of the recovered images is also analysed Two images are acquired, 26 m below the surface of the Red sea at two different polarisation angles using an Aqua-Polaricam; with the image in which only the water background is seen selected for further processing. The method can enhance stability, recover veiling light as well as derive a depth map of the image. Noise sensitivity problem of the images is also addressed by the authors. Fig. 3 shows the resultant image using the algorithm of an image taken in the Red sea.

Non-scanning recovery method is discussed by Treibitz and Schechner [5]. Using images with artificial illumination to study the 3D scene structure, the proposed method uses simple hardware and polychromatic polarised illumination. The polariser gives two frames of the scene, which follows a recovery algorithm for the acquisition. However, subsequent analysis on limitations and noise sensitivity shows that the method is limited within a certain effective range due to image noise.

2.1.2 Remotely operated vehicles: ROV; a system, which is used for underwater detection and measurement, has proposed by Zischen *et al.* [6]. The ROV based system consists of artificial lighting, video cameras and thrusters, with the system kept at different sea conditions to obtain samples of the sea conditions. Radiance of light that is reflected is simulated using a computer, before using the Weiner filter on the images based on the observations of the sea conditions, to restore the blurred images. By using the method with proper parameters, restoration of blurry images in scattering seawater is shown to be practicable.

2.1.3 Range gated imaging: Range gated imaging is applicable when the camera is adjacent to the light source with the target behind the scattering medium. With this image processing method, the camera is designed to only open its gate at a preconfigured short period of time, to eliminate backscattering of light. When the light source sends light pulse onto the object, the camera closes its gate as the pulse travels. The gate is only opened for a short period of time as the pulse returns after hitting the object and then, closed immediately thereafter.

Table 1 Classification of the hardware-based approach

Methods	Details
polarisers	• Schechner and Karpel [4] inversion of image formation model • Treibitz and Schechner [5] visibility recovery approach
ROVs	• Zhishen *et al.* [6] ROV based image processing
range-gated imaging	• Tan *et al.* [7] reflected image temporal profile (RITP) + contrast limited adaptive histogram equalisation (CLAHE) • Li *et al.* [8] speckle noise suppression
stereo imaging	• Roser *et al.* [9] Bayesian approach

Table 2 Classification of the network-based approach

Methods	Details
CNN	• Anwar *et al.*, [10] CNN • Hu *et al.* [11] CNN with estimation network • Shin *et al.* [12] ambient light and transmission estimation network • Lu *et al.* [13] DCP with joint restoration filter • Wang *et al.* [14] colour correction and haze removal
GAN	• Fabbri *et al.* [15] GAN • Li *et al.* [16] GAN with colour correction

Tan *et al.* [7] propose a two-step design system: with hardware upgrades and system optimisation methods, for an underwater robotic vehicle involved in sub-sea inspections and repair missions, to improve underwater visibility. The hardware upgrades involve an advanced range-gated imaging system called Tail-gating, which uses the principle of delaying the camera gating process towards the tail of the RITP. CLAHE is then used as system optimisation, to further enhance the range-gated images. This method is similar to that proposed by Hitam *et al.* [55].

Li *et al.* [8] propose variations of the range gated imaging method, by using an imaging system which consists of a pulsed laser system, control and synchronous logics, and a high-speed gated camera. As a highly coherent light source is used, speckle noises resulting from the interference of scattered light rays, are expected in the images obtained from the system. To suppress these speckle noises, the multidirectional morphological filtering algorithm is used. The filtering algorithm has the characteristics of morphology's multi-resolution analysis and fast-computing, which includes square filtering and median filtering. Input images are sent to the square filtering window, with omnidirectional structuring element sets chosen, before passing it on to the median filter. Sub-images are then combined to form output image, which not only suppressed the speckle noise but also preserved feature details effectively.

2.1.4 Stereo imaging: This type of imaging process involves the use of two cameras to take pictures of the same target at different views, to recover depth estimation information of the image.

Roser *et al.* [9] propose a stereo-imaging method for autonomous underwater vehicles (AUVs) to recover underwater images in naturally lit turbid coastal environments, by estimating visibility coefficients. The proposed method is designed using real-time algorithms, consisting of two enhancement methods. The first image enhancement step attempts to recover important scene content and image structures in areas with bad visibility. For stereo retrieval of data, a Bayesian approach is used to create a prior on disparities from robustly matched support points. This prior yields a coarse 3D map of the scene. Using the physical light attenuation model and utilising the coarse 3D map, visibility coefficient, as

Table 3 Classification of the software-based approach

Methods	Details
restoration filters	• Wang and Diao [17] distance-dependent formation algorithm • Wang *et al.* [18] Weiner filtering with a knife-edge function • Lu *et al.* [19] fast weighted guided normalised domain filtering algorithm • Sahu *et al.* [20] un-sharp masking • Wang *et al.* [21] Wiener filter with multilayer transfer model • Trucco and Olmos-Antillon [22] self-tuning restoration filter • Bazeille *et al.* [23] homomorphic filter
colour correction	• Shamsuddin *et al.* [24] colour diminishment and stretching • Kaeli and co-authors [25] colour correction techniques using information from sensor modules • Iqbal *et al.*, [26] equalisation of RGB colour space • Petit *et al.* [27] colour dynamic compression using quaternions • Iqbal *et al.* [28] contrast stretching in RGB colour space, saturation and intensity stretching in HSI colour space • Gibson [29] contrast enhancement and turbulence mitigation • Arnold-Bos *et al.* [30] adaptive smoothing • Arnold-Bos *et al.* [31] Weiner filtering • Chambah *et al.* [32] automatic colour equalisation • Fu *et al.* [33] retinex based approach
fusion	• Ancuti and Ancuti [34] multi-scale fusion • Ancuti *et al.* [35] fusion principle • Khan [36] fusion principle with wavelet transform • Borker and Bonde [37] homomorphic filtering and adaptive histogram equalisation
dark channel prior	• Xie *et al.* [38] dark channel prior to underwater reflection models • Wang *et al.* [39] DCP based on blue-green channels • Gupta and Faruq [40] DCP with FFT • Galdran *et al.* [41] DCP with inverted red, green and blue channels • Wen *et al.* [42] DCP with blue and green channels • Drews *et al.* [43] DCP with blue and green channels • He *et al.* [44] DCP with a median filter • Yang *et al.* [45] DCP with soft matting • Carlevaris-Bianco *et al.* [46] DCP with MIP • Liu and Meng [47] DCP with filtering
light and wavelength compensation	• Yang *et al.* [48] light reflection decomposition • Wu *et al.* [49] underwater colour correction using depth compensation with non-local image de-hazing algorithm • Li *et al.* [50] minimum information loss principle • Emberton *et al.* [51] hierarchical rank-based approach • Chen *et al.* [52] region-varied changes in the ambient light are taken into consideration for de-hazing and colour compensation • Chiang and Chen [2] compensation for the artificial light source, wavelength compensation
histogram equalisation	• Wong *et al.* [53] AGW and DHE • Gao *et al.* [54] bright channel prior • Hitam *et al.* [55] adaptive histogram equalisation • Deperlioglu *et al.* [56] histogram equalisation in HSV space

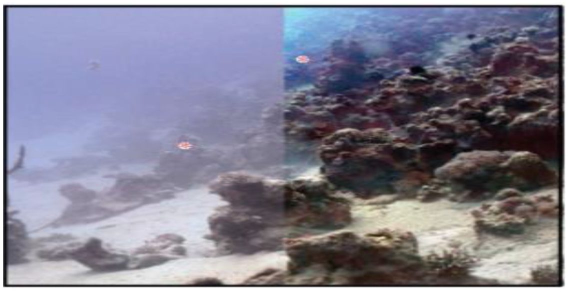


Fig. 3 *Comparison between the raw image (L) and the colour corrected image (R), as of Karpel et al. [4]*

well as ambient illumination, are estimated. To achieve a dense and edge-preserving depth map, an image matting approach is performed, which refines the coarse disparity map and extrapolates information to unmatchable areas based on observed intensity values, to form a ‘pseudo-3D map’. This image is then passed to the second enhancement stage where disparity gaps are filled using a Random Sample Consensus (RANSAC) process. These steps are repeated to create an ‘improved stereo’ map, which is further refined by utilising a discontinuity, by using preserving gap interpolation method, and by image inpainting for large areas with missing 3D information. The final map is then used with the gap interpolated map to recover scene radiances, as shown in Fig. 4.

2.2 Software-based approaches

Software-based approaches use efficient algorithms to recover underwater images. The major classifications of the software approach are filters, DCP, convolutional neural networks (CNNs), colour correction, fusion, light and wavelength compensation, Histogram equalisation and so on. Normally, these techniques are based on assumptions on different coefficients which may sometimes be vague or take up presumed values. Compared to hardware-based approach, software-based approach scores well; giving less computational time, better designs, easy modulations and fewer investment costs.

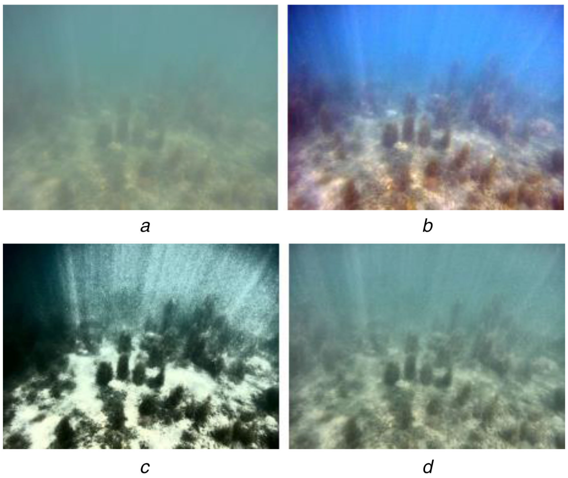


Fig. 4 *Comparisons between the*
(a) Input image, and output images using, ***(b)*** Method by Roser *et al.* [9], ***(c)*** Histogram equalisation method, ***(d)*** Adaptive histogram equalisation method as of Roser *et al.* [9]

Fig. 5 *Image with artificial light as of Chiang and Chen [2]*

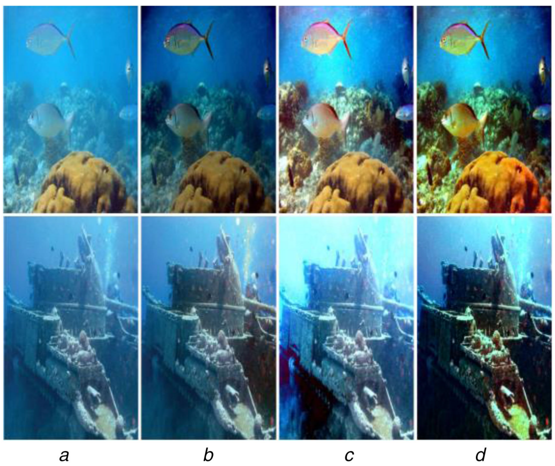


Fig. 6 *Comparisons between*
(a) original image, and output image from, ***(b)*** Fattal's result [57], ***(c)*** Carlevaris's-Bianco [46] result, ***(d)*** Wen's result, as of Wen *et al.* [42]

2.2.1 Dark channel prior: He *et al.* [44] introduce Dark Channel Prior (DCP). Although originally proposed for haze removal, it is the most common method used for underwater image enhancement process. The method is based on the observation that, in an image, there will be at least one channel with low intensity. This low-intensity channel may be used for depth mapping and creating transmission map. The three main reasons for the low-value pixels or dark pixels are shadows that fall on the image, colourful objects and dark objects. The next important assumptions used is that the dark pixels in an image are regarded as those close to the camera as they get less brightening effect, whereas the bright pixels are regarded far from the camera. However, this assumption fails in the presence of an artificial lighting source. Fig. 5 shows the picture taken with the artificial source with its foreground appearing brighter than its background. DCP is also not useful for deeper depths underwater. The reason is that red light has shorter penetration underwater, so while the darkest of the channels is considered for depth and transmission mapping, red channel always ends up being considered with the lowest intensity which gives erroneous results.

As DCP experiences problems in processing underwater images, variations of the methods are subsequently proposed in the literature. DCP (GB) is proposed by Drews *et al.* [43], Wen *et al.* [42]; considering the green and blue channels only whilst neglecting the red channel. Drews *et al.* [43] estimate background light using

$$B_c = I^c\left(\arg\min_{x}\left(I^{r}_{\text{dark}}(x) - \max_{k'}\left(I^{k'}_{\text{dark}}(x)\right)\right)\right) \tag{2}$$

The red channel is suppressed with the assumption $I^{r}{}_{\text{dark}}(x)$ and with the image restored using the equation.

Wen *et al.* [42] propose suppressing the red channel by considering the prior $p(x)$, using

$$I^{\text{GB}}_{\text{dark}} = I^{C}\left(\arg\max_{x}\ p(x)\right) \tag{3}$$

Fig. 6 shows the results of image restoration using the method. This method is based on the fact that underwater images are predominantly bluish-green in colour and these two lights form the basis for underwater visual information. However, this method is found erroneous when the results are analysed based on red coloured target images.

Wang *et al.* [39] analyse images based on the blue-green channels, using a two-stage method. First, backscattering is removed using a binary quadratic function, before blue-green DCP is used to eliminate forward scattering and non-uniform lighting. Gupta and Faruq [40] formulate dark channel based method with fast Fourier transform (FFT) enhancement. Transmission map is obtained from residual energy ratios of the wavelength of each attenuating light, with morphological operations used for contrast adjustments. FFT is then used to recover the scene radiance. Fig. 7 shows the results acquired by Gupta and Faruq [40].

Other variation of DCP method is DCP (R′GB), which is proposed by Galdran *et al.* [41] that dealt with inverted red channels as well as the green and blue channels. This method rectifies the shortcomings of the DCP method for deeper depth; whereby the red channel always ends up being the darkest channel for the depth of >80 m. DCP (R′GB) effectively restores the red channel as well as colours with shorter wavelengths

$$I^{\text{R}'\text{GB}}_{\text{dark}} = I^{C}\left(\arg\min_{x \in p10\%}\left(I^{r}(x)\right)\right) \tag{4}$$

where p is the prior for I^c and $I^r(x)$ is the value of pixel x of the red channel. Values of pixels from the red channel are chosen from the minimum values of pixel x belonging to the 10% category of the prior among $I^r(x)$.

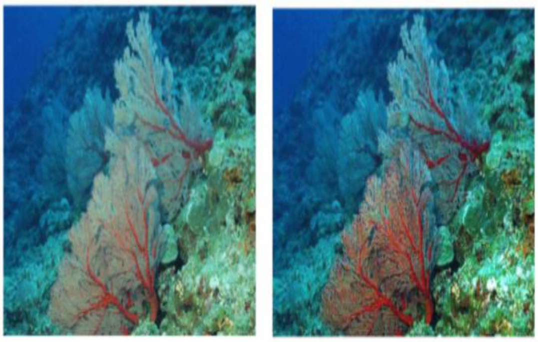
Xie *et al.* [38] use DCP method to find the darkest channel and then, underwater reflection model for restoration and enhancement of the image. Liu and Meng [47] put forward the method called the Dark Channel Prior (DCP), with the assumptions that in water free images, there is at least one channel which has very low intensity. By this way, the effect of water can be removed and the clarity in the images can be achieved. Fig. 8 shows the result of the algorithm.

Yang *et al.* [45] propose the DCP method, but instead of using soft matting procedure, the median filter is used for restoration. Moreover, the authors also propose a colour correction model which enhances the contrast of the image. Using this method, execution time and computing resources can be reduced.

2.2.2 Restoration filters: Filters are commonly used to remove blurriness in an image. Wang and Diao [17] use a distant dependant formation algorithm to restore the images; then a homomorphic filter is used to get rid of the non-linear disturbances in the

a b c

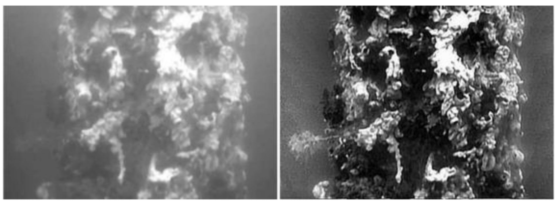
Fig. 7 *Comparisons between*
(a) Original Image, and output image using, ***(b)*** Quaternions method, ***(c)*** Dark Channel Method based on FFT, as of Gupta and Faruq [40]



a b

Fig. 8 *Comparisons between*
(a) Image before processing, ***(b)*** Image after processing with DCP, as of Liu and Meng [47]

Fig. 9 *Original image (T) and restored image with the self-tuning filter (B) as of Trucco and Olmos-Antillon [22]*



a b

Fig. 10 *Comparisons between*
(a) Original image, ***(b)*** Output image as of Gibson [29]

distance-dependent model. The restored underwater image is then obtained by solving a Poisson equation that is derived based on the similar distance of neighbourhood pixels.

Lu *et al.* [19] develop a fast weighted guided normalised convolution domain filtering algorithm for restoring underwater images. The algorithm also compensates for light attenuation along the propagation path. Sahu *et al.* [20] propose a method for enhancement based on un-sharp masking. Un-sharp masking is subtracting an image from its blurred version, which to clearly show the details in an image. The un-sharp masking is used to normalise the colour stretched image, and it is filtered to detect the presence of edges. The un-sharp mask is formed with a sharpened image, and the normalised image is used to increase the contrast and enhance the image.

Wang *et al.* [21] propose an approach to formulate a model, which includes both Point Spread Function (PSF) and backscattered noise; with image restoration parameters estimated from in situ measurements of the background. Weiner filter is then applied for restoration purpose. A self-tuning image restoration filter based on a simplified version of Jaffe-McGlamery image formation model is proposed by Trucco and Olmos-Antillon [22]. The values for filter parameters are estimated automatically based on a global contrast measure. Fig. 9 shows the results of the original image processed with the self-tuning filter.

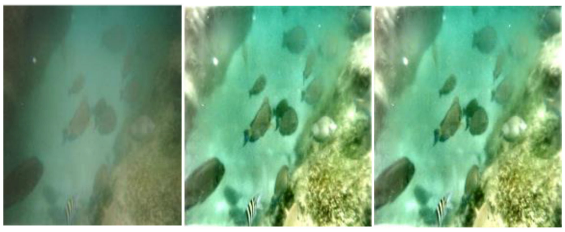
Wang *et al.* [18] develop a restoration method by designing the optimal window size and calculating motion blur parameters. Knife-edge function is used to determine the system degradation function. Finally, the derived image is passed through a Weiner filter to obtain the restored image. Bazeille *et al.* [23] design an algorithm by working in the YCbCr space. Initially, sampling is performed to eliminate the Moire effect. After resizing to a chosen value, RGB space is converted to YCbCr space, before it is passed through a homomorphic filter to eliminate non-uniform illumination. Wavelet denoising is then performed on the image. To improve image segmentation, the image is passed through an anisotropic filter, before final conversion back to RGB space from YCbCr space; to obtain the restored image.

2.2.3 Colour correction: To correct the colours in RGB space, algorithms that evaluate every pixel based on colour absorption are developed. Singh and co-authors [25] propose a method by estimating attenuation coefficients and strobe beam pattern, using overlapped underwater colour images, with the help of a Doppler velocity log. These inputs are then used to colour correct the images. Iqbal *et al.* [26] design an algorithm based on colour balancing and colour correction in RGB and HSI colour space. As a first step, the colour cast is reduced by equalising the colour values. Red intensity is then increased by stretching the histogram whilst blue intensity is reduced by diminishing the histogram. HSI model is finally used for colour correction.

Petit *et al.* [27] propose an algorithm based on light attenuation inversion. Geometric transformations are computed using quaternions with reference axis taken as a hue vector characterising the watercolour. Using this method, the contrast is significantly improved. Iqbal *et al.* [28] perform a two-step approach: first, contrast stretching in RGB space, and second, saturation and intensity stretching in HSI. RGB stretching equalises overall colour contrast of the image, resulting in the improvement of the image.

Gibson [29] develop a method for turbulence mitigation and contrast enhancement to eliminate noise, increase local contrast, mitigate marine snow, and increase the sharpness of the image. In the developed method, noise is first removed with the help of a spatial median operator of size 3×3. Adaptive Gray-level Grouping filter is used to enhance the image contrast. With the images arranged globally, the adaptive correlation filter is used to estimate its global motion, whilst the optical flow method is used to estimate local motion. Consequently, frame averaging is performed with the help of a temporal median filter. Finally, the deblurring method is used to obtain the desired contrast-enhanced output, as shown in Fig. 10.

Arnold-Bos *et al.* [30] develop an underwater image denoising algorithm using Current preprocessing method, by concentrating on local contrast. The authors have also shown that additional use of adaptive smoothing helps in denoising the remaining sources of noise and improve edge detection of image. As a first step, contrast equalisation is performed on the input image; by taking a low-pass

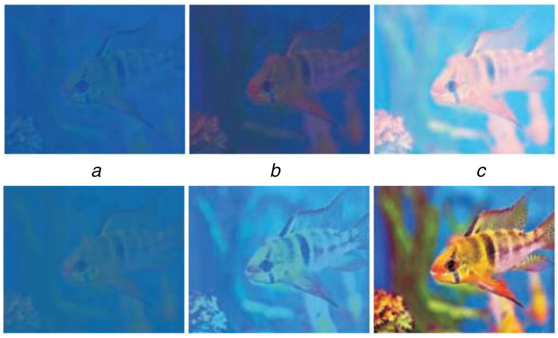


a b c

Fig. 11 *Comparisons between*
(a) Input image, and final image after adaptive smoothing, ***(b)*** Without, ***(c)*** With forward scattering deconvolution as of Arnold-Bos *et al.* [31]

a b

Fig. 12 *Comparisons between*
(a) Original underwater image, ***(b)*** Method by Fu *et al.* as of Fu *et al.* [33]



a b c d e f

Fig. 13 *Various methods*
(a) Original, ***(b)*** Colour correction, ***(c)*** White balance, ***(d)*** Histogram stretching, ***(e)*** Histogram equalisation, ***(f)*** Cosmin's result as of Ancuti *et al.* [35]

a b

Fig. 14 *Comparisons between*
(a) Original underwater image, ***(b)*** Restored result as of Khan [36]

filtered version of the image and passing it through a Gaussian filter, to address the backscattering effect. However, contrast equalisation naturally increases the amount of noise in fewer contrast areas of the input image. To counter this, the local gain is calculated and then multiplied by the standard deviation of the noise, to reduce the effect of noise in selective areas. Adaptive smoothing is then performed to preserve the edges; with less filtering in the edges to preserved the edges. Finally, the image goes through anisotropic and wavelet filtering processes to obtain the output. The authors further extend their work to address forward scattering in [31]; using forward scattering deconvolution method together with Weiner filtering. Fig. 11 shows the original input image, image results using the proposed method with adaptive smoothing without forward scattering deconvolution and with forward scattering deconvolution.

Chambah *et al.* [32] propose a colour correction method for underwater images which is applicable for live fish recognition. For unsupervised image enhancement, Automatic Colour Equalisation (ACE) method is used, which merges the Gray version of the image with White Patch equalisation mechanisms, whilst taking into account of the spatial distribution of colour information. This merging method is based on the human visual system (HVS); combining both lightness constancy and colour constancy. Lightness constancy allows observation of a scene regardless of changes in mean luminance intensity, whilst colour constancy allows stable observation of a scene regardless of changes in the colour of the illuminant. The ACE method has been proven to be capable of dealing with varying lighting conditions, enhancing the images as well as useful for feature extraction and classification.

Fu *et al.* [33] propose a retinex based colour correction method for denoising. Initially, the mean value and mean square error of each RGB component are calculated. A retinex based method, which is based on the human visual system, is then used for reducing over exposure and fuzz, by decomposing illuminance and reflectance layer of the first stage output image. Consequently, CLAHE algorithm is used to enhance the reflectance component and a slight histogram adjustment is made to enhance the illumination component. Final processed image using the method is shown in Fig. 12. Shamsuddin *et al.* [24] propose a method based on colour diminishment, where auto, as well as manual colour correction, is made. The automatic colour correction is made with histogram clipping, wherein the manual is done based on human perception.

2.2.4 Fusion method: The fusion process is based on the fusion of information from a collection of images of the target, which may include degraded, colour corrected and contrast-enhanced versions of the images. Ancuti *et al.* [35] propose a fusion method, using multiple degraded versions of the image as inputs. To overcome the limitations inherent in underwater images, two inputs are utilised; colour corrected and contrast-enhanced versions of the original underwater images, as well as four weight maps that are used to increase the visibility of the degraded object. This results in the output image with less noise level, improved global contrast and significantly enhanced edges. Fig. 13 shows the results of the proposed method, with comparison to other previous existing algorithms.

Ancuti and Ancuti [34] suggest a multi-scale fusion method. Inputs from contrast corrected and white balanced version of the image are considered, to produce an artefact free resultant image.

Combination of fusion principle with wavelet transform has been proposed by Khan [36], with inputs taken from white balanced, minimum and maximum versions of the degraded raw image. Weight maps are derived from the luminance, global contrast, chroma and the original saliency features. Consequently, the inputs and the weight maps are blended according to the fusion principle, before performing wavelet transformations, to obtain the final output, as shown in Fig. 14.

Borker and Bonde [37] propose using two images which are derived from homomorphic filtering and adaptive histogram equalisation, as the two inputs for the fusion process. Image passing through homomorphic filter undergoes contrast stretching whilst image going through adaptive histogram equalisation is smoothened, before the two images are fused together. Colour correction is then performed on the fused image. Fig. 15 shows the results of the proposed algorithm and comparison results to other algorithms.

2.2.5 Light and wavelength compensation: Since different wavelengths of light have different penetration levels, it is necessary to compensate for the light, for images taken in the Aphotic zone. Numerous algorithms have been proposed to this effect. Wu *et al.* [59] estimate global background light using a hierarchical search based on the quad-tree subdivision. Underwater images are colour corrected using depth compensation with a multi-channel guided image filter, which is then restored using non-local image de-hazing algorithm. Yang *et al.* [48] introduce an approach that focuses on inshore water body optical properties. Instead of replacing the back-scattering with theoretical maximum,

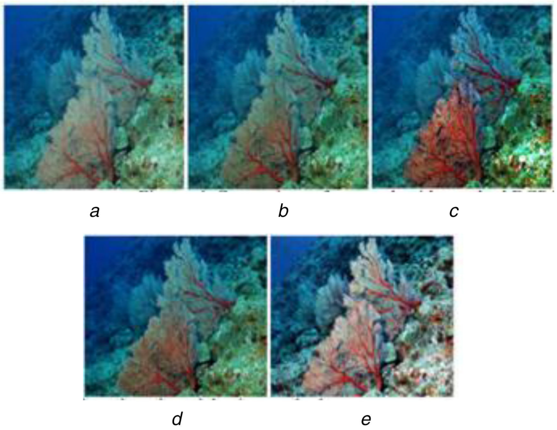


Fig. 15 *Comparisons between*
(a) Original underwater image, and output images using, ***(b)*** He *et al.* [44] method, ***(c)*** Meng *et al.* [49] method, ***(d)*** Zhu *et al.* [58] method, ***(e)*** Samarth *et al.* method as of Borker and Bonde [37]

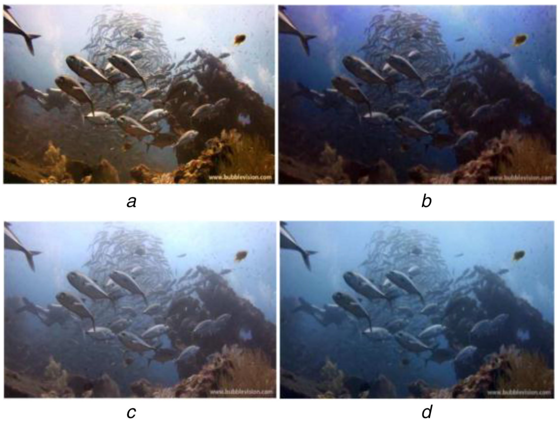


Fig. 16 *Image processed using*
(a) Chiang and Chen [2] method, ***(b)*** Dark channel based method, ***(c)*** Chromatism based method, ***(d)*** Histogram equalisation as of Chiang and Chen [2]

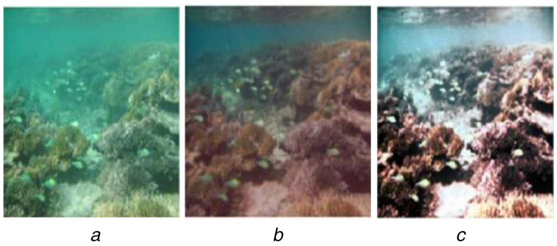


Fig. 17 *Comparisons between*
(a) Input image, ***(b)*** Ancuti *et al.* [35] method, ***(c)*** Deperlioglu *et al.* method as of Deperlioglu *et al.* [56]

back-scatter lighting estimation method is proposed based on the phenomenon of the interaction of light rays with particles in the medium. Transmission map is the estimated by applying lighting reflection decomposition as well as statistical prior of inshore water body attenuation coefficients. Resultant image from the method proves well on sharpness and total colour metrics. Emberton *et al.* [51] put forth a single image de-hazing method for underwater images, by hierarchically ranking regions of an image to locate the most likely veiling light regions, and then using transmission estimation method to produce the resulting image. Background regions are located through a super pixel segmentation and clustering process, with the transmission values adapted to avoid oversaturation and artefacts.

Chen *et al.* [52] introduce a method based on region specialised underwater image restoration, using data sets of hazy images. Out of all the separated channels, a channel with the brightest intensity is considered. The image is first segmented into different regions of illumination based on the bright channel; with regions influenced by ambient light having thicker haze than regions having less ambient light. Depth map and scattering light are estimated at the different regions, before performing region based de-hazing with colour compensation to produce the restored image.

The de-hazing algorithm that takes into account artificial light sources and compensates for attenuation loss, is proposed by Chiang and Chen [2]. By choosing $I^{\mathrm{RGB}}{}_{\mathrm{dark}}$ as the prior, the background light is calculated by taking the maximum value of pixel among all the pixels in $I^c{}_{\mathrm{dark}}(x)$, using

$$B^c = I^C\left(\arg\max_x \left(I^c_{\mathrm{dark}}(x)\right)\right) \tag{5}$$

Firstly, the depth map of the image is estimated, before it is segmented into foreground and background pixels. The segments are then used to determine the presence of artificial illumination, which needs to be compensated. The discrepancy in attenuation of different channels is then made up using the de-hazing algorithm. Fig. 16 shows the comparative results of Dark Channel method, Histogram equalisation and chromatism based methods. It may be seen that superior colour fidelity is obtained using the proposed algorithm.

Li *et al.* [60] estimate background light effectively using quadtree subdivision and graph-based segmentation, with a transmission map derived using the minimum information loss principle. It has been shown that resultant image using the method is capable of improving vision, colour and contrast enhancement [60].

2.2.6 Histogram equalisation: Histogram of an image is its tonal distribution representation in graphical form. Hitam *et al.* [55] deal with mixture CLAHE algorithm, which operates on RGB and HSV colour models, and results combined together using Euclidean norm. It is shown that the resultant image has its contrast enhanced with reduced artefacts. Gao *et al.* [54] propose a method, based on DCP method. In the first instance, the underwater images are improved by estimating the bright channel image, atmospheric light and transmittance image, which are then used to rectify and refined the image. It is then processed using histogram equalisation to clear colour distortion; to produce the resulting restored image. Wong *et al.* [53] introduce an Adaptive Gray World (AGW) and Differential Gray-Levels Histogram Equalisation (DHE) for image restoration. AGW method is applied to remove the colour cast caused by light absorption whilst DHE is used to improve the contrast of the underwater images.

Deperlioglu *et al.* [56] propose an underwater image enhancement method; using a histogram equalisation technique by utilising the HSV colour space. The image is separated into RGB components and then converted onto the HSV space. Extension of V element is performed, before it is reconverted back onto RGB colour space, where it undergoes histogram equalisation for each R, G and B components. The R, G and B components are then, merged to form a colour image. Finally, the Gaussian low-pass filter is applied to retrieve the underwater image. Fig. 17 shows the resultant image from Deperlioglu *et al.* [56], which is compared to the resultant image from with Ancuti *et al.* [35].

2.3 Network-based approaches

Network-based approach forms the framework for many machine learning algorithms, which process complex data inputs, with trained data sets.

2.3.1 Convolutional neural networks: CNNs are a class of networks consisting of multiple layers, with an input, output and other middle layers which pass their convoluted results to the other subsequent connected layers. This, effectually, reduces the computational time of the process. Anwar *et al.* [10] propose a novel CNN based image enhancement model, i.e. UWCNN. By relying on an automatic end-to-end and data-driven training mechanism using databases of synthetic underwater images, the

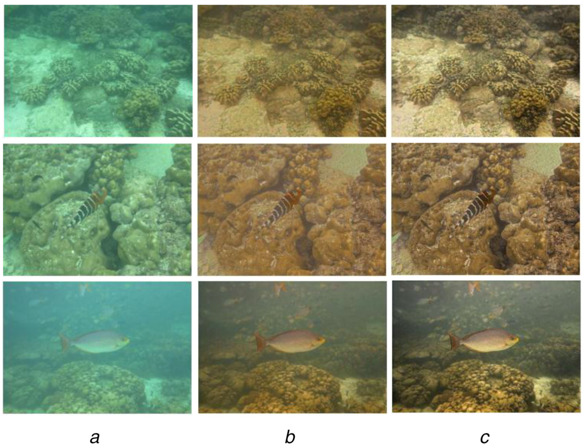


Fig. 18 *Comparisons between*
(a) Original images, ***(b)*** Processed with UWCNN, ***(c)*** Processed with UWCNN+ as of Anwar *et al.* [10]

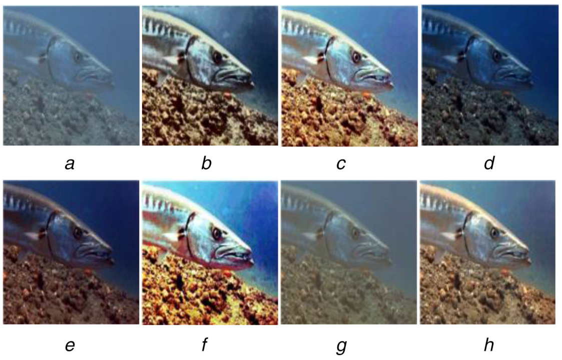


Fig. 19 *Comparison of underwater images*
(a) Input image, ***(b)*** Fu *et al.* [33] method, ***(c)*** Zhang *et al.* [61] method, ***(d)*** He *et al.* [44] method, ***(e)*** Galdran *et al.* [41] method, ***(f)*** Li *et al.* [50] method, ***(g)*** Shin *et al.* [12] method, ***(h)*** Hu *et al.* [11] method as of Hu *et al.* [11]

model can reconstruct underwater images clearly. Ten different marine image databases are synthesised; by considering the optical properties and other conditions of the water, from which multiple UWCNN models are trained for each underwater image formation type. For enhanced clarity, the post-processing step of UWCNN+ is proposed. This method proves well quantitatively and qualitatively as well as able to eliminate the greenish tint of underwater images. Fig. 18 shows the results of the proposed method.

Lu *et al.* [13] propose a CNN with the variation of Dark Channel method with a joint restoration filter to restore the images. Wang *et al.* [14] propose a CNN based network and named it as UIE-Net, which is trained to perform colour correction and haze removal; this combined process stands as a strong training feature. A pixel disrupting strategy is used for speed and accuracy. Hu *et al.* [11] propose an effective CNN based approach for underwater image restoration, which consists of a transmission estimation network (T-network) and a global ambient light estimation network (A-network). The method mainly considers blue channel transmission maps and global ambient light. The T-network is used to prevent halo artefacts, to preserve edge features and to estimate blue channel transmission map of the underwater image. An underwater image synthetic method for training, which can simulate underwater images captured in various underwater environments, has also been developed, with the main aim of improving colour cast and image contrast. To preserve detailed features, a cross-layer connection and multi-scale estimation are also made. The first and penultimate convolutional layers are connected to compensate for the edge information loss, and a multi-level pyramid pooling adopted as the second pooling layer. An up-sampling layer after the output of every scale is formed, with output from the small scale added to the next scale as a feature map. This multi-scale approach provides a better way of applying local image details over varying resolutions. Estimation is then

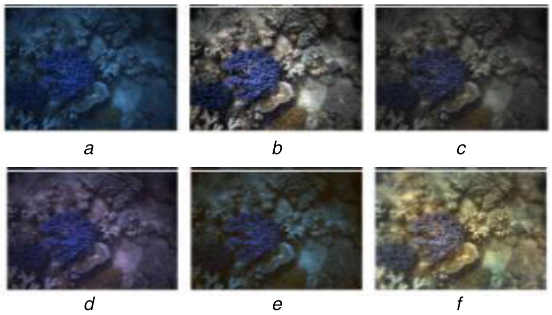


Fig. 20 *Comparisons between*
(a) Raw underwater image, ***(b)*** Histogram equalisation, ***(c)*** Gray world, ***(d)*** Modified Jaffe-Mc Glamery method, ***(e)*** Shin *et al.* [12] method, ***(f)*** Li *et al.* [16] method as of Li *et al.* [16]

made by varying image resolution. This is done to prevent halo artefacts and preserve edge features. Training datasets are synthesised using underwater optical model and publicly available depth datasets. Fig. 19 shows the result from the algorithm as compared to other methods.

2.3.2 Generative adversarial network (GAN): GAN is trained to translate an image from any arbitrary domain X to another arbitrary domain Y; to generate a paired dataset. If X and Y are taken to be a set of undistorted and distorted underwater images, respectively, an image that appears to be underwater while retaining ground truth may be derived using paired datasets derived using GAN.

Fabbri *et al.* [15] develop GANs by proposing a method for generating datasets for image restoration that is applicable for any visually-guided underwater robots. It has been shown that the proposed approach [15] can generate more visually appealing images and increase accuracy for a diver tracking algorithm.

Li *et al.* [16] propose WaterGAN, which is a variation of GAN, for restoring monocular underwater images. The method creates a pipeline architecture which consists of WaterGAN as its first component, taking in-air images and depth maps as input and generates corresponding synthetic underwater images as output. The dataset with corresponding depth data, in-air colour, and synthetic underwater colour, act as real ground truth of depth and colour, to allow training of a colour correction network. For restoration, a colour correction network has been proposed that takes raw unlabelled underwater images as inputs and restored images as outputs. The colour correction network has two sub-networks: depth estimation and restoration networks. Depth estimation network uses a coarse relative depth map, reconstructed from the downsampled synthetic underwater image. Restoration is performed by the colour correction network from the input of both underwater image and its estimated relative depth map. Fig. 20 shows the resultant image from using the proposed method as compared to other methods. In particular, it is compared to the method proposed by Shin *et al.* [12], which uses a traditional neural network to perform convolution, as well as to estimate transmission and global ambient light. However, instead of images, local patches are generated, to be used as the training dataset.

2.3.3 Few other methods: Liu *et al.* [62] propose a method for calculating PSF and Modulation Transfer Function (MTF) of seawater; to predict light attenuation and underwater image quality, using laboratory measurement of PSF and MTF. Fig. 21 shows the original image and it's after effects of blurring and final restoration results.

Mohan and co-authors [46] propose Maximum Intensity Prior (MIP). Taking D_{mip} as the prior for p, background light may be calculated by estimating the minimum value of pixels in the original transmission map, as follows:

$$B^c = I^C\left(\arg\min_x (t(x))\right) \tag{6}$$

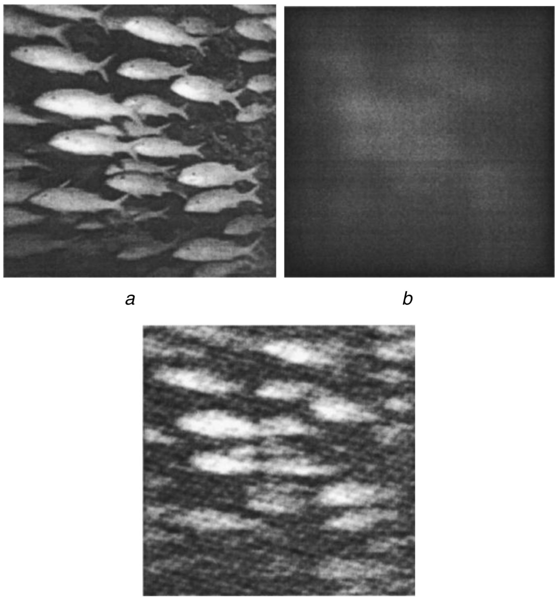


Fig. 21 *Comparisons between*
(a) Original image, ***(b)*** Blurred image, ***(c)*** Restored image as of Liu *et al.* [62]

D_{mip} may then be used to find transmission map $T(x)$.

$$T_x = D_{\mathrm{mip}}(x) + \left(1 - \max_x D_{\mathrm{mip}}(x)\right) \tag{7}$$

According to this method, the difference between the maximum intensity of the red channel and that of the green and blue channels is taken to find the transmission map. However, the MIP method fails to produce accurate results in dim background light as well as when artificial light sources are present. As the use of artificial light source gives an image which has a bright foreground compared to the background, erroneous results are obtained when using MIP; taking the bright foreground pixels as being far away from the camera and dark background pixels as nearer to the camera.

Çelebi and Erturk [63] propose an empirical mode decomposition method. Initially, each spectral component is decomposed into small intrinsic mode functions, then the enhanced image is obtained by combining the intrinsic mode functions with different weights; with the weight estimation process carried out using a genetic algorithm. This method is found superior compared to contrast stretching and histogram equalisation approaches.

Method to estimate the depth map of underwater images based on image blurriness estimation is proposed by Peng *et al.* [64]. The blurriness of the pixels is estimated using the difference between the original image and the multi-scale Gaussian filtered image. A maximum filter is applied to the pixel blurriness map to find a rough estimate of the depth map; refining the depth map by the morphological operations with the guided filter. The enhanced output is obtained using the refined map in the IFM. Enhanced underwater images under different lighting conditions are obtained as a result. Fig. 22 shows the algorithm results and compared results along with the depth maps. Peng *et al.* [65] extended his paper by estimating the background light and finding the depth based on the red content, estimated background light values and blurriness.

3 Conclusion

A comparative study of various methods used for underwater image restoration is presented in this paper. Earlier methods consist of hardware elements such as polarisers, sensors, lasers and so on, which are used to capture a set of images of the same scene and then, passed for processing using algorithms, to obtain a clearer image. It is noted that hardware approaches require complex hardware arrangements and generally, do not cost efficient.

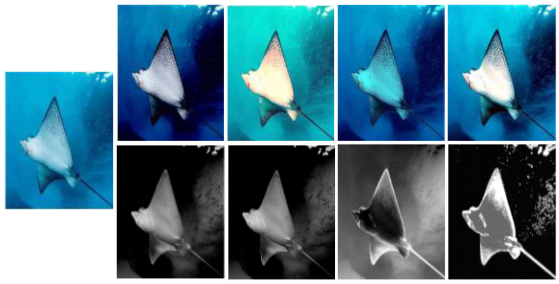


Fig. 22 *Comparisons between*
(a) Underwater image, and enhanced images and corresponding depth maps obtained using, ***(b)*** Carlevaris-Bianco *et al.* [46] method, ***(c)*** Yang *et al.* [45] method, ***(d)*** Chiang and Chen [2] method, ***(e)*** Peng *et al.* [64] method as of Peng *et al.* [64]

Nowadays, computer vision techniques have been developed and optical models have been derived for image formation in underwater environments which suffer from visibility degradation. DCP, histogram equalisation and colour correction are some of the most commonly used methods. Image restoration based on an optical model has also been demonstrated in the literature. Wavelength compensation approach combined with artificial light detection and elimination has been shown to good quality result. Recently, multi-scale fusion technique, CNNs, generative adversarial methods have been introduced; capable of reducing computational effort and time. But for these methods, the well-trained dataset is necessary which require multiple images with various lighting conditions and depths to be acquired. With proper algorithms, underwater images can be restored effectively.

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