[1] **Pradnya Ravindra Narvekar**

[2] **Dr. Manasi R. Dixit**

Recent Advancement in Underwater Image Enhancement Strategies: A Review

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Abstract: - In the process of ocean world exploration, a key role is played by underwater imaging technology. However, due to light attenuation phenomenon, underwater imaging severely suffers from quality degradation. Technological advancement provides both hardware and software solutions to improve underwater image quality. However, software solutions are observed to be more viable and cost effective. At the beginning, underwater image enhancing approaches are designed using conventional image processing methods. Later development in this sector involved specific method tailoring of image enhancement models by considering underwater environmental conditions. Most of the methods are developed to target specific issues and designed for noise removal, deblurring, colour correction, contrast enhancement and dehazing to enhance underwater image quality. Progression in the artificial intelligence based approaches is also reviewed to assess recent advancement in this sector. Present survey specifically reviews very recent attempts of underwater image enhancements based on these approaches. The inference of the review reveals the scope of improvement.

Keywords: Underwater images, Image enhancement, Software improvement, Colour correction, Machine learning, Image dehazing.

I. Introduction

Underwater world significantly impacts on overall earth environment, hence enormous research is carried to explore this world. One of the important ways to explore this world is imaging. Vision based technologies are flourished in this aspect since it can capture highly dense information [1]. These images can be used for variety of applications such as under water target tracking, rescue missions, marine biology exploration, ecological monitoring, man-made structures inspection, environmental protection, ecological monitoring, [2]–[4]. However, water attenuates red, green and blue light differently and the suspended particles in water shows absorption and scattering of light, this makes underwater imaging difficult. Due to these underwater light attenuation phenomena, images captured shows effective colour cast, low-contrast, presence of haze or fog and this makes image appearance blur [5]. This limits the information content in the image. Thus, to extract valuable information from underwater images, quality improvement of these images is highly important. To address these issues lot of research is being conducted to enhance and restore image quality. Various algorithms are suggested based on image processing methods such as fog removal, clarity improvement using filters, addressing blurring and background scattering, and contrast enhancement. However, in order to invent new image quality enhancing methods or improve existing techniques it is essential to understand underwater optical imaging modelling which will eventually lead towards designing new robust and effective enhancement strategies. However, emotion recognition can help in determining human actions, reactions and their social concerns [9]. Therefore, emotion recognition is considered as a major and fundamental aspect while developing an interactive computer system [10] – [12]. Recognizing facial emotion/expression is a very important basic feature required for the further meaningful development of various applications in the sectors like social life uses, such as smart protection, lie detection, smart medical practice such as psychological distress and pain detection [13]. Therefore, psychology, sociology, and automatic expression recognition streams identified the emotion recognition process as considerably important while featuring the user affable software and user agent. By virtue of which large implications of automatic facial expression recognition (FER) are considered while featuring human computer interaction (HCI) field [14]. Now a days, the affective computing is counted as high impact area in HCI, intending the improvement in the human–machine interaction using clear recognition of the emotional state from the given human faces.

[1] Department of Electronics Engineering Shivaji University Kolhapur, Maharashtra, India. Email: pradnyanarvekar20@gmail.com
[2] Department of Electronics &Telecommunication Engineering Kolhapur (Empowered Autonomous) Maharashtra,India. Email: dixit.manasi@kitcoek.in

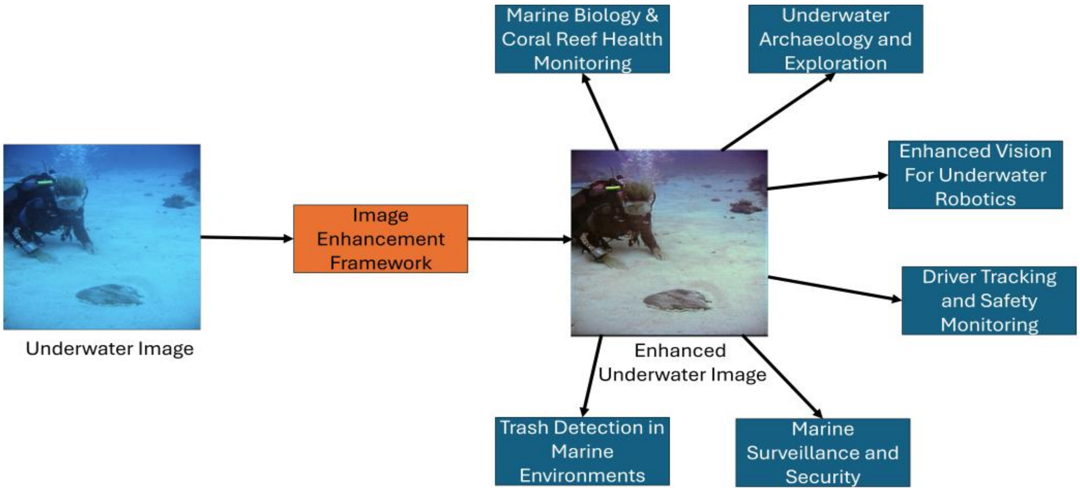

Fig. 1. Underwater Image Enhancement Framework.

Many software solutions are suggested to enhance and restore underwater images. Certainly, both enhancement and restoration of underwater image suggests output quality improvement. Image enhancement signifies the improvement in visual appearance of the image. This is being done without altering image content (attenuation and scattering coefficients are not used) and only focusing on characteristics of the human visual system, hence no explicit information about the image environment is required. On the other hand, explicit knowledge about the degradation function and the noise characteristics (both derived from imaging system response and medium effects) is needed to construct restoration model. In the view of this information, present review takes in to account image enhancement methods and illustrates different strategies implemented by researchers. Section II discusses about the broad categorization of enhancement methods. Section III reviews and illustrates the conventional methods of image processing employed to enhance underwater images. Section IV takes account of some artificial intelligence based strategies employed to enhance quality of underwater images. With all these different aspects, review is concluded in Section V.

II. DIFFERENT STRATEGIES TO ENHANCE UNDERWATER IMAGE QUALITY

Variety of strategies are employed form the realm of image processing to enhance underwater image quality. As stated earlier, to obtain enhanced visual results, methods are designed based on characteristics of the human visual system. In some of the earlier approaches, underwater images are enhanced using outdoor image enhancement methods. This image enhancement signifies the improvement in visual appearance of the image, wherein pixel intensity re-distribution method is commonly used for improving colour and contrast of image. However, later development shows evolution in image processing approaches, wherein, image quality enhancement methods are designed specifically considering the underwater image characteristics. Underwater images show prominent characteristics effect such as hazing, colour cast, and low contrast. In order to enhance image quality few methods are designed in which pixel values are tailored either in spatial domain or a frequency domain, while some methods adopt combined approach. Apart from these conventional image processing based approaches, latest artificial intelligent (AI) based methods are also explored. Considering the proficiency of the AI techniques, variety of approaches can be designed to reveal hidden features in the underwater image. Based on these aspects, few methods using convolutional neural network (CNN) and generative adversarial network (GAN) are developed for underwater image enhancement. Information of all the below discussed approaches is given in Table 1 to present a brief overview of methods along with specific details of used dataset and end results of evaluation metrics.

III. NEW APPROACHES BASED ON CONVENTIONAL IMAGE ENHANCING METHODS

Spatial-domain image enhancement methods use gray mapping theory, in which gray levels are expanded to complete redistribution of histogram intensity [17]. The same method is followed in for different colour schemes. Redistribution of histogram intensity can be completed using single colour model or multiple colour model. Some of the latest developments are reviewed as follows. A group of researchers, demonstrated the use of colour filter array (CFA) and retinex method to enhance image. The image is captured using camera equipped with CFA, due to which RGB values of image are coupled and show dependency. A model is designed to achieve more accurate illumination intensity and simultaneously, for histogram transformation an adaptive linear function is proposed [18]. In another approach, researchers proposed Retinex-based enhancement of the contrast limited adaptive histogram equalization (CLAHE) processed image. To further enhance edges and reduce blurriness, bilateral filtering of Retinex processed image is suggested. Later on, perform bilateral filtering on the Retinex processed image. Moreover, suitable parameter values are determined to figure out maximum utility of each of CLAHE, Retinex and bilateral filtering algorithms [19]. Further, it is known that Retinex transmission map estimation decouples unknown background light which reduces error accumulation. Making use of this, an approach is developed, wherein, prior to estimation of the transmission map, the global white balance is performed on image. In this proposed method, further betterment is achieved by introducing adaptive colour correction strategy, which smartly opts for better choice in-between two colour correction methods [20]. A group of researchers proposed two step strategy for better dehazing performance. Using Gray World assumption and optimal color-compensated approach, a white-balancing approach is determined. Further, using gamma-correction operation, multiple versions of underexposure are created. A weighing system using ‘contrast’, ‘saturation’, and ‘well-exposedness’ is formed to execute multi-scale fusing scheme [21]. In a hybrid approach, first colour correction is achieved using white balance and contrast enhancement after which the hazeline technique is employed to remove haze and enhance overall image. Further using these enhanced images researchers also reconstructed 3D underwater real world scenario [22]. Another hybrid approach is designed to enhance image quality. In this approach, an improved UWB is used in conjunction with histogram stretching to remove colour castings. Further improvement in contrast and saturation is achieved for dehazing [23]. A combined approach is proposed by a group of researchers as multi-scale fusion. For this, colour correction is achieved using multi-scale retinex, contrast is corrected using CLAHE and in conjunction with this, sharpening algorithm is used to enhance image. Finally, layer-by-layer fusion reconstruction is achieved using Laplacian pyramid and Gaussian pyramid [24].

IV. Artificial Intelligence Based Strategies For Enhancing Underwater Images

Now a days, remarkable development is evident in the sectors wherein underwater discoveries are involved. This is possible due to the participation of advanced technology in every sector. Use of AI is one of those advanced technologies which revolutionized the many technical and digital processing methods. Many researchers are involved in use of deep learning network for enhancing underwater image quality. Some recent attempts are reviewed as follows. Underwater environment is often weak illuminated and produces low quality images, to address this issue a group of researchers developed a model. First, using max-RGB method and shades of gray method vision enhancement is achieved. Later on a two different CNN based schemes are used to solve weak illumination issue and results are compared [25]. It is observed that if image statistics as prior is used for enhancing image, it often results in developing colour artefacts and haze residuals. To overcome this a strategy is framed, wherein, a CNN is trained for learning hierarchical statistical features which are then used for olor correction (CC-Net) and contrast enhancement (CE-Net). The CC-Net and CE-Net, are built for colour correction and contrast enhancement on spatial domain by generating transmission map and pixel-wise colour cast. Additionally, to overcome training dataset deficiency, synthetic underwater patches are derived which show similarity with another existing database [26]. In another research, a framework named as multi-scale spatial and channel attention fusion (MSSCANet) is established for effectively enhancing image details. At first, using existing dataset a synthetic dataset UIRDs is generated. Later, image detail enhancement is achieved using constructed multi-loss function [27]. In an approach, a group of researchers built a network which derives feature maps from channel and spatial information of the multi-scale underwater images. First, images are enhanced using Histogram Equalization, White Balance and Gamma Correction after which using feature fusion strategy enhanced images are fused. Further contrast enhancement in luminance, colors and high-frequency is achieved by using loss function which is built using combination of MAE loss functions, MS-SSIM and perceptual [28]. Another approach on the similar operational lines is proposed by a group of researchers. Implementation of pseudo color technique often introduces gray-scale loss which is addressed in this method. First, the multi-scale image is processed for bit depth quantization, further this data is processed using the proposed high gray-scale enhancement algorithm for enhancing colour. Then features of the multi-scale image are extracted using CNN which is trained for compact learning. The gradient dispersion and fogginess are controlled using jump connection. Similarly, style cost function is introduced in the process to increase colour correction proficiency of the proposed method [29]. It is well known that dark underwater images taken in low illumination environment are of low visual quality due to noise. Most of the state of art image enhancing algorithms may introduce artefacts during enhancing. In another approach researchers considered characteristics of underwater imaging and for enhancing image a structure decomposition based CNN is developed. Depending on theoretical analysis, decomposition of image into high-frequency and low-frequency domain is proposed. Using deep learning network, direct enhancement in high-frequency part is done. While, another network is formed using joint component map (transmission map and background light) to enhance low-frequency part [30]. Another method used to enhance underwater image quality is based on GAN. Herein, underwater images are synthetically generated using cycleconsistent adversarial networks (CycleGAN) and use to train CNN model. Further, residual learning based deep learning model is developed for image enhancement and recognized as very-deep super-resolution reconstruction model (VDSR). Further improvement is suggested in training mode and multiterm loss function to achieve maximum detail enhancement with colour correction [31]. It has been observed that image enhancing algorithms for high-resolution images and for real time applications are very limited. A group of researchers provided a GAN based method as a solution for this. To design this, based on structural similarity loss, adversarial loss, and content loss, a multiterm loss function is proposed [32]. Similar to this, large-size underwater image enhancement is also in demand. A GAN based solution to address spatial inconsistency problem is offered in the form of simplified network structure [33]. It is also important to enhance the image with more details, better contrast and vivid colours, for which, a SpiralGAN model is developed. An objective function taking in to account pixelwise losses is designed. Using generator based on deconv-conv blocks, details of distorted images are preserved. This is generalized using spiral learning strategy through which underwater images from real-world can be effectively enhanced [34]. It has been observed that better perceptual quality of the images can be achieved using adversarial-based architectures and CNN based methods performed better if compared using quantitative tests. Considering this, a group of researchers proposed a hybrid technique which can club together maximum benefits of CNN and GAN both. The training dataset is generated using generator component. For dehazing, CNN based approach is adopted, while colour correction and contrast enhancement is achieved using GAN based approach [35].

Table 1: Brief Overview of Methods Along with Specific Details of Used Dataset and End Results of Evaluation Metrics.

Reference	Method	Dataset	Evaluation Metrics
[18]	Images with CFA equipped camera followed by Retinex-based enhancement technique and improvement using adaptive linear histogram conversion.	UIEB	Entropy-7.73, NIQE-3.57, UCIQE-0.48, UIQE-4.39
[19]	Image processing respectively using CLAHE processing, Retinex-based enhancement technique, bilateral filtering	RUIE	Quantitative values in terms of UIQM, Indicator r and e
[20]	Image processing respectively using global white balance, Retinex transmission map and adaptive colour correction strategy	UIEB	PSNR-19.31, SSIM-0.79, UCIQE-0.63, UIQM-2.83
[21]	Image processing respectively using white-balancing, multi-scale fusing scheme	UIEB	UCIQE-0.63, UIQM-5.47
[22]	Image processing respectively using white balance and contrast enhancement, haze-line technique	SQUID, ChinaMM	UICONM-1.164, UICM -3.403, UISM -7.106, UIQM -6.163, UCIQE -33.956
[23]	Improved underwater white balance and variational contrast and saturation	UIEB	UCIQE-0.63, UIQM-1.53, MEON-22.91, PCQI-1.23
[24]	Multi-scale retinex, CLAHE, sharpening algorithm	UIEB	Entropy-7.756, UIQM-2.085, UCIQE-0.459
[26]	CNN for color correction (CC-Net) and contrast enhancement (CE-Net)	UIEB	PSNR-19.88, SSIM-0.86, UIQM-2.534
[27]	UIRDs dataset synthetically constructed, multi-loss function for multi-scale spatial and channel attention fusion (MS-SCANet)	UIEB, EUVP	PSNR-26.43, SSIM-0.931, SSEQ-21.013, NIQE-4.932, OG-IQA-0.861, UIQM-5.237
[28]	Histogram Equalization, White Balance, Gamma Correction and feature fusion strategy and loss function	UIEB	PSNR-22.9286, SSIM-0.9290, UCIQE-0.6192, UIQM-2.6908
[29]	Dynamic Heterogeneous Feature Fusion Neural Network	OCA	PSNR-20.66, SSIM-0.859, NIQE-4.08, BRISQUE-32.60
[30]	A Two-Stage structure decomposition based CNN	U45	UIQM-5.11, UCIQE-0.61

Reference	Method	Dataset	Evaluation Metrics
[31]	Synthetic generation of database by CycleGAN, residual learning based VDSR method for image enhancement	Synthetic database	PSNR-41.79, SSIM-0.84
[32]	High resolution enhancement using a multiterm loss function (structural similarity loss, adversarial loss, and content loss)	EUVP	PSNR-21.98, SSIM-0.785
[33]	GAN based simplified network structure to resolve spatial inconsistency	UIEB	SSIM-0.8450, PSNR-19.16, PCQI-0.8226, UISM-6.864, UICM-4.370, UIConM-0.852, UIQM-5.146, UCIQE-0.6213, CCF-21.08
[34]	A Spiral-GAN model for better contrast and vivid colours of distorted images	EUVP	UISM-6.853, UICM-3.665, UIConM-0.7728, UIQM-4.8899
[35]	CNN and GAN based hybrid model, CNN for dehazing and GAN for colour correction and contrast enhancement	EUVP	PSNR-20.67, SSIM-0.9558

V. CONCLUSION

This paper provides a review of the very latest developments in the underwater enhancing approaches, methods to implement them and performance analysis. Recent advancement in this sector more efficiently considers potential quality degradation events which occur during underwater imaging. Hence, the image enhancement strategies are taking in to account light attenuation phenomenon which takes place in underwater environment. To deal with quality issues of underwater images, specific targeted approach to perform noise removal, deblurring, colour correction, contrast enhancement and dehazing are designed specifically. In most of the cases conventional approaches are capable to deal with certain types of underwater images or an image with certain characteristics. This is because, most of the conventional methods are developed using different modules to achieve each targeted enhancement and clubbing them together to form a complete method for underwater image enhancement. However, these methods are observed to provide limited resilience to the complex and changing underwater environment. On the other hand, since AI based approaches involved training using many samples from many complex and changed underwater environment, these models show relatively better image enhancing performance for varied underwater images. However, literature review suggested that still there is limited availability of the datasets which are needed to train AI networks for better performance. Most of the conventional approaches are capable of dealing with a specific type of underwater image environment, in this case adaptability and robustness may yield better performance. This signify that, there is lot of scope for improvements in image enhancing approaches.

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