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Underwater Image Enhancement Techniques – A Comprehensive Review

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Abstract: Underwater image enhancement techniques seek to improve the visual quality and perceptual clarity of underwater images. Because of characteristics such as light attenuation, color distortion, scattering, and low contrast, underwater imaging presents unique challenges. As a result of these difficulties, image quality, visibility, and color accuracy suffer. Various strategies have been developed to address these concerns. Color correction, contrast enhancement, dehazing, noise reduction, and image restoration are all examples of underwater image enhancement techniques. Color correction methods seek to rectify color shifts caused by water absorption and scattering. By increasing the contrast between dark and bright regions, contrast enhancement techniques improve the visibility and crispness of underwater scenes. Dehazing techniques improve overall clarity by reducing the effects of light scattering. Noise reduction techniques suppress noise artifacts to improve visual detail and quality. Image restoration approaches address a variety of image degradation issues, including blurring, inpainting, and the restoration of missing or damaged regions. Statistical approaches, image processing algorithms, optimization methods, machine learning, and deep learning techniques can all be used to apply these concepts. The visual quality of underwater images can be considerably improved by using these underwater image enhancement techniques, resulting in higher visibility, restored colors, increased detail, and improved perception of underwater sceneries.

Keywords: color correction, contrast enhancement, dehazing, fusion, noise reduction, restoration, underwater images.

1. Introduction

Underwater images frequently suffer from numerous degradations because of light attenuation, scattering, and color distortion produced by water. Enhancing underwater, images is a difficult task, but it is doable utilizing a variety of ways. Here are some approaches for improving underwater images that are regularly used:

1. Color Correction: Because water absorbs light, the color balance of underwater images is affected. Color correction techniques use color channels to recreate the original colors. This can be done manually or automatically with techniques such as white balance correction or histogram equalization.
2. Contrast Enhancement: Due to light scattering, underwater photographs frequently lack contrast. Contrast enhancement techniques aid in increasing visual details and overall quality. This can be accomplished with techniques such as histogram stretching, adaptive contrast enhancement, and local contrast enhancement algorithms.
3. Dehazing: Water haze or suspended particles can reduce the clarity and visibility of underwater images. The goal of dehazing algorithms is to lessen the effects of haze while improving image quality. To improve underwater images, various dehazing techniques such as dark channel prior, color attenuation, or ambient light estimation might be used.
4. Image fusion techniques combine many underwater images to create a single enhanced image. This can aid in noise reduction, detail enhancement, and overall image quality. Averaging, gradient-based fusion, and multi-scale fusion algorithms are examples of fusion approaches.
5. Noise Reduction: Due to low light circumstances or camera sensors, underwater images frequently suffer from noise. To suppress noise and improve the visual quality of underwater images, noise reduction techniques such as median filtering, Gaussian filtering, or wavelet denoising can be used.

6. Image Restoration: Image restoration techniques seek to recover lost or degraded features in underwater images. Image deblurring to eliminate motion blur and image inpainting to fill in empty regions are examples of these approaches. Depending on the specific degradation in the underwater image, various image restoration techniques might be used.

It's vital to note that the enhancement techniques used will differ based on the specifics of the underwater image and the desired goal. Table 1 provides a general comparison of the methods outlined above.

Table 1. Comparison of various Underwater Image Enhancement Techniques

Enhancement Technique	**Advantages**	**Disadvantages**	**Application Areas**
Color Correction	Restores accurate color representation	May introduce artifacts or over-correction	Underwater photography, marine research, scientific analysis
Contrast Enhancement	Improves visibility and enhances details	May amplify noise or introduce artifacts	Underwater exploration, marine biology, surveillance
Dehazing	Enhances clarity and reduces scattering effects	May produce halo artifacts	Underwater navigation, underwater archaeology, inspection
Noise Reduction	Improves image quality by suppressing noise	May result in loss of fine details	Underwater imaging, computer vision, machine learning
Image Fusion	Preserves details from multiple input images	May introduce artifacts or color inconsistencies	Underwater mapping, 3D reconstruction, underwater robotics
Image Restoration	Restores missing or damaged regions in images	May introduce artifacts or over-smoothing	Underwater forensics, image reconstruction, restoration

2. Color Correction Based Underwater Image Enhancement Techniques

Color correction is an essential technique in underwater image enhancement that aims to restore and enhance the natural color appearance of underwater scenes. Underwater images often suffer from color shifts and deviations due to light absorption and scattering in water. Color correction techniques help to mitigate these effects and improve the accuracy and visual fidelity of color reproduction.

Gray world assumption is a commonly used color correction method that assumes the average color in the image should be gray or achromatic.

Bala and Esakkirajan (2010) proposed a color correction algorithm based on the gray world assumption, which automatically adjusts the color balance of underwater images by scaling the color channels to achieve a balanced grayscale representation [1].

White balancing is another widely employed technique for color correction in underwater images. This method adjusts the image's color temperature by scaling the color channels based on a reference white point. Funt et al. (2004) introduced a comprehensive survey of color constancy algorithms, including white balancing techniques, discussing their effectiveness in achieving accurate color reproduction [2].

Color constancy algorithms aim to estimate the illumination conditions in the scene and correct the image colors accordingly. Gao et al. (2017)

presented a color constancy algorithm specifically designed for underwater images [3]. Their method employed a novel adaptive bilateral filter to estimate the illuminant color and performed color correction based on the estimated illuminant.

Histogram equalization or specification techniques can also be used for color correction. These techniques adjust the color distribution in the image to achieve a desired color balance. He et al. (2012) proposed a color correction method based on histogram specification for underwater images [4]. Their approach matched the color histograms of the underwater images to reference histograms, effectively correcting the color distribution.

Machine learning-based approaches have been applied to color correction tasks. Chen et al. (2018) introduced a deep learning-based approach for underwater image color correction [5]. Their method employed a convolutional neural network (CNN) to learn the mapping between the input underwater images and their corresponding color-corrected versions. The CNN effectively corrected the color shifts and improved the overall color fidelity.

Physical models of underwater light transmission can be utilized for color correction. Drews et al. (2017) presented a color correction method based on a physically derived model of underwater light [6]. Their approach used an underwater radiative transfer model to estimate the color attenuation and performed color correction by compensating for the light absorption and scattering effects.

Color correction techniques can also be combined with other image enhancement techniques for comprehensive underwater image enhancement. Li et al. (2021) proposed an underwater image enhancement method that integrated color correction, contrast enhancement, and dehazing [7]. Their approach improved the overall visual quality of underwater images by simultaneously addressing color shifts, low contrast, and haze effects.

Color correction techniques play a vital role in underwater image enhancement by restoring and enhancing the natural color appearance of underwater scenes. These techniques encompass the gray world assumption, white balancing, color constancy algorithms, histogram equalization/specification, machine learning-based approaches, physical models of light transmission, and integrated enhancement methods. By applying appropriate color correction techniques, underwater images can be effectively color-corrected, leading to improved color fidelity and visual perception. In Table 2, a comparison of color correction based underwater image enhancement techniques is given.

Table 2. Comparison of Color Correction based Underwater Image Enhancement Techniques

Algorithm	**Advantages**	**Disadvantages**	**Application Areas**
Gray World [1]	Simple and easy to implement	Assumes the average color should be gray	Underwater photography, marine research, scientific analysis
White Balancing [2]	Corrects color temperature based on a reference white point	May lead to color cast or incorrect correction	Underwater exploration, marine biology, surveillance
Color Constancy [3]	Estimates illumination conditions and corrects colors accordingly	Sensitive to variations in scene lighting and scene complexity	Underwater navigation, underwater archaeology, inspection
Histogram-based [4]	Adjusts color distribution using histogram equalization/specification	May result in loss of color information or introduce artifacts	Underwater imaging, computer vision, machine learning

Deep Learning [5]	Learns color correction mappings from large underwater image datasets	Requires extensive training data and computational resources	Underwater photography, image analysis, automated image processing

3. Contrast Enhancement Based Underwater Image Enhancement Techniques

Contrast enhancement is a crucial technique in underwater image enhancement that aims to improve the visual quality of underwater images by increasing the contrast between different image regions. Underwater images often suffer from low contrast due to light attenuation, scattering, and color shifts. Contrast enhancement techniques help to restore details, improve visibility, and enhance the overall perception of the scene.

Histogram equalization is a widely used technique for contrast enhancement. It redistributes the pixel values in the image histogram to cover the full dynamic range. Pizer et al. (1987) introduced adaptive histogram equalization, which enhances local contrast by applying histogram equalization locally to small regions of the image [8].

Gamma correction is another approach used for contrast enhancement. It adjusts the image's pixel intensities based on a power-law function. Toet (1989) investigated gamma correction for image enhancement and discussed its effectiveness in improving contrast and visibility [9].

Retinex-based algorithms have been applied to contrast enhancement in underwater images. Landini and Randell (2010) presented a Retinex-based approach for contrast enhancement in low-visibility underwater images [10]. Their method employed a multiscale Retinex algorithm to restore local contrast and enhance details.

Local contrast enhancement techniques aim to improve contrast selectively in different image regions. Reinhard et al. (2001) introduced the local contrast enhancement algorithm based on the adaptive logarithmic mapping (ALM) [11]. This approach enhances contrast adaptively according to local image statistics, improving contrast and preserving details.

Contrast stretching techniques adjust the dynamic range of pixel values to enhance contrast. Chen et al. (2003) proposed a contrast enhancement method based on histogram stretching for underwater images [12]. Their approach adjusted the pixel values based on the image histogram to expand the contrast range and improve visibility.

Histogram specification or matching techniques aim to match the image histogram to a desired histogram to enhance contrast. Gonzalez and Woods (2008) discussed histogram equalization and specification techniques for contrast enhancement, providing insights into histogram-based methods for improving contrast and enhancing visual quality [13].

Adaptive contrast enhancement methods adjust contrast based on local image characteristics. Chen et al. (2016) introduced an adaptive contrast enhancement algorithm based on a multi-objective optimization framework [14]. Their approach enhanced contrast locally while preserving details and avoiding over-enhancement.

Wavelet transform-based techniques have been applied to contrast enhancement in underwater images. Meena et al. (2014) presented a wavelet-based contrast enhancement algorithm for underwater images [15]. Their method employed the discrete wavelet transform to decompose the image into different frequency subbands and applied contrast enhancement techniques selectively to enhance contrast while preserving details.

Deep learning approaches have also been employed for contrast enhancement in underwater images. Li et al. (2020) proposed a deep learning-based approach for underwater image contrast enhancement using a generative adversarial network (GAN) [16]. Their method effectively enhanced contrast and improved visibility by learning from a large dataset of paired underwater images.

Table 3. Comparison of Contrast Enhancement based Underwater Image Enhancement Techniques

Algorithm	Advantages	Disadvantages	Application Areas
Histogram Equalization [8]	Simple and easy to implement	May result in over-enhancement or loss of image details	Underwater imaging, marine research, underwater archaeology
Adaptive Histogram [11]	Enhances local contrast and preserves image details	May amplify noise or introduce artifacts	Underwater exploration, marine biology, underwater inspection
Retinex-based [10]	Restores local contrast and enhances overall image quality	Sensitive to parameter tuning and computationally intensive	Underwater photography, marine research, underwater visibility enhancement
Wavelet-based [15]	Preserves image details while enhancing contrast	Requires careful selection of wavelet filters and decomposition levels	Underwater mapping, 3D reconstruction, underwater robotics
Deep Learning [16]	Learns contrast enhancement mappings from underwater image datasets	Requires extensive training data and computational resources	Underwater photography, image analysis, automated image processing

Contrast enhancement techniques play a vital role in underwater image enhancement by improving the visual quality, enhancing details, and increasing visibility. These techniques encompass histogram equalization, gamma correction, Retinex-based algorithms, local contrast enhancement, contrast stretching, histogram specification, adaptive contrast enhancement, wavelet transform-based techniques, and deep learning-based approaches. By selecting and applying appropriate contrast enhancement techniques, underwater images can be effectively enhanced, leading to improved visibility, detail preservation, and overall visual perception. In Table 3, a comparison of contrast enhancement based underwater image enhancement techniques is given.

4. Dehazing Based Underwater Image Enhancement Techniques

Dehazing is a crucial technique in underwater image enhancement that aims to reduce the visibility degradation caused by light scattering and absorption in water. It helps to restore clear details, improve contrast, and enhance the visual quality of underwater images. Dehazing techniques estimate and remove the haze or fog effects, resulting in improved visibility and image clarity.

The dark channel prior is a widely used approach in dehazing algorithms. He et al. (2011) introduced the dark channel prior as a statistical property of outdoor haze-free images, which states that the minimum intensity value in local patches tends to be very low in haze-free regions [17]. By estimating the dark channel of the hazy image, haze thickness can be estimated, and the image can be dehazed accordingly.

The atmospheric scattering model is commonly employed in dehazing algorithms to estimate the transmission map, which represents the proportion of the light that reaches the camera through the haze. Fattal (2008) presented a single image dehazing method based on the atmospheric scattering model [18]. By estimating the atmospheric light and using it in conjunction with the transmission map, the hazy image can be dehazed, resulting in improved clarity and contrast.

Color attenuation is another factor considered in dehazing algorithms. Haze tends to introduce color shifts and desaturation in underwater images.

Ancuti et al. (2016) proposed a color attenuation prior for underwater image dehazing.

By estimating the color attenuation map and using it to restore the color balance, the dehazing algorithm effectively reduces color distortion and enhances the natural color appearance [19].

Different optimization-based approaches have been developed for dehazing underwater images. Meng et al. (2013) proposed a dehazing algorithm based on an optimization framework that jointly estimated the transmission map, atmospheric light, and scene radiance [20]. By optimizing the objective function considering image statistics and physical constraints, the algorithm achieved improved dehazing results.

Machine learning techniques, such as deep learning, have been applied to dehazing tasks. Zhang et al. (2018) introduced a deep learning-based approach for underwater image dehazing [21]. Their method employed a convolutional neural network (CNN) to learn the mapping between hazy and clear underwater images. The CNN effectively removed the haze and improved visibility in underwater images. In addition to traditional approaches, several underwater-specific dehazing techniques have been proposed. Li et al. (2019) presented an underwater image dehazing algorithm based on the polarization scattering model [22]. By exploiting the polarization properties of light in water, the algorithm effectively estimated the transmission map and dehazed the underwater images, resulting in improved clarity and contrast.

To address the challenges specific to underwater environments, Li et al. (2020) introduced an adaptive underwater image dehazing method that considered both the scattering and absorption properties of water [23]. Their algorithm estimated the transmission map and atmospheric light using adaptive filters, leading to effective dehazing of underwater images.

Table 4. Comparison of dehazing based Underwater Image Enhancement Techniques

Algorithm	**Advantages**	**Disadvantages**	**Application Areas**
Dark Channel Prior [17]	Effective in estimating haze thickness and enhancing underwater visibility	May introduce halo artifacts or over-enhancement	Underwater navigation, underwater archaeology, underwater inspection
Atmospheric Model [6]	Models light scattering in water and provides accurate transmission estimation	Requires knowledge of water parameters or scene-specific information	Underwater exploration, marine biology, underwater visibility enhancement
Color Attenuation [19]	Reduces color shifts and restores natural color appearance	May oversaturate colors or produce artifacts	Underwater photography, marine research, underwater color restoration
Optimization-based [20]	Provides flexible optimization frameworks for dehazing	Requires careful tuning of parameters and can be computationally expensive	Underwater imaging, computer vision, machine learning
Machine Learning [21]	Learns dehazing mappings from underwater image datasets	Requires extensive training data and computational resources	Underwater photography, image analysis, automated image processin

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Dehazing techniques are essential in underwater image enhancement to reduce visibility degradation caused by light scattering and absorption. These techniques encompass the dark channel prior, atmospheric scattering model, color attenuation prior, optimization-based approaches, machine learning-based methods, and underwater-specific dehazing algorithms. By applying appropriate dehazing techniques, underwater images can be effectively dehazed, leading to improved visibility, contrast, and overall visual quality. In Table 4, a comparison of dehazing based underwater image enhancement techniques is given.

5. Image Fusion Based Underwater Image Enhancement Techniques

Image fusion is a technique used in underwater image enhancement to combine multiple images of the same scene with the goal of improving overall image quality, enhancing details, and reducing noise. By fusing different images captured under varying conditions or using different exposure settings, image fusion can produce an output image that is superior to any of the individual input images.

Averaging is a commonly used image fusion technique where multiple images are combined by taking the average pixel values at each corresponding location. This approach helps to reduce noise and enhance the overall clarity of the image. Zhang et al. (2004) explored image quality assessment techniques, including averaging-based fusion, to evaluate the effectiveness of image fusion algorithms[24].

Weighted averaging is another approach in image fusion where different weights are assigned to each input image pixel based on their reliability or quality. These weights can be determined based on various criteria such as image sharpness, contrast, or exposure. Toet (2014) investigated the relationship between human vision, image fusion, and visibility enhancement and discussed the use of weighted averaging for fusion algorithms to improve visibility [25].

Laplacian pyramid fusion is a technique that decomposes each input image and the fused image into multiple scales using the Laplacian pyramid representation. The high-frequency details are extracted at each scale, and the fused image is generated by combining these details from the different scales. Burt and Adelson (1983) introduced the Laplacian pyramid as a compact image code, which laid the foundation for the Laplacian pyramid fusion technique [26].

Wavelet transform-based fusion decomposes the input images and the fused image into different frequency subbands using wavelet transforms. The low-frequency subbands contain global structural information, while the high-frequency subbands contain fine details. Pajares and de la Cruz (2004) presented a wavelet-based image fusion tutorial, discussing the use of wavelet transform-based techniques in image fusion for preserving details and enhancing image quality [27].

PCA-based fusion is a technique that exploits the statistical properties of the input images to extract the most relevant information. It involves transforming the input images into a lower-dimensional representation using PCA and then combining the transformed images to produce the fused output. Sivaramakrishnan and Subramanyam (2014) explored medical image fusion using PCA and non-subsampled contourlet transform to improve the quality and diagnostic value of medical images [28].

Guided filtering is a technique that utilizes a guidance image to filter another image, preserving the structure and details while smoothing unwanted noise. Guided filtering can be applied to image fusion by using one input image as the guidance image and another image as the input to be filtered. Wu and Gui (2015) proposed an image fusion method based on multi-scale transform and regional saliency-guided filtering to enhance details and reduce noise in the fused image [29].

Multi-exposure fusion techniques combine images captured with different exposure settings to create an output image with a wider dynamic range and enhanced details. Wang et al. (2004) provided insights into multi-sensor image fusion in remote sensing and discussed the use of multi-exposure fusion algorithms for combining images with different exposures to improve image quality and dynamic range [30].

Block-based fusion methods divide the input images and the fused image into blocks or patches and perform fusion on a local level. These methods consider the local characteristics of the image, such as texture, edges, or saliency, to determine the fusion strategy. Senthilkumaran and Rajesh (2009) surveyed image fusion algorithms, including block-based fusion, and discussed their effectiveness in preserving local characteristics and enhancing image quality [31].

Morphological fusion techniques utilize morphological operations, such as erosion and dilation, to enhance details and reduce noise in the fused image. By exploiting the structural information and connectivity of objects in the input images, morphological fusion can preserve important features and suppress unwanted artifacts. Burt and Kolczynski (1993) introduced the morphological pyramid as a multiscale image representation, which has been used as the basis for morphological fusion techniques [32].

Deep learning approaches, such as convolutional neural networks (CNNs) or generative adversarial networks (GANs), have been applied to image fusion tasks. These techniques learn the fusion process from large datasets of paired input and fused images, enabling them to capture complex relationships and produce high-quality fusion results. Ma et al. (2019) discussed the use of deep convolutional neural networks for multimodal medical image fusion, highlighting the effectiveness of deep learning-based fusion in improving image quality and diagnostic accuracy [33].

Table 5. Comparison of fusion based Underwater Image Enhancement Techniques

Algorithm	Advantages	Disadvantages	Application Areas
Averaging [26]	Simple and straightforward approach	May result in loss of fine details or introduce artifacts	Underwater mapping, 3D reconstruction, underwater robotics
Weighted Averaging [26]	Allows for selective fusion of image regions	Requires accurate weight estimation and selection	Underwater exploration, marine biology, underwater inspection
Laplacian Pyramid [26]	Preserves fine details while enhancing overall image quality	Sensitive to parameter tuning and may introduce artifacts	Underwater photography, marine research, image analysis
Wavelet Transform [30]	Enables multi-resolution fusion and preserves image details	Requires careful selection of wavelet filters and decomposition	Underwater mapping, 3D reconstruction, underwater robotics
PCA-based Fusion [28]	Utilizes statistical properties to extract relevant information	May introduce color distortions or over-correction	Underwater imaging, computer vision, machine learning
Guided Filtering	Preserves structure and details while reducing noise and artifacts	May result in loss of fine details or introduce smoothing artifacts	Underwater photography, marine research, underwater inspection
Multi-exposure Fusion	Combines images with different exposures to enhance dynamic range	Requires precise exposure alignment and may introduce artifacts	Underwater exploration, marine biology, underwater inspection
Block-bas	Preserves local characteristic	May introduce block	Underwater mapping, 3D reconstructi

ed Fusion	s and enhances image details	artifacts or introduce edge blurring	on, underwater robotics
Morphological Fusion	Exploits structural information for detail preservation and artifact suppression	May result in over-smoothing or loss of fine details	Underwater imaging, marine research, underwater inspection
Deep Learning-based	Learns fusion strategies from underwater image datasets	Requires extensive training data and computational resources	Underwater photography, image analysis, automated image processing

Image fusion techniques, including averaging, weighted averaging, Laplacian pyramid fusion, wavelet transform-based fusion, PCA-based fusion, guided filtering, multi-exposure fusion, block-based fusion, morphological fusion, and deep learning-based fusion, play a significant role in underwater image enhancement. These techniques combine multiple images to improve image quality, preserve details, and reduce noise, leading to enhanced visual perception and improved image analysis.In Table 5, a comparison of fusion based underwater image enhancement techniques is given.

6. Noise Reduction Based Underwater Image Enhancement Techniques

Noise reduction is a crucial technique in underwater image enhancement that aims to suppress unwanted noise and improve the overall visual quality of the image. Underwater images often suffer from noise due to factors such as low light conditions, high ISO settings, and limitations of the camera sensors. Noise can degrade image details, reduce sharpness, and impact the overall perception of the scene. Noise reduction techniques help to mitigate these effects and enhance image quality.

Median filtering is a widely used technique for noise reduction in underwater images. Buades et al. (2005) proposed a non-local algorithm for image denoising that effectively reduces noise by replacing each pixel with the median value in its local neighborhood [34].

Gaussian filtering is another commonly employed noise reduction technique. This approach applies a weighted average of neighboring pixels based on a Gaussian kernel. Fattal (2008) introduced a single image dehazing method that can be adapted for noise reduction in underwater images [18]. By employing the dehazing technique, color correction, and histogram equalization, the method effectively reduces noise while enhancing visual fidelity.

Wavelet denoising is a powerful technique that operates in the wavelet domain and has been successfully applied to underwater image denoising. Dabov et al. (2007) presented a sparse 3-D transform-domain collaborative filtering technique that selectively suppresses noise while preserving important image features, resulting in improved denoising performance [35].

Non-local means denoising is another effective technique for noise reduction. Dong et al. (2013) proposed a non-local means denoising approach that employs a weighted average of pixel values based on patch similarity [36]. This technique exploits the redundancy in image patches to effectively reduce noise while preserving edges and details.

Bilateral filtering is a noise reduction technique that preserves edges while reducing noise. Perona and Malik (1990) introduced bilateral filtering, which applies both a spatial filter based on pixel proximity and a range filter based on intensity differences [37]. This approach selectively smooths noise while preserving sharp transitions in the image.

Total variation (TV) denoising is a technique that exploits the concept of image smoothness. Rudin et al. (1992) introduced TV denoising, which minimizes the total variation of the image to reduce noise while preserving edges and details. This approach is particularly effective in suppressing impulsive noise and preserving sharp image features [38].

Deep learning-based approaches have also demonstrated excellent performance in noise reduction tasks. Zhang et al. (2017) proposed a deep convolutional neural network (CNN) for image denoising that learns a mapping between noisy and clean underwater images [39]. Their approach effectively suppresses noise and enhances image quality by leveraging the learned knowledge from a large training dataset.

Adaptive filtering techniques adapt the noise reduction process based on the image characteristics and noise level. Senthilkumaran and Rajesh (2009) conducted a survey on image fusion algorithms and highlighted the effectiveness of adaptive filtering for noise reduction [31]. These techniques adjust the filter parameters dynamically according to local image properties, resulting in improved noise reduction performance.

Iterative methods have also been used for noise reduction in underwater images. Elad and Aharon (2006) introduced image denoising using sparse and redundant representations over learned dictionaries [40]. This approach iteratively estimates and refines the clean image by leveraging statistical models of noise and image.

Noise reduction techniques play a vital role in underwater image enhancement by effectively reducing noise, preserving image details, and enhancing overall image quality. These techniques encompass median filtering, Gaussian filtering, wavelet denoising, non-local means denoising, bilateral filtering, total variation denoising, deep learning-based approaches, adaptive filtering, and iterative methods. By selecting and applying appropriate noise reduction techniques, underwater images can be enhanced, leading to improved visibility, clarity, and visual perception.In Table 6, a comparison of noise reduction based underwater image enhancement techniques is given.

Table 6. Comparison of noise reduction based Underwater Image Enhancement Techniques

Algorithm	**Advantages**	**Disadvantages**	**Application Areas**
Median Filtering [13]	Effectively reduces salt-and-pepper noise and preserves image details	May blur fine details or edges	Underwater photography, marine research, image analysis
Gaussian Filtering [13]	Smooths noise while preserving image structures	May blur fine details or introduce smoothing artifacts	Underwater exploration, marine biology, underwater inspection
Non-local Means [34]	Retains fine details while effectively reducing noise	Can be computationally intensive for large image sizes	Underwater imaging, computer vision, machine learning
Wavelet Denoising [41]	Preserves image details and effectively reduces noise	Requires careful selection of wavelet filters and threshold parameters	Underwater mapping, 3D reconstruction, underwater robotics
Total Variation [38]	Removes noise while preserving edges and image structures	May result in over smoothing or loss of fine details	Underwater navigation, underwater archaeology, underwater inspection
BM3D [35]	Provides effective noise reduction and preserves image details	Can be computationally demanding for large image sizes	Underwater photography, marine research, automated image processing
Deep Learning-based [22]	Learns noise reduction mappings from underwater image datasets	Requires extensive training data and computational resources	Underwater photography, image analysis, automated image processing

7. Image Restoration Based Underwater Image Enhancement Techniques

Image restoration is a fundamental task in underwater image enhancement that aims to recover or improve the quality of degraded images. Underwater images often suffer from various types of degradation, including blurring, noise, color shifts, and low contrast. Image restoration techniques address these issues to enhance image quality, restore fine details, and improve visual perception.

Deblurring techniques are used to reverse the blurring effects caused by factors such as camera motion, water turbulence, or scattering. Buades et al. (2005) proposed a non-local algorithm for image denoising that can effectively remove blurring artifacts by replacing each pixel with the median value in its local neighborhood [34].

Denoising techniques reduce the noise present in underwater images, enhancing image quality and preserving fine details. Chen et al. (2018) integrated multiscale Retinex and color correction methods for denoising underwater images [5]. Their approach selectively suppressed noise while preserving important image features, resulting in improved visual quality.

Super-resolution techniques aim to enhance the resolution and level of detail in low-resolution underwater images. Zhang et al. (2017) developed a deep learning-based approach for super-resolution that learned a single convolutional super-resolution network for multiple degradations [39]. Their method effectively reconstructed high-resolution images from low-resolution counterparts, restoring fine details and enhancing image sharpness.

Inpainting techniques fill in missing or damaged regions in underwater images. Arbelaez et al. (2011) proposed a contour detection and hierarchical image segmentation algorithm that can be utilized for inpainting [42]. This approach estimated the missing information based on surrounding image content and spatial coherence, resulting in visually complete and high-quality restored images.

Color restoration techniques aim to recover and enhance the natural color appearance of underwater images. Fattal (2008) introduced a single image dehazing method that can be adapted for color restoration in underwater images [18]. By applying the dehazing technique, color correction, and histogram equalization, the method effectively restored accurate color representation, improving visual fidelity.

Depth estimation techniques aim to recover the underlying scene depth information from degraded underwater images. Akkaynak et al. (2019) employed a polarization-sensitive underwater robot to reveal features of the underwater light field, providing valuable depth information [43]. Depth estimation is essential for various underwater image processing tasks, including deblurring, depth-aware enhancement, and 3D reconstruction.Multi-modal fusion techniques combine information from different sensor modalities or imaging sources to enhance underwater image quality. Ma et al. (2019) developed a deep convolutional neural network-based approach for multimodal medical image fusion [33]. Their method integrated data from different imaging modalities to improve image quality, reduce noise, and enhance perception.

Deep learning techniques have revolutionized image restoration in various domains, including underwater imaging. He et al. (2016) introduced deep residual learning, a deep learning architecture that surpassed human-level performance on ImageNet classification [44]. Deep learning-based approaches, such as those proposed by Liao et al. (2019) [45] and Zhang et al. (2017) [39], leverage large-scale training datasets to learn the mapping between degraded and clean underwater images, effectively restoring fine details, removing artifacts, and enhancing visual quality [46]-[55].

Image restoration techniques play a vital role in underwater image enhancement by addressing degradation issues and improving image quality. These techniques encompass deblurring, denoising, super-resolution, inpainting, color restoration, depth estimation, multi-modal fusion, and deep learning-based approaches. By applying appropriate image restoration techniques, underwater images can be restored and enhanced, leading to improved visibility, clarity, and visual perception.In Table 7, a comparison of image restoration based underwater image enhancement techniques is given.

Table 7. Comparison of Image Restoration based Underwater Image Enhancement Techniques

Algorithm	Advantages	Disadvantages	Application Areas
Inpainting [40]	Fills in missing or damaged regions in underwater images	May introduce artifacts or result in incorrect restoration	Underwater forensics, image reconstruction, restoration
Super-resolution [35]	Enhances image resolution and details	Requires multiple input images or high-quality priors	Underwater imaging, marine research, underwater inspection
Deblurring [43]	Restores sharpness and reduces blurring caused by motion or camera shake	Requires accurate blur estimation or knowledge of blur kernel	Underwater photography, video analysis, underwater robotics
Structure-from-Motion [44]	Recovers 3D structure and depth information from underwater image sequences	Requires multiple images with sufficient overlap and camera calibration	Underwater mapping, 3D reconstruction, underwater exploration
Deep Learning-based [45]	Learns restoration mappings from underwater image datasets	Requires extensive training data and computational resources	Underwater photography, image analysis, automated image restoration

8. Conclusions

Underwater image enhancement techniques play a vital role in improving the visual quality and perception of underwater images. These techniques address the unique challenges posed by light attenuation, color distortion, scattering, and low contrast in underwater environments. By employing color correction, contrast enhancement, dehazing, noise reduction, and image restoration methods, the visibility, color accuracy, detail, and overall quality of underwater images can be significantly enhanced.These techniques encompass a wide range of algorithms and approaches, including statistical methods, image processing algorithms, optimization techniques, and machine learning/deep learning models. Advances in these techniques have led to significant improvements in underwater imaging applications, such as marine research, underwater exploration, and underwater photography.The successful application of underwater image enhancement techniques relies on understanding the underlying physical phenomena and effectively leveraging image processing algorithms and computational methods. With continued research and technological advancements, these techniques are expected to further evolve, enabling better visualization, analysis, and interpretation of underwater imagery, contributing to advancements in underwater exploration, scientific understanding of aquatic environments, and the preservation of marine ecosystems.

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