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Numerical Simulation and Design of Hybrid Underwater Image Restoration and Enhancement with Deep Learning

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Abstract: Academicians from all over the world have been researching underwater images and the ability to capture crystal clear images for the past few years. Additionally, restoring the acquired images requires a laborious process in its entirety. The obtained underwater images have some flaws because of the scientific phenomena of absorption and scattering. These images suffer from colour distortion, blurriness, and low contrast effects, which are the main issues. For researchers in the field of image processing, overcoming these deficiencies is a herculean task. When light passes through water, its path is constrained. Pictures become submerged and turn greenish blue as they fall short on certain frequency parts in this case because the larger frequencies are influenced more than the more restricted ones. For instance, a picture taken at a depth of about 4-5 m underwater would require red frequency because the more extended frequency ranges of the apparent range are weaker first. Other frequency segments will start to lose significance with further increase. As a result, the pictures suffer from the negative effects of limited perceivability range, uneven lighting, and the presence of splendid antiquities. The proposed research work uses a deep learning model to improve the underwater images to get around this.

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Keywords- *Mathematical model, Underwater Images, Deep Learning, Decision Tree, Convolutional Neural Network.*

1. Introduction

There is a lot of research being done in the field of underwater image processing, which is a promising area of image processing. For visual site mapping [1], fish localization and identification [2], detecting corrosion of metal structures in underwater settings [3], and other uses, underwater image processing is utilized. Underwater photographs are hampered by noise brought on by bodies of water and suspended particles, as well as by the attenuation of longer wavelengths of light as depth increases. Due to our inability to discriminate between distinguishing characteristics and easily get information from raw collected photographs, this has a negative impact on the quality of underwater pictures.

In order to deal with artifacts that have been introduced into the acquired image, we first explore the field of image restoration, which models the reasons why picture quality has declined and allows us to make corrections for the restored image using the model. Image enhancement is used to enhance the output image's quality and increase contrast in the image. To post-process the image in a single step and shorten the time needed for additional processing, a method that combines image enhancement and restoration is utilized.

Research on the utilization of marine resources has increased as a result of the major issues brought on by population growth, the limitation of terrestrial resources, and environmental degradation. The capture of subsea images is frequently hampered by poor visibility events brought on by challenging underwater imaging conditions, which creates a host of challenges for the discovery of marine resources. To overcome the difficulties of underwater photography, it is crucial to provide a framework that enables effective and reliable underwater image processing approaches [1].

Numerous strategies have been put up to address the issue of underwater picture deterioration in order to enhance image visibility and clarity. The present efforts are often split into two categories: underwater image enhancement and restoration [2]–[7] depending on whether they rely on the underwater image creation paradigm. These current solutions could work well, as shown by objective assessments, but they don't take into account all of the deterioration and loss of important information, which limits their applicability. Regarding restoration algorithms, they depend heavily on the accurate prior assumptions and call for extra prior information of the imaging circumstances. However,

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much as in the atmosphere, it is challenging to generalize the majority of scenarios in the complex and unstable undersea environment. As a result, it can have limited resilience and yield subpar outcomes. The production of red artifacts by enhancement algorithms is a typical issue.

The two fundamental difficulties with submerged photographs are light ingestion and the natural structure of the sea. Additionally, the impacts of dimming submerged pictures are examined in this study endeavor. Depending on the design of the water, the sunshine reflects light in a variety of ways. A key characteristic of vertical polarization is that it reduces sparkle, which helps to capture deep tones that would otherwise be impossible to capture. The reflected light is partly trapped on a level plane and enters the water largely vertically. The thickness of the seawater, which has been seen on several occasions to be denser than air, is another significant issue related to the images acquired at great depths. As a result, some light is partially reflected as it passes from the air to the water, and at the same time, some light begins to enter the water. When we start diving further into the sea, the amount of sunshine that reaches the water will decrease.

Water particles also absorb a certain quantity of light. Due to increases in depth, the submerged images are consequently becoming darker and hazier. When light travels far into the water, it not only loses brightness but also affects colors owing to the tone frequency. For instance, the initial red tone disappears at a depth of 3 m. As we move further, the orange tone also disappears. At 5 m of depth, the orange tone will likewise disappear. Thirdly, the majority of the yellow color disappears at a depth of 10 meters, and finally, the green and purple tones likewise disappear at greater depths. [2], [3], [4], [9], and [10].

2. Literature Review

In this section, we've looked at both image restoration and image enhancement algorithms that can be used in the underwater environment. It can be done in two ways: through hardware and through software. Underwater Image Processing: State of the Art of Restoration and Image Enhancement Methods [8], A Survey on Underwater Image Enhancement Techniques [9], and Underwater Optical Image Processing: A Comprehensive Review [10] all talk about hardware and software approaches.

The hardware approach solves some of the problems caused by water in the images that are taken, but it costs more to run, requires more skilled workers, and takes longer to develop and process the images. Recovery of Underwater Visibility and Structure by Polarization Analysis [11] by Y. Schechner and N. Karpel uses the above method to fix the degradation in underwater images by taking pictures with a polarizer at different angles. The method is based on the idea that the main effects of wear and tear are related to the way light is partially polarized. The software approach, on the other hand, doesn't need this kind of specialized hardware. Instead, it uses different image processing methods to try to bring back the image.

In [8], the papers reviewed by the author explain how they work and what their results are. However, there is neither a quantitative nor a qualitative evaluation of the papers based on parameters that give a measure of how well the output image is corrected. In [9] and [10], the authors put the selected underwater image processing papers into groups based on how they were done and then review how well they improved the image quality. This paper looks at a wider range of papers and different ways to fix the distortions in images from submarines. But the lack of data for quantitative analysis makes it hard to compare papers, since the comparison is based on how the papers are used by users.

In [7], the authors explain how to improve the contrast of an underwater image by first stretching the contrast of the RGB parts of the image and then stretching the saturation and intensity of the HSI parts of the image to fix the distorted image. Contrast stretching stretches the color channel so that the full range of values can be used to represent the color channel. This makes the contrast of the image in between better. Then, HSI color domain conversion is done to make the contrast of the final image even stronger. At the last step, the intermediate HSI image is turned into an RGB image and shown. But this algorithm doesn't guarantee good results for most hazy underwater environments because the final image looks fake and it only makes the contrast better without restoring the image. Thismethod also doesn't fix the fact that underwater photos often have lighting that isn't the same everywhere.

In Single Image Dehazing by Multi-Scale Fusion [12], the authors suggest a way to dehaze a single image by using two hazy images as inputs and then adjusting the white balance and boosting the contrast. The luminance, chromaticity, and saliency of both images are calculated, which are then used to filter the important parts of the images. This is done so that areas with good visibility are kept and the information from the two images is used well. The method based on fusion works at the pixel level. In their multiscale approach to design, the authors use a Laplacian pyramid representation to get rid of the problems that arise when weight maps are used. The researcher found that the results from this method were as good as, or even better than, those from more advanced and complicated techniques. With the right weight maps and inputs, this fusion-based multiscale strategy can dehaze images using only a single degraded image and give accurate results. This method depends on two fuzzy inputs, which is harder to do and costs more to compute. It is also hard to get two images that are exactly the same.

In another paper, Color Balance and Fusion for Enhancing Underwater Images [13], the authors took a single underwater image and used gamma correction and white balancing on different versions of the same input image. Then, multiscale fusion is used to combine these two images into a single output image. This method only needs one input, and it can bring back colors and edges that have faded, but it can't fully get rid of haze.

Dark Channel Prior is a new way to get rid of haze that is based on the statistical properties of images without haze. The assumption is that some patches of pixels in images without haze have very low brightness in at least one color because of airlight. So, these pixels can be used to tell which pixels are adding to the haze. This creates a rough transmission map, which, when smoothed, can be used to make a model of the haze in the image. During the process of getting rid of the haze, you can also make a depth map of the image. For the Dark Channel Prior algorithm to work, you only need a single image. But Dark Channel Prior doesn't take into account the fact that water soaks up light and makes longer wavelengths of light less bright.

In [4], the authors apply the Dark Channel Prior algorithm to a sub-aqueous environment with the right changes to reflect the change in the environment. The intensity of the red channel in the original image is changed to show that red light scatters more in water than other colors. The Dark Channel Prior equation is then used to change the values of the parameters in the color channels that were sent in. The authors also show that the algorithm clears up images taken with artificial lighting. But the algorithm makes the red channel in the output image too full, so it doesn't make a true haze-free image of an underwater scene. When there is artificial light, there is too much red near the source of light, which makes the image very blurry.

The authors of Initial Results in Underwater Single Image Dehazing [14] use the Dark Channel Algorithm as a foundation to restore underwater images. But their approach is different from that of A. Galdran, D. Pardo, A. Picon, and A. Alvarez-Gila. They use Markov random field (MRF) to model the scene radiance while taking white Gaussian noise into account. They then use the Min Cuts/Max Flow minimization algorithm to find the maximum a posteriori (MAP) of the dehazed image. In this paper, they try to clear up the confusion between scene depth and direct transmission by focusing only on the effects of

Light that is scattered causes a change in shape. To figure out how deep an image is, they figure out the difference between the most intense red color channel, the most intense green color channel, and the most intense blue color channel in a small patch.

This is done over and over for the whole image, and thresholding is used to get rid of the noise. Modeling the scene as a Markov Random Field with white Gaussian noise and then figuring out the maximum a posteriori estimate of the actual scene radiance gives the scene radiance. Airlight is calculated based on the rules. But this method uses a lot of assumptions that haven't been proven for the haze model. Also, they haven't thought about how absorption changes images when they are taken underwater.

The Single Underwater Restoration by Blue-Green Channel Dehazing and Red Channel Correction [15] is another version of the Dark Channel Prior algorithm. In this case, the blue and green channels are both dehazed with Dark Channel Prior, and the red channel of the image is improved with Gray World assumptions. This method doesn't work in all environments because it assumes that the attenuation of the blue and green channels is the same in water, no matter how deep it is or what else is going on.

The authors of Underwater Image Enhancement using Wavelength Compensation and Dehazing [16] use Dark Channel Prior to figure out how deep the environment is. Segmentation is used to separate the foreground and background images so that the true depth can be calculated. Then, the difference between the intensity of the foreground and the intensity of the background shows the amount of artificial light in the scene. The amount of artificial light has been taken into account, and the image is now clear of haze and has much better contrast. But there are a lot of things that are taken for granted.

3. Proposed Methodology

The McGlamery [8] and Jaffe [9] did thorough studies of the underwater image formation model. They found that the total irradiance that hits the image plane in an underwater medium is made up of three parts: the direct component, the forward scattering, and the back scattering. The direct component is the light that comes straight from the object and doesn't get spread out in the water as:

$$ED(x) = J(x)e^{-\tau d(x)} \qquad (1)$$

where J (x) is the scene's brightness. d(x) is the distance between the camera and the target scene at point x. stands for the attenuation coefficient, which depends on the wavelength and is thought of as a constant in some situations.

Forward scattering and backward scattering are two other major types of degradation. Forward scattering happens when tiny particles in the medium change the way light travels. The bad effect is caused by random deviation or a fuzzy edge. Most of the time, the effect of this component can be guessed by combining the effects of direct components. The second one, on the other hand, is caused by light reflected back to the camera by floating particles in water.

$$E_{BS}(x) = B(x)(1 - e^{-\tau d(x)}) \qquad (2)$$

Where B is the light that bounces back. Most of the time, back-scattering is the main cause of color distortion and loss of detail in underwater images, and forward-scattering is often overlooked. Then, the total amount of light that hit the device can be written as:

$$I(x) = J(x)t(x) + B(x)(1 - t(x)) \qquad (3)$$

Where I is the total irradiance. J is the irradiation of target scene. t is the transmission map, which is used to represent $e^{-\tau d}$ in preceding equations. Where I is the total amount of light. J is the target scene's irradiation. t is the transmission map, which stands for ed in the equations that came before.
Formally, the underwater image formation model of (3) is similar to Koschmieder's [10] model of how the atmosphere breaks down. But it doesn't take into account the fact that the rate at which a light ray gets weaker as it travels through water goes down as the wavelength goes up. Because of this, the model is flawed.

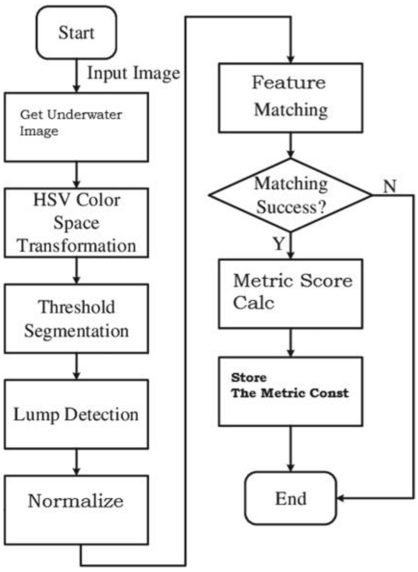

Figure 1- Proposed Methodology

The main goal of the proposed systems is to improve the quality of the object using filters, image segmentation using wavelet filters, image classification using Deep Neural Network, and underwater image detection using Deep Neural Network.

First, read the test image that was sent in by resizing it to a common matrix size to make it easier to work with. Gray scale conversion is done on the resized images, and then histogram equalization is done. The imbinarize command is then used to change the equalized images into binary. Then, the histogram equalization technique and the HSV colour correction technique are used to make the image even more clear. Using the given technique, the red, green, and blue bands have more contrast and are all set up the same way. The MSE, RSME, and PSNR have been calculated to figure out how unique the test image is.

The proposed system uses a method called "three-point feature mapping," which uses the MSER, Harris, and surf feature extraction methods. The unique points in the test image are thought to be the strongest points of the features and are mapped.

The connected component vector and object area are calculated based on the salient object's extracted features and blob area in the tested image. Also, the feature values are split into training and testing inputs to evaluate the hybrid algorithm, which is a combination of the KNN decision model and the Decision Tree hierarchical model to classify the object (Fig. 2).

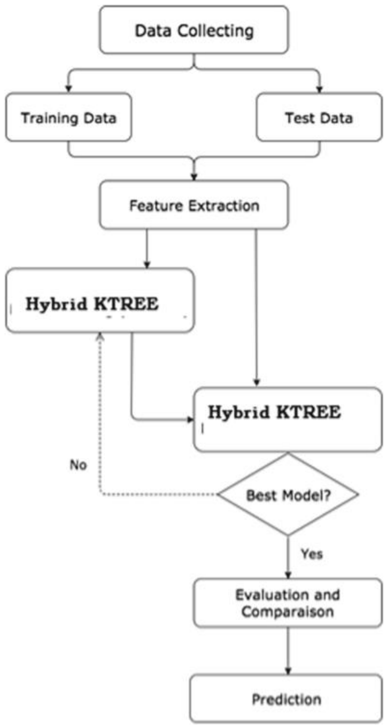

Figure 2. Hybrid Model for Deep Learning

The flow of Except for the new work, real model-based processes follow the improved picture development models, which recognize that the reducing coefficients are only properties of the water and are the same across the scene per hiding channel. This assumption makes people feel uneasy and is obviously not a good thing. The force and theory of significant learning-based low-overhaul methods will fall behind the standard state-of-the-art methods.

This research work combines the KNN algorithm and the Decision tree algorithm to make an improved hybrid K-Tree algorithm. It will be used to train the model and then test pictures taken below the surface. Its state and structure, as well as its accuracy, will be judged by a few key characteristics.

This method is usually used to figure out how far apart different pictures are, especially when the useful information in an image tends to make the differences smaller. By making this change, the powers will show up better on the histogram. This takes into account the spaces with less distance between them to make the difference stand out more. Histogram balance does this by spreading out the most common power regards in a reasonable way. The process is important in pictures that have both beautiful and boring wide shots and close-ups. In particular, the procedure can make it easier to see how bones are growing in x-rays and to see more detail in photos that are too bright or too dark. One of the best things about the system is that it is a very quick way to do things and can't be turned off. Along these lines, the principal histogram can be found if the histogram balance work is known.

For each group of pixels taken from similar situations in all single-channel data pictures, the limit assigns the histogram repository value to the target picture. The headings of the compartment are limited by the possible gains of pixels in this data bundle. For each piece of information, the value of each output picture pixel shows how likely it is that the related input pixel pack has a spot on the thing whose histogram is used.

Decision Tree Classification Algorithm is supervised learning technique that has dual nature. It can be utilized for regression and classification although it is preferred for the latter. This in terms of an object can be represented as a tree. The data features are present in the internal nodes, decision rules being present in the branches and the outcome being present in the leaf node. Essentially, the two parts can be summed up as the decision node and leaf node. Decision nodes are utilized to make calls and have multiple accessories for the same along with the leaf nodes which are utilized for the result of the decision without the additional branches. Evaluation is performed on the basis of the data features. Solutions to a problem based on situations can be displayed visually using graphs. Cart algorithm is utilized for building this approach. The process is simplifying with a dual response present, choosing either one would the divide the process into sub trees.

4. Result Analysis

In this paper, we propose an algorithm that can take a single underwater image and improve it so that it has better contrast and looks more natural. Our algorithm has two parts: an image restoration component and an image enhancement component. The image restoration component fixes any distortions in the intermediate image, and the image enhancement component makes the final image stand out more. In this proposed algorithm, we show an algorithm with a part for image restoration and a part for image enhancement that works together to make pictures with high image contrast and little distortion from the environment. In the past, most work has been done on either image restoration algorithms that model how the environment distorts the image and then fix it, leaving the final image with low contrast, or image enhancement algorithms that make the final image have good contrast but a lot of distortions because of the environment.

Figure 3- Conversion of RGB to GrayScale

Figure 4- Conversion to Binary Image

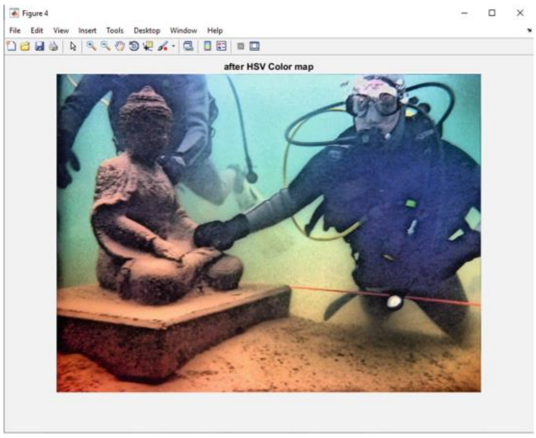

Figure 5- Effect of Color Mapping

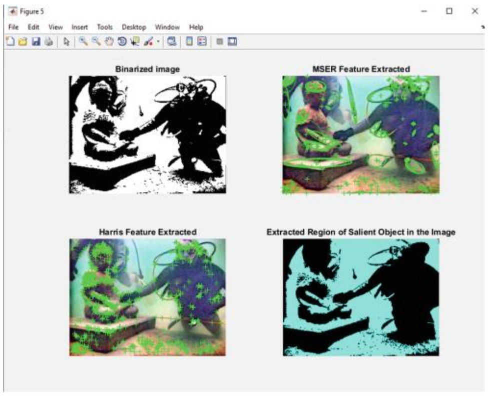

Figure 6- Extraction of Features

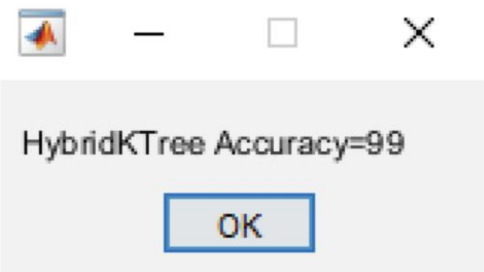

Figure 7- Accuracy of Hybrid System

When these two ways of processing images are used together, we can fix distortions and make clear images at the same time. During the testing phase, these methods are the best at using a training dataset to learn. This article uses deep learning tools like Decision Tree. The simulations were run with matlab. In terms of accuracy and the number of mistakes, the results of the simulation show a big improvement. Research on underwater image repair and improvement has been summed up, and ideas for future research have been given. Simulations show that the proposed hybrid techniques are 99% accurate and have a 0.45 percent classification error, while DT based method was 99.48% accurate and had a 0.52 percent classification.

5. Conclusion and Future Work

The way light travels through water makes image processing one of the hardest parts of making robots that can work on their own under water. Some ways to fix damaged photos can get rid of the haze, but they require a lot of photos from the same place, which makes them impractical for real-time systems. Underwater image processing includes things like fixing pictures, making them look better, making the colors stand out more, and other similar things. There are some problems with this process because of how bright it is and how blurry the setting is. There have been a number of ways to deal with these problems. Machine learning and deep learning are already helping many applications, such as processing images taken underwater. We've made new deep learning models to offer a solution for improving underwater pictures that also includes underwater image restoration. In some ways, our algorithm does better than previous work in both qualitative and quantitative analysis. In terms of quality, the proposed algorithm makes an image that looks natural and has good contrast. The quality of the image is good in a variety of settings, such as underwater images with hazy water, background objects that are hard to see, and underwater images with too much color saturation. In quantitative analysis, the output image is judged by its entropy and its histogram. This paper has good results in terms of entropy, and the histogram shows that each of the color images has a high contrast and a higher intensity distribution. We also used a homomorphic filter to improve the image by getting rid of the uneven scene lighting. This made the final image look more real.We hope to work on underwater videos in the future and use our algorithm frame by frame. This would cut down on the time needed to fix and improve the video's images. However, early results show that the proposed algorithm is hard to program and that processing frames one by one takes too long. This algorithm can also be used to map the underwater terrain visually, which has a number of uses. This lets researchers and other people make a map of the bottom of a body of water quickly without having to worry about separate image restoration and image enhancement processing.

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