UNDERWATER IMAGE SUPER RESOLUTION RECONSTRUCTION USING A WAVELET BASED DEEP LEARNING METHOD

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Abstract - *Traditional processing approaches such as picture enhancement, restoration, and reconstruction have been consistently investigated to combat the scattering degradation induced by turbulence and suspended particles in underwater photography. In order to increase the algorithm's accuracy and efficiency, the wavelet basis was chosen to replace the neuron fitting function, which can successfully imitate the waveform and features of underwater turbulence.*

Key words: convolutional neural network, The Wide Activation Super-Resolution (WDSR), Deep Learning, Dense block Layer, super-resolution, signal to noise ratio.

1. INTRODUCTION

In the fields of marine military, underwater resource development, and environmental monitoring, imaging detection is a hot topic. According to prior research, light absorption and scattering, suspended particles, turbulence distortion, and other factors contribute to the substantial loss of underwater image quality, with turbulence degradation being the most serious issue in natural water. Setting up a degradation model to optimize picture enhancement algorithms is an efficient technique to improve image quality while keeping hardware costs low. Image enhancement and restoration techniques [1]-[4] are examples of traditional underwater image processing approaches. In recent years, researchers have presented numerous mathematical methods to improve the quality of underwater picture restoration and reconstruction, including estimate [5]-[8], fusion [9], colour correction [10]-[12], and the combination of depth neural network [13]-[15].

However, the following are some typical problems with the methods mentioned above: (1) It's challenging to regulate the relationship between noise reduction and contrast enhancement, resulting in inadequate noise removal or lost features in reconstructed pictures. (2) Digital pictures are two-dimensional or three-dimensional digital matrices, respectively with a significant amount of data and an algorithm iteration time too long to enable real-time performance. As a result, the traditional approach of underwater image processing is unable to produce high-quality underwater image restoration results in a timely and precise manner. (3) The application scope and real-time performance are limited by the problem of low efficiency and reliance on models.

As a result, finding a quick and effective way to analyze underwater photos in order to acquire images with a high signal-to-noise ratio and good quality in real-time underwater imaging is critical. Since the rapid development of super-resolution reconstruction technology based on deep learning in recent years, this study uses it to increase the quality of underwater images in a unique way. Deep learning-based image super-resolution reconstruction has become a research hotspot in recent years. Shen et al. developed a MODIS super-resolution reconstruction technique and contributed to adaptive norm selection for regularised picture restoration and super-resolution.

The EDSR approach was proposed by Lim et al. The most notable change is the removal of superfluous SRResNet modules, which allowed the model's size to be increased and the quality of the results to be improved. To improve performance, EDSR can stack additional network layers or extract more features from each tier using the same computational resources. Wang et al. proposed the SFTGAN method, which uses the image segmentation mask as the prior feature condition of the super-resolution and the prior category information to solve the problem of unreal super-resolution texture and restore the image's real super-resolution texture using depth space feature transformation. For the perception index, Zhang et al.

proposed the RankSRGAN approach and an optimised SR model. They developed Ranker, which uses ranking learning to learn the behaviour of perceptual indicators. To achieve the greatest performance in perception metrics and restore more realistic texture, RankSRGAN could utilise the advantages of multiple SR approaches.

2. LITERATURE SURVEY

In order to improve the visual quality of underwater photos, Y. Chen et al. [1] presented MAP-regularized robust reconstruction for underwater imaging detection. Although enhancement and restoration applications can be used, the resolution is still restricted. The technique of super-resolution reconstruction is commonly utilised to improve resolution beyond the capabilities of imaging systems. The performance of reconstruction can be improved further by understanding the point spread function and regularisation approaches.

With the advent of deep convolutional neural networks, X. Yang et al. [2] developed a Deep recurrent fusion network for single-image super-resolution with a large factor, showing that single-image super-resolution has progressed substantially (CNNs). The great majority of CNN-based models employ a preset up scaling operator, such as bi-cubic interpolation, to upscale input low-resolution pictures to the required size and learn nonlinear mapping between the interpolated image and ground truth high-resolution (HR) image.

J. Kim et al. [3] investigated a single-image super resolution (SR) approach that was very accurate. Our method employs an extremely deep convolutional network inspired by the VGG-net used for ImageNet classification, which exhibits a considerable gain in accuracy when network depth is increased. Contextual information over vast image regions is efficiently exploited by cascading tiny filters many times in a deep network topology.

Using a deeply-recursive convolutional network, J. K. Lee et al. [4] suggested an image super-resolution approach (SR) (DRCN). Our network features a recursive layer that is incredibly deep (up to 16 recursions). Without introducing new parameters for extra convolutions, increasing recursion depth can increase performance. Despite the benefits, learning a DRCN via a regular gradient descent method is difficult due to exploding/vanishing gradients. We suggest two enhancements to make training easier: recursive-supervision and skip-connection. By a wide margin, our strategy outperforms earlier methods.

Underwater photographs frequently suffer from hue shift and contrast loss due to light absorption and scattering when travelling through water, according to X. FU et al. [5]. To address these concerns, two sub-problems must be solved in order to improve underwater image quality. To address the colour distortion, first offer an effective colour correcting approach based on piece-wise linear transformation. Then, to solve the poor contrast, discuss a novel optimal contrast improvement method that is efficient and can decrease artefacts. Because the majority of operations are pixel-wise calculations, the suggested method is simple to implement and suitable for real-time use.

Cosmin Ancuti et al. [6] propose a ground-breaking underwater video and image enhancing technique. The degraded version of the image is simply used to create the inputs and weight measurements in our approach, which is based on fusion principles. We create two inputs that represent color-corrected and contrast-enhanced copies of the original underwater image/frame, as well as four weight maps that attempt to improve the visibility of distant objects that have been harmed by medium scattering and absorption.

Light absorption and scattering in the aqueous medium produce significant quality loss and distortion in underwater pictures, according to Wei Song et al. [7]. A hazed picture generation approach is often used to restore image quality. Two optical factors that impact it are the background light (BL) and the transmission map (TM). From an image processing viewpoint, colour and contrast adjustments can assist improve underwater pictures. By providing an excellent underwater image enhancement technique for underwater pictures, in the design of underwater picture restoration and colour correction.

According to Yan Wang et al. [8,] underwater photos play an essential role in ocean exploration, but their quality is usually degraded owing to light absorption and scattering in the water medium. Despite recent developments in the field of image enhancement and restoration in general, the use of new technologies to improve the quality of underwater photographs has yet to be decided. For typical underwater image defects, as well as some extreme degradations and distortions, below are various image enhancement and restoration approaches.

3. **METHODS**

1) CNN:

The proposed CNN comprises five layers, each of which is coloured differently.

i)Conv+PReLU: To create 64 feature maps, 64 filters of sizes 33, 55, and 59 with strides 1 and 2 are used, and PReLU (parametric rectified linear unit) is used for nonlinearity.

ii) Deconv+PReLU: To produce 64 feature maps, 64 filters of size 99, 55, and 33 with strides 2 and 1 are employed, with PReLU as the activation function.

iii) Conv+BN+PReLU: This method uses 64 filters of size 3 3 and batch normalisation between convolution and PReLU.

iv) Conv: The output is reconstructed using three 11-size filters.

v) Skip connection: the add operation is used to link two layers feature maps.

2) **Extraction of wavelet features:**

A wavelet function is a form of scaling function that met all four MRA scaling function requirements listed in the previous subsection. The scaling function is similar to the wavelet function. Integer and binary scaling are both taken into account. For every k Z that span the space Wj where Wj = (_kspan) (j,k) (x), the function (x) is defined as j, k (x) = 2j/2 (2j x-k) for all k Z.

As shown in the diagram, the wavelet function covers the difference between any two adjacent scalingsubspaces, Vj and Vj+1.

As a result, the following equation is generated to describe the link between the scaling and wavelet function spaces:

$$W_j + V_{j+1} = V_{j+1}$$

3) **Dense Block:** In convolutional neural networks, a Dense Block is a module that connects all layers (with matching feature-map sizes) directly to each other. It was proposed as part of the Dense Net architecture at first. Each layer takes extra inputs from all preceding levels and passes on its own feature-maps to all following layers to maintain the feed-forward nature.

4. DESIGN OF THE SYSTEM

4.1 Architecture of the System

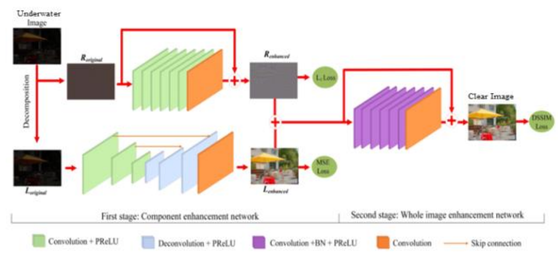

Fig-1 : System Design

The system is in the process of being created. When a user loads an underwater image as an input, the system decomposes the image and extracts the features. The system then loads the pre-trained model and improves the image quality. The clear image will be saved to the local disc by the system.

5. EXPERIMENTAL OUTCOMES

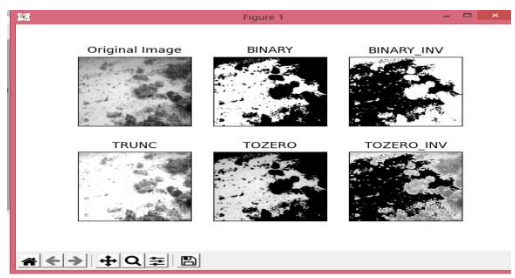

Fig-2: Convolution Layers of Images

The experimental results reveal that the image reconstruction results of the ROBUST and DRFN methods are rather poor, whereas the VDSR, DRCN, and proposed methods produce superior results. Because the datasets are primarily developed for turbidity, the suggested method outperforms existing methods in the milk and Chlorophyll datasets. The scattering is mostly affected by the formation of turbidity, according to the datasets report.

Fig-3: Reconstructed Image

As a result, the robust light scattering model and the light scattering model that takes particle scattering into account will provide a superior recovery effect. In the turbulent state, neither the ROBUST method, the DRFN method, nor the measurement model based on measurement parameters can produce satisfactory results. The method suggested in this paper is more practical because it is applicable to both turbulence and particle scattering settings. This strategy can help you figure out how to lessen the impact of turbulence on underwater imagery.

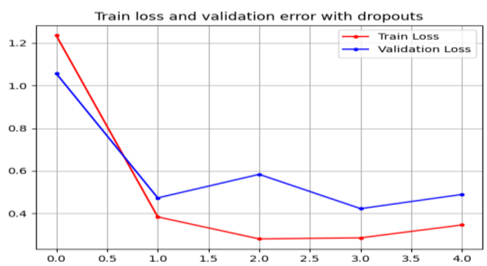

Chart-1: Loss and validation error graph

The underwater turbulence experimental setup is set up with a 532 nm green semiconductor laser as the light source and a high-speed CMOS image sensor to collect images. The laser spot is 10-20 mm in diameter and has a power of 200 MW. The experimental water tank is built of a high-transmittance acrylic panel. As evaluation indices, peak signal-to-noise ratio (PSNR) and structure similarity index (SSIM) were chosen. Each algorithm's reconstructed image from the sample image obtained.

6. CONCLUSION

This research proposes an upgraded deep-intensive convolution neural network based on the concept of deep learning. The wavelet basis is integrated into the deep learning convolution kernel based on the turbulence structure, and a better dense block structure is proposed as the key innovation. The experimental results demonstrate that when there is a reference image, the PSNR and SSIM values are much enhanced; when there is no reference image, the BM, GMG, and LS values are also significantly improved. As a result, it can be inferred that the proposed strategy may successfully improve the depth neural network's effect in super resolution imaging in turbulent water.

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