An Underwater Image Reconstruction Method With Different Applications

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Abstract: Several deep neural network-based models for single picture super-resolution have recently achieved tremendous success in terms of both reconstruction accuracy and computing performance. Before reconstruction, a single filter, often bicubic interpolation, is used to upgrade the low resolution (LR) input image to the high resolution (HR) space. The super-resolution (SR) procedure is thus carried out in HR space. We show that this is inefficient and increases computing complexity. The first convolutional neural network (CNN) capable of real-time SR of 1080p videos on a single K2 GPU is shown in this paper.

We propose an unique CNN architecture in which the feature maps are extracted in the LR space to achieve this. Furthermore, we present an efficient sub-pixel convolution layer that trains an array of up scaling filters to upscale the final LR feature maps into the HR output. By doing so, we may effectively replace the handcrafted bicubic filter in the SR pipeline with more complex up scaling filters that are specially trained for each feature map, while also lowering the entire SR operation's computational complexity. We demonstrate that the suggested method performs much better (+0.15dB on Photos and +0.39dB on Videos) and is an order of magnitude faster than earlier CNN-based methods utilizing images and videos from publicly available datasets.

Key words: **convolutional neural network, The Wide Activation Super-Resolution (WDSR), super-resolution, signal to noise ratio.**

I. Introduction

MARINE ecosystem exploration has clearly been more difficult than terrestrial ecosystem exploration over the years due to a lack of surviving endurance. Oceanography, marine warfare, information navigation, and marine life analysis are all areas that require exploration. Underwater exploration has gotten a lot of attention from the machine vision research field in recent years. The investigation on the aforementioned needs was carried out by completing high-level vision tasks on underwater photos and movies, such as semantic segmentation, classification, and so on.

On these high-level vision tasks, deep CNNs outperformed prior-based approaches by a significant margin [2]. When used with seen/unseen noisy data, however, they generally produce poor results [3]. In addition, a few studies have shown that an unperceivable noise disturbance can deceive deep CNNs for high-level vision tasks [4]. Pre-processing noisy data with low-level vision tasks like picture denoising and restoration has been one simple answer to these challenges [5, 6]. Underwater photos, unlike outdoor images, have more intricate lighting circumstances and color casts, making restoration more difficult. The non-uniform attenuation of light that changes with wavelength [7] is one of the main causes of such visual illusions. Additionally, the visibility of the underwater biosphere through the lens is largely reliant on the presence of marine snow, which increases the light scattering effect [8].

II. LITERATURE SURVEY:

Because light is scattered and absorbed when passing through water, underwater photographs generally suffer from color distortion and low contrast, according to Yan-Tsung Peng et al. [1]. Images with different colour tones might be captured in a range of lighting conditions, making restoration and enhancement difficult. The image formation model (IFM) is a depth-adjusted approach for underwater photographs based on picture blurriness and light absorption that may be used to repair and enhance them.

Model-based optimization methods and discriminative learning methods have been the two prominent methodologies for tackling various inverse issues in low-level vision, according to Kai Zhang et al. [2]. Model-based optimization methods, for example, are versatile for solving varied inverse issues but are typically time-consuming with complicated priors for the aim of high performance.

Due to the non-uniform attenuation of light as it propagates through the water, Prasen Kumar Sharma et al. [3] argued that underwater photographs suffer from low contrast and severe color aberrations in general. Furthermore, the degree of attenuation varies with wavelength, leading in asymmetric color traversing. Despite the abundance of deep learning-based underwater image restoration (UIR) research, the above asymmetry has not been addressed in network engineering.

The implementation of deep learning by Angel Villar et al. [4] has resulted in considerable gains in single image super-resolution (SR) research. State-of-the-art algorithms frequently fail to rebuild high-resolution images from noisy copies of their low-resolution counterparts due to noise amplification during the up sampling phases.

Raw underwater pictures suffer from low contrast, fuzzy details, and color distortion owing to reflectivity, absorbance, and scattered light by suspension particles in water, according to Yuan Zhou et al. [5.] These characteristics can have a big influence on how visible underwater pictures are, as well as how well Segmentation and tracking are examples of visual tasks. To address this problem, an innovative resilient adversarial learning system based on physics model-based feedback control and domain adaptation was developed for enhancing underwater images and achieving realistic results.

Peigen Luo et al. [6] created a deep residual network-based predictive model for underwater photography single image super-resolution (SISR) for remotely operated underwater robots, as well as a supervised learning pipeline for learning SISR from paired data. We devised an objective function to monitor the training that evaluates each image's perceptual quality based on its production possibilities, colour, and regional design information.

The underwater image enhancement described by Chongyi Li et al. [7] has gotten a lot of attention because of its importance in marine engineering and aquatic robotics. In recent years, a slew of underwater picture enhancing techniques have been proposed. These algorithms are primarily tested on synthetic datasets or a small number of real-world photos.

III. METHODS:

A. *Model For Forming Underwater Images:*

According to the Jaffe-McGlamery imaging model, an underwater picture may be viewed as a linear superposition of two components if the camera is not far away from the scene.

1) The direct component is light that enters the camera without being dispersed or absorbed by the intervening water.
2) backscatter is light that enters the camera without being reflected by the object.

A formula for it is as follows:

I(x) = J(x) = I(x) = I(x) = I(x) = I(x) t(x)+B (1 - t (x)); red, green, and blue (1)

where I(x) is the acquired underwater picture and J(x) is the desired clear latent image (also known as scene radiance). The uniform global background light is denoted by the letter B. x is a position in the underwater scene; and is the wavelengths of light in the red, green, and blue channels The medium energy ratio t in an underwater scenario (x) is the fraction of scene radiance that reached the camera after reflecting from point x, resulting in a color cast and reduced contrast. To put it another way, t (x) is a function of the light wavelength and the distance between the camera and the object surface d(x):

t (x) = Nrer()d(x); red, green, and blue (2)

Where Nrer() is the commonly recognised residual energy, defined as the ratio of residual energy to beginning energy per unit of distance and proportional to light wavelength. Most underwater photos, for example, have a blue tone due to the red wavelength's rapid attenuation in open water due to its longer wavelength than the blue and green ones.

B. Domain Adaptation:

The assumption behind traditional machine learning methods is that the training and test data come out of the same underlying distribution i.i.d. Additionally, there is often a discrepancy (domain gap) between training and testing data. During the testing phase, domain adaptation seeks to correct this mismatch and tweak the models for greater generalization. Various learning-based approaches necessitate a synthetic dataset in order to train improvement models that can be applied to real-world underwater images in the underwater image enhancement community and many other low-level jobs. These methods, on the other hand, overlooked their model's capacity to generalise was limited by the domain gap between synthetic training data and real-world testing data. To address this issue, a domain adaptable approach was developed to bridge the domain gap between synthetic and real-world underwater pictures, allowing the network trained on synthetic images to be applied to real-world underwater images the synthetic dataset to be applied to real-world underwater photos.

C. Underwater Image Processing Related Work:

Because of the importance of underwater vision, a number of techniques for improving underwater picture quality have been developed to address image degradation issues. The three types of algorithms that may be discovered include learning-based convolutional neural networks(CNNs), model-based restoration techniques, and model-free improvement techniques. Underwater image recovery is approached as an inverse problem, with underwater pictures being recovered by estimating underwater image production model parameters. For calculating scene depth in a single picture, the dark-channel prior is the most commonly employed prior.

D. SISR for Underwater Imaging:

On the other hand, underwater SISR methods have gotten considerably less attention. This is due to a lack of large-scale datasets that capture the distribution of the strange distortions seen in underwater pictures, as mentioned in the preceding section. The current datasets are only suitable for underwater object identification and picture enhancement applications since their image quality is generally restricted to 256 X 256 and they usually contain manufactured images. As a result, little study has been done on the performance and usability of existing and new SISR models for underwater photography.

Nonetheless, a few attempts of underwater SISR have been performed, with the primary goal of reconstructing superior quality underwater images from noisy or blurred counterparts. SISR models have been employed in other comparable ways to improve underwater image sequence and fish detection performance. Although these models perform admirably in their particular applications, they still have a long way to go to equal SOTA's performance.

E. The Wide Activation Super-Resolution (WDSR):

A foundation for studying architectures for combined denoising and super-resolution. It is divided into two sections. The primary path, which consists of a user-defined number B of residual blocks, is at the top. Two convolutional layers are followed by weight normalisation and ReLU activation in each block. A residual connection can be seen on the bottom path. Low-level features are provided from the input to the output, which is vital for SR activities. A pixel shuffle layer is present in both pathways, which accomplishes the up sampling for image super resolution. The WDSR algorithm is sensitive to input images that have been distorted by additive noise.

IV. Conclusions

SISR, this study provides a quick overview of modern deep learning techniques. It categorises recent research into two groups: deep architectures for simulating the SISR process and optimization objectives for optimising the entire process. Despite the encouraging results so far, 14 there are still numerous underlying issues. The key issues are divided into three categories: deep model acceleration, deep model extensive comprehension, and objective function design and evaluation criteria. Aside from these issues, there are several avenues that could be pursued in the future.

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