A TWO-STAGE UNDERWATER ENHANCEMENT NETWORK BASED ON STRUCTUREDECOMPOSITION AND CHARACTERISTICS OFUNDERWATER IMAGING

VINODHA V, SRAVANTHI KALAL

MCA, AMCEC

ABSTRACT

The underwater image typically has low contrast, colour distortion, and fuzzy features because of the light's attenuation and scattering in the water. By taking into account the specifics of underwater photography, a unique two-stage underwater image convolutional neural network (CNN)based on structure decomposition for underwater picture enhancement is offered as a solution to these issues. On the basis of a theoretical analysis of the underwater imaging, the raw underwater image is specifically divided into high-frequency and low-frequency components. On the foundation of a simultaneous estimation of illumination and reflectance in the linear domain, a new probabilistic method for picture enhancement is proposed. We demonstrate that in comparison to logarithmic domain, the linear domain A prototype may describe more precisely prior knowledge for better assessment ofreflectance and illumination.

It uses a maximum a posteriori (MAP) formulation with light and reflectance priors. The MAP problem is solved by using factors in sequential order tocalculate estimates light and reflectance.The experimental results demonstrate the good performance of the suggested approach to obtain lighting and reflectance with increased visual results and a promising convergence rate. The proposed testing approach produces comparable or superior results on both subjective and objective evaluations when compared to previous testing methods. The efficiency of each component is confirmed by the ablation study, and application experiments further demonstrate how different methods can provide underwater photographs with improved visual quality.

Keyword:CNN,MAP, visual quality.

I. INTRODUCTION

An image can be improved using a variety of techniques, such as filtering, grayscale manipulation, and Histogram Equalisation (HE). One of the well-known image improvement techniques is histogram equalisation. Due to its ease of use and efficiency, this approach for contrast augmentation quickly gained popularity. Inthe latter scenario, maintaining the image'sinput brightness is necessary to prevent thecreation of fictitious artefacts in the final image.

We'll base our comparison on both subjective and objective criteria. Visual quality and calculation time are subjective parameters, while Mean squared error (MSE), Peak signal-to-noise ratio (PSNR), Normalized Absolute Error (NAE), Normalised Correlation, Error Colour, and

Composite Peak Signal to Noise Ratio (CPSNR) are objective parameters. Sight isthe most potent of the five faculties used by humans to understand their surroundings: hearing, touch, smell, and taste. A significant portion of human humans' dailycerebral activity when awake is spent receiving and analysing visuals.

In fact, the processing of visual cortex-derived images accounts for more than 99%of all brain activity. A visual imagecontains a wealth of data. In the words of Confucius, "a picture is worth a thousand words." The most straightforward and visually appealing aspect of all digital image processing methods is imageenhancement.

The basic goal of image enhancement is to reveal hidden details in an image or to boost low contrast images' contrast.

The histogram's grey level probabilitydensity function is used to split the originalimage into two equal-sized sub-images. in this innovative histogram equalisation technique. The two sub-images are theneach equalised. After the processed sub- images are combined into a single image, we finally receive the outcome.

Literature Survey

Robust reconstruction with MAP regularisation for a picture underwater detection

Year: 2017

[1] Methodology: Applications like enhancement and restoration can be used to enhance the quality of the image of underwater photographs, but the resolution is still constrained. The technique of super- resolution reconstruction is frequently employed to increase resolution beyond the study proposed a reliable picture super-resolution reconstruction method withregularisation by the point spread function in a maximum a posteriori framework. Capabilities of imaging systems. Reconstruction can be further enhanced with comprehension of the idea spread function and regularisation methods. For underwater imaging detection, the offered The success of the reconstruction is measured using unbiased picture qualitymeasurements. The suggested approach can successfully raise the resolution and qualityof underwater imaging detection, accordingto experimental results.

Deep recurrent fusion network (DRFN) forlarge-factor single-image super-resolution

Year: 2019

[2] Methodology: Deep convolutional neural networks (CNNs) have recently achieved significant advancements insingle-image super-resolution. The great majority of CNN-based models upscale input low-resolution images to the desired size using a pre-defined up sampling operator, like bicubic interpolation, and then train a non-linear mapping between theinterpolated picture and the real picture high-resolution (HR) image. However, interpolation processing, especially when the super-resolution factor is large, might result in visual artefacts as details are over-smoothed. In this study, we present a Deep Recurrent Fusion Network (DRFN), which fuses various level characteristics retrieved from recurrent residual blocks to rebuild thefinal HR pictures instead of bicubic interpolation or transposed convolution.

Super-resolution of accurate images with incredibly deep convolutional networks

Year: 2016

[3]Methodology: We describe a single-image super resolution (SR) technique that is incredibly exact. The VGG-net utilised for Image Netcategorization served as inspiration for the very deep convolutional network employedin our method. We discover that improvingour network's depth results in a noticeable increase in accuracy. 20 weight layers are used in our final model. Contextual information over broad image regions is effectively accessed by repeatedly cascading tiny filters in a deep network topology. Convergence speed, however, becomes a crucial problem during training with very deep networks. We provide astraightforward but efficient training method. With configurable gradientclipping, we can achieve exceptionally highlearning rates (104 times greater than SRCNN) while learning only residuals.

Convolutional network with deep recursionfor super-resolution of images

Year: 2016
Methodology[4]

We suggest a deeply recursiveconvolutional network (DRCN)-based picture super-resolution technique (SR). With up to 16 recursions, our network features a very deep recursive layer. Performance can be enhanced by increasingrecursion depth without adding new parameters for extra convolutions. Despite its benefits, learning a DRCN using a traditional gradient descent method is highly challenging because of exploding/vanishing gradients. Recursive- supervision and skip-connection are twoextensions we suggest to lessen the challenge of exercise. Our method outperforms earlier methods by a wide margin.

Enhancing a single underwater image intwo steps.

Year: 2017[5]

[4]Methodology: Because of light's absorption and dispersion while moving through water, underwater photographs frequently experience colour shift and contrast loss. We discuss and address two sub-problems to enhance underwater image quality in order to address these concerns. To address the colour distortion, we first offer a powerful color-correcting technique based on piece-wise linear transformation. Then, in order to address the poor contrast, we discuss an innovative, efficient, and artifact-reduction capable optimal contrast improvement approach.

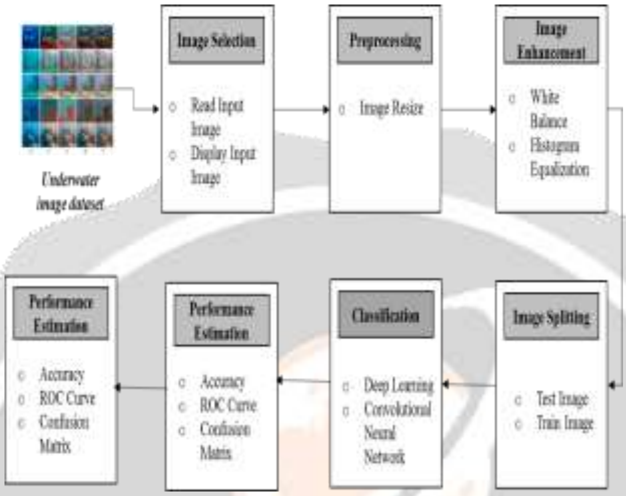

Fig 1.Proposed architecture

EXISTING WORK

In the current approach, a deep learning network directly improves the high- frequency portion, and an underwater imaging - based low - frequencyenhancement network integrates transmission map and background light intoa joint component map. The refinement network is created in the second stage to further optimise the colour of the underwater image while taking underwaterphotography difficulty into account. Thetrial outcomes of both fabricated andauthentic underwater photos and movies

show that the suggested UWCNN-SD approach is capable of colour retouching and enhancement on various underwaterphoto and video types.

The efficiency of every element is IMPLEMENTATION

INPUT SELECTION

A dataset called the underwater image dataset is used as input. The dataset was obtained from a repository of datasets.

The input dataset is in the '.png, '.jpg format.

In this stage, we must use the imread () method to read or load the input image.

The input image is used to enhance theoutput image's quality.

In our procedure, we chose the input imageusing the tkinter file dialogue box.

IMAGE PREPROCESSING

We have to downsize the image and turn itinto grayscale as part of our process.
You can enlarge an image by using theresize () method on it and providing a two-integer tuple parameter that

specifies the image's new width and height.
The function returns a new Image with the updated dimensions rather than altering the original image. Confirmed by the ablation study, and application experiments show further that the proposed UWCNN-SD approach can provide underwater images with improved visual quality.

The efficiency of every element is confirmed by the ablation study, and application experiments show further that the proposed UWCNN-SD approach can provide underwater images with improved

visual quality

It is ineffective for handling big amountsof data.

- There is poor performance.
- Training demands more time.
- The image's quality is poor.

PROPOSED METHODOLOGY

The dataset for underwater photographs in this system is gathered from a dataset repository. The image pre-processing step must then be implemented. In order to enhance or increase the image quality, we must apply white balance and history equalisation in this stage. The deep learningalgorithm, such as the Convolutional Neural Network (CNN), must then be put into practise. Results of the experiment demonstrate the ROC curve, confusion matrix, and accuracy. Finally, use the procedures indicated above to improve the supplied image's quality.

It is effective for a wide number of datasets, requires little training time, and produces good-quality input images.

IMAGE ENHANCEMENT

We must use white balance and histogram equalisation in our procedure.
In order for things that are white in life to appear white in your shot, you must first remove any artificial colour casts using thewhite balancing (WB) technique.
The "colour temperature" of a light source, which describes the relative warmth or coolness of white light, must beaccounted for for appropriate camera white balance. Histogram equalisation is a technique for altering image intensities to boost contrast. This technique typically boosts the overall contrast of a lot of photos, particularlywhen the image's useable data is represented by close contrast values.

IMAGE SPLITTING

Machine learning requires data in order forlearning to take place.
In addition to the data needed for training, test data are also necessary to assess the algorithm's performance and determinehow well it performs.
In our method, we divided the input datasetinto training and testing portions, with the remaining 30% serving as training data.
The act of dividing available data into two pieces, typically for cross-validator reasons, is known as data splitting.
One portion of the data is used to create a predictive model, and the other portion is used to gauge the effectiveness of the model.
Data mining model evaluation involves dividing data into training and testing sets.

CLASSIFICATION

Convolutional Neural Networks (CNN) andother machine learning algorithms must beused in our procedure.

CNN Convolutional neural networks (CNN, or ConvNet) are a family of deep neural networks used most frequently to analyse visual vision in deep learning.Multilayer perceptron derivatives,or CNNs, are regularised variants. Fully linked networks, or multilayer perceptron, refer to networks where All of the neurons in one layer are linked to every neuron in the layer above it.

RESPONSE GENERATION

CONCLUSION

We arrive at the realisation that the source underwater photographs came from a dataset store. Then, in order to enhance or improve image quality, we invented image enhancing techniques including white balance and histogram equalisation. We created the Convolutional Neural Network (CNN), a deep learning system. The experimental data then demonstrates that employing white balance and histogram equalisation improved the image. Then, performance indicators including accuracy,confusion matrix, and ROC curve are computed.

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