Variance Reduction in Low Light Image Enhancement Model

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Abstract In image processing, enhancement of images taken in low light is considered to be a tricky and intricate process, especially for the images captured at nighttime. It is because various factors of the image such as contrast, sharpness and color coordination should be handled simultaneously and effectively. To reduce the blurs or noises on the low-light images, many papers have contributed by proposing different techniques. One such technique addresses this problem using a pipeline neural network. Due to some irregularity in the working of the pipeline neural networks model [1], a hidden layer is added to the model which results in a decrease in irregularity.

Keywords: Image enhancement, Machine learning, Neural network, Pipeline.

I. INTRODUCTION

Low light images are those type of images which are captured at very little light. Such kind of images is not clear. They lack a few essential features of the image which results in looking unclear or noisy. Some of the essential features which are being lost are the sharpness, brightness and color coordination of the image. Adjusting the pixel level is a simple way to enhance an input image. But this did not prove to be a perfect method to enhance an image completely. Then several models for image enhancement were found by scientists across the globe. Retinex theory [7], dehazing model, deep refinement networks are some of the algorithms used in low light image enhancement so far. Histogram equalization [3] method was used to improve contrast in images. This is done by stretching out the intensity range of an image which allows for areas of low contrast to gain higher contrast. However, balancing dark region recovery and bright region preserving is a difficult task and this model proved to have minimal image enhancement capability. Retinex theory (single and multi-scaled) is based on how the retinex in human eye works. But this method resulted in an image that was under or overly enhanced. The pipeline neural network model is one of the techniques used for enhancing a low light image. The model uses the concept of denoising, DWT, logarithmic transformation, SRCNN (Single image super-resolution convolution neural network), Autoencoder [1] and blending function. We elaborated the model by adding a hidden layer called PCA [2] and combined the output of PCA and Autoencoder. The chances of losing some important features has been reduced in our proposed model. It was found that our model gives better results than the existing LLIE model [1].

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II. REVIEW CRITERIA

Several methods and techniques have been established for the enhancement of the low light images. Every image can be tonally distributed. The representation of this distribution is called as histogram. Initially, Histogram equalization [3] was introduced for the betterment of contrast of an image by using tone transfer adjustment functions. It is plotted by taking intensity on x-axis and frequency or probability of those intensities on y- axis. Further modifications led to CLAHE [3], BBHE, DHE and QBHE. It provides better results for either over-exposed or under-exposed images and is little less efficient when non-linear functions are involved. Linear correction helps in providing a better perception of an image. By using non-linear functions, visible changes can be brought in the contrast of both dark and bright regions of an image.

III. EXISTING SYSTEM

A pipeline neural network model [1] is designed for enhancing an image taken in low light. The low light image is sent through a denoising network. Firstly, they acquire the low frequency part of the image using DWT. This brighten up the image a little. However, the size reduces into 4 times of the original size. And at the same logarithmic transformation of the image is also acquired which will be used later. The task of super-resolution reconstruction is separated out and a small SRCNN is built consisting of only three convolution layers. The output of SRCNN is taken as an input by the Autoencoder, which combines the deep and shallow features. Finally, the output of Autoencoder and logarithmic transformation (sent through 1X1 CONV) are combined together using a blending function

IV. PROPOSED MODEL

Pipeline neural network model is considered as a more efficient way than other techniques to enhance a low light image. The model can be improved by adding hidden layers. We are elaborating its efficiency by adding a hidden layer called PCA. (Principle Component Analysis). The Autoencoder used in the Pipeline neural network model does not work perfectly in a consistent way. This is a major disadvantage for Autoencoders. Sometimes it might lose the most important features of an image. This irregularity in the working of an Autoencoder might lead to producing an unconventional result. Adding of PCA would manage the inconsistent working of Autoencoders. PCA works more invariably compared to Autoencoders. So, once the output of PCA and Autoencoders is combined, even if the features had been lost by the Autoencoders, PCA would take care of it.

A. Abbreviations and Acronyms

PCA. (Principle Component Analysis)., SRCNN (Single image super-resolution convolution neural network), DWT(Discrete wavelet transform), PCA (Principal Component Analysis).

B. Equations

$Po = c \log (Pi + 1)$
Po- pixel value of the output image.
Pi- pixel value of the input image c-constant.

C . Figures and Tables

METHODS	SSIM	PSNR (db)	ILNIQE
Input	0.28	8.69	26.62
LIME	0.71	15.76	47.89
MSRCR	0.88	16.88	25.37
SRIE	0.49	11.64	28.49
NPE	0.57	12.37	29.19
LLIE	0.92	21.22	22.07
Ours	0.94	23.15	21.6

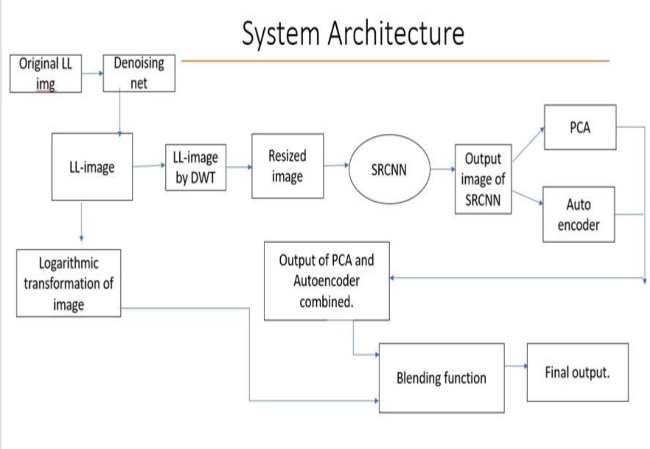
Performance Analysis

It is necessary that the values of PSNR and SSIM values must be greater and the ILNIQUE values must be smaller than the state-of-the-art methods. By using the above parameters, it is proved, that our model has shown better results in each and every aspect.

Original low light image.

V. SYSTEM ARCHITECTURE:

The low light image is denoised first using a denoising net. The logarithmic transformation and discrete wavelet transform(dwt) of the denoised image is done simultaneously. The result of dwt on the image is 4 times smaller than the input image. To bring it back to its original size, resizing of image is carried out. It is enhanced into a higher resolution format using SRCNN. The output of Single Image Super Resolution Convolutional Neural Network is sent into an Autoencoder and a PCA [2] at the same time. The output from both the modules are combined. This output is collaborated with logarithmically transformed image using blending function to get an enhanced output.

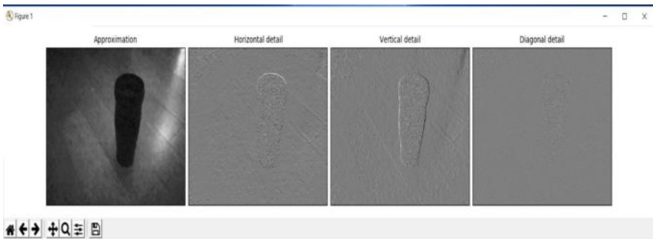


4.1 DENOISING

The process of eliminating noise from an image is is generally referred as denoising. There are different types of noises in an image. Some of the types of noises are Gaussian noise, Poisson noise and speckle noise. The existing LLIE model has a denoising net which concentrates more on removing only gaussian noise of the image. There is a method /function to remove every type of noise. One can identify whether the image's noise is removed or not just by looking at it. The level of noise been removed can be evaluated by comparing it with the original image. The denoising techniques are done in such a way that the sharp edges and textile features are maintained throughout the process. To accomplish an amazing quality of denoising, the time taken for the process will be more. The first process that takes place in the pipeline neural networks model is denoising. In this model only the gaussian noise is removed from the low light image.

4.2 DWT

Discrete wavelet transform is one of the efficient and popular techniques used for compression of images. In this technique, firstly the image pixels are being converted into wavelets and then the compression of image takes place using the wavelets. The images are compressed in such a way that the low frequency parts of the image are brought to one point and the high frequency parts of the image are brought to another point. Usually the high frequency parts contain all the unwanted details of the image. Hence in order to omit those unwanted details DWT is performed. The low frequency part of the image contains all the important details of the image. After splitting the image into two parts, the low frequency part is used for the enhancement process whereas the high frequency part is completely omitted. The output of DWT consists of four forms of the input image This can be done using Haar Basis function. The four forms are the LL band, LH band, HL band, HH band. The LL band consists of the low frequency part of the image and the remaining three bands has the high frequency part. Usually once DWT is performed the image size will reduce to four times its original size. The reduced image is then brought back to its original size using the resize function. After denoising, the DWT process is done in the pipeline neural networks model.



Output after performing denoising and DWT

4.3 LOGARITHMIC TRANSFORMATION

The logarithmic transformation of an image means, every pixel value of the image is being converted into its logarithmic form. During this process the dark pixel values gets expanded whereas all the high pixel values are converted into their log form. This leads to an output image which looks a little brighter than the input image. And finally, according to each pixel's intensity different forms of output images will be produced. This process would help the model to store all the different levels of brightness possibilities of the low light image.

4.4 SRCNN

The full form of SRCNN is Super-Resolution Convolutional Neural Network. The main aim of a SRCNN is to convert a low-resolution image to a high-resolution image. SRCNN performs 4 main operations. The first operation is Upscaling. The process of upscaling a low-resolution image to a desired high-resolution size is called upscaling. The second operation is called Extraction of features. The process of extracting only the essential features of the low-resolution image is called feature extraction. These extracted features are highlighted in the high-resolution image which makes the image look clearer. The third operation is Mapping. All the feature maps representing the change from low resolution patches to High resolution patches are mapped. Finally, the reconstruction of the HR image from HR patches is done. The SRCNN gives a better scaling and color for the image. As a result, the image becomes more interpretable.

All the output forms would look brighter than the original low light image. The resized output of DWT module is considered as the input for SRCNN.

4.5 AUTOENCODERS

Every Autoencoder consists of two main parts. They are, an encoder and a decoder. The encoder encodes all the required data of the image according to the given condition. The decoder decodes the original image with the help of the encoded data. The decoder high lightens all the encoded features as it is considered as the important features of an image. There are different types of Autoencoders available. Each Autoencoder can perform a unique task. For example, suppose there is an autoencoder which must identify all object that are plants. The condition given is- object should be green (as plants are green in color mostly) So, the autoencoder would declare any object that is green in color as a plant. There are some limitations for Autoencoders. However, its ability to produce an output image which looks very much similar to its input image makes it a unique processor. It is mainly used for dimensionality reduction and image compression. The output of SRCNN acts as an input for Autoencoder. It basically combines the shallow features and the deep features. Since the autoencoder of this model concentrates only on the shallow and deep features it doesn't care about the other features of the image. The Autoencoder restricts itself to the given condition. As a result, the Autoencoder encodes only the shallow and deep features. And finally, it decodes the original image with the help of only shallow and deep features.

4.6 PCA

PCA (Principal Component Analysis) is a method of analyzing data by reducing the dimensions. This is done by identifying the main/principal components in a data. PCA is used to identify the presence of any patterns in the data. This shows the similarities and differences in a set of data.

The data is compressed (reduction in dimensionality) without any loss, which is its biggest advantage. It also reduces the noise present in the data. PCA allows to redistribute the orientation of input data and view at a different angle. The main pros of PCA is its way of reducing the dimensions without any loss and the way it works fast. Although PCA doesn't characterize the non-linear information present in the image.

In the LLIE pipelined network, autoencoders have been used. This led to some disadvantages like slow processing, inefficiency to work in every image, etc. So, in our project we have used autoencoders and clubbed its output with the output of PCA in an aim to balance out the cons of the two methods. That is, linear features are recognized by PCA while the non-linear features are recognized by autoencoders. Also, PCA works faster than autoencoders. In this way we do not tend to lose any features of our dataset(images).

4.7 COMBINING PCA OUTPUT AND AUTOENCODER OUTPUT

Finally, the outputs are combined. This process ensures that no important features of the image are being lost by the model during the enhancement process. Like mentioned above, when an Autoencoder misses some features, the PCA will act as a backup and prevents the model from producing an unconventional result. Likewise, PCA cannot characterize non-linear transformations of an image. Now the Autoencoders act as a backup for PCA. It ensures that most of the required non-linear transformations are extracted effectively. Generally, PCA works very fast. Hence, there won't be any increase in the time (caused by PCA) taken by the model for the enhancement process.

4.8 BLENDING FUNCTION

The process of blending two images according to their RGB values of the pixels is called as blending function. Basically, the color blending process takes place between two images. Blending function is a very simple process. It can be achieved by sending the images through a 1*1 Convolution layer. Using a set of rules, the pixel values chosen from both the images are combined. The desired output from the logarithmic transformation function is blended along with the combined result of PCA and Autoencoder. By incorporating this function, we can acquire the sharpness and brightness of the image from logarithmic transformation and the color from the combined result of PCA and Autoencoder.

VI. RESULT AND DISCUSSION

It is necessary that the values of PSNR and SSIM values must be greater and the ILNIQUE values must be smaller than the state-of-the-art methods. By using the above parameters, it is proved, that our model has shown better results in each and every aspect.

VII. CONCLUSION

In the proposed system, it is found that the output is slightly enhanced than the existing system. This is due to the inclusion of PCA as hidden layer.
As mentioned above, the drawback of Autoencoder is balanced by including PCA. The chances of losing the important features has been comparatively low.
One of the biggest advantages of Autoencoder is, it can identify the nonlinear transformations in an effective way. Combining the two modules will ensure that no linear and non-linear transformations of the image are lost. The limitations of our model is, adding an extra hidden layer would make the model a little bit more complex. The complexity in the system can be reduced by creating a single module that does the work of both PCA and Autoencoder.

OUTPUT

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