A Novel Deep Edge Aware Filter based Image Contrast Enhancer

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Abstract : Most of the existing contrast enhancement methods, adjust the tone curve to correct the contrast of an input image but doesn't work efficiently due to limited amount of information contained in a single image. In this research, the Deep Edge Contrast Enhancer (DECE) is proposed. By applying CNN with Edge aware filter technique, the input low contrast images are capable to adapt according to high quality enhancement accordingly over-exposed or underexposed input image. The result analysis shows that the developed DECE significantly advantages over existing methods.

Keywords: Digital Image Processing, Image Enhancement, CNN, PSNR, SSIM.

1. Introduction

In the last decade, we saw a surge in multimedia content generated across the world. With the arrival of digital equipment like cameras, camcorders, etc., it became feasible for a large section of the world's population to generate such content. These devices have become increasingly popular, especially to improve their performance, their gradual loss of prices and their integration into mobile phones [1]. In fact, with the increasing mobility of these devices via mobile phones, combined with advances in low-cost storage, it was possible to capture multimedia content in the form of images and videos in an instant. The quality of an image are affected due to several conditions such as by poor illumination, atmospheric condition, wrong lens aperture setting of the camera, noise, etc [2]. So, such degraded/low exposure images are needed to be enhanced by increasing the brightness as well as its contrast and this can be possible by the method of image enhancement.

In digital image processing field one of the preprocessing technique is image enhancement which generates improved quality of the image out of the distorted or low enhanced image which shows its efficiency for applications in many areas and human interactions The image enhancement techniques are divided into two types, one is spatial techniques and other is frequency domain image enhancement [3,4]. In spatial domain image enhancement methodology, the pixels of an image enhance themselves directly in order to improve the image quality. Whereas in frequency domain image enhancement techniques, frequency transformation is performed on the pixel intensity values for their enhancement. As it is known that due to external atmospheric conditions such as fog or haze and many settings of camera or quality effects the image quality. So, there is requirement of such enhancement technique [5].

So, the degraded quality of image is enhanced by enhancing brightness as well as its contrast level. This can be done by many techniques or methodologies. Many researchers are contributing their efforts in this field as it has wide applications. The most common approach is to denoise the image by enhancing the pixel intensity as well as luminosity of an image. Some research work are only intended to enhance image contrast and some are intended for denoising. But in real time application there is need for such adaptable algorithm that can enhance both according to the requirements [6-10].

2. Related Work

Xianghong et al. [1] designed image enhancement algorithm for colored medical images. According to the algorithm, first of all the two features are extracted i.e. color space and wavelet transform. Input image is sub-divided and wavelet analysis is performed. The RGB color space is converted into HSV color space and further calculations are performed and adjust the intensity of the input image and further converted back to RGB color space.

Verma et al. [2] proposed image enhancement using genetic algorithm because the fitness of the intensity of the spatial edge of the image. According to the algorithm, input image is sub-divided into sub blocks. According to the fitness value of the sub-blocks is selected with higher fitness value. PCA is applied for mutation of the genetic algorithm and outperforms better result.

Khan et al. [3] used DDFB diffusion filter and Hong filter for image enhancement of the fingerprint images in order to magnify the minutiae of the fingerprint images. The orientation of the fingerprint are calculated using multi-scale DDFB. The experimental result shows that this proposed algorithm is more reliable and efficient as compared to all other algorithms.

Shanmugavadivu et al. [4] designed an image contrast enhancement technique by applying histogr a contrast enhancement technique using histogram equalization. According to this proposed technique, the histogram obtained from image is first of all divided into two parts based on Otsu threshold. Further particle swarm optimization is applied on each part respectively. Each part is separately optimized and finally joined together and enhance the brightness of the image.

Gorai et al. [5] proposed an image enhancement technique using particle swarm optimization (PSO) because this algorithm optimizes the objective function and its parameters. The local and global information are optimized to retrieve best options. The intensity of an image are optimized by applying this algorithm. Intensity transformation function are obtained as an result from this algorithm. Edge information and entropy are used as an objective function to be maximized. And finally, scaling is used to enhance the image quality. The algorithm gives better performance as compared to other techniques such as histogram equalization, filtering, etc.

Benala et al. [6] proposed an algorithm for magnification and enhancement of an image and termed this algorithm as ABC optimization algorithm. The result of this optimization is better as compared to genetic algorithm because the chance of dropping the local parameter optimization is less as in ABC algorithm. This algorithm improves the local maxima search ability such that global maxima will also be enhanced.

Hanumantharaju et al. [7] designed a technique by applying particle swarm optimization for enhancement of an image. Edge information and entropy of an image is used for enhancement of an image. Particle swarm optimization is thus used to optimize the parameters of the techniques such as multiscale retinex, Gaussian surround space constants, etc. The simulation result shows better performance as compared to these methods without optimization and this algorithm also gives better performance as compared to other techniques such as histogram equalization, filtering, etc.

Zhou et al. [8] proposed an image enhancement technique based on fuzzy logic in which parameters or features are optimized using genetic algorithm. In this technique an image is first of all transformed into spatial domain and further fuzzy rules are designed on these domains. Then fuzzy rules are optimized using genetic algorithm. And lastly the image is restored back into image from fuzzy domain using defuzzification and thus enhanced image is formed. The experimental results shows enhanced performance with respect to existing algorithms.

Malik et al. [10] considered the problem of low light image restoration through joint contrast enhancement and denoising. Deep convolutional neural networks (CNNs) based on residual learning have been successful in achieving state of the art performance in image denoising. However, their application to joint contrast enhancement and denoising poses challenges owing to the nature of the distortion process involving both loss of details and noise. Thus, we propose a multiscale learning approach by learning the sub-bands obtained in a Laplacian pyramid decomposition through a sub-band CNN (SCNN). The enhanced sub-bands at multiple scales are then combined to obtain the final restored image using a re-composition CNN (ReCNN). We refer to the overall network involving SCNN and ReCNN as low light restoration network (LLRNet). We show through extensive experiments based on the 'See in the Dark' Dataset that our approach produces better quality restored images when compared to other contrast enhancement techniques and CNN based approaches.

3. Methodology

Traditional MEF algorithms are mainly designed at pixel level such that weight map are constructed out of these pixels and are of same size as that the image is [10].

Therefore, finding the appropriate weight tables is the most important task in this approach. The contributions of the proposed work are summarized as follows:

1. To build a large scale, multi-exposure dataset that contains low contrast images with different exposure levels based reference image. It also provides a platform to quantitatively evaluate, at least to some extent, the performance of different contrast enhancement algorithms.
2. With the constructed dataset, a well designed DECE is trained, which demonstrates significant advantages over existing method..

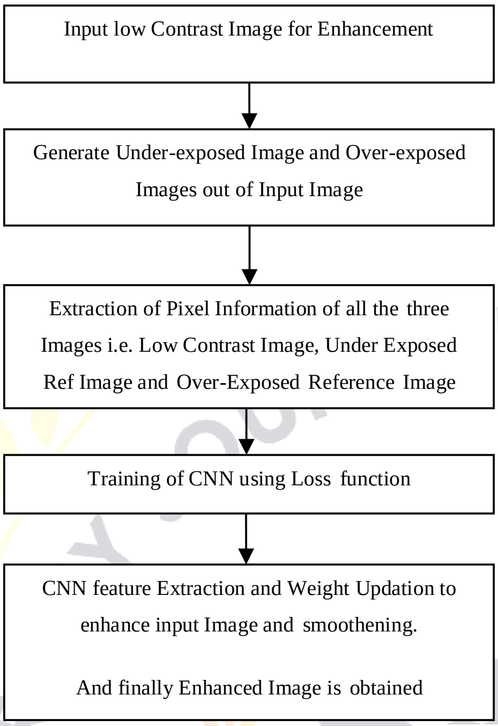

Figure 1: Flowchart of Proposed Methodology

In order to gain above mentioned objectives, images are collected with low-exposure image sequences of natural scenes.

Following Steps are performed while enhancing the contrast of images:

Step 1: Input the low contrast image

Step 2: Generation of Under-exposed Image and Over-exposed Images out of Input Low Contrast Image and considered it as Reference Images

Step 3: Extraction of Pixel Component out of low contrast image as well as from both reference images

Step 4: Training the proposed CNN network and generate CNN features with smallest DSSIM loss function

Step 5: Updation of low contrast image pixel intensity as well as global gradient value according to CNN features and smoothening with edge aware filtration method.

Step 6: Evaluation of Performance Parameters such as SSIM, FSIM and PSNR values.

The details of all the steps are described as follows:

A. Data Collection

In order to design robust and efficient low contrast image enhancement technique, it is required to collect input images from real-world natural scene. In this research, different image sequences are collected from different camera and collected as a common dataset. For creating low contrast image dataset, the exposure value of the camera are set and collected different sequences of indoor and outdoor scenes. After collecting the low contrast input images, under exposed and over exposed images are created by manipulating the exposure value and save as a reference images.

B. Reference Image Generation

For reference image generation, HDR algorithm is used to generate under exposed and over exposed high quality reference images.

C. Deep Edge Contrast Enhancer (DECE)

The traditional image contrast enhancement techniques is based on histogram equalization which increases the intensity value of the pixels by distributing or equalizing the intensity value of image according to the neighboring pixel values. This illuminates the intensity value of the low contrast image. However, these algorithm is not quite efficient to generate high quality image with respect to low contrast images just due to complex background intensity values in the natural scene images.

With the constructed dataset, the proposed work will designed a Deep Edge Contrast Enhancer to know and map a equalization function among low contrast image I(x, y) and its respective reference images $Iref_{under\text{-}exposed}$ (x, y) and $Iref_{over\text{-}exposed}$ (x, y). This work is performed in two step. In first step CNN is used to update the pixel intensity values and further edge aware filter is used to preserve the edges and its properties, finally enhanced image is obtained.

D. CNN Network Architecture

The proposed CNN has 5 convolutional layers and 3 fully connected layer which are shown in Figure 2.

i. Conv with 96 filters of size 11*11 with strides 4 are used to generate 96 feature maps
ii. For nonlinearity in network, ReLU (Rectified Linear Unit) is applied.
iii. Max Pooling with 3*3 with stride 2
iv. Conv with 256 filters of size 5*5 with 1 stride that generate 256 feature maps
v. For nonlinearity in network, ReLU (Rectified Linear Unit) is applied.
vi. Max Pooling with 3*3 with stride 2
vii. Conv with 384 filters of size 3*3 with 1 stride that generate 384 feature maps
viii. For nonlinearity in network, ReLU (Rectified Linear Unit) is applied.
ix. Max Pooling with 3*3 with stride 2

x. Conv with 384 filters of size 3*3 with 1 stride that generate 384 feature maps
xi. For nonlinearity in network, ReLU (Rectified Linear Unit) is applied.
xii. Conv with 256 filters of size 3*3 with 1 stride that generate 256 feature maps
xiii. For nonlinearity in network, ReLU (Rectified Linear Unit) is applied.
xiv. Max Pooling with 3*3 with stride 2
xv. Fully connected layer with 4096 neurons each for adding the operation that is used to attach the feature maps.

The basic idea of the CNN architecture is as follows:

i. Copy convolution layers into different GPUs
ii. Distribute the fully connected layers into different GPUs.
iii. Feed one batch of training data into convolutional layers for every GPU (Data Parallel).
iv. Feed the results of convolutional layers into the distributed fully connected layers batch by batch (Model Parallel) When the last step is done for every GPU. Backpropagate gradients batch by batch and synchronize the weights of the convolutional layers.

E. Stride Convolution

The feature map generated according to the network is reduced by the convolutional operations. Padding is done to the output images before performing convolution, as output image has to be of same size as that of input image [5]. But this padding may cause artifact in the input image. So, this network is designed with deconvolution layer to make the output size be similar to input size. This deconvolution layer not only decreases the artifacts as well as reduces the computational overhead by applying filters.

F. Rectified Linear Unit

Rectified Linear Unit (ReLU) are used in many CNN architectures as an activation function for the network. In this activation function, the negative co-efficient are replaced with zero value which is represented by the local features of the input image. The function is represented as:

$$f(x) = \begin{Bmatrix} 0 \; for \; x < 0 \\ x \; for \; x \geq 0 \end{Bmatrix}$$

Some of the neurons dropped because they do not contribute to forward passage and do not participate in backpropagation. Every time an input is presented, the neural network analyzes another architecture, but all these architectures share a common weight. This technique reduces the complex adaptations of neurons because a neuron cannot rely on the presence of some other neurons.

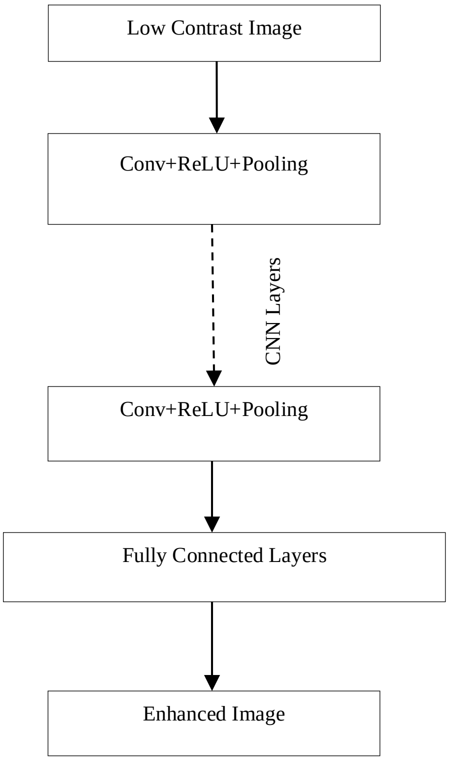

Figure 2: Proposed CNN Architecture

The proposed Deep Edge aware contrast enhancer is designed to enhance the contrast of the input image I(x,y) with respect to the reference images by learning the mapping function between the luminance component of the input low-contrast image and the luminance component of the under exposed and over exposed reference images.

During training of the network, the weight functions are updated according to loss function. The loss function used here is stated as:

$$DSSIM(W) = \frac{1}{N}\sum_{I}^{n}(1 - ssim(I_{ref}^{i} - H(I^{i}, W)))/2$$

Where, SSIM= Structural Similarity

G. Edge Aware Filtering on CNN Weights

After feature extraction of the input low contrast image. The intensity and gradient values are updated. So, weight is updated in two steps:

- In first step pixel intensities are updated
- In second step global gradients are updated

Deep Edge Contrast Enhancer (DECE) process produces weighted average of the processed pixel vector and performs the “smoothing” operation. The final result is obtained by further applying edge filter for restoring the sharp edges, corresponding to “edge-aware” processing.

Once CNN weight (CNNwt) is obtained, function is used, together with CNNwt, to apply the Edge-Aware Filters. It corresponds to the testing pass with the convolutional neural network. For a given image I, we first transform it into gradient domain and feed it into the network to get the filtered gradients. The final image S is obtained by solving the reconstruction function with its optimal CNNwt.

By using the deep edge aware filter the proposed methodology is used for enhancing the luminance values of the pixels of the low contrast image. As the input images is low-contrast that contains both dark as well as bright pixel values. By using the CNN network, the low contrast image is enhanced to high contrast image by shifting the color intensity value. Therefore, the proposed methodology merges the under-exposed and over-exposed components and enhance the image and introduce CNN filter to refine it to the respective reference images.

3. Database Description

The Images were collected from different resources such as :

i. VV: This dataset is collected by Vassilios Vonikakis in his daily life to provide the most challenging cases for enhancement. Each image in the dataset has a part that is correctly exposed and a part that is severely under/over-exposed. A good enhancement algorithm should enhance the under/overexposed regions while not affect the correctly exposed one [11].

ii. LIME-data: This dataset contains 10 low-light images used in [12].

iii. NPE3: This dataset contains 85 low-light images downloaded from Internet. NPE-data contains 8 outdoor nature scene images which are used in [13]. NPE-ex1, NPE-ex2 and NPE-ex3 are three supplementary datasets including cloudy daytime, daybreak, nightfall and nighttime scenes.

iv. DICM4: It contains 69 captured images from commercial digital cameras collected by [14].

v. MEF5: This dataset was provided by [15]. It contains 17 high-quality image sequences including natural sceneries, indoor and outdoor views and man-made architectures. Each image sequence has several multi-exposure images, we select one of poor-exposed images as input to perform evaluation.

4. Performance Parameters

In this research work two performance parameters are used for image quality assessment. These parameters are:

Peak Signal to Noise Ratio (PSNR)

PSNR represents the degradation of the enhanced image with reference images i.e. under exposed and over exposed. It is expressed as a decibel scale. Higher the value of PSNR higher the quality of image. PSNR is represented as:

$$PSNR = 10log10(\frac{(X * Y)}{MSE}$$

Where,

X and Y are height and width respectively of the image.

MSE= Mean Square Error between enhanced image and reference images

Feature Similarity Index (FSIM)

Feature-similarity (FSIM) index is based on the fact that human visual system (HVS) understands an image mainly according to its low-level features. Specifically, the phase congruency (PC), which is a dimensionless measure of the significance of a local structure, is used as the primary feature in FSIM. The image gradient magnitude (GM) is employed as the secondary feature in FSIM. PC and GM play complementary roles in characterizing the image local quality [10].

The feature similarity is calculated as the measurement between $f_1(x)$ and $f_2(x)$ into two components, each for PC or GM. First, the similarity measure for $PC_1(x)$ and $PC_2(x)$ is defined as:

$$S_{pc}(x) = \frac{2PC_1(x) * PC_2(x) + T}{PC_1^2(x) + PC_2^2(x) + T}$$

Where, S_{pc} = similarity measure for phase congruency

PC_1= phase congruency of low contrast image

PC_2= phase congruency of reference image

T = A +ve constant to increase the stability of S_{PC}

Similarly, the similarity measure for $GM_1(x)$ and $GM_2(x)$ is defined as:

$$S_{GM}(x) = \frac{2GM_1(x) * GM_2(x) + T}{GM_1^2(x) + GM_2^2(x) + T}$$

Where, S_{GM} = similarity measure for gradient magnitude

GM_1= gradient magnitude of low contrast image

GM_2= gradient magnitude of reference image

T = A positive constant to increase the stability of S_{GM}

Structural Similarity Index (SSIM)

The structural similarity (SSIM) index is a method for predicting the perceived quality of digital television and cinematic pictures, as well as other kinds of digital images and videos. SSIM is used for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measurement or prediction of image quality is based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods such as peak signal-to-noise ratio (PSNR) and mean squared error (MSE). The SSIM index is calculated on various windows of an image. The measure between two windows x and y of common size N×N is:

$$SSIM\ (x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Where, μ_x= mean of x

μ_y = mean of y

σ_x^2 = variance of x

σ_y^2= variance of y

σ_{xy}= co-variance of x and y

c_1 and c_2 are variables to stabilize the division with weak denominator

5. Conclusion

In this research, work is focused on designing of multiple exposure image enhancement technique. For this dataset is taken with different exposure images. For processing, a high-quality reference image is generated and used for enhancement of the input low contrast images. Test is also conducted for various input images. The proposed work developed using Deep Edge contrast enhancer (DECE). By applying this technique, the input low contrast images are capable to adapt according to high quality enhancement accordingly over-exposed or underexposed input image. After result analysis, the proposed method is compared to the existing methods on the basis of image quality measure such as SSIM, FSIM and PSNR values. It is observed that average SSIM obtained is 0.89 and average FSIM obtained is 0.95. Similarly, average PSNR obtained is 18.69.

The result analysis shows that the developed DECE significantly outperforms better as compared to existing work about 27% with respect to FSIM. Similarly, the proposed methodology outperforms about 15% better PSNR value with respect to existing work.

References

[1] Xianghong, W., Shi, Y., Xinsheng, X.: An effective method to colour medical image enhancement, published in IEEE/ICME International Conference on Complex Medical Engineering, pp. 874–877, IEEE, 2007.

[2] Verma, A., Goel, S., Kumar, N.: Gray level enhancement to emphasize less dynamic region within image using genetic algorithm, published in 3rd International conference on Advance Computing Conference (IACC), pp. 1171–1176. IEEE, 2013.

[3] Khan, T.M., Khan, M.A., Kong, Y.: Fingerprint image enhancement using multi-scale DDFB based diffusion filters and modified Hong filters, published in Optik-International Journal for Light and Electron Optics Vol. 125, No. 16, pp. 4206–4214, 2014.

[4] Shanmugavadivu, P., Balasubramanian, K.: Particle swarm optimized multi-objective histogram equalization for image enhancement, published in Optics Laser Technology, Vol. 57, pp. 243–251, 2014.

[5] Gorai, A.,Ghosh, A.: Hue-Preserving Color Image Enhancement Using Particle Swarm Optimization, published in IEEE, pp. 563–568, 2011.

[6] Benala, T.R., Jampala, S.D., Villa, S.H., Konathala, B.: A novel approach to image edge enhancement using artificial bee colony optimization algorithm for hybridized smoothening filters, published in IEEE, pp. 1071–1076, 2009.

[7] Hanumantharaju, M.C., Aradhya, V.N.M., Ravishankar, M., Mamatha, A.: A Particle Swarm Optimization Method for Tuning the Parameters of Multiscale Retinex Based Color Image Enhancement, published in ICACCI'12, Chennai, T Nadu, India, ACM, pp. 721–727, August 3–5, 2012.

[8] Zhou, X., Sun, G., Zhao, D., Wang, Z., Gao, L., Wang, X., Jin, Y.: A Fuzzy Enhancement Method for Transmission Line Image Based on Genetic Algorithm, published in Ninth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, pp. 223–226, 2013.

[9] Singh, P.K., Sangwan, O.P., Sharma, A.: A Systematic Review on Fault Based Mutation Testing Techniques and Tools for Aspect-J Programs, published in 3rd IEEE International Advance Computing Conference, IACC-2013 at AKGEC Ghaziabad, IEEE Xplore, pp. 1455–1461, 2013.

[10] S. Malik and R. Soundararajan, "Llrnet: A Multiscale Subband Learning Approach for Low Light Image Restoration," 2019 IEEE International Conference on Image Processing (ICIP), Taipei, Taiwan, 2019, pp. 779-783.

[11] https://sites.google.com/site/vonikakis/datasets

[12] http://cs.tju.edu.cn/orgs/vision/~xguo/LIME.htm

[13] http://blog.sina.com.cn/s/blog a0a06f190101cvon.html

[14] http://mcl.korea.ac.kr/projects/LDR/LDR TEST IMAGES DICM.zip

[15] https://ece.uwaterloo.ca/~k29ma