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Enhancing Multi Exposure Images Using Convolution Neural Network

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ABSTRACT

Due to the poor lighting condition and restricted dynamic vary of digital imaging devices, the recorded photos are usually under-/over-exposed and with low distinction. Most of the previous single image distinction improvement (SICE) strategies modify the tone curve to correct the distinction of an associated input image. Those strategies, however, typically fail in revealing image details due to the restricted data in a very single image. On the opposite hand, the SICE task is often higher accomplished if we will learn additional info from suitably collected coaching information. In this paper, we have a tendency to propose to use the convolutional neural network (CNN) to coach SICE attention. One key issue is the way to construct a coaching information set of low-contrast and high-contrast image pairs for end-to-end CNN learning. To this finish, we have a tendency to build a large-scale multi-exposure image knowledge set, that contains 589 in an elaborate way chosen high-resolution multi-exposure sequences with four, 413 images. Thirteen representatives multi-exposure image fusion and stack-based high dynamic vary imaging algorithms are accustomed urge the excellence enhanced footage for each sequence, and subjective experiments are conducted to screen the best quality one because of the reference image of every scene. With the constructed data set, a CNN can be easily trained as the SICE enhancer to improve the contrast of an under-/over-exposure image. Experimental results demonstrate the benefits of our methodology over existing SICE strategies with a major margin.

Keywords : Single Image Contrast Enhancement, Multi-Exposure Image Fusion, Convolutional Neural Network.

I. INTRODUCTION

In reality, when we capture an image in a low light environment, the image quality would be strongly influenced by noise and low contrast, which makes it more difficult to deal with the following tasks such as image segmentation, object detection etc. At present, digital video technology has been widely used in various fields, for example, safety monitoring of important places, traffic management, driving assistance and so on. Under the condition of good daytime illumination, the image quality can meet the application requirements, but when it comes tonight, the image quality of low light image worsens, which brings a big challenge in the digital image process. Sorts of enhancement methods were proposed and they can be divided into three categories: methods based on histogram equalization algorithms (HE), Retinex theory, and using dehazing model. In this paper, we present a new method different from existing methods. The contribution of our work can be summed up into three aspects: First of all, we describe the relationship between MSR and CNN.

Secondly, we elaborate on a pipeline network, which learns a function for denoising and low light enhancement. And finally, the performance evaluated on a number of low light natural images reveal that our method achieves better performance in comparison with other state-of-the-art approaches. Overall, the contribution of our work can be generalized to three aspects:(1) We explain the relationship between CNN and MSR and we find out blending the low-low component of the image DWT with the output of MSR can improve the result. (2) We consider the low light image enhancement as a machine learning problem and we elaborate our neural network for this task, furthermore, we present a pipeline neural network including denoising and enhancement. (3) And we measure our results quantitatively and qualitatively. The performance of our LLIE-net is better than the existing methods in both the synthetic low light images and real-world low light images.

II. RELATED WORK

A. Single Image Contrast Enhancement

Single image contrast enhancement (SICE) aims to improve the visibility of the scene in a given single low-contrast image. It provides a way to enhance the low contrast photographs captured from a high dynamic range scene [10]. Many histogram and Retinex based SICE methods have been proposed in the past decades. Histogram-based methods [1], [2] have been widely used because of their simplicity in enhancing low-contrast images. Those methods attempt to redistribute the luminous intensity on the histogram in a global or local manner. However, such simple redistribution operations may produce serious unrealistic effects in the enhanced images since they ignore image structural information [4]. To excavate the structural information from the low-contrast image, Retinex- based methods [3], [5] decompose the input image into albedo and illumination layers and adopt different strategies to enhance the reflectance and illumination components. Most of the previous SICE methods are based on some assumptions on high-quality images, while they may not fully exploit the information in the input image. On another hand, the enhancement capability of existing SICE methods is rather limited due to the limited information in a single low-contrast image [9]. Recently, methods [6], [8] have been proposed to train a CNN network to map the low dynamic range (LDR) images to HDR images. In [7], CNN is trained to set the parameters of bilateral filters, which are then used to enhance an input image to the desired image edited by professional photographers. Since further data will be learned from the external dataset, during this work, we are going to in an elaborate way build a dataset to be told a robust CNN-based SICE foil from multi-exposure pictures.

B. Image Dataset Generation

In order to learn the parameters of LLIE-net, we construct a new image dataset, which contains a number of normal light (NL) and low-light (LL) natural images. All images selected are real-world scenes. We have collected the normal light images, some of which are from Google search, UCID [14] and BSD [15] dataset. And many of these images are strong motion blur, out of focus blur, low contrast, underexposure or overexposure, and substantial sensor noise are deleted. Finally, we acquire 800 images. For every image, we generate 10 low-light images by two steps. Firstly, we scale the V (Value) component with a random factor between 0.5 and 1, by transforming the image to HSV space. And then we use gamma transform with parameters ranging between 1 and 3 to darken the image further [16]. Then, we obtain a dataset with 8,000 pairs of NL/LL images, some examples of which are shown in Figure 7. We randomly select 7,000 images in the dataset to generate one million 64×64 NL/LL patches for training. The remaining 1000 images are used to evaluate our network in the test phase. In addition, to guarantee to evaluate our approach objectively and impartially, we test our model using the real-world lowlight images form the public MEF dataset [11], [12], DICM dataset [13] and LIME dataset [17].

III. EXISTING SYSTEM

Over the past few decades, many methods have been proposed to enhance degraded images. However, fewer methods can generate ideal results when they are applied to weakly illuminated images. For example, histogram-based methods [21] usually increase the dynamic range of gray values, which leads to suboptimum enhancement performance for image details. For another example, physical model-based methods [19,26] usually produce unnatural and unrealistic results since some priors or assumptions do not always hold for varying illumination conditions. In contrary to familiar image improved ways, there may be fewer strategies that enhance infirm lighted pictures. Several existing enhancement methods [19,20,26] are based on the observation that the inverted low-light images intuitively look like haze images. Such a technique initially inverts associate input low-light image then employs a picture dehazing algorithmic rule on the inverted image, finally achieves the improved image by inverting the dehazed image. Dehazing-like methods can enhance the visual quality of low-light images to some extent, however, this method lacks cogent physical explanation and tend to produce unrealistic results. Recently, Fotiadou et al. [22] proposed a novel method to enhance low-light images based on the framework of Sparse Representations. Fotiadou et al. used two dictionaries (i.e ., night dictionary and day dictionary) to transform the Sparse Representation of low-light image patches to the corresponding enhanced image patches. The enhanced results significantly relied on the accuracy of the learned dictionaries. Fu et al. [23] used fusion primarily based technique for infirm lighted image improvement, which fused luminance-improved and contrast-enhanced versions of input by two designed weights. Besides, multi-scale fusion system was applied to scale back the amplified artifacts. The enhanced results may have characteristic with improved brightness, contrast, and details. However, like different fusion-based image improved strategies, such a technique tends to provide over-enhanced, over-saturated, and unreal results because of ignoring the physical properties of weak illumination image degradation. Lore et al. [25] proposed a deep learning-based method to adaptively enhance and denoise images captured under low-light environments, namely LLNet. Lore et al. directly employed an existing deep neural network architecture (i.e., stack sparse denoising autoencoder) to build the relationship between the low-light images and the corresponding enhanced and denoised images. The experimental results demonstrated that deep learning-based method is suitable for low light image enhancement. Guo et al. [24] proposed a simple low-light image enhancement method, namely LIME. This methodology was initially calculable the illumination of every component within the low-light image, then refined the initial illumination map by a structure prior, finally the enhanced image was achieved based on Retinex model exploitation the calculable illumination map. Besides, so as to scale back the amplified noise, associate existing image denoising algorithmic rule was used as post-processing within the LIME methodology.

A.MEF and Stack-Based HDR

Because of the limited dynamic range, traditional digital imaging systems may lose structural details when shooting a natural scene [10]. To address this issue, stack-based HDR ways in which [14], [15] propose to merge bracketed multiple exposure images into associate HDR irradiance map, then use a tone mapping operator to compress the dynamic range of HDR irradiance map so that the high-contrast image can be displayed on regular monitors. Different from the HDR approaches, MEF methods [2], [13] attempt to fuse the images directly in the non-linear brightness domain to reproduce a high-visibility image. Despite their successes on well-aligned image sequences, the existence of camera shake and object motion in several scenes usually results in ghosting artifacts within the final increased results, limiting the applications of MEF and HDR in practice. In the last decade, researchers have spent many efforts to design de-ghosting algorithms [2], [14], [18] and learning-based methods like [33] proposed to map the multi-exposure image sequences to an HDR image. However, it remains a difficult drawback in MEF and HDR for dynamic scenes. In this work, we elaborately select the well-aligned image sequences to generate a good reference image by MEF and HDR reconstruction methods.

IV. PROPOSED SYSTEM

Though low-light image enhancement belongs to low-level image processing tasks, it differs a lot from super-resolution and image denoising. For these both tasks, component values in degraded pictures may be round the true values, and also the average element values nearly don't a modification, that is totally different in our task. Therefore, we design a different but effective CNN architecture to enhance low-light images. In many computer vision tasks, deeper networks have better performance than those non-deep ones. However, when stacked convolutional layers go deeper, the network will meet a serious problem of vanishing gradients, which will hamper convergence during training several layers of different sizes are connected to a previous layer, and therefore the output information of those layers may be concatenated into one output vector.

A. Network Architecture

We format a special convolutional module to make our network. Since deeper networks typically yield higher performance, we have a tendency to tend to style deeper networks. Thus, we've got to deal with vanishing gradient drawback. The design of our convolutional module is galvanized by beginning module and residual learning. The module can be divided into two stages. In the initial stage, information may be processed in 2 separate methods. One method may be a 1×1 convolutional layer and also the alternative way is 3×3 convolutional layers. We contact them along to create the input of the second stage. The first stage is comparable to the beginning module. We don't concatenate the results however add them instead. In the second stage, there are a couple of methods. The first way is to process data using two 3×3 convolutional layers while in a second way, the input data is bypassed directly, which will provide the desired output.

B. Deep Learning Methods for Image Processing

Driven by large datasets and the improvement of calculation capability, deep learning-based methods have shown great success in low-level image processing applications. For super-resolution, VDSR [9] utilizes VGG filters and uses twenty convolutional layers to get impressive results. When referring to image denoising, DnCNN [10] uses a similar network to VDSR and adds batch normalization layers after convolutional layers, which achieves higher PSNR than traditional image denoising methods. As so much as we all know, LLNet [11] is that the sole methodology exploitation deep neural networks to reinforce low-light pictures. The network could be a variant of the stacked-sparse denoising autoencoder, and it doesn't use convolutional layers. Natural pictures will darken exploitation nonlinear technique to simulate low light-weight conditions. These images are set as training data. After training, the network can enhance low-light images.

V. CONCLUSION

We built a multi-exposure image dataset, which has 589 image sequences and 4,413 high-resolution images of different exposures. For each sequence, a correspondingly high-quality reference image was generated by using 13 MEF and stack-based HDR algorithms. Subjective tests are also conducted to screen the best quality one as the reference image of each scene. The availability of low-contrast images and their high-quality reference images in our dataset allows the end-to-end learning of high-performance SICE methods. As a demonstration, we developed a simple yet powerful CNN-based SICE enhancer, which is capable of adaptively generating high-quality enhancement result for a single overexposed or underexposed input image. Our experimental results showed that the developed SICE enhancer significantly outperforms state-of-the-art SICE methods, and even outperforms MEF and stack-based HDR methods for dynamic scenes. Video enhancement is another important application. To apply the planned ways to videos, we tend to might take into account enlarging our dataset and learning an LSTM (long short term memory) primarily based CNN attention to convert the standard videos to HDR videos. This will be one of our future works.

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