International Journal of Electrical, Electronics and Computer Engineering 7(2): 91-97(2018)

ISSN No. (Online): 2277-2626

Image Enhancement Methods and Applications in Computational Photography

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(Received 07 September, 2018 Accepted 26 November, 2018)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: As seen, the image visibility may be poor due to sudden illumination change and cast of shadows due to nearby object. Due to that, it requires the image enhancement which has been an extensively used process for the better visual perception of the image. Amongst many methods of image enhancement, the histogram equalization is the most commonly used method due to its ease. However, the global histogram equalization method enhances the region in image where sometimes it does not require the manipulation. In order to handle this situation, image enhancement method is proposed that preserve the color component and improve the visibility in the highly contrast reason. In this work, we utilized computational photography technique for local contrast is improved without disturbing the color component of the image. A weighted value is determined to estimate the correct pixels at certain location for the better visibility. Experimental results on some standard datasets show that the proposed method enhances the degraded image effectively without deteriorating the color component of the images.

I. INTRODUCTION

It is observed that the image enhancement is a crucial pre-processing step for many computer vision systems. Sometime, the acquisition devices fail to adapt the high dynamics changes in the scene. So many image enhancement processes has been proposed in the literature that apply on different sets of criteria. As seen, the scene or image may be affected due to many reason such as change in illumination, shadows cast by neighbour object, fail in range handling capacity of device, noise during acquisition, transmission and reception. The above factors may affect and change the actual colour, brightness, contrast. Therefore, the multiscale image enhancement has become the great area of research in computer vision. The challenges before one has to preserve the color, edges, tonal and proper contrast of the images. However, a direct multi-scale image enhancement algorithm capable of independently and/or simultaneously providing adequate contrast enhancement, tonal rendition, active range compression, and accurate edge preservation in a controlled method has yet to be produced.

The improvement in contrast effectively recovers the visual quality that helps to understand the image content and distinguish the object in the region of interest from the background. The simplicity and quickness make the histogram equalization technique as most extensively used tool for image enhancement. Further to improve the local region of the image, the sub-image enhancement technique is proposed in the previous work. A non-linear diffusion equation is proposed to reduce the sudden illumination change in [1]. The diffusion strength in textural image is estimated and the neighbour's suppression is done for the degraded images. In this work, we have proposed the image enhancement techniques that utilize the contrast enhancement in the degraded region and preserve the colour of the input image. The other section of the paper is organized as follows. In Section II, related study is done of some widely used effective image enhancement techniques. Proposed method is explained in Section III. The Experimental results on some standard dataset are presented in Section Iv. The paper is concluded in V.

II. RELATED STUDIES

Authors used a non-linear diffusion equation is utilized to improve the diffusive strength in the textural areas of an image. It achieved two benefits that the method is capable to preserve the boundary of the image due to the sudden illumination and also the halo artifact is eliminated. The second strength of the algorithm is to preserve the texture details of the images under the illumination condition. Since the illumination suppression requires the suppression of the pixels in images that may change the contrast and destroy the original information of the scene [1].

In [2], authors proposed optimization-based framework that employ the convolution term, a fidelity and a prior term that regularizes the pixel value and obtained the image that is resembled with the original one. It utilizes the approximation of the median filtering process with the generalized Gaussian as the distribution model and estimated the pixels of the original one.

The GMM framework is used in this method that accumulates the similar patches using the multivariate Gaussian probability. It improves the local contrast greatly and preserves the tonal value of the images. The idea is patch based clustering approach that provides better goodness-of-fit to statistical properties of natural images [3].

Authors proposed used to preserve the backlight-scaled images as much as possible. It utilizes the luminance and chrominance components which account into an integral manner [4].

In this method the entropy maximization process is used for the tone preserving. It constructed the K-edges maximum-weight path that optimizes the correct brightness and estimated the correct pixels at the spot [5].

In [6], authors used the weighted transformation functions have been used to enhance the contrast of the image. The mean value is used to calculate the similarity and dissimilarity that further calculated the weighted transformation functions. The bin of the histogram is filtered out to increase the dynamic range of the enhanced image.

In [7], the author proposed a real time filtering is proposed to enhance the finger print image. It split a modified anisotropic Gaussian filter into two orthogonal Gaussians and an oriented line Gaussian which in turns developed the architecture to adjust the dynamics of the scene.

In [8], authors used the output image of low resolution camera and the high resolution RGN camera for exploiting the statistical correlation. It used the guided weight function for the dependency modelling that updated the depth of the image with a optimal restoration.

In [9], the authors proposed the histogram modification framework to enhance the colour and depth of the images. It partitioned the image into subinterval using the Gaussian mixture model. The spatially similar pixels having the same intensity level is grouped together. A mapping is proposed to enhance the depth and contrast of the image without over enhancing the contrast of the image.

In [10]. The author proposed an adaptive contrast enhancement algorithm by preserving the one dimensional histogram and the histogram obtained by gray level difference between the two neighboring pixels. The one dimensional histogram is utilized in enhancing the contrast of the image while 2d histogram used to improve the detail of the frequently occurring the non-smoothing area in an image.

III. PROPOSED WORK

In my framework, the image formation process is modeled as a two-step process. In the first step, low-resolution images $\{g_i\}$, i = 1, ..., N, are generated from a high-resolution image f through a sequence of linear operations: image warping $\{M_i\}$, image blurring B with a common space-invariant point spread function (PSF), and down sampling D. This first step of the imaging process can be formulated as

$$g_i = DBM_if \quad \ldots(3.1)$$

In the second step, a single-image blur process is formulated as:

$$ge_i = H_ig_i, \quad \ldots(3.2)$$

where g_i is the latent image, H_i is the matrix associated with the blur kernel, and ge_i is the blurred image.

The reason I separate the imaging process into two steps is that large motion blur will be dealt with and therefore the motion field from the input images $\{ge_i\}$ cannot be reliably estimated. I first need to deblur $\{ge_i\}$ to obtain the latent images $\{g_i\}$, and then estimate motion field, which will then be used in the super-resolution step.

Because the estimated blur kernels and therefore the deblurred images $\{g_i\}$ may not be accurate, I will use a weighted cost function for the super-resolution restoration step, where a weight w_i associated with an input image reflects the reliability of the corresponding kernel estimate and the deblurred image.

The framework to achieve super-resolution of motion blurred images is given in Fig. 3.1. The motion deblurring step estimates the motion blur kernels $\{H_i\}$ and the latent (deblurred) images $\{g_i\}$ from the input images $\{ge_i\}$. The weights $\{w_i\}$, reflecting the reliability of motion deblurring, are estimated. The optical flow step estimates the motion vectors $\{M_i\}$ between the reference image g_r which is selected from N deblurred images and the input images $\{g_i\}$.

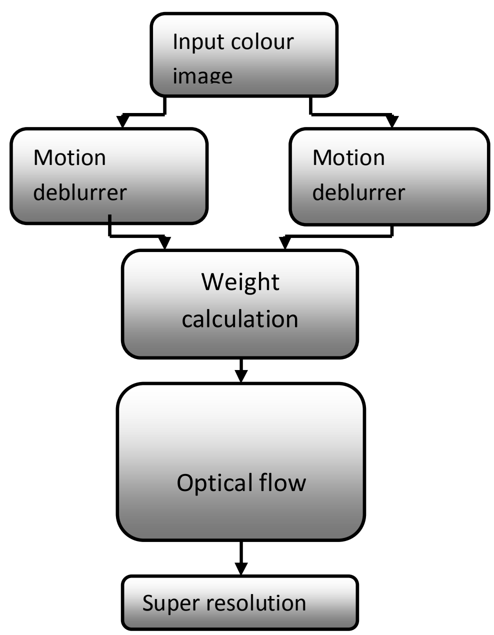


Fig. 3.1.

In the last step, I apply weighting-based super-resolution where motion deblurred images $\{g_i\}$, estimated motion vectors $\{M_i\}$ and calculated weights $\{w_i\}$ are taken as input, with g_r set as the reference image. The super-resolution image is denoted as f.

$$E(g_i) = k g e_i - H_i g_i k_1 + \lambda k\ g_i k_2, \quad (3.3)$$

Single image motion deblurring using TV-L1 model My single image deblurring algorithm consists of three steps. First, the blur kernel is initial-ized using the kernel initialization method presented by Cho. Second, the kernel is refined through hard thresholding by setting kernel values that are less than the 10 percent of the maximum value in the kernel to 0. While Xu also presented a kernel refinement step, it is computationally costly and did not improve significantly over the simple hard thresholding method mentioned. Finally, the latent image is estimated from the estimated blur kernel and original blurred image. It is well-known that L2 norm in the data fidelity term is not effective to avoid outliers; in addition, L2 norm in the regularization term also results in over-smooth restoration. To achieve robustness to outliers as well as sharp results, I used the TV-L1 based method, which minimizes the energy function where H_i is the estimated blur kernel, ge_i is the original blurred image, g_i is the latent image to be estimated, and λ is the regularization parameter. Clearly, it brings non-linearity and non-differentiability to both data and regularization terms, resulting in computational difficulty to solve this problem. To overcome the computational difficulties, Wang proposed an alternating minimization method based on half quadratic splitting to solve the TV-L1 optimization problem. I followed the exact algorithm to achieve motion deblurring. In my implementation, the regularization parameter λ is set to be 10.

Optical flow method for motion estimation between deblurred images.

Given the motion deblurred images, the motion vectors are estimated. The reason motion estimation is done with deblurred images is that motion blur may degrade the accuracy of motion estimation significantly, causing undesired artifacts in the restored image. As shown in Figure 3.1, g_r is chosen as the reference image and $\{g_i\}$ are chosen as target images for SR restoration. I first up-sample both the reference image and target images to the desired high-resolution lattice, and then estimate the motion fields between the upsampled reference image and the upsampled target images using the optical flow method.

This optical flow method is based on a robust data term and discontinuity-preserving total-variation regularization and results in accurate dense flow fields. Using this method, I obtain the motion fields $\{M_i\}$ between the reference image g_r and the target images $\{g_i\}$.
(Note that $M_r = 0$.)

Weighting-based super-resolution (SR) restoration method.

The standard SR algorithm with Tikhonov regularization minimizes the following cost function:

$$C(f) = k g_i - DBM_i f k^2_2 + \lambda k\ f k^2_2 \quad (3.4)$$

where λ is regularization parameter. In order to be able to deal with estimation errors from the motion deblurring step, I modify this cost function to include the reliability of each motion deblurred image:

$$C(f) = w_i k g_i - DBM_i f k^2_2 + \lambda k\ f k^2_2 \quad (3.5)$$

where w_i is the weight associated with the motion deblurred image, indicating the contribution of the corresponding motion deblurred image in the overall cost to be minimized. It is reasonable to assign more weights to reliable motion deblurred images, whereas less weights to unreliable motion deblurred images.
Each weight will be calculated using the reconstruction error $k g e_i - H_i g_i k_2$. A small reconstruction error indicates accurate blur kernel estimate and deblurred image; while a large reconstruction error indicates less reliable kernel estimate and deblurred image. The weight should then be inversely proportional to the reconstruction. The un-normalized weight we_i is defined as

$$we_i = k g e_i - H_i g_i k_2 + \varrho \quad (3.6)$$

where ϱ is a small scalar to avoid singularity. Since we have more confidence in the well deblurred images than poorly deblurred images, we need to normalize the weights and assign more weights to well deblurred images than to poorly deblurred images, the normalization
is defined as

$$w_i = (we_i/\max\{we_i\})^4 \ldots(3.7)$$

where the fourth power is chosen empirically. The objective function in Equation 3.5 is a weighted least squares problem with Tikhonov regularization. Due to the pixel-wise warping operation in the imaging process, a closed form solution is not possible; however, the optimization can be achieved iteratively using the gradient descent technique.

Starting with an initial estimate f(0), the updated estimate at the *n*th iteration is

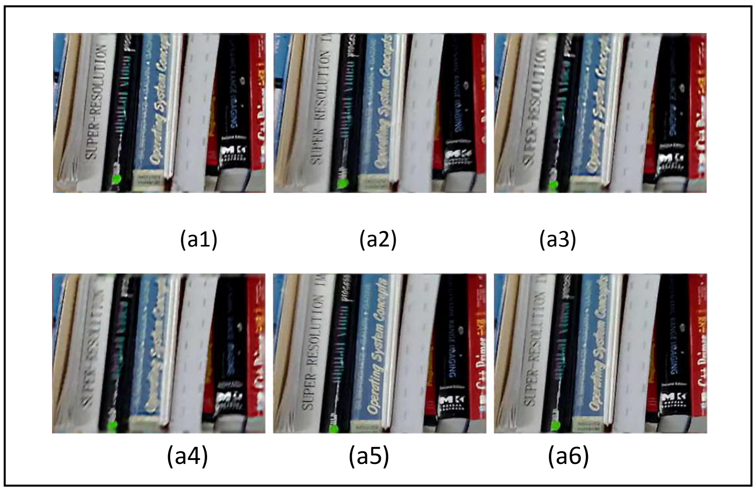
$$f^{(n+1)} = f^{(n)} - \mu \nabla C(f^{(n)}$$
$$= X_i^{f^{(n)}} w_i M_i^T B^T B^T D^T \left(g_i - DBM_i f^{(n)}\right) -$$
$$\mu \lambda \nabla^T (\nabla \mathrm{f}^{(n)}) \quad (3.8)$$

where μ is the step size, which we empirically set to 0.1 in my experiment. Also, in my experiment, I empirically set regularization parameter λ to be 0.2. The stopping condition for gradient descent method is predetermined number of iterations, which is set to be 80 in our experiment.

While $\{H_i\}$ are estimated for all input images and incorporate large motion blur as well as other blur types such as out-of-focus and sensor blurs, in my model I also have the blur B which is common to all images. The simplest choice for this blur is identity matrix, which corresponds to a blur kernel of delta function. Instead of a delta function, a small blur kernel is also possible which would model spatial averaging before down sampling. (In my implementation, I used a 3 × 3 Gaussian kernel with standard deviation equal to 1.)

IV. RESULT AND ANALYSIS

I conduct an experiment to examine the performance of the proposed super-resolution method under unknown motion blur kernels and arbitrary mutual motions. In the experiment, a video sequence is captured with a hand-held camera and six of the video frames are used to reconstruct a super-resolution image. The input images are shown in Figures 4.1(a1)-4.1(a6). The estimated blur kernels corresponding to these images are given in Figures 4.1(b1)-4.1(b6), respectively; and the motion deblurred images are given in Figures 4.1(c1)-4.1(c6).



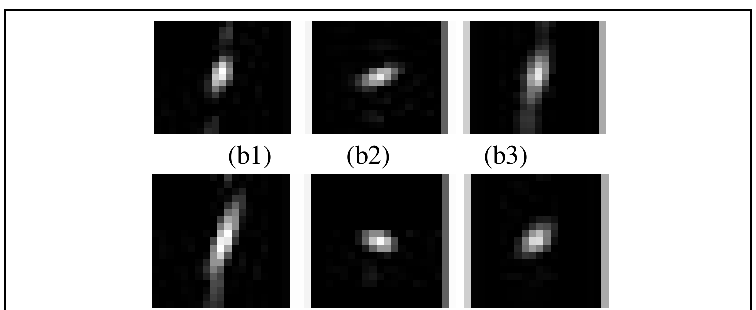
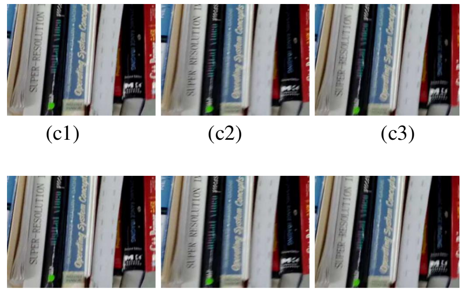


Fig. 4.1(b1)-4.1(b6),

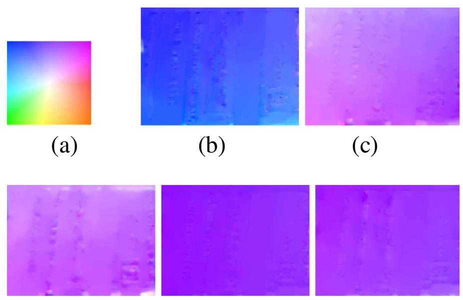
It is clear that the motion deblurring worked well for some input images, such as the one in Figure 4.1(a5), but not as well for some others, such as the one in Figure 4.1(a4). The weights $\{w_i\}$ are 0.23, 0.67, 0.14, 0.15, 1.0 and 0.74, respectively; and they indeed reflect the quality of motion deblurring as can be seen from Figures 4.1(c1)-4.1(c6). To do super-resolution restoration, first, the motion fields need to be estimated. The first input image is set as the reference; and Figures 4.2(b)-4.2(f) show the estimated motion fields from the motion deblurred images in Figures 4.1(c) to the reference image in Figure 4.1(c1).



(c1) (c2) (c3)

(c4) (c5) (c6)

Fig. 4.1(c1)-4.1(c6),

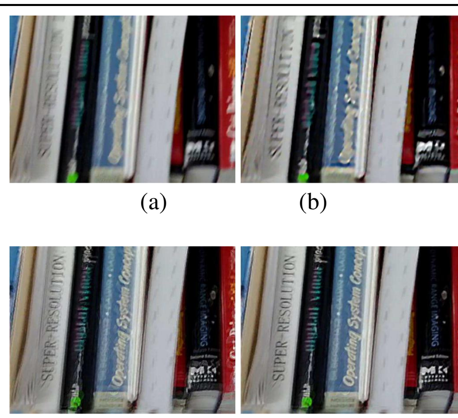


(a) (b) (c)

(d) (e) (f)

Fig. 4.2(a-f)

Next, super-resolution restoration is applied to improve the resolution by a factor of two (in Figure 4.3). Figure 4.3(a) shows the bilinearly interpolated reference image; and Figure 4.3(b) shows its motion deblurred version. Figure 4.3(c) shows the result with standard super-resolution without any weights; Figure 4.3(d) shows the result with the proposed super-resolution algorithm where the weights are included. While no significant difference between the standard and proposed algorithms is visible in Figure 4.3; We can observe that the proposed algorithm has less artifacts than the standard algorithm in the zoomed-in regions given in Figure 4.4.



(a) (b)

(c) (d)

Fig 4.3 (a-d)

Fig. 4.4

The effect of including weights becomes dramatic when the initial estimate is very poor. Figure 4.5 provides results when the fourth input image, given in Figure 4.1(a4) is set as the reference.

Fig. 4.5

As seen in the zoomed-in regions (Fig. 4.6), the proposed algorithm provides much better result than the standard algorithm.

Fig. 4.6

CONCLUSION

Computational photography has the tendency to bring novel applications and experiences to industry. Apple Inc. introduced HDR photos to iPhone4 or later which enables the user to combine three separate exposures into a single HDR photo. Adobe Inc. incorporated focus stacking as new feature into Photoshop which enables the user to create all-in-focus image from multiple images with narrow depth-of-field. Also, in Max 2011 Sneak Peak, Adobe product team announced the new feature in Photoshop that allows the user to remove blurriness from digital photos caused by camera shake.

Lytro Inc. brings light field camera to the common customers which allows the user to refocus the photo to either background or foreground after the photo is taken. In my dissertation, I also bring computational photography applications such as super-resolution imaging, HDR imaging and focus stacking to PC and/or Android platform. The emerging market of computational photography indicates that vast investigation of image enhancement techniques in computational photography has been motivated by research teams in industry from the marketing point of view. Image quality is degraded by image formation process in traditional photography. As a consequence, image enhancement methods seek to compensate for image degradations such that it can escape the limitations of traditional photography.

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