IMAGE RESTORATION BY INTEGRATING MISALIGNED IMAGES USING LOCAL LINEAR MODEL

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Abstract
A new image integration technique is proposed for integrating a flash and long-exposure image pair to capture a dark scene or to capture an image under low lighting conditions without incurring blurring or noisy artefacts. Most of the existing methods require perfectly-aligned images for the integration, which is often a burdensome restriction in practical use. We address this issue by an image integration method based on local linear model which transfers the colours of the flash images locally using a small fraction of the matched pixels between the image pair. The proposed method makes it possible to integrate the colour of the long exposure image with the detail of the flash image without causing any harmful effects to its contrast, where there is no need for perfect alignment between the images in our new integration method. We show that our method successfully outperforms the other conventional image integration and reference-based colour transfer methods for challenging misaligned data sets.

Index Terms: Local color transfer, Image registration, Image integration, pixel selection, SIFT algorithm.

I. INTRODUCTION

The amount of light captured by a camera sensor under low lighting conditions is often inadequate for recording an image with a clear contrast. The problem can be addressed using some photographic techniques. Reducing the shutter speed increases the brightness of the image, but it also easily causes motion blur due to camera shakes or object motion. Amplifying the signals by setting a high ISO sensitivity (before being stored as pixel values) can shorten the exposure time, and hence, reduce the motion blur, but it also enhances the sensor noise as well. Image restoration problems, such as denoising and deblurring, have been extensively studied in the past as in [1],[12]and[13]. Despite these successes, restoring a sharp image from a very noisy or blurred image remains a challenging problem. One simple but efficient approach to exceed the limit is to use multiple images. Many literatures discuss significant improvement in image quality by using an additional image such as a flash image as in [8]-[10]. In [8]-[10], they combine the features of the images to integrate the colorfulness of a non-flash image with the vivid contrast of a flash image. Some of these methods have sufficient deblurring or denoising capabilities especially under dim lighting conditions, but they require perfectly aligned images. This is a severe restriction in practical use, since a camera needs to be fixed on a tripod, and a scene must be stationary. In [3] and [7], they propose colour grading methods for a misaligned image pair. Their methods work well even for scenes with non-rigid motion, but they sometimes fail when the images have large lighting or colour differences. We propose a new image integration approach for a misaligned image pair. In our framework, two kinds of images are used to restore an image with vivid colours and a high contrast under dim lighting conditions. One is a long-exposure image taken at a slow shutter speed and low ISO sensitivity. The image is blurry due to the low lighting illumination. The other image is a flash image, which is taken with a flash light and a faster shutter speed. The flash image has a sharper contrast, but contains unnatural colour caused by the artificial light. Our method, like the previous approaches as in [8]-[10], aims to combine the preferable features in both images to acquire a sharp image in a low lighting environment. Our approach does not require a perfect alignment between the images by virtue of our new integration principle and can yield an image with natural colours and a sharp contrast even when the illumination in the images largely differ. This paper begins with a review of the related work including image integration, colour transfer, and correspondence algorithms. Next, our method is described in detail. Furthermore, a performance comparison with conventional method and a discussion is presented.

II. RELATED WORK

A. Image Integration for restoration of dark scene

Restoring a high quality image from a blurred or very noisy image is a challenging task as in [11] and [13]. Deblurring from a single image requires simultaneous estimation of a latent clear image and the blur kernels, which often comes down to an ill-posed problem. Some methods as in [16] and [17] use multiple images to improve deblurring performance. Some of them yield accurate kernel estimation and high quality deblurring but it is difficult to completely avoid blur and ringing artefacts. Furthermore, the quality of the estimation may be further degraded when the kernel is time-varying, and thus, these approaches can barely handle any blurring due to partial object motion. Despite the existence of many sophisticated denoising methods as in [1], [12],[18] it is still hard to completely remove noise without degrading the image contrast. The use of a flash/no-flash image pair as in [8] and[9] can significantly improve the denoising performance. Petschnigg *et al.* [8] combine the colourfulness of the no-flash image and the vivid contrast of the flash image by using a joint bilateral filter, and later made some improvements in [9] and [19]. In [10] it restores an image using a flash/long-exposure image pair to restore a dark scene. A significant drawback with this is that all of these methods require a perfectly aligned image pair, and even a little misalignment yields serious degradation of the result.

B. Colour Transferring, Colorization, and Other Related Methods

The proposed integration technique can also be thought of as colour transferring. Reinhard *et al.* [5] introduced a colour correction (also called colour grading) approach that transfers the colour characteristics by matching the statistic features between two images. Pitié *et al.* [20] achieves the colour transfer by using colour histogram matching, and it was later improved by introducing a constraint in a gradient domain as in [2]. These approaches based on the histogram approximation can be flexibly applied to many situations. However, they lack careful consideration in the spatial domain, and thus, the resultant images sometimes tend to have unnatural or fake colours, especially when colour illumination spatially varies. Some papers such as [21] and [22] proposed example-based colorization. This method finds similar textures in an image pair and transfers the colour of the example to the gray-scale target image. The example-based process [30] is automatic, but additional segmented references are needed. This automatic colorization can be applied to the colour transfer problem. However, representative colours should be precisely specified, and a colour mismatch may yield catastrophic damage in the resultant images. HaCohen *et al.* introduced a method (known as NRDC) for colour grading [3].That method looks for the dense correspondence between two inputs and then designs the tone curves of the RGB channels using the correspondences obtained. In [7], Hwang *et al.* find a colour mapping operator for each colour and achieve an accurate colour transfer by applying the mapping operator. Both these methods [3] and [7] work well for misaligned images. However, both of them may fail for images with large colour differences or local changes in the lighting, as is shown in the experiments. The proposed method partially resembles inpainting techniques [23] and [24]. In this situation, however, we assume that only a small number of correspondences can be specified, and most of regions are given as holes. Thus it is difficult to directly apply the inpainting methods to this problem. On the other hand, this method has the source image (i.e. flash image), and this method takes full advantage of it.

C. Correspondence Algorithms

Correspondence algorithms are a key technique in the integration of a misaligned image pair [5]. The classical approaches such as the SIFT descriptor [21] expresses local features in the images using feature vectors. The SIFT descriptor is invariant to the scaling and rotation and robustly works for various lighting conditions, as confirmed experimentally in [21]. Other sophisticated dense correspondence algorithms [3] and [5] have the capability to achieve more robust matching than the sparse correspondence methods especially for an image pair with large displacement or non-rigid motion. The NRDC [3] finds a dense correspondence between two images by using a modified version of the generalized *Patch Match* [25], and then, designs the RGB tone curves on the basis of that correspondence. While this method can handle images with non-rigid motion, it does not work well when the local lighting spatially varies and the colour balances locally change. The objective of our method is similar to the one in [3]. While the NRDC achieves robust correspondences for images with large displacements, it was sometimes erroneous in our examples. We show a detailed comparison in Sec.V.

III. IMAGE RESTORATION USING LOCAL LINEAR MODEL

The overall procedure of the proposed method is shown in Fig. (1). A pair of two images is used as the input for our algorithm. One image is taken with a flash light and the other is taken under natural lighting. The two input images are a *flash image* **P** and a *long-exposure image* **Q**. The flash image is taken with a low ISO sensitivity and a short exposure time. With the help of the flash light, the flash image has a high SNR and a sharp contrast, but contains unnatural colour caused by the flash light. The long-exposure image is taken at a slower shutter speed and long exposure time. In this framework, the image is blurry but has more natural colour tone than the flash image. These two images may be misaligned due to motion blur and camera view change as shown in Fig. 3(a) and Fig. 3 (b) as in [1]. Our purpose is to reconstruct a high quality output image from the before mentioned image set **P** and **Q** by combining their features. We start with the image registration process through pixel matching between the two images. This method uses only a sparse set of matched pixel pairs. Then we transform the colour in the whole flash image based on the sparse set. This process ensures robustness to local illumination change, and it works well even if only a fraction of reliable matched pixel pairs are found. Our algorithm is briefly stated as follows:

- *Image registration using SIFT*

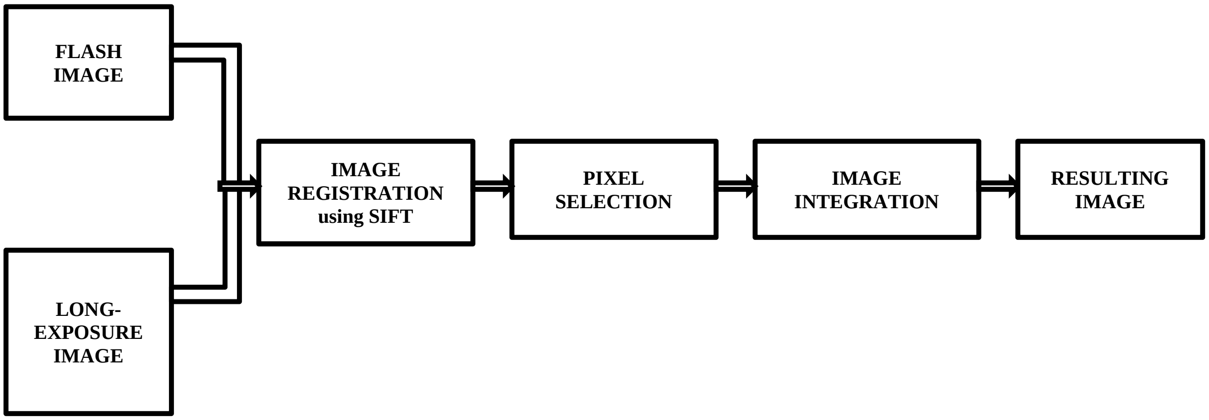
In this step, first find the matching between the two input images. Based on the matching between them, we transform the long-exposure image to align the image set (Fig. 3(c)). We adopt the SIFT flow [5] algorithm for this purpose.

- *Pixel selection*

We select only a small number of the matched pixels from the aligned image pair, which improves the robustness to local illumination change.

- *Image integration*

Finally the two images are integrated to obtain a high quality image. The image integration procedure is based on the local linear model (LLM). This model integrates the colour information of the long-exposure image with the details of the flash image while maintaining its local features. The three steps are explained in detail in Sec. III-A, III-B and III-C, respectively .



A. Image Registration using SIFT

Image registration is the process of aligning two or more images of the same scene. It enables us to compare common features in the two images. This is necessary to compare or integrate/fuse the data obtained from multiple images. This process involves assuming one image as the reference image and applying transformations to the other image so that it aligns with the reference image. For this purpose, we first search for matching between the two input images. Since the two input images contain different illuminations, the feature based methods perform well. So, we use sift flow to detect initial set of correspondences between the two images.

Finding key points using SIFT: SIFT algorithm consists of four steps.

Scale-space extrema detection: Search over multiple scales and image locations and extract key points which are invariant to scaling using DOG pyramid.

Key point Localization: Determines location and scale for each key point and eliminates low contrast key points and edges.

Orientation Assignment: Assign one or more orientations to each key point to calculate the rotational invariance.

Key point Descriptor: Uses local image gradients at the selected scales and generates feature vectors for each key point. The key point is uniquely identified by this feature vector. SIFT flowchart is shown in Fig. 2 as in [22].

Now, we have a list of key point's features from the two images. Compute the Euclidean distance from each key point in image 1 to all the key points in image 2. Key points between two images are matched by identifying their nearest neighbours with minimum Euclidean distance. But in some cases, the second closest-match may be very near to the first. It may happen due to noise or some other reasons. In that case, ratio of closest-distance to second-closest distance is taken. If it is greater than 0.8, they are rejected. It eliminates around 90% of false matches. Based on the correspondences obtained, it transforms the long-exposure image to align the image set. The aligned image is represented by and is shown in Fig. 3(c). The pixels in the aligned region are represented by a set and are shown in Fig. 3(d). Calculate registration error between flash image and aligned image to detect the accuracy of alignment algorithm. The registration error is shown in Fig. 3(e)

Although SIFT flow algorithm finds correspondences and fulfil a reliable image alignment, some misaligned pixels still remain when the displacement between two images is large. To select reliable pixel pairs from the aligned image, we go for pixel selection.

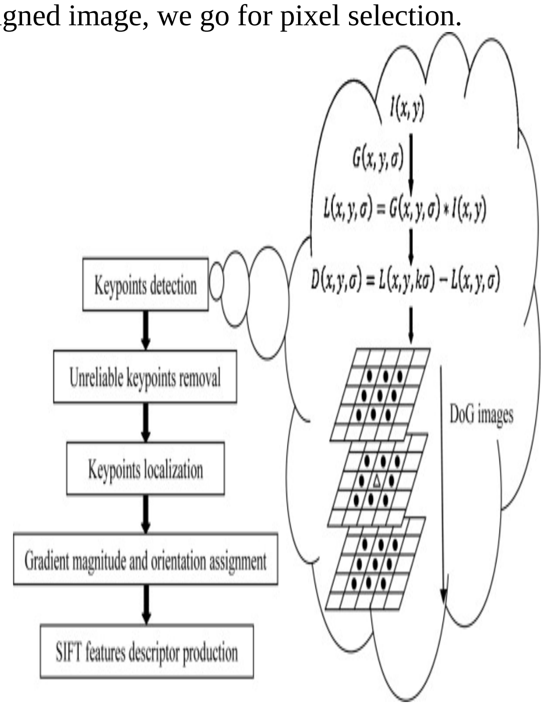


Fig. (2) Flow chart for SIFT flow

Fig.3 (a) Flash Image P

Fig.3 (b) Long Exposure Image Q

Fig.3 (c) Aligned Image Q'

Fig.3 (d) Aligned Region S'

Fig.3 (e) Registration Error

B. Pixel selection

The roughly aligned images obtained usually have mismatches since the long exposure image is blurred. So, to select the reliable pixel pairs from the aligned image set, we calculate the difference in local variance between the flash image and the aligned image. It is represented by

$$d_i := \left|\sigma^2_{p^Y,i} - \sigma^2_{q'^Y,i}\right| \tag{1}$$

Where, $\sigma^2_{p^Y,i}$ is the local variance of the flash image P and $\sigma^2_{q'^Y,i}$ is the local variance of the aligned image

The Local variance is defined as the average of sum of the squared differences of each Pixel in the distribution from the mean. If the difference in local variance between two image pixels is large i.e., >10^-2 as in [1], that pixels are removed from the aligned image. The remaining reliable pixels are represented by a set S such that

$$S := \{s \varepsilon S' \mid d_s \leq \tau\} \tag{2}$$

The remaining reliable pixels of the aligned image are used as representative pixels for Image integration.

Fig. (4) Reliable Pixels

C. Image Integration using Local color transfer

Image integration means given two images, produces a third that has maintained the semantic content of the one while acquiring the colours of the second. Here it is required to change colour of the Flash image P into natural colour based on the colour of the long exposure image Q. One of the simplest approaches for the colour correction is to globally apply colour transform to the whole flash image P to fit Q'. The global transforms sometimes work well, but they do not adapt to local colour changes, which is a significant drawback especially when only a fraction of pixel correspondences are found. In this section, we address the problem by introducing a method based on the local linear transform. The following procedure integrates the colour information of the long-exposure image and the details of the flash image. So, Reinhard's Image Colour Transfer as in [5] is used for image integration. Here, colour transfer is done locally i.e.; patch wise as in [4]. The algorithm used for local colour transfer goes like this:

Step 1: Input a source and a target image. The source image contains the colour that we want our target image to mimic. Here the source image is long-exposure image and target image is flash image.

Step 2: Convert both the source and the target image to the $l\alpha\beta$ Colour space. The $l\alpha\beta$ colour space models perceptual uniformity, where a small change in an amount of colour value should also produce a relatively equal change in colour importance.

Step 3: Split the channels for both the source and target images for processing.

Step 4**:** Compute the mean and standard deviation of each of the $l\alpha\beta$ channels for the source and target images.

Step5: Subtract the means of the $l\alpha\beta$ channels of the source image from target channels.

$$l^* = l - l_s \qquad \alpha^* = \alpha - \alpha_s \qquad \beta^* = \beta - \beta_s$$

Step 6: Scale the resulting target channels of above step by the ratio of the standard deviation of the target divided by the standard deviation of the source.

$$l' = \frac{\sigma_t^l}{\sigma_s^l} l^* \qquad \alpha' = \frac{\sigma_t^\alpha}{\sigma_s^\alpha} \alpha^* \qquad \beta' = \frac{\sigma_t^\beta}{\sigma_s^\beta} \beta^*$$

Step 7: Add in the means of the target $l\alpha\beta$ channels to the resulting channel values obtained above.

$$l'' = l' + l_t \qquad \alpha'' = \alpha' + \alpha_t \qquad \beta'' = \beta' + \beta_t$$

Step 8: Merge the channels back together.

Step 9: Convert the image back to the RGB color space from the $l\alpha\beta$ color space.

The above mentioned processing steps are applied to each local patch of the image i.e., 3x 3 matrixes as in [4]. Thus, the resulting image will have the details of flash image and colors of long-exposure image.

IV. PERFORMANCE EVALUATION METRICS

A. Entropy

The entropy is a measure of information content of an image. Entropy is sensitive to the noise an unwanted rapid fluctuations. The image with high information content would have high entropy [14].

$$He = \sum_{i=0}^{L} h_{I_f}(i) \log_2 h_{I_f}(i) \tag{3}$$

The unit of entropy is bits/pixel.

B. Peak signal to noise ratio (PSNR)

Its value will be high when the reconstructed and reference images are similar. Higher PSNR value implies better reconstruction. The peak signal to noise ratio is computed as:

$$PSNR = 10\log_{10}\left(\frac{L^2}{\frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}\left(I_r(x,y) - I_c(x,y)\right)^2}\right) \tag{4}$$

Where, L is the number of gray levels in the image

C. Structural Similarity Index Measure (SSIM)

The Structural Similarity (SSIM) Index quality assessment index as in [15] is based on the computation of three terms, namely the luminance term, the contrast term and the structural term.

$$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \tag{5}$$

Where, μ_x , μ_y, σ_x, σ_y and σ_{xy} are the local means, standard deviations, and cross-covariance for images x, y.

By default,

- C1 = (0.01*L).^2, where L is the specified Dynamic Range value.
- C2 = (0.03*L).^2, where L is the specified Dynamic Range value.
- C3 = C2/2

D. Colour Histogram

A colour histogram is plotted for color comparison of images using imhist command of MATLAB for red, blue and green bands. The histogram is plotted for pixel count against gray levels.

V. RESULTS AND DISCUSSION

The Image restoration process using Local Linear model is implemented using MATLAB. Here the misaligned images are taken as input, the input images are Flash image and Long Exposure image are shown in Fig. 3(a) and 3(b). The resultant integrated image with respective histogram is shown in Fig. (5).

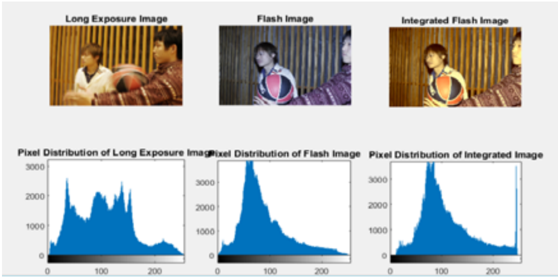


Fig. (5) Resultant Image

A long exposure image contains natural color but the details are not clear whereas in flash image details are clear but color is not natural due to artificial lighting. So, in this paper the misaligned images are integrated using local linear model then the resultant image integrates details of flash image with color of long exposure image.

The proposed method is compared with existing method using various sets of images and the resultant images are listed in Fig. 6.

The color comparison of input long exposure image Q with the Existing image and proposed image is shown in Fig.7 (a), (b), (c) respectively.

The performance evaluation metrics which are compared with existing method Non-Rigid Dense Correspondence Algorithm is shown in Table 1.

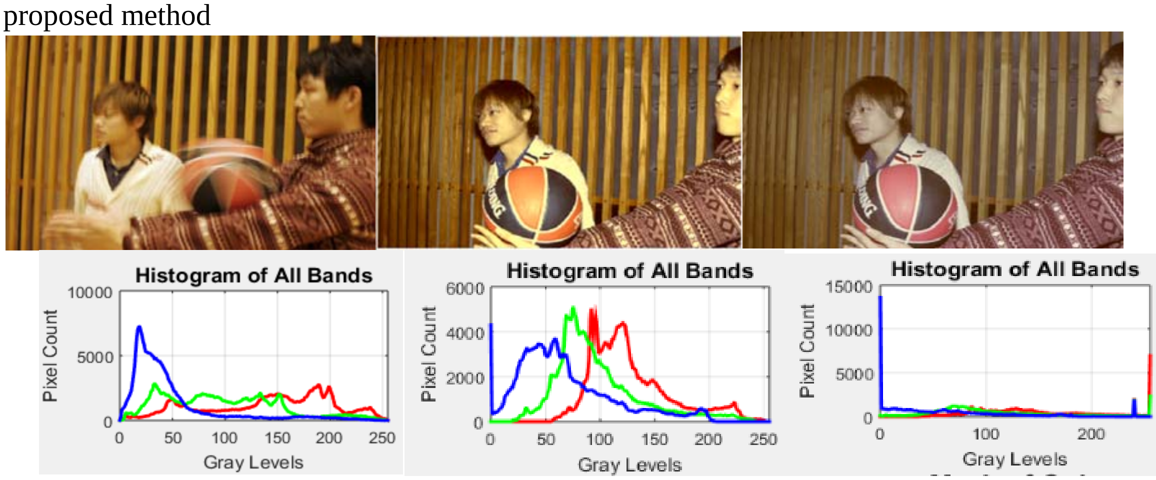
Table1. Comparison

Performance Metrics	Existing Method	Proposed Method
Entropy	7.5037	**7.6846**
PSNR	15.9183	**16.3510**
SSIM	0.9508	**0.9581**

Hence, from the comparison it can be observed that Local Linear Model gives better results as compared to the existing method named Non-Rigid Dense Correspondence Algorithm. The metrics shown with bold indicates better results.

(a) *(b)* *(c)* *(d)*

Fig.(6) Comparison with Conventional method (a) Flash Image (b) Long exposure image(c) NRDC (d) proposed method



(a)Long Exposure image Q (b) Existing method (c) Proposed method

Fig.7 Comparison of colour information with conventional method

VI. CONCLUSION

An image integration method that preserves the detail of a flash image for a misalignment image pair was presented in this paper and various performance evaluation metrics are calculated and compared with existing method[3]. The conventional methods for colour transfer yield an unnatural image and incur low contrast. We introduced the LLM into the image integration method to transfer the colour of long exposure image to the flash image while maintaining the natural colour of long exposure image and high-contrast of the flash image. This method restores more natural images without experiencing contrast deterioration.

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