Structure from Motion with Integrated Deblurring

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***Abstract*—This paper studies structure from motion (SfM) using non-blurred and blurred images. In the studied SfM, a deblurring process is integrated. A blurred image is firstly matched to a non-blurred image by a feature point matching generally equipped in the SfM systems, the blurred image is, then, deblurred by a scheme which uses a matched pair of blurred and non-blurred images. The studied SfM increases images from which feature points can be extracted more and reconstructs three dimensional model more accurately. Experimental results show the effectiveness of this deblurring integration to SfM.**

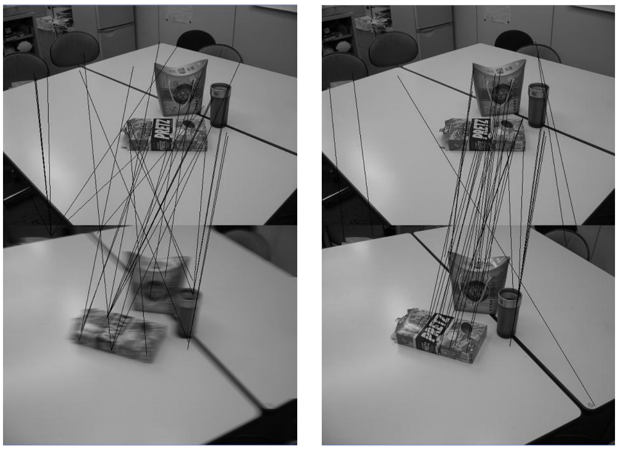
I. Introduction

A structure from motion (SfM) is a method for obtaining information about the geometry of three dimensional scene from two dimensional images which are captured from various perspectives accordingly to a well organized capturing plan. It was too much cost to reconstruct three dimensional model while SfM enable to reconstruct at low cost than before. SfM techniques are used in a wide range of applications such as machine interface, augmented reality system, autonomous walking robot, and so on.

The most fundamental problem in SfM is to reconstruct positional relation of a three dimensional object from corresponding feature points between multiple two dimensional images. In general, to correspond feature points, images should be aligned well in advance. Meanwhile, SfM with consumer generated images which acquired from non-controlled viewpoints by different people at various time have been studied these days [1], [2]. In such application, not only non-blurred images which suit for SfM but also blurred images may be employed for keeping various perspectives. Such images are difficult to extract or match feature points and prevent the system from reconstructing the three dimensional object.

Deblurring image is also an important issue in image processing. Since motion blur is one of the most common artifacts in digital photography, deblurring methods have been studied for many years. Because a blurred image is modeled as a convolution of the original image and the blur kernel, estimating blur kernel is required for non-blind deconvolution. Blur kernel is obtained from blurred and noisy image pair have been proposed [3]. In addition, align method using kernel sparseness has been exploited [4].

This paper studies SfM with non-blurred and blurred images. A blurred image is firstly matched to a non-blurred image according to feature points matching in ordinary SfM systems, and the blurred image is then deblurred by a scheme, e.g., [3]. By this deblurring integrated to SfM, the object reconstruction is improved.



(a) Blurred. (b) Non-blurred.

Fig. 1. Feature point matching.

II. Preliminary

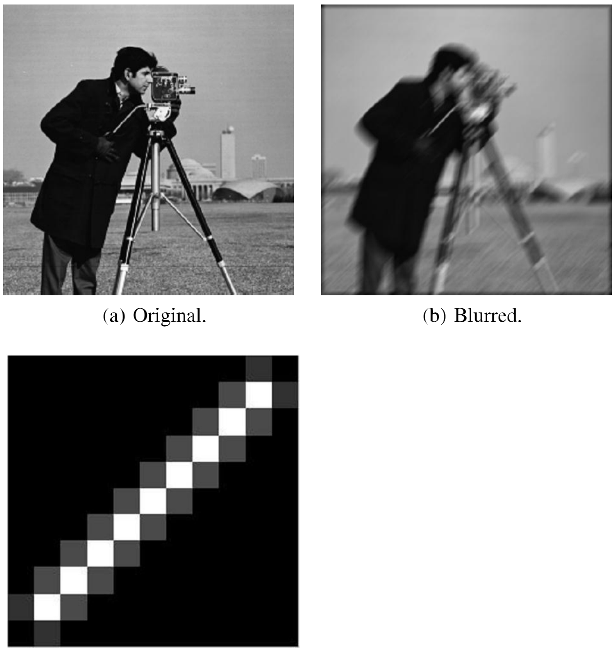
This section firstly gives an overview of a typical SfM system. Then, SfM using images acquired from non-controlled viewpoint by different people at various time is mentioned. In addition, a deblurring method using blurred and non-blurred images is briefly introduced.

A. SfM System Overview

Input images are two dimensional images captured the same scene with different perspectives. To obtain corresponding relations between these images, feature points are extracted from each individual image. Then, the matrix which suggests the corresponding relation is generated. Three dimensional coordinates of each feature points and camera position is estimated by factorization of the matrix.

B. Reconstruction from Non-Aligned Images

Several works have proposed SfM systems with images captured in various angles by many different people, i.e., not along with a well organized capturing plan [1], [2]. Input images are collected from a large public image database by feature point matching. Such a huge number of images seem to be effective to reconstruct buildings or streets. However these images are not well aligned, so it is difficult to extract many feature points and it is likely to find incorrect corresponding feature points between images. These images may bring a inaccurate reconstruction results. Figure 1 reveals the effect of a blurred image on extracting and matching feature points.



(a) Original. (b) Blurred.

(c) Blur kernel.

Fig. 2. An original image is blurred by a blur kernel.

Less feature points are extracted from a blurred image shown in Fig. 1 (a) than from non-blurred image shown in Fig. 1 (b), and it makes inaccurate feature point matching.

C. Deblurring

To deblur an image, the SfM system studied in Sect. III uses a deblurred scheme [3]. While this scheme uses the corresponding noisy but non-blurred image for deblurring a blurred image, this study uses a non-blurred images taken from a different angle which is matched to the deblurred image is used. The scheme [3] has three steps.

1) Kernel estimation using Landweber method.
2) Alignment using sparseness prior.
3) Deconvolution using Richardson Lucy method.

Subsequent sections provide each step of the scheme.

1) Kernel Estimation using Landweber Method: An input blurred image B is represented by the convolution of the original image I and the blur kernel k, i.e.,

$$B = I \otimes k$$

where $\otimes$ is the convolution operator. Kernel k can be computed in the linear least-squares sense. The iterative Tikhonov regularization can be expressed as an iterative matrix inversion algorithm which starts with an initial guess and coverages to $k = I^{-1}B$ as follows.

Step 1. $K^0 = \delta$.
Step 2. $K^{n+1} = K^n + \beta\left(I^T - \left(I^T I + \lambda I\right) K^n\right)$.
Step 3. Set $K_i^{n+1} = 0$, if $K_i^{n+1} < 0$, and normalize

$$K_i^{n+1} = \frac{K_i^{n+1}}{\sum_i K_i^{n+1}}. \quad (1)$$

Here, δ is the Dirac delta function, β is the convergence parameter which controls the convergence, and λ is the regularization parameter with a default value of 5. However, since I is unknown, a non-blurred image captured from different angle from I is used in place of I in the deblurred part integrated to the studied SfM system.

2) Alignment Using Sparseness Prior: In this process, a scheme [4] is used. The brightness value in the kernel suggests the duration of the camera exposure. Fig. 2 shows a non-blurred image, a blurred image from the non-blurred image, and the blur kernel used to blur the non-blurred image. That is, Fig. 2 (a) is blurred to Fig. 2 (b) by Fig.2 (c). It is known that all kernels tend to be sparse as shown Fig. 2 (c). Most values in the kernel are zeros (black) and the non-zeros form curve-like paths:

$$p(k_i) \propto \left(w_1 \exp\left(\frac{-K_i}{\beta_1}\right) + (1 - w_1)\exp\left(\frac{-K_i}{\beta_2}\right)\right),$$

where k_i is the i-th element in kernel k, and w_1, β_1, and β_2 are parameters of two exponential distributions. The parameters of two exponential distribution of the kernel k is

$$P(k) = \prod_i p(k_i). \quad (2)$$

In addition, the following equation measures the sparseness of a given kernel.

$$E_{\text{sparse}}(k) = -\frac{1}{Z}\sum_i \ln p(k_i). \quad (3)$$

The parameters in distribution $p(K)$ can be estimated by maximum likelihood estimation.

A pair of blurred and non-blurred images captured from different angle is aligned by Eq. (3). Since the true kernel is sparse, when the given kernel is most sparsest, the pair of images is aligned. That is, to align the two images, the most smallest $E_{\text{sparse}}(k)$ should be obtained by adjusting scale and rotation of two images.

3) Deconvolution Using Richardson Lucy method: Given blur kernel k, the true image can be reconstructed from a standard Richardson Lucy algorithm [9] which is one of the ratio-based iterative approaches.

III. Studied System

Figure 3 shows the studied SfM. As well as non-blurred images, a blurred image is matched to another images by feature point matching in ordinary SfM systems based on a feature such as scale-invariant feature transform (SIFT) [5] or speeded-up robust features (SURF) [6]. In the studied system, however, a blurred image is deblurred using a deblurring scheme using a matched image pair [3] instead of being thrown away. Since deblurred images can give more feature points than blurred images, a reconstructed three dimensional model is expected to be more accurate.

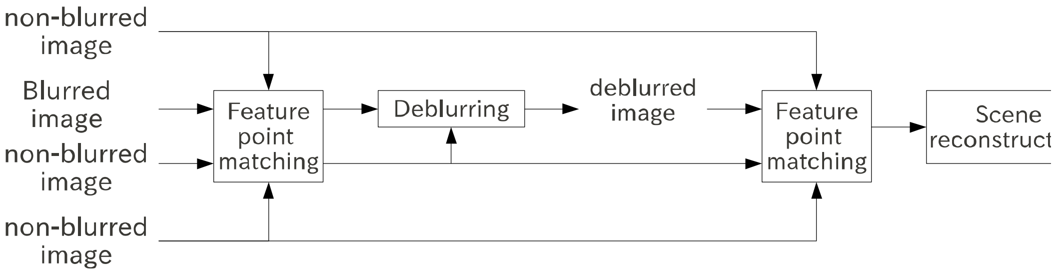


Fig. 3. Structure from motion with integrated deblurring.

(a) No.1. (b) No.2. (c) No.3. (d) No.4.
(e) No.5. (f) No.6. (g) No.7. (h) No.8.
(i) No.9. (j) No.10. (k) No.11. (l) Blurred No.3.

Fig. 4. Images captured from different angles.

A. Feature

The feature of this studied system is its integrated deblurring process. The studied system matches images including blurred images as well as the ordinary systems, the system, however, tries to deblur the blurred image, whereas the ordinary systems throw the blurred images away. By using the deblurring scheme which deblurs a blurred image with its corresponding non-blurred image [3], the studied system deblurs the blurred image in the system without employing an extra deblurring subsystem. This feature of the system contributes to serve a more accurate three dimensional model.

IV. Experimental Results

By using 11 real photos shown in Fig. 4, the effectiveness of the studied system is evaluated. In this lab experiment, a blurred image shown in Fig. 4 (l) is used which is generated from the image shown in Fig. 4 (c). That is, it is assumed that the deblurred image shown in Fig. 4 (c) is obtained from the blurred image shown in Fig. 4 (l) by the scheme using a blurred and non-blurred image pair [3].

Bundler [2] based on SIFT is used for bundle adjustment corresponding feature points. In addition, patch-based multi-view stereo software (PMVS2) [5], [6] is used for reconstructing three dimensional model.

When reconstructing three dimentional models, 9 images are available from a set of non-blurred images. On the other

(a) With a blurred image.

(b) With a non-blurred image.

Fig. 5. Reconstructed three dimensional models.

hand, only 4 images are available from a set of blurred images because the blurred image caused insufficient fature point matching with other images.

Fig. 5 shows the reconstructed three dimensional models. The model shown in Fig. 5 (a) is reconstructed from a set including a blurred image, i.e., reconstructed from photos shown in Figs. 4 excepting Fig. 4 (c); Fig. 4 (l) is used instead of Fig. 4 (c). Fig. 5 (b) shows the model reconstructed from non-blurred photos, i.e., in the scenario with a deblurred image. From Fig. 5, the studied SfM reconstructs the three dimensional models more accurately with a deblurred image than with a blurred image. That is, many feature points are extracted and matched in the deblurred image, and this contributes an accurate reconstructed model.

V. Conclusions

This paper has studied the structure from motion with integrated deblurring. The studied SfM matches images including blurred images as well as the ordinary SfM. Whereas the ordinary SfM throws blurred images away, the studied SfM deblurs blurred images with a scheme using a matched image pair. That is, the deblurring part is integrated in the studied SfM instead of employing an extra deblurring subsystem. This feature of the studied SfM is expected to be useful, in particular, for SfM using images captured without along with a well organized capturing plan [1], [2].

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