MVA2000 IAPR Workshop on Machine Vision Applications, Nov. 28–30, 2000, The University of Tokyo, Japan

15—3

Feature-Based Lens Distortion Correction for Image Mosaicing

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Abstract

We propose a method of correcting lens distortion for image mosaicing. Conventional calibration methods are tedious to use since they require special calibration patterns. While a few methods that do not use a calibration pattern have been proposed, these methods are slow to compute because they are based on a non-linear minimization framework.

Our method does not require any special calibration pattern. Compared with previous works not requiring a calibration pattern, our method is faster and numerically stable since it uses a linear function to solve the radial lens distortion coefficient. Our method uses feature correspondences, established by optical flow estimation, to correct distortion after obtaining homography between images.

1 Introduction

Image mosaicing has become an active research area, because it can construct a large, high-resolution panoramic image from a collection of standard images. Applications include the construction of aerial and satellite photographs, photo editing, and the creation of virtual environments.

Radial lens distortion must be corrected for the lenses used on recent digital still cameras. This is because the lenses are low-cost and sometimes zoom-lenses, which cause severe distortion. This paper proposes an automatic lens distortion correction for image mosaicing.

Several techniques have been proposed for camera calibration. Conventional techniques use special calibration patterns. This poses some difficulties for users in making panoramic images. Sawhney et al. have proposed a method which does not require a special calibration pattern [5]. This method, however, is computationally expensive because it is based on a non-linear minimization framework.

We propose a feature-based method that does not require special calibration patterns and is faster than previous methods. Since this method is based on linear computations for both obtaining the transformation between images and the distortion parameter, the computational cost is lower than that of previous methods.

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2 Related work

Conventional techniques for obtaining lens distortion parameters can be categorized into two types. The first type uses special calibration patterns. Several techniques require patterns for providing 3D coordinates [4]. A recent technique proposed in [6] is more flexible. However, it still requires a planar calibration pattern.

The second type does not require any calibration pattern. Stein has proposed a method which uses only images of the scene[2]. This method, however, requires a computer-driven rotating table to give a rotation angle. Stein has also proposed a method which does not need calibration patterns nor rotation tables [3]. This method, however, cannot be applied directly to image mosaicing because its purpose is for 3D reconstruction. Another problem of this method is that the computational cost is high because it is based on a non-linear minimization framework.

Sawhney et al. have proposed a method for image mosaicing[5]. This method incorporates the lens distortion parameter into the homography computation between images. This method, however, has the following two problems. First, the computational cost is high. Second, it is difficult to use with the large displacements that are common in still images. This is because it requires good initial estimates. The reason for these problems is that it is based on a non-linear minimization framework. We propose a feature-based method for image mosaicing that does not require any calibration pattern and is faster than previous methods.

3 Image mosaicing by using homography

Given two images taken from the same viewpoint, or images of a planar scene taken from different viewpoints, the relationship between the images can be described by a planar projective transformation called homography.

A number of techniques have been proposed. Most of them, however, are based on a non-linear minimization framework. A feature-based method has been proposed in [1]. This method is faster than other methods because it uses a linear function to compute a homography matrix. We extend this method to incorporate lens distortion correction.

4 Radial lens distortion

4.1 Error function for distortion parameter

Let (u_t, v_t) be the true (distortion-free) pixel image coordinates, and (u_a, v_a) the corresponding actual (observed) image coordinates. We then have the following equations:

$$\begin{aligned} u_a &= u_t + (u_t - u_0)kr^2 \\ v_a &= v_t + (v_t - v_0)kr^2 \\ r^2 &= (u_t - u_0)^2 + (v_t - v_0)^t \end{aligned} \tag{1}$$

where k is the coefficient of the radial distortion and (u_0, v_0) are the center coordinates of the distortion.

When we have points $\mathbf{p}_i$ in the first image and their corresponding points $\mathbf{p}'_i$ in the second image related by the homography H, we define the reprojection error E as follows:

$$E = \sum_i (\mathbf{p}_i - H(\mathbf{p}'_i))^2 \tag{2}$$

If we consider the lens distortion k with the constant center coordinates (u_0, v_0), we can rewrite the error E as follows:

$$E(k) = \sum_i (\mathbf{p}_i(k) - \mathbf{q}_i(k))^2 \tag{3}$$

where $\mathbf{q} = H\mathbf{p}$. After obtaining the homography matrix H with the actual image coordinates, we can obtain the corresponding coefficient k by minimizing the error E.

We use the Newton-Raphson method to solve the error E in terms of k. When the change δk of the coefficient k is small, we have the following equation by Taylor expansion.

$$E(k + \delta k) = E(k) + \delta k E'(k) \tag{4}$$

where E' is the first derivative of the error E. Since we need to find δk to minimize the error E, we obtain the following equation.

$$E(k + \delta k) = 0 \tag{5}$$

By substituting the equation (5) into (4), we can obtain δk as follows.

$$\delta k = -\frac{E(k)}{E'(k)} \tag{6}$$

We can obtain δk iteratively as follows:

$$\delta k_{i+1} = \delta k_i - \frac{E(k)}{E'(k)} \tag{7}$$

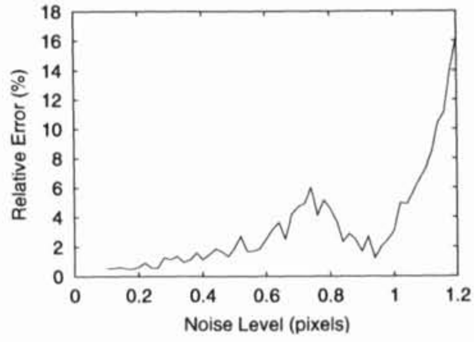

Figure 1: Errors by varying noise levels

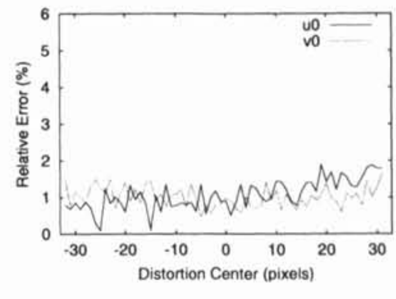

Figure 2: Errors by varying the center coordinates

4.2 Feature correspondence

We establish feature correspondence automatically by using optical flow estimation. We show the algorithm as follows:

1. Rough alignment
   We use correlation with low-resolution images.

2. Feature selection
   We select prominent features such as corners.

3. Coarse-to-fine optical flow estimation
   We use the Lucas-Kanade method for resolution pyramids

4. Feature correspondence
   We establish feature correspondence by using the flow estimate in subpixels.

We obtain the homography between two images from these feature correspondences. The details are described in [1]. We use these feature correspondences to obtain the radial distortion coefficient k as well.

5 Experiments

5.1 Computer simulations

We conducted two experiments on synthetic data. The image size of the simulated camera is 640 by 480 pixels. The focal length is 640 in pixels. We placed points in 3D at the equal distance from the optical center. The points were aligned 50 pixel apart on the first image plane. We rotated the camera horizontally around the optical center by 30 degrees for the second image. Half of the image plane was overlapped with the first image. We obtained 37 pairs of corresponding points between the first and the second images.

In the first experiment, we evaluated the performance with regard to the noise level in feature correspondence. We added gaussian noise with 0 mean and σ standard deviation to the point coordinates on the second image. We varied the noise level from 0.1 pixel to 1.2 pixels. For each noise level, we performed 100 independent trials, and the results shown in the average. We compared the estimated lens distortion coefficient to the ground truth. Setting the ground truth as -3.0e-7, figure 1 shows the errors at different noise levels. As we can see from figure 1, the errors were less than 5 % until the 0.5 noise level.

In the second experiment, we evaluated the performance with regard to the deviation of the center coordinates of the radial lens distortion. Fixing the noise level at 0.3 pixel, we varied the horizontal center coordinates from -32.0 to 32.0 pixels. Although our method assumes that the center of the distortion corresponds to the center of the image, the errors to the offset of the distortion center were smaller than we expected.

5.2 Real data

We conducted experiments on real images. Figure 3 shows the original images. The images were taken by a hand-held digital still camera (SANYO V100), not video. The image size is 640×480 pixels. We obtained feature correspondence by the method described in 4.2. The number of feature correspondences was 55 pairs. Figure 4 shows the curve of the error E in (3) by varying the coefficient k. The computed coefficient k by using the above method was - 2.27e-7, when we selected the starting point as $k = 0$. The result is very close to the minimum of the error curve. The error E has been reduced from 52.2 to 23.3, which is 44 %. To confirm the convergence of the method, we selected two different starting points, - 5e-7 and 3e-7. The results were -2.28e-7 and -2.27e-7 respectively. These are also close to the minimum of the error curve. The number of iterations was five or six.

Since our method does not require any iterative rewarpings, the computational cost is lower than previous methods. The computation time for obtaining the coefficient k from the homography and the feature correspondences was less than one second on an SGI Indigo 2 195MHz.

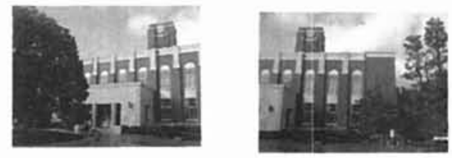

Figure 3: Original images (SANYO V100)

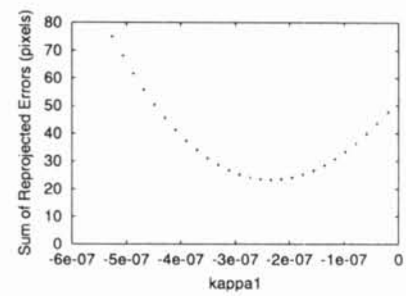

Figure 4: Error curve by varying the radial distortion coefficient k

We conducted another experiment with a different camera to show the effectiveness of our method. Figure 5 shows the original images taken by a hand-held digital still camera (Nikon CoolPix 950), which is equipped with a zoomlens. We obtained the lens distortion coefficient as -3.48e-7 from 23 feature correspondences.

Figure 6 shows the effectiveness of correcting lens distortion for image mosaicing. Figure 6 right shows the mosaic without lens distortion correction. Figure 6 left shows the mosaic corrected by the lens distortion coefficient. While the edges of the book are curved in the right image, those in the left image are straight.

5.3 Comparison

We compared the results with a previous method developed by Zhang [6], which uses a planar calibration pattern. Table 1 shows the comparison with

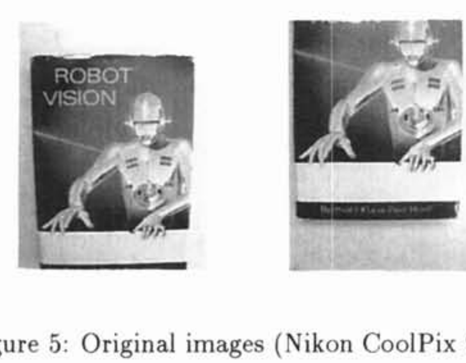

Figure 5: Original images (Nikon CoolPix 950)

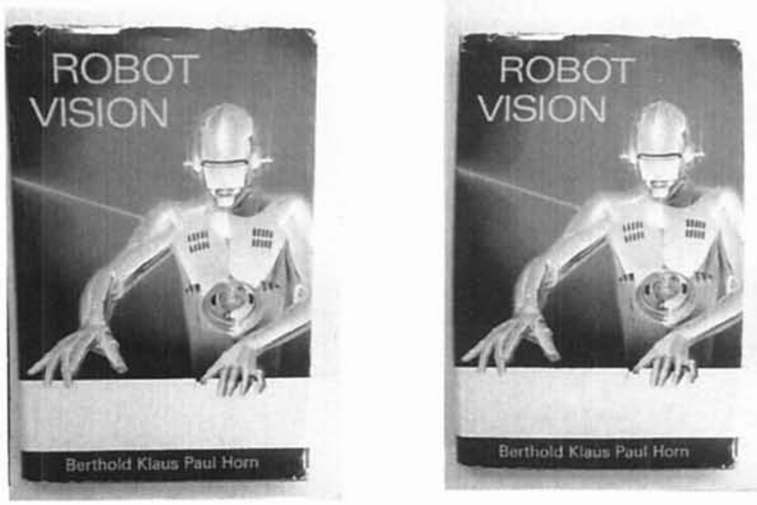

Figure 6: Left shows the mosaic with lens distortion correction. Right shows the mosaic without lens distortion correction.

Table 1: Comparison

Camera	Error(%)	Proposed	Zhang
V100	3.65	2.27e-7	-2.19e-7
CoolPix950	1.14	-3.48e-7	-3.52e-7

two different cameras. From Table 1, we can see that the errors in comparison with Zhang's method are less than 5%. While we obtained the parameter from general images, Zhang's method required a special calibration pattern.

For Zhang's method, we used a calibration pattern which has 108 circles printed on a sheet of paper by a laser printer. The circles were aligned in a 12 by 9 formation with displacements of 20mm. The center coordinates of each circle was computed after the circle pixels were extracted by binarization followed by a labeling technique. We used five images taken from different viewpoints to estimate the internal camera parameters. Our implementation does not take into account the second term of radial distortion coefficients and assumes that the skew parameter equals zero.

6 Discussion

The accuracy of the method is comparable to the previous methods. Only from general images taken with a digital still camera, we could obtain a reasonable distortion coefficient. We are also able to recover other parmeters such as image center coordinates and the second term of the distortion coefficients, or focal length as well. However, the computation may include non-linear minimization.

7 Conclusion

In this paper, we have illustrated an automatic method of correcting radial lens-distortion for image mosaicing. The method has three advantages over existing techniques. First, it does not require any special calibration patterns. Second, it is faster than previous methods. Third, it can deal with not only video frames but also still images that have larger displacements.

In future work, we plan to analyze the effectiveness of considering the second distortion parameter k_2 for image mosaicing.

Acknowledgement We thank Takashi Iida for his code to extract circles for Zhang's method.

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