Fully Automatic Matching of Circular Markers for Camera Calibration

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Abstract

Camera calibration is one of critical steps in computer vision, also an exhaustive process because substantial human computer interactions are frequently required to deal with the matching problem. In this paper, an automatic matching method of markers for camera calibration is presented based on the local architecture characteristics of a new planar circle pattern, which can be applied to a wide range of spoiled images including those of distortion, noise, and blur. Firstly, a robust ellipse detector is developed to extract ellipses from the image. After the centroids of the ellipses are triangulated into triangle network by Delaunay method to find k annular neighborhood of each ellipse, a cost function is defined to locate orientation ellipses for the homography matrix between the image and the calibration pattern. Then the correspondences between the marker ellipses and the marker circles are established by a homography method followed by a point sets registration strategy. Finally, the method is tested with real and transformed images to show its accuracy and robustness, which is entirely unsupervised and easily embedded into the exiting algorithms

1. Introduction

Camera calibration is an essential process to accurately recover metric information from 2D scene images. Many calibration techniques have been intensively studied over the past few decades. The fundamental structure of camera calibration consists of two sequential steps. Firstly, the features from the images of pattern are recognized, then to be matched with those of calibration pattern. Secondly, the intrinsic and extrinsic parameters are calculated. Most published calibration procedures in the computer vision literature have been concentrated on the second step [1,2]. In contract, there has been a little bit of attention paid to the first step. Unfortunately, features were usually extracted and matched manually, which is obviously inconvenient to users who are not familiar with computer vision. With the increasing popularity of cameras used in offices, it is significant to find an automatic method to overcome the above problem.

From 3D to 0D (self-calibration), various calibration apparatuses are introduced in many literatures. Planar patterns provide an easy and inexpensive solution and have become popular in camera calibration since Zhang presented a flexible calibration technique [2,3,4]. The most commonly used planar pattern is the chessboard pattern whose alternating black and white squares make strong corner features. So far, the existing algorithms focus on dealing with the checkerboard pattern, whose disadvantage is quite sensitive to noise and blur in the images [5,6]. Circle patterns have already been used in several camera calibration works [7,8]. The features of the planar circle pattern should be recognized and located automatically, which is less concerned unfortunately. The reason is that the projected center of circle is not necessarily mapped to the centroid of ellipse, even circle may not be mapped to ellipse under the circumstance of radial and tangential distortion. Some researchers are prevented from using circles in calibration targets duo to the projective effect, which has been partly resolved by minimizing perspective bias using dots as target features or iteratively correcting feature locations. Perspective effect also could be compensated by calculating invariant points resulted from common tangents to coplanar ellipses and the resulting accuracy of 0.05 pixels was reported [9]. Subsequently, using a model-based ellipse extraction strategy, Redert and Hendriks put forward a robust algorithm to combine accuracy and high insensitivity to noise and reported that the localization precision is 0.01 pixels in high-quality images and 0.03 pixels in very bad quality images (high noise, low contrast, lens distortion, CCD misplacements) respectively [10]. These obtained improvements of the

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localization precision of circle pattern are very evident and clearly indicate the feasibility of using circle pattern. A recent comparative study on planar patterns for camera calibration has showed that circular dot patterns are truly practical if the diameters of dots are roughly less than 10 pixels to avoid bias introduction [11].

Our main aim is to develop a circle marker matching method that is robust and automatic. The rest of this paper is organized as follows. Section 2 gives a new calibration pattern used in this study. Section 3 discusses how to effectually detect ellipses in an image. In section 4, an automatic algorithm is presented to find the coordinates of projections of five big circles. Section 5 develops a robust matching method combining a homography algorithm with a registration algorithm. Experimental results are presented in section 6. Finally, conclusions and discussions are presented in section 7.

2. Calibration Pattern

A variant of circle pattern is designed in this work, see Fig. 1. The calibration pattern is a planar, black object with 11x9 white circle markers placed on a grid which has same longitudinal and latitudinal intervals of 35mm. Five big circles in the pattern are used for orientations and encoded by C_1-C_5. The diameters of small circle and big circle are 7mm and 16mm respectively. The coordinates of markers are defined as the circle centers.

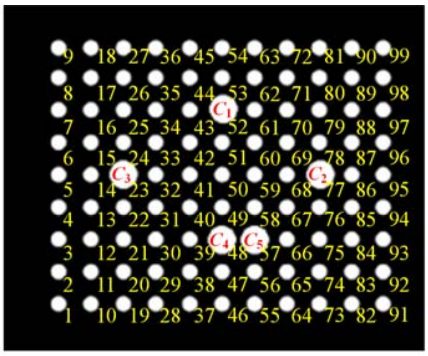


Fig. 1. The sketch of the proposed calibration pattern

3. Ellipses Detection

Given an image, the first step is to detect ellipses, which is a standard problem in computer vision. In this section, we present a robust and fast algorithm for detecting ellipses in images of calibration pattern placed in various environments. We will describe it in a style of pseudocode we will use throughout this paper.

Algorithm 1 ELLIPSESDETECTION(I)

Input. An image I of calibration pattern

Output. A set E containing the ellipses in I

1. Extract edges in the image I applying Canny operator
2. Thin each edge, namely reducing the thickness of each edge to just a single pixel
3. Link broken edges to recover continuous edge information, simultaneously remove short edges
4. Fit ellipses to points of edges with a least squares algorithm, resulting in a set $E=\{e_i|i=1,2,\ldots,n_e\}$
5. **return** E

The first step in algorithm 1 is to extract edges of image. The Canny operator [12] is probably the most widely used edge detector due to its good performance with respect to other gradient operators. Edges with multiple pixels width are usually obtained. So, a thinning algorithm is demanded to produce a single-pixel wide skeleton from edge image [13]. In addition, edge operators based on partial derivatives generally fail to return continuous edge image. To address this problem, a supplementary edge linking step is required to complete the initial edge information [14]. Then short edges whose lengths are less than 10 pixels (a size selected empirically) are removed to reduce information redundancy. Finally, an efficient least squares algorithm is executed for fitting ellipses to edges [15].

4. Detection of Orientation Ellipses

Normally the number of detected ellipses is greater than the number of markers in the calibration pattern to avoid leaving good candidates over. Our calibration pattern has a fixed number of markers so we are interested in detecting only the same number of ellipses in the image plane. We first locate five orientation ellipses, i.e. the image projections of five big circle makers in calibration pattern, in order to subsequently solve a matching problem. Five ellipses with the longest semi-axes can easily be found and usually answers, but possibly results in false locations for large-distortion images. Intuitively, the good candidate of orientation ellipse would be one whose 8-neighbors are regularly distributed around this ellipse and whose long semi-axis is obviously greater than one of median ellipse in 8-neighbors.

We develop a robust algorithm which is able to accurately find five orientation ellipses even for the images with large distortion and with complex background features. Let $X=\{x_i|i=1,2,\ldots,n_e\}$ be the point representation of set E where x_i is the center point of e_i. Let $C=\{c_i|i=1,2,\ldots n_e\}$ be a set which contains the cost function values of ellipses. The algorithm can now be described as follows.

Algorithm 2 FINDFIVEORIENTATIONELLIPSES(E)
Input. A set E containing the ellipses
Output. A set F of five orientation ellipses
1. T←TRIANGULATE (X)
2. **for** i←1 **to** n_e
3. G←FIND8ANNULARNEI.HBORHOOD (x_i, X, T)
4. Re←REGULARITY(G)
5. Ra←Compute the ratio of long semi-axis of ellipse e_i to median long semi-axis of its 8 annular neighbors
6. cf_i←Compute the cost function using equation (1)
7. Find the set Q by searching five ellipses whose cost function values are minimal
8. F←SORTFIVEORIENTATIONELLIPSES(Q)
9. **return** F

In the first line of algorithm 2, the TRIANGULATE procedure constructs a Delaunay triangulation of point set X. The Delaunay triangulation of set X can be represented as a pair of sets $T\{X, B\}$, a set of vertices X, and a set of edges B. The Delaunay triangulation is very useful in many neighbor searching problems in computational geometry. Before we begin our analysis of algorithm, we must define some terms to be used.

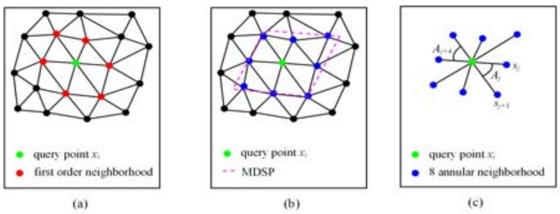


Fig. 2. Neighborhood structure. (a) first order neighborhood, (b) MDSP, (c) 8 annular neighborhood

A particularly important neighborhood structure is the first order neighborhood structure as illustrated in Fig. 2(a), where for each pair of points x_i and x_j that share a common edge, we make x_j a neighbor of x_i, and x_i a neighbor of x_j. We denote by N_F the first order neighborhood of a point. Assume CH is convex hull of N_F of the query point, a minimal distance sum parallelogram (MDSP) of the query point is defined as a parallelogram that encloses CH and the sum of the distances from the query point to the corners of MDSP is minimal among all such parallelograms. The k annular neighborhood of a query point is defined as k points which are nearest to the minimal distance sum parallelogram (MDSP) of the query point. The MDSP and 8 annular neighborhood are illustrated in Fig. 2(b) and (c) respectively.

In the following subsections, we will discuss the implementations of other subroutines in detail.

4.1. *k* Annular Neighborhood (*k*AN)

In order to investigate the local structure characteristic of each point, we prefer annular neighborhood rather than nearest neighborhood. An algorithm how to find 8 annular neighborhood of query point now is as follows.

Subroutine FIND8ANNULARNEI.HBORHOOD(x_i, T)
Input. x_i is query point and T is Delaunay triangulation of set X
Output. G is the 8 annular neighborhood of x_i
1. Find the first order neighborhood of x_i. Let N_F be the found set
2. Compute the convex hull of N_F, resulting in a set CH
3. Compute the minimal distance sum parallelogram P_a of x_i
4. Find 8 points that are closest to the parallelogram P_a, resulting in a set G
5. **return** G

The critical step is line 3. Fortunately, former related work has been done on finding the minimal area enclosing parallelogram in linear time [16]. With a little modification, we can extend their method by computing minimal distance sum instead of minimal area.

4.2. Neighborhood Regularity

Regularity is a distributed characteristic of neighborhood. Subroutine REGULARITY for computing neighborhood regularity of a point is summarized as follows.

Subroutine REGULARITY(x_i ,G)
Input. A set G containing the 8 annular neighborhood of x_i
Output. Re is the neighborhood regularity of x_i
1. Sort the point set G in a clockwise fashion, resulting in a set $S=\{s_j|j=1,2,\ldots,8\}$
2. **for** j←1 **to** 8
   A_j←Compute the angle between line segment $\overline{x_i s_j}$ and $\overline{x_i s_{j+1}}$, see Fig. 2(c)
3. **for** i←1 **to** 4
   r_i←$|A_i/A_{i+4}|$
   if r_i is greater than 1
   r_i←$1/r_i$
4. Re←Compute the mean of r_i (i=1,2,3,4)

5. **return** *Re*

For one orientation ellipse, its neighborhood regularity should be apparent and approximately equal to 1.

4.3. Cost Function

A cost function is utilized to determine which ellipses from the set E are most possible candidates of orientation ellipses. Let Rt be the ratio of diameter of big circle in calibration pattern to one of small circle. Once the calibration pattern has been designed, Rt is fixed. For our designed calibration pattern, Rt is about 2.29≈16/7. So the cost function of the selection of orientation ellipse is defined as a linear combination of Re and Ra.

$$cf = w_1|Re-1| + w_2|Ra-Rt| \quad (1)$$

where w_1 and w_2 are weight coefficients, which respectively equal to 0.5 and 0.5 in this paper.

4.3. Sort Orientation Ellipses

Next, we need to establish correspondences between five orientation ellipses and five orientation circles. To obtain this result, a rather straightforward sorting algorithm is given as follows.

Subroutine SORTFIVEORIENTATIONELLIPSES(Q)

Input. A set Q of five orientation ellipses

Output. A set F of five sorted orientation ellipses

1. Find the two closest ellipses in set Q, and assume they are q_1 and q_2 without loss of generality
2. Find the two farthest ellipses in set $Q \setminus \{ q_1, q_2 \}$, and assume they are q_3 and q_4
3. The remaining ellipse q_5 must correspond to the orientation circle C_1 in calibration pattern, denoted by f_1
4. **if** q_3 lies to the left of directed line from q_1 to f_1
   q_3 corresponds to the orientation circle C_3, denoted by f_3
   q_4 corresponds to the orientation circle C_4, denoted by f_4
   else q_4 corresponds to the orientation circle C_3, denoted by f_3
   q_3 corresponds to the orientation circle C_4, denoted by f_4
5. The same trick is done to find the images of orientation circle C_2 and C_5, respectively denoted by f_2 and f_5
6. Put orderly the ellipses $f_1, f_2, \ldots f_5$ in set F
7. **return** F

The Step 4 needs some explanation: How do we test whether a point lies to the left or the right of a directed line. This is one of the primitive operations required in most geometric algorithm. Throughout this paper we assume that such operations are available.

5. Match Ellipses with Makers

If the markers are initially ordered like in Fig. 1 then we have to order the ellipses on the image in the same way, taking into account that the calibrator may be horizontal, vertical or in any other orientation. In the rest of this paper, for convenience of representation, each ellipse or circle is replaced by its center point. Let P_f, P_c and P_m are respectively the homogeneous coordinate representations of the centers of F, five orientation circles and all maker circles. So a robust matching strategy can be designed as follows.

Algorithm 3 MATHMARKERSWITHELLIPSES(P_f, P_c, P_m)

Input. Point sets P_f, P_c and P_m are respectively the homogeneous coordinate representations of the centers of F, five orientation circles and all maker circles

Output. A set U containing the ordered image coordinates of all coded maker circles

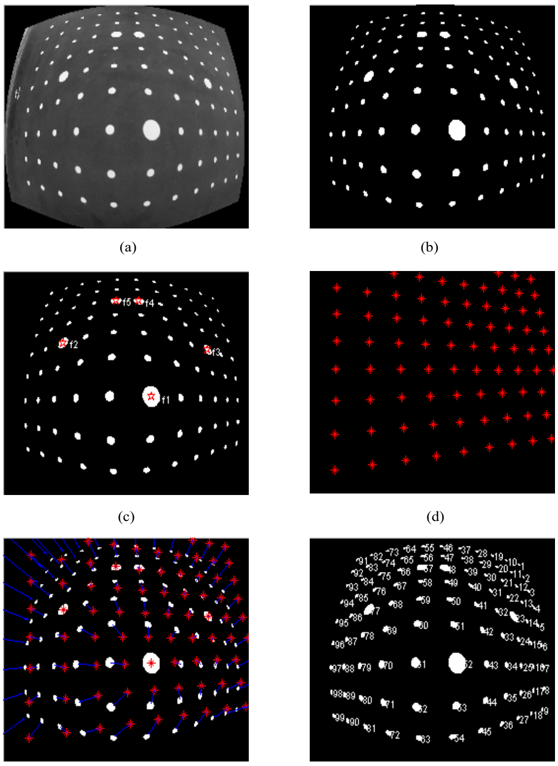
1. **H**←Compute the homography matrix **H** by 5 corresponding pairs of points between P_f and P_c
2. Y_0←Compute the estimated coordinates of marker ellipses using equation $Y_0 = \mathbf{H}P_m$
3. Y←POINTSETREGISTRATION(Y_0, X)
4. U←Compute the closest point set of X to Y
5. **return** U

Our algorithm is similar to the recent research by [6] except the step 3 added. Yu and Peng ignored lens distortion of a camera and implicitly assumed that the transformed image coordinates, i.e. Y_0, are adequately close to the real image coordinates. However, a desktop camera usually exhibits significant lens distortion. It is necessary to use a robust algorithm of point sets registration to make the matching procedure correct in the presence of distortion. Many algorithms exist for point sets registration. A popular one is the Iterative Closest Point (ICP) algorithm [17], which iterates two steps until it reaches the local minimum: (1) finds the best correspondence between the two point sets based on spatial distance, (2) updates the transformation based on the found correspondence. Nonetheless ICP requires that the initial pose of the two point sets be adequately close, which is not always possible, especially when transformation is non-rigid [18]. ICP does not usually guarantee that the correspondences are one-to-one. Its performance degenerates quickly with outliers, even if some robustness control is added [19]. Myronenko introduced a probabilistic method for point set registration called the Coherent Point Drift (CPD) method [20]. They treated the registration as a Maximum Likelihood (ML) estimation problem with motion coherence constraint over the velocity field such that one point set moves coherently to align with the second set. In this paper, CPD method is preferred because it outperforms ICP algorithm in the presence of noise, outliers and distortion.

Finally, U is refined by a subpixel centers-finding algorithm to get accurate center coordinates of maker ellipses. All coordinates of the maker ellipses are straightly used in a calibration program to compute the intrinsic and extrinsic parameters of the camera.

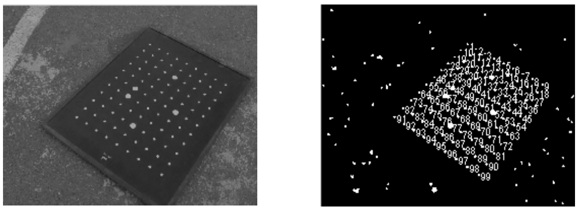
6. Experiments

In this section, we test the proposed algorithm with various images. Due to space limitation, we only provide the matching results of two images, which are labeled **distortion** and **noise** respectively. The first image has been generated by a distorting algorithm. The second is image real images.



(a) (b) (c) (d) (e) (f)

Fig. 3. Scene **distortion:** the main processes of the proposed algorithm. (a) original image, (b) ellipse detection, (c) detection of five orientation ellipse, (d) the estimated positions of marker ellipses using a homography transformation, (e) point sets registration, (f) matching results



(a) (b)

Fig. 4. scene **noise**: (a) original image, (b) matching results

In first experiment, a distorted image is used to illustrate the main processes of the proposed algorithm, as shown in Fig. 3. After candidate ellipses are detected, five orientation ellipses can be located robustly. Then a homography method is used to estimate the positions of marker ellipses. One can see from the Fig. 3(e) that the estimated positions of marker ellipses (as denoted by asterisks) are far from the detected positions of marker ellipses (as denoted by white regions). So a robust algorithm of point sets registration is performed to obtain the correct matching results, see Fig. 3 (f).

For convenience of discussion, we only provide the original image and matching results for the following experiment. In Fig. 4, the original image is taken by CCD camera. The image contains easily visible noise and its size is 768×576 pixels. Though the some ellipse-like objects are found, there are mismatches when using the proposed algorithm. The matched ellipses are labeled by the ordered numbers.

7. Conclusions

In this work, we present an automatic matching method for camera calibration based on the local architecture characteristics of a new planar circle pattern. After all candidate ellipses are detected, Delaunay triangulation of the centroids of ellipses is implemented to create the connectivities between the isolating feature points. Sequentially a robust algorithm is developed to locate the orientation ellipses. A homography method is used to estimate the projected positions of marker ellipses. Then a point sets registration algorithm is adopted to find correspondences between marker ellipses in image and marker circles in calibration pattern. The experimental results demonstrate that our method provides a correct and robust solution under unconstrained conditions such as uneven illumination, noise and image blur. The proposed method is totally free of user intervention after submitting photos. For future work, we plan to further improve the computing speed of the method by adding more efficient ellipse detection algorithms and point sets registration techniques.

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