A Robust Recognition Technique for Dense Checkerboard Patterns

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Abstract—The checkerboard pattern is widely used in computer vision techniques for camera calibration and simple geometry acquisition, both in practical use and research. However, most of the current techniques fail to recognize the checkerboard pattern under distorted, occluded or discontinuous conditions, especially when the checkerboard pattern is dense. This paper proposes a novel checkerboard recognition technique that is robust to noise, surface distortion or discontinuity, supporting checkerboard recognition in dynamic conditions for a wider range of applications. When the checkerboard pattern is used in a projector-camera system for geometry reconstruction, by using epipolar geometry, this technique can recognize the corresponding positions of the crossing points, even if the checkerboard pattern is only partly detected.

Keywords-checkerboard; pattern recognition; geometry reconstruction; handheld projector-camera

I. INTRODUCTION

A checkerboard pattern is used widely in many computer vision’s processes, like a camera calibration[1], or in a multiple projector system to register the projection areas for each projectors. A checkerboard pattern is also used to measure geometry structure by projecting from a projector-camera system[7], [9]. The checkerboard pattern is preferred in many computer vision systems because the basic crossing feature points are robustly detected and refined to sub-pixel accuracy. However, until now checkerboard recognition techniques are mainly proposed for camera calibration purpose, and the recognition process is usually sensitive to the pattern’s distortion and noise.

Our proposed technique can recognize a checkerboard pattern as groups of feature points connected by adaptively detected feature edges (Figure 1). Feature points and feature edges are first categorized by their direction, and then they are grouped by connections with each other following strong topological rules. In this paper, a checkerboard matching method for printed checkerboard patterns and a checkerboard matching method for geometry reconstruction based on epipolar geometry are described.

II. RELATED WORKS

The recognition process is usually divided into the detection process and the checkerboard matching process. In a checkerboard pattern, the crossing corners can be detected by several different approaches. A common approach to finding the checkerboard corners is to use the universal corner detectors such as that by Harris [5] or SUSAN [8], and then to analyze the corners’ geometric relations to eliminate noise[4]. However, these detectors usually produce too many redundant corners, which are not specific to the checkerboard’s internal crossing points.

Using the characteristics of the checkerboard, Wang et al. determine the checkerboard’s corners as the intersections of grid lines[10]. The drawback of this approach is that it can only find the corners when the checkerboard pattern is on a planar surface. In the OpenCV library [2], the widely used cvFindChessBoardCorner function searches for the checkerboard’s corners as the common vertices of different rectangular areas. This approach is quite robust to noise and global light illumination; it allows for a small amount of surface distortion, but it fails frequently when the pattern gets denser and the illumination is complex. Recently, Sun et al. proposed using the linear extension of the surrounds of a point and count for the intensity changes in each surrounding layers to identify the crossing corners[9]. With sufficient neighboring points, this direct approach can detect the crossing corners robustly under various different light conditions and distortion.

However, in the matching process, most current techniques cannot deal with discontinuity, occlusion or false detection problems, which occur frequently when a checkerboard pattern is used to measure surface geometry. In this paper, we propose a solution to the problem addressed above.
III. CHECKERBOARD DETECTION

We use three steps in detecting a checkerboard. First, crossing feature points are detected, categorized and refined to subpixel accuracy. In the second step, feature edges are detected based on the detected feature points and then categorized by direction. In the third step, feature points and feature edges are connected, following topological rules, to create meshes of feature points and to eliminate noise.

A. Feature point detection

Feature points are first approximately detected by using the method proposed by Sun et al.[9]. This method detects all pixels $P$ that have four alternate black and white areas surround by extending its neighboring pixels at the same level to one-dimensional array, and counting for the intensity shifts (Figure 2). For the next step, we merge all the detected pixel corners that are adjacent to each other, then take the center of mass as the initial corner position for refining to subpixel accuracy. We use the method described in the OpenCV library [2] to find the radial saddle point. This method does not require the radial saddle point to be inside the initial pixel position, and it gives good convergence after several iterations. Finally, feature points are categorized by using a linear filter as in Figure 3. The filter in Figure 3(c) is efficient for categorizing feature points that are relatively aligned in the horizontal or vertical directions. By rotating the recognition image to an appropriate angle given by the trend line of detected feature points, we can always apply this filter.

![Figure 2. Extension of neighboring pixels](image)

B. Feature edge detection

Feature edge detection has been subject to intensive research in image processing, and various techniques have been proposed[8], [3]. However, these techniques are universal; they detect many false edges due to noise that is not specific to the checkerboard pattern. For the checkerboard, we concentrate on the step edges that are the boundaries of the black and white areas in the checkerboard pattern. There are exactly four edges connecting each feature point. In the first detection step, we use four different Sobel filters (Figure 4) to differentiate the image in different directions. For each edge image, we find the corresponding feature edges by dynamically expanding the pixel connecting the feature points. At the crossing feature point, the convolution integral used to apply the Sobel filters usually returns zero or a very small value; thus, the edges’ ending points are found by taking the pixels with largest value on the second neighboring pixel of each feature point. The threshold for deciding the continuity of an edge is taken to be half of the value at its ends. An edge connecting with two feature points will have two different continuity thresholds at its ends. In this case, we take the smallest value and merge the connected edges into one.

C. Grouping

After having applied the above processes, we have a collection of categorized feature points \{P+,P–\} and feature edges \{H+,H–,V+,V–\}. At this step, we apply some constraints to eliminate falsely detected points and edges:

- A feature point must connect four feature edges in different categories.
- If a feature edge connects two feature points, the feature points must be in different categories.

Geometrically:

- If an edge is in the H+/H– category, then its left feature point must be in the P+/P– and its right feature point must be in the P–/P+ category.
- If an edge is in the V+/V– category, then its upper feature point must be in the P+/P– and its lower feature point must be in the P–/P+ category.

These constraints are invariant to checkerboard direction because they only depend on the geometrical structure. By following the connections made by feature edges, we can reconstruct a strong grid structure from the collection of feature points. However, there may still be errors caused by occlusion or discontinuity on the object’s surface, and the error may spread during the indexing process(Figure 5). These errors can be detected by checking the consistency of the loops in the groups. However, it is not obvious where the error is in the example shown in Figure 5. The feature points in positions (1,0) and (2,0) may be falsely detected, or...
the edges between feature points (0,1)–(3,1), (0,2)–(3,2) and (0,3)–(3,3) may be in error due to edge collapse. Because edge collapse is rare and falsely detected feature points are more common, we solve the problem by setting the priority of the detected feature points based on their number of neighbors, then start the indexing process with points from high to low priority.

IV. CHECKERBOARD MATCHING

By grouping the feature points into groups and using the edge constraints to index the feature points in a grid order, we can easily match a checkerboard pattern with the group having equal width and height with the checkerboard pattern. It helps to find the matching group when the checkerboard pattern is partially occluded but while its dimensions are preserved. In the case where the occluded area is large, or when groups of feature points are segmented by a surface discontinuity and no group has the same dimension with the checkerboard pattern, the matching process is complicated or impossible to solve by only using the groups’ dimensions.

However, if the checkerboard pattern is displayed on a calibrated projector camera system, we can find the corresponding position for the groups of feature points based on epipolar geometry. If all of the corresponding epipolar lines are separated from each other, and all detected feature points lie exactly on the predefined epipolar lines, the checkerboard matching can be carried out for each feature point [6]. When the checkerboard pattern is dense, these conditions are rarely satisfied; feature point detection is affected by noise, and different feature points may map to the same epipolar line.

These ambiguities are resolved when the groups are composed of feature points in more than two different epipolar lines. Where multiple feature points map to the same epipolar line, we can arrange the orientation of the projector and the camera such that the epipole on the camera image is not at infinity. In this manner, we can ensure that the neighboring feature points of those points do not map to the same epipolar line and are thus distinguishable. This is because in a checkerboard pattern the crossing points lie on a parallel grid, whereas, in an image, all epipolar lines go through the same epipole and are not parallel with each other.

In a group, if the corresponding position of a point is defined, the corresponding positions of all points in the group are consequently decided. We can choose a feature point with the highest number of neighbors to be the origin of the group, then search for the corresponding epipolar line of this origin feature point by taking the one which minimizes the sum of the distance from all feature points in the group to the equivalent epipolar lines.

V. EXPERIMENT

We have conducted several experiments to investigate the validity of the method. In our experiments, a Logitech camera (QCAM-200V 640 × 480) was used to recognize a printed checkerboard pattern under severe distorted and partially occluded conditions (Figure 1). We verified that the recognition result is robust to surface distortion and partial occlusion. By projecting the checkerboard pattern on a surface of a colored box, we confirmed that the recognition technique is minimally affected by the surface color (Figure 6). We reconstructed a human face by projecting a 40 × 40 checkerboard pattern as in Figure 7. In this case, when the matching is not decided by the size of the groups, we use epipolar geometry to search for the corresponding position of the detected groups of feature points. Using a computer with an Intel Core 2 Duo 2.4 GHz CPU and a 2 GB RAM, our implementation achieved a recognition speed of 12 to 13 fps for a 30 × 20 checkerboard pattern and 5 to 6 fps for a 40 × 40 checkerboard pattern.

VI. CONCLUSION

In this paper, we proposed a checkerboard pattern recognition technique by means of the recognition of feature points and feature edges, and we proposed a matching technique based on the grouping of the checkerboard pattern. Our method is rapid and robust to noise. It is also minimally affected by surface color, and light conditions. In the future, we will implement this technique on a mobile projector camera system to reconstruct a 3D model of an object in real time.

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Figure 7. Face geometry reconstruction: a) checkerboard pattern is focus on a human face, b) partially recognized result, c) right view, d) front view, and e) left view of the face’s geometry.

REFERENCES


