A FEATURE DETECTION ALGORITHM FOR AUTONOMOUS CAMERA CALIBRATION

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Abstract: This paper presents an adaptive and robust algorithm for automatic corner detection. Ordinary camera calibration methods require that a set of feature points – usually, corner points of a chessboard type of pattern – be presented to the camera in a controlled manner. On the other hand, the proposed approach automatically locates the feature points even in the presence of cluttered background, change in illumination, arbitrary poses of the pattern, etc. As the results demonstrate, the proposed technique is much more appropriate to automatic camera calibration than other existing methods.

1 INTRODUCTION

In any automatic camera calibration procedure, one must devise an algorithm that can – without human intervention – accurately and reliably: 1) identify special features in a set of images; and 2) correspond the features over the image set so they can be used as calibration points. In order to accomplish that, such algorithm must be able not only to detect as many features as possible, but it also needs to determine the pixel coordinates of the features in a consistent manner throughout the image set.

The existing algorithms for camera calibration (Zhang 1998) (Huang and Boufama 2006) (Weng 1992) (Tsai 1987) rely mainly on detecting corners on a chessboard-like calibration pattern, or the centroid of circles in a dotted calibration pattern (Kim and Kwon 2001). Other approaches (Chen 2005) (Baker and Aloimonos 2000) try to avoid using such patterns, but despite the method used, a set of corresponding points in multiple images must always be obtained

The main problem with some of these approaches (Zhang 1998) (Huang and Boufama 2006) (Weng 1992) (Tsai 1987) is that, while a large number of feature points can be easily obtained, the correspondences between features can be compromised by perspective distortions, changes in illumination, etc. That is, due to, for example, the relative pose of the pattern with respect to the illumination source, the same corner point found in one image of the set may be detected by the algorithm a few pixels off from its actual location. Moreover, many of the algorithms above mentioned require that the user define the location and/or size of a search window where the algorithm will look for the feature points (Harris and Stephen 1988). In an automatic calibration procedure, where the pattern may be presented to the camera at different depths (scale), a restriction on the size of the window would obviously render the algorithm useless.

In this paper, we present an algorithm for automatic camera calibration that relies on a line detection method (Hough Transforms) to find the feature points. In our system, a sequence of images is captured by the camera(s) while a calibration pattern is arbitrarily moved in front of the camera(s).

The proposed algorithm automatically searches for feature points on the pattern that will be used for calibration. As in the above algorithms, the feature points are the corners of the squares in a chessboard pattern, but unlike in these algorithms, the points are now defined by the intersection of the many vertical and horizontal lines running over the edge of the squares.

That is, instead of looking for localized feature discontinuities inside a small search window, as in traditional corner detection algorithms, our algorithm uses a global property of the pattern to localize the corner more accurately.

Our algorithm is very robust to cluttered background and it can reject points outside the perimeter of the pattern even if the background presents distinctive features similar to the ones in the

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pattern. Also, due to the use of global rather than local features, the calculated pixel coordinates of the corners are significatively more accurate than those obtained using corner detection algorithms, leading to a much more accurate final camera calibration.

2 PROPOSED ALGORITHM

The proposed algorithm consists of two main parts. In the first stage, the algorithm searches for visible features in a set of images of the calibration pattern. Once the features are located, the algorithm determines the feature correspondence between images. The output of this stage of the algorithm is a list of world coordinates of the features and their corresponding pixel coordinates in the various images used.

The second stage of the algorithm implements a camera calibration procedure based on Zhang's algorithm (Zhang 1998). This part of the algorithm is outside the scope of this paper and will not be covered here. In the next section we will present the first stage of the algorithm in more detail.

2.1 Feature Detection

Our algorithm uses a chess board pattern as depicted in Figure 1. The pattern contains one gray square in the middle, while all others are black. The reason for this special square is for the algorithm to be able to locate the origin of the pixel coordinate system and to assign coordinates to the features automatically. The main constrain imposed to this algorithm is to detect a significant number of points so that the calibration error can be minimized.

Through experimentation, it was determined that at least 150 points out a total of 196 points of the pattern must be detected for good calibration. Thus, in the ideal case, the algorithm must find a total of 28 lines – i.e. 14 horizontal lines and 14 vertical lines. The corner points are defined by the intersections of the two sets of fourteen lines.

2.2 The Hough Transform

The Hough Transform (Hough 1966) is one of the most popular methods for extracting lines from images. It is used to transform *u-v* pixel coordinates of points on a line into the parameters of such line. That is, consider, for example, the equation of a straight line in the image space, $v = m * u + c$. Where m is the slope and c is the vertical intercept. This equation can be represented by a single point in the parametric space. Since the actual m and c of such a line is initially unknown, the Hough transformation can be performed by accumulating "votes" from every point (u, v) on the line. That is, every point (u, v) will vote for all points of the line $c = m * u - v$ in the *m-c* space. Since all *u,v*-points on the same line will vote for a common *m-c* point in this parametric space, one point will accumulate more votes than any other point – which can be used to detect the original line in the image. Due to noise, the Hough algorithm could detect more than one set of parameters for a single line in the image. One of the key points in the proposed algorithm is to eliminate those erroneous detections. For that, the proposed algorithm must adapt to different situation, such as the orientation and size of the pattern, different illumination conditions, etc.

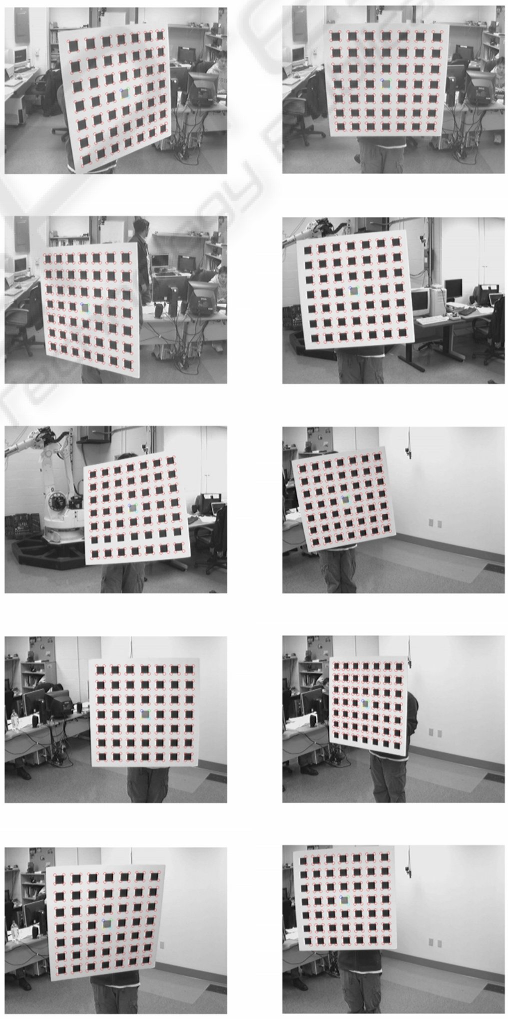


Figure 1: A sample of the typical poses of the pattern presented to the camera for calibration.

2.3 Detailed Algorithm

The first step of the algorithm is an edge detection. Then the Hough transformation is applied to all points on the edge images. Next, as we explained earlier, our algorithm searches for the intersections of all lines obtained from the Hough transform. At that point, due to noise in the images, two erroneous situations may arise. First, spurious lines outside the pattern may be detected. Second, multiple lines can be detected for a single line in the pattern.

The first erroneous case is handled by the algorithm using a set of simple but comprehensive heuristics, such as: 1) the slope of any line must be similar to the slope of thirteen other mostly vertical or horizontal lines; 2) the distance between lines must be consistent among the two sets of lines (vertical and horizontal); and 3) the number of expected lines.

It is important to mention here that the two sets of lines, vertical and horizontal, are not necessarily as so. That is, the algorithm allows for the pattern to be presented in any orientation – as it is demonstrated in Figure 1. The use of the term "vertical" and "horizontal" above is just for clarity of the explanation.

The second erroneous detection is illustrated by Figure 3(b). As it is shown in this figure, the Hough transform may detect multiple lines for a single line on the pattern. That results in multiple intersections for a single corner. In order to handle these cases, the algorithm first groups these points by their Euclidean distances. Once the clustering is obtained, the algorithm uses some stochastic criteria to eliminate erroneously detected corners. For example, the algorithm eliminates outliers farther than ½ standard deviations from the mean and recalculates the pixel coordinate of the corner afterwards. Once the algorithm processes the steps above, it then calculates the mean of each cluster. These means represent the corner points of the pattern. A predefined order of the corners allows us to search and label the corner points starting from the center of the pattern. For this reason, finding the exact position of the center square (gray square) is a critical step of the proposed algorithm. Figure 2 shows a brief flow chart of the proposed algorithm

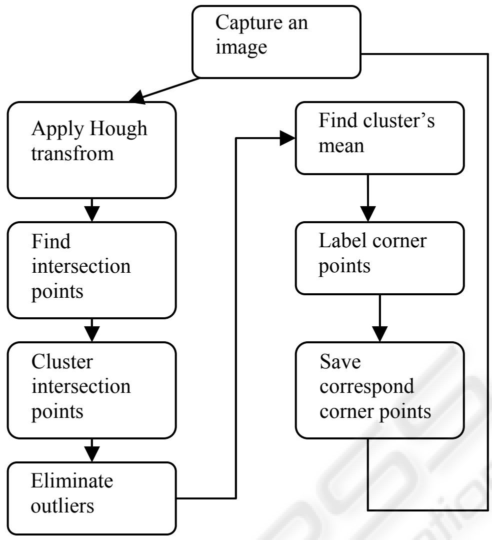


Figure 2: A brief flow chart of the proposed algorithm.

3 RESULTS

In this section we detailed two of the tests performed to validate our algorithm. In the first test, we compared a corner detection algorithm found in the literature (Harris and Stephens 1988) against our proposed method. In the second test, we present the final accuracy in 3D reconstruction after employing our algorithm to calibrate a multi-stereo rig composed of 6 cameras.

3.1 Corner Detection

In order to compare our method with a traditional corner detection algorithm, we collected 196 points in one image of the pattern at a typical position and orientation (Figure 4).

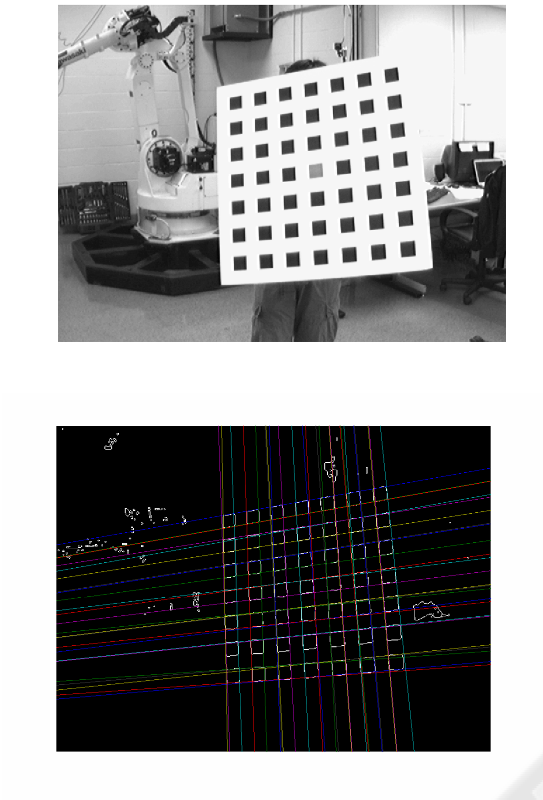


Figure 3: (a) Original image, (b) Detected Lines.

As the red circles in the figure depicts, the corner detection algorithm finds many spurious points in the image outside the boundaries of the pattern. As explained earlier, these types of algorithms require the delineation of regions of interests for their proper operation. Since our goal is to use the algorithm autonomously, such delineation must not be performed, which leads to a bad performance of the corner detection.

On the other hand, most of the points detected by our proposed algorithm lie within the pattern boundaries. However, even if one or more points happen to fall outside the pattern boundary – due to erroneous extraction of lines outside the pattern – the second stage of the algorithm can still reject those points (as explained in Section 2.3).

As it can be seen in the blown-up images of the pattern, the corner detection algorithm presents a very large variance in the actual determination of the pixel coordinates of the features.

Table 1 presents a quantitative measurement of the performance of both algorithms regarding this variation in the position of the corners.

In order to obtain such measurement, we defined a *ground truth* by manually clicking on 42 corner points in the image. The so defined ground truth was then used to compare both algorithms.

As it is demonstrated in Table 1, the proposed algorithm outperformed the corner detection algorithm in terms of the distance between the detected coordinate of the corner and the expected coordinate of that same corner. That average distance in the proposed algorithm is less than half of the distance from the other algorithm. That difference in performance can lead to a very bad calibration of the camera, as pointed out earlier.

Another important point to make about the advantage of the proposed algorithm can be demonstrated by Figure 1. As that figure shows, our algorithm is quite robust to changes in pose of the pattern and background. To validate that point, we took 100 snapshots of the pattern from 6 different cameras in our lab. In all cases, the algorithm detected the feature points in the pattern without any problems.

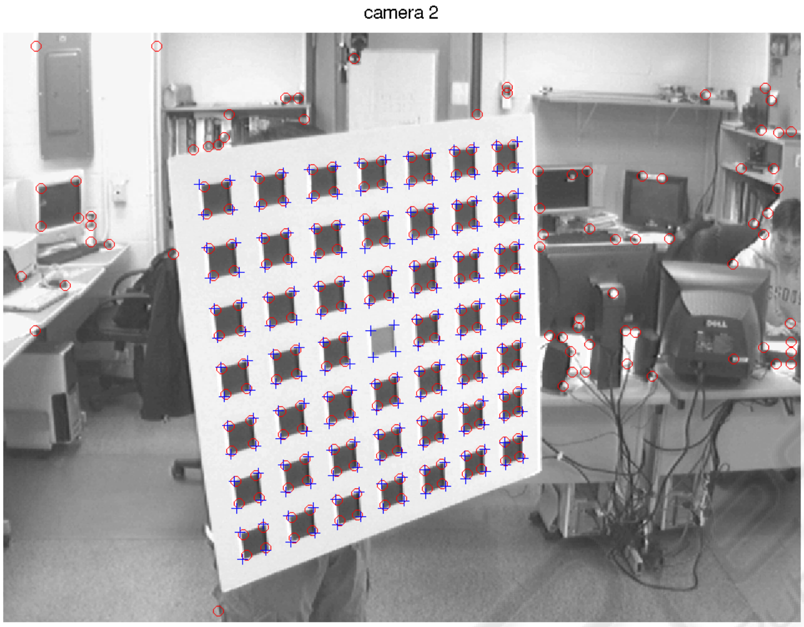
Table 1: Distance in pixels between detected features and ground truth.

	Average distance (in pixels)	**Stdrd deviation (in pixels)**
Proposed algorithm	0.955	0.7159
Algorithm in (Harris and Stephens 1988)	2.324	0.7883

3.2 Result from 3D Reconstruction

52Next, we tested our algorithm by carrying out the complete calibration of a total of 6 cameras and by determining the 3D coordinates of a set of arbitrary points in space using the calibrated camera. That is, using the calibration matrix obtained using the proposed algorithm and the pixel coordinates of a set of predefined points in all 6 cameras, we reconstruct the spatial coordinates of these points and compared the calculated values with the real ones. The points in space were defined by making special marks on a ruler.

The calibration error was measured by averaging the result from 20 different snapshots while holding the ruler. The marks on the ruler were placed at exactly 50cm apart. Each snapshot is taken by all 6 cameras, so a total of 120 images were used for this test. The accuracy of the final calibration was determined by calculating the distance between the two marks. Figure 5 illustrates the above procedure.



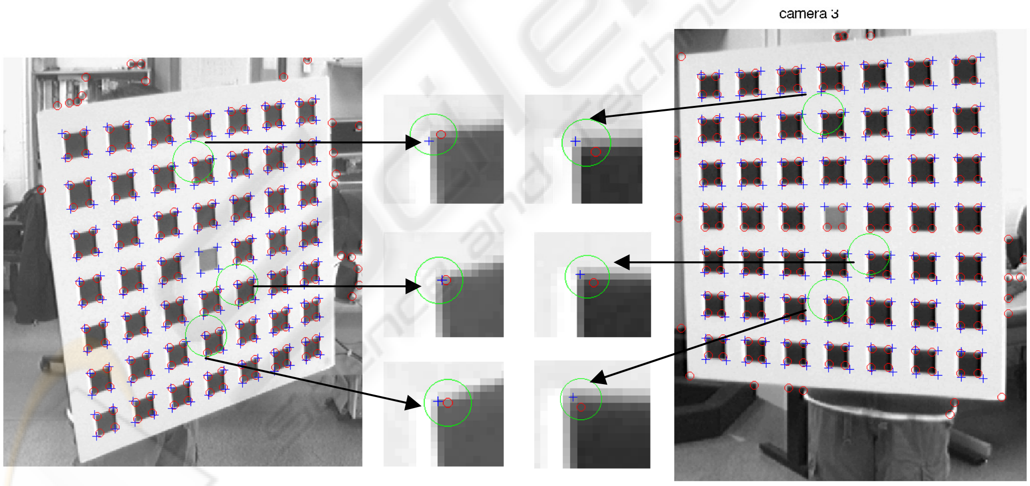


Figure 4: (a) Comparisons between a corner detection algorithm (Harris and Stephens 1988) and the proposed algorithm. The red circles indicate the result from the corner detection algorithm, while the crosses indicate the output of the proposed algorithm. (b) Discrepancies of feature points in (Harris and Stephens) corner detection technique.

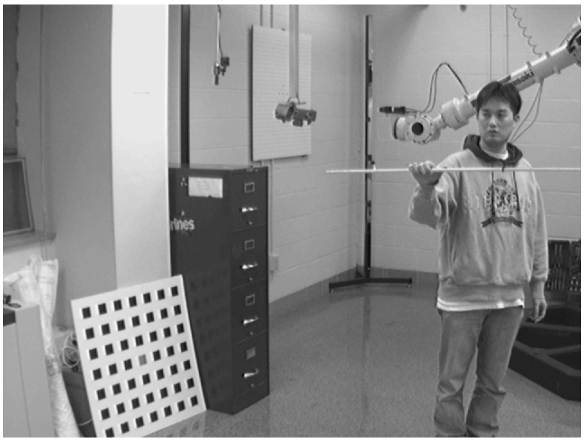


Figure 5: One of the 120 testing images used for 3D reconstruction.

As can be seen from Table 2, the accuracy in 3D reconstruction is quite reasonable – less than 1.5% of the actual distance. Also, the small standard deviation shows that the calibration obtained with our algorithm give a very consistent 3D reconstruction.

Table 2: Mean distances of 20 positions of the ruler.

The number of positions of the ruler	Mean distance between the two points (cm)	Error standard deviation (cm)
20	50.6264	0.2498

4 CONCLUSION

We presented an autonomous feature detection algorithm using Hough transforms. The proposed algorithm was compared against other traditional corner detection algorithms and the results indicate that not only our algorithm is more consistent regarding the detection of the feature points, but it is also more robust with respect to cluttered backgrounds. Both properties of the algorithm allow its use in an autonomous camera calibration procedure – which was the main motivation for this work.

Finally, the experimental results obtained demonstrate the superiority of our approach when compared to other existing algorithms. The proposed algorithm presented an average error of less than half of that of a traditional corner detection algorithm. Also, in terms of the final accuracy in 3D reconstruction using our algorithm, the results showed a quite insignificant error – just a few millimeters. In fact, such small error could be originated from the pixel quantization used in our tests. That is, as it is shown in Table 3, the simple quantization of one or two pixels can lead to approximately the same error in 3D reconstruction as the one from our algorithm.

Table 3: Error in 3D reconstruction due to pixel quantization.

Trial #	Error due to 1 pixel off (cm)	Error due to 2 pixel off (cm)
1	0.2130	0.4398
2	0.1576	0.3135
3	0.2420	0.4785

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