Robust feature matching across widely separated color images

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Abstract

We present a novel method for feature matching across widely separated color images. The proposed approach is robust and can support various correspondence based algorithms e.g. the recovery of epipolar geometry. Our algorithm extends an existing gray-scale corner detector to color. The feature matching algorithm robustly segments the area around the feature into significant color regions using the mean shift mode estimator. The recovered data structures are matched under all possible rotations and the best rotation and its corresponding matches are selected. The results of the matching algorithm are used for recovery of the epipolar geometry from wide base line stereo image pairs. The algorithm has been tested extensively yielding good results over a wide range of scenes and viewpoints. A small subset of these results are presented in the paper.

1 Introduction

The problem of finding corresponding features from two images is a known bottleneck of computer vision. Finding correspondences from wide baseline image pairs is a hard problem. This is due to the changes in the appearance of the features both geometrically and photometrically. While color images contain more information the change in viewpoint affects the color, making the matching of features non trivial.

The proposed algorithm is composed of two phases. First feature detection and then feature matching. Feature detection is based on an extension of the SUSAN [8] corner detector to color images. The improved detector has a better detection rate than the gray scale detector. In the matching phase each corner is characterized by the colors composing the region surrounding it, which are detected robustly using mean shift mode estimator (MSME) algorithm [2, 3]. These regions are then matched taking into account the existence of a global rotation between the two images.

Feature matching has been investigated as part of stereo vision systems with small and wide baselines. A wide-spread method for feature matching in small baseline stereo is correlation. It is used in the majority of papers for feature matching (e.g.[9]). In [5] Lan and Mohr used robust estimators to find a part that is not occluded. On this part partial correlation is performed.

Gouet et al. [4] describe a matching method by first order differential invariants. A vector of features, which are invariant to translation and rotation is built in RGB color space. Features are matched by Euclidean vector distance.

Healey et al. in [7] presented an algorithm for feature matching using a color circle. A circular window is taken around a feature, and it is divided into n segments. Then a vector containing the colors of the segments as values is constructed. The circles are compared by the distance between the vectors. In order to deal with the rotation of the image, the circle is rotated to all possible angles and the minimal distance between all the comparisons is taken. The algorithm was tested on a very limited set of images without dealing with a full change of the viewing position.

The open issue of Healey's algorithm is how to choose the colors of segments robustly. This question has been investigated in the color segmentation area. P. Meer and D. Comaniciu in [3] have proposed a robust color segmentation algorithm using the MSME algorithm. MSME looks for the probability density maximum by iteratively moving the center of the kernel to the mean of its neighborhood. The algorithm repeats this action until convergence.

Our algorithm combines the MSME robust color segmentation with Heally's matching approach extending it to deal with images taken from varying viewing conditions of the scene robustly. To demonstrate the applicability of the proposed algorithm under extreme conditions we have tested our method within the framework of epipolar geometry recovery process. The system recovered the fundamental matrix from

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many pairs of images having large differences in viewing conditions.

2 Approach

2.1 Color corner detection

Due to the fact that corners are encountered almost in every image and that their appearance is robust to image transformations and provide a convenient way to compute image constraints, we chose corners as matching features. Since we used color images and did not want to lose corner information we developed a color corner detector. As the base of our color corner detector we used the Susan corner detector [8]. By extending it to color we improve the corner detector's results.

2.2 Feature matching

The main contribution of this work is the feature matching process. In this section we are going to describe a novel method for feature matching based on color information. The proposed approach should overcome the geometric and photometric changes in the corner neighborhood when the camera position changes considerably between the two images and undergoes rotation. Under such transformations colors are not well defined on the border between regions.

The first part of the algorithm detects the stable color in the neighborhoods of the corner. Apriori the number of stable colors is unknown, we therefore apply the mean shift algorithm on the color space to detect the modes of the color distribution. The mean shift algorithm is an iterative process applied to each pixel in the region around the corner, possibly converging to one of the modes. As a result each pixel can be associated to one of the modes. The border pixels, on the other hand, will not be associated in a similar way. We divide the circular region around the corner into many equally spaced small sectors, as illustrated in Figure 1. Next we would like to segment these corner regions into well defined sectors, where each one of the small sectors is associated with one of the colors we found using the mean shift procedure.

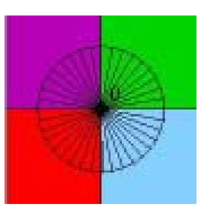
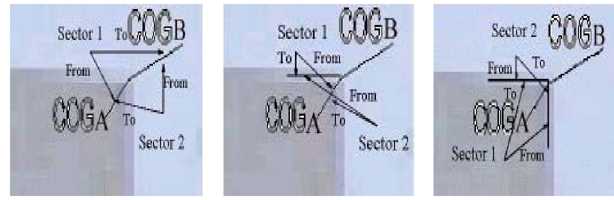


Figure 1. Matching circle

The segmentation process consists of the following steps. First modes of the color distribution which are associated with less than 20% are discarded. For the remaining colors the center of gravity (COG) of all pixels associated with this color is computed. The last step is to find the borders between adjacent sectors. Given two adjacent colors A and B, and their center of gravity as shown in Figure 2, a border has to be established between COG(A) and COG(B). We first set the border such that all the pixels belong to sector B (see Figure 2.2). We then apply Algorithm 1 which changes the border between the sectors one degree at a time and finds the optimal position for the border. Optimality is defined as the position where the sum of squares of the correctly classified pixels is maximal.



(a) Start of algorithm 1 (b) Moving border (c) Algorithm results

Figure 2. Dividing to sectors

Algorithm 1 Sector finding algorithm

A_{num} and B_{num} number of pixels of color A and B in the sector
Initialize $A_c = 0, B_c = B_{num}$ the number of correctly classified pixels in the two sectors
$Score = A_c^2 + B_c^2$
for all degrees of the sector **do**
  compute

$$A_c = A_c + A_{degree} \quad B_c = B_c - B_{degree},$$

  where A_{degree} - number of pixels with color A and B_{degree} - number of pixels with the color B in one degree sector.
  compute new $Score$.
end for
set border to angle with maximal $Score$.

In the algorithm A_c and B_c represent the number of the correctly classified pixels in the two sectors, and A_{degree} and B_{degree} denote the number of pixels of colors A and B in a one degree sector.

The results of this algorithm are used to characterize the corners. For every corner we divide the circular region around the corner into small sectors of size 10°. Each sector is given the color of the region to which it belongs. If the border of the region is contained in the small sector the color of the sector is set as "don't care". As a result each corner is represented by a vector of colors. Comparing two vectors is done by com-

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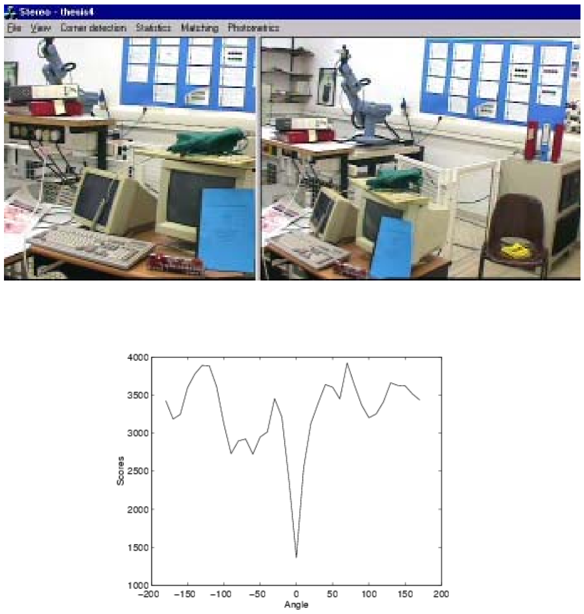

Figure 3. (A) Input pair of images (B) A plot of Sum_{kL} as a function of the rotation angle

puting the Euclidian distance between them.

A match is chosen using the "winner takes all" strategy, i.e., we choose a pair of corners (C, C'), if and only if C is the best match for C' in the first image and C' is the best match for C in the other image. The problem is that this matching scheme is not robust to rotations in the image plane. To solve this problem we assume that all corners underwent the same image plane rotation. Thus, we apply the "winner takes all" strategy a number of times, each time rotating the second image by different amount. This is done by each time rotating all the circles in the second image by one sector. Each rotation angle is given a robust score Sum_{kL} which is the sum of the first k smallest Euclidean distances of matching candidates. The output of the algorithm is an array of arrays of matching pairs which is sorted in ascending order by Sum_{kL}. The number of pairs k, has been determined empirically, such that the correct rotation will have at least k correct matches.

In Fig. 3 we plot the result of determining image plane rotation using the value of Sum_{kL} distribution. Note that at the correct rotation angle the function achieves a distinct minimum.

3 Results

To test our algorithm we conducted extensive experiments including indoor and outdoor scenes with images having large baseline, undergoing considerable rotations. We will present two types of results. First pure matching results, and then results of embedding our matching system into a RANSAC based fundamental matrix recovery system.

In Fig. 4 we show an example the running of the matching algorithm. When a large number of corners was found by the corner detector and there are repeated patterns in the image, a large number of false matches is still present. In order to reduce the number of false matches, we use the ROR algorithm [1], which in most cases considerably reduces the number of false matches. The ROR algorithm requires to be given the internal parameters of the camera. When these parameters are available, ROR can significantly improve the matching results, as can be seen in Table 1. In all cases a sufficient number of correct matches was detected to recover the fundamental matrix.

Figure 4. Example 2 of the results of the matching algorithm

Next we present results of our system on indoor and outdoor images. All results were obtained automatically. Two color images are given as input to our system and the resulting fundamental matrix is computed. For the corner detector we used a circular area of radius 4 pixels.

In Fig. 5 and 6 the computed epipolar lines are shown. As

Example	Correct matches	Total	%
1	27	48	56
2	19	73	26
3	20	86	23
4	13	67	19
4 + ROR	9	22	41
5	22	73	30
5 + ROR	19	44	43
6	18	101	18
6 + ROR	14	40	35
7	13	54	24
7 + ROR	11	24	45
8	43	227	19
8 + ROR	28	65	43
9	17	55	31

Table 1. Summary of the results of the running of the matching phase.

can be seen, that despite the large rotation between the images of approximately 60°, we computed the epipolar geometry correctly. Using arrows we point at corresponding points, which as can be seen, laying on the corresponding epipolar lines.

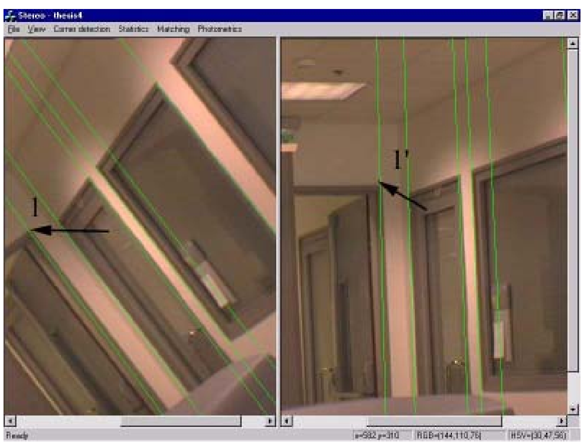

Figure 5. Running of the full algorithm (indoor images)

4 Conclusion

We have introduced methods and tools, which have enabled epipolar geometry finding between two color images of the same scene. The framework presented in this research addressed several aspects of this problem such as: feature detection, feature matching, robust computation of epipolar geometry from matching pairs using the RANSAC paradigm and Hartley's 8-point algorithm.

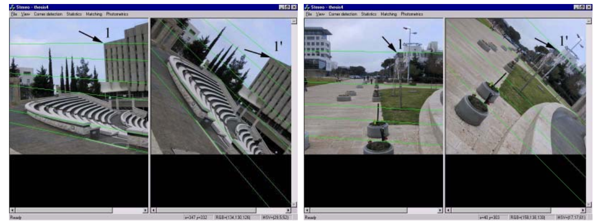

Figure 6. Running the full algorithm (outdoor images)

An experimental system applying our framework has been implemented and tested on many indoor and outdoor images. In this paper, we have presented the results of the various steps of the algorithm and demonstrated the results of running our algorithm on a number of indoor and outdoor scenes. The results we presented were tested on images which had significant changes in camera position and orientation. Our method for color circle matching has proved its feasibility. The results prove the efficiency of our approach. It helped us to solve this hard problem of epipolar geometry finding from two images with significant changes in camera position and orientation.

Our system was successfully incorporated into a visual homing application [6] in which a robot with a camera mounted on it guided itself into a position where a target image was taken.

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