Image Correspondence Problem
– Integration of Intensity and Geometric information –

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Abstract. In this paper, we present a new approach for matching features in a pair of images of the same scene/object. The process is to match triangular patches whose corners are extracted feature corners using Harris filter. Handling such patches combines the use of both intensity information and topological relations, while addressing the scale and rotation invariance issue.

1. Introduction

Solving the correspondence problem between different images of the same scene is a crucial computer vision issue that has been thoroughly challenged. Many approaches start from finding feature points such as corners detected by Harris filter[1]. For instance, Zhang[2] applied a simple template matching on Harris filtered sets of points. Kanatani[3] also used template matching but with automatic thresholding. The weakness of traditional template matching is its sensitivity to scaling and rotations of the scene. Torr[4] proposed a multi-resolution template matching to tackle the rotation and scale invariance issue. Mikolajczyk[5] proposed a multi-resolution approach to detect scale invariant feature corners. Our new approach stresses on the match of triangular patches built from sets of Harris filtered feature points. While it implicitly addresses the issue of rotation and scale invariance, it also uses the content of the triangle-bordered regions to perform the matching.

2. Features detection

Our approach focuses on matching feature corners assuming they are vertices of triangular patches that will be matched later in the process. Several corner-detection methods have been published, and we chose to use an improved version of the Harris filter proposed in Schmid[6]'s evaluation of interest point detectors. Major assets that justify our choice are its rotation invariance and its good repeatability (ability to find feature corners on both images).

3. Creating and correlating patches

The first step of the triangle sets construction consists in generating the Delaunay triangulation on the sets of points detected on input images. Because of the content-independence of this triangulation, these sets of triangles are expanded adding with the following patches:

 a) Dual triangles: given two triangles sharing an edge, both the other triangles using the same four vertices for each triangle, random triangles built from neighbor vertices

 b) Circular-permutations of all the triangles

After having oriented the images' space, a cross-correlation is performed between the two sets of triangular patches. The cross-correlation copes with luminosity variance by correlating the intensity behavior of the patches around their mean.

Due to the use of this correlation on patches whose shapes differ, we perform a geometrical normalization before correlating two patches. The latter are interpolated to an isosceles right triangle whose pixel resolution is parameterized.

Finally, results are stored in a correlation matrix M whose element $M(i,j)$ accounts for the correlation coefficient between the i-th patch of the first set of triangles and the j-th patch of the second set.

4. Searching and matching

The correlation matrix is then interpreted with the following methods:

 a) The "greedy" approach finds the highest correlation value in the matrix at each step, matches the corresponding triangles and suppresses the row and column where this value was found. This suppression discards all other pairs to whom one of the matched triangles belongs. Though this method may yield patent results, it remains sensitive to noise that may lead to ambiguous correlations, thus wrong matches.

 b) A tree approach can deal with such mistakes by anticipating the consequences of a match. Assuming that a high-correlated but wrong match may lead to further low-correlated wrong matches, the path that maximizes the sum of correlations over several next steps is considered the right fit, and this path's first match is selected.
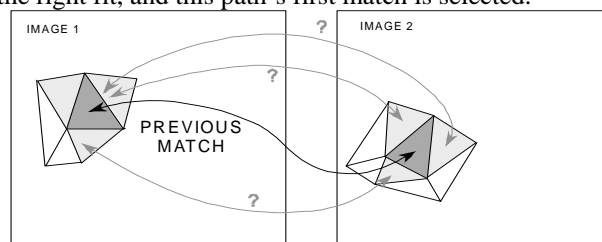

Figure 1: at each step of the matching process, the next good match is looked up within matches of neighbor patches.

Finally, a region-growing method improves the matching by using neighborhood constraints (topological information). At each step, instead of looking for the next match through all the remaining matches, this method first looks up into neighbor matches (Fig. 1). If no good match is found within neighbors, the next match is selected among all the other matches.

5. Experiments

We tested our method on a set of images of the same scene under different viewpoints.

The first step was to match a series of rotated copies of the same image. The rotations are done with a bilinear interpolation algorithm. Results on this series of images prove almost perfect.

We then matched images of neighbor viewpoints. As shown on Fig. 2, this method reveals great efficiency for such pairs of images, especially when the textures are varied (alarm clock) or heavily shaded (cat model). It also shows that uniform areas (white ball) or high level pattern repetitions (calendar) are expectedly not matched properly.
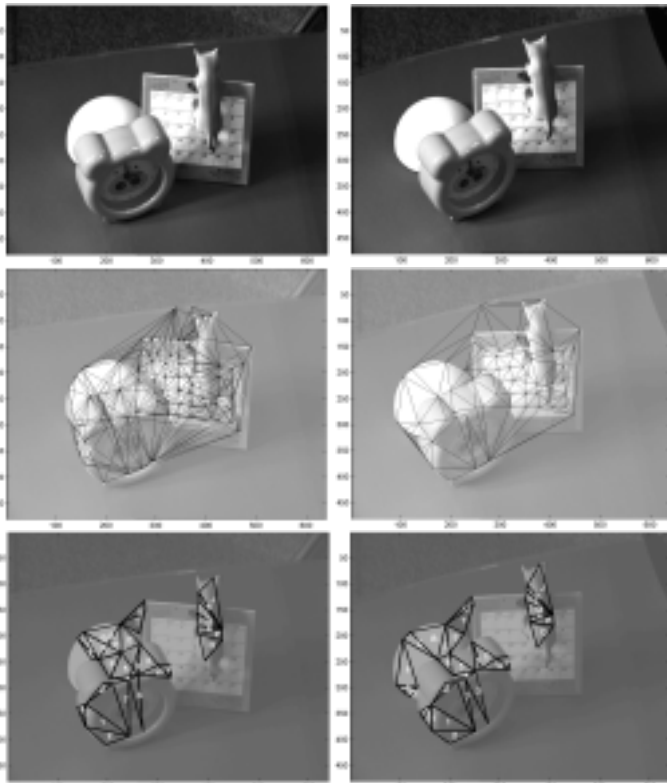

Figure 2: corners are detected on input images (top); triangular patches are then built (middle) and matched (bottom).
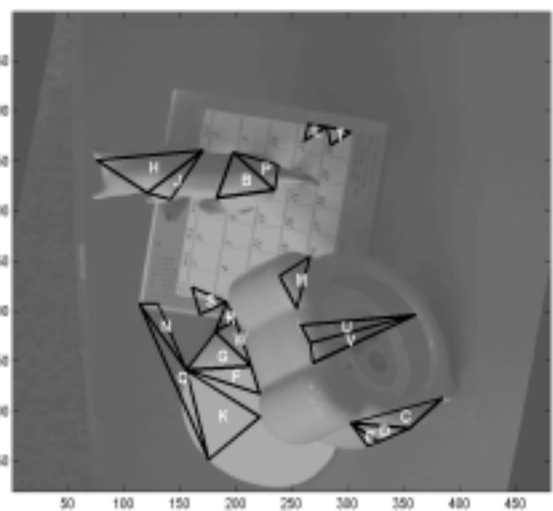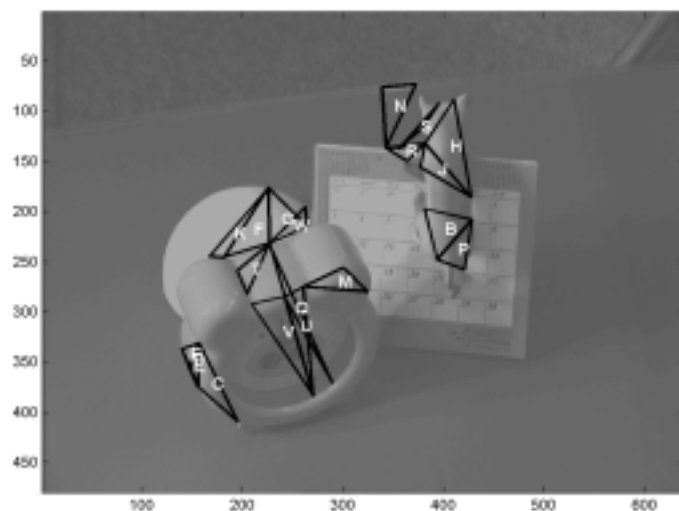
The third experiment we led was a match between neighbor images when one of them is rotated. Fig. 3 shows the same pair of images where the right one was rotated by 80 degrees. Though less efficient than in the first experiment, the algorithm is still good enough for more traditional post-processing to work efficiently.

6. Conclusion

We tried to address the correspondence problem with rotation and scaling with a triangle-matching method. Even though scaling has yet to be further investigated because of Harris filter's weakness against scale, the robustness of our method against rotation is sufficient enough for traditional post-processing methods, like template matching, or determination of epipolar geometry with RANSAC algorithm.

References

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Figure 3: triangle matching on neighbor images, where the right image was rotated clockwise by 80 degrees