World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:6, No:12, 2012

Image Segment Matching Using Affine-Invariant Regions

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***Abstract*—**In this paper, a method for matching image segments using triangle-based (geometrical) regions is proposed. Triangular regions are formed from triples of vertex points obtained from a keypoint detector (SIFT). However, triangle regions are subject to noise and distortion around the edges and vertices (especially acute angles). Therefore, these triangles are expanded into parallelogram-shaped regions. The extracted image segments inherit an important triangle property; the invariance to affine distortion. Given two images, matching corresponding regions is conducted by computing the relative affine matrix, rectifying one of the regions w.r.t. the other one, then calculating the similarity between the reference and rectified region. The experimental tests show the efficiency and robustness of the proposed algorithm against geometrical distortion.

***Keywords*—**Image matching, key point detection, affine invariant, triangle-shaped segments.

I. Introduction

NOWADAYS there is great interest of researchers in image matching and retrieval research area which is still evolving due to the unsolved problems in this area. One of the main challenges in this field is how to match geometrically distorted images. Usually, we cannot get two identical images of the same scene if captured in different contexts and with different capturing devices. Any change of the angles between the scene and the camera (such as: zoom, tilt, movement, or rotation) will result in a geometrically distorted image due to the change of projection parameters between the real 3D world and the 2D plane of the captured image.

It is widely believed that performance of the existing image retrieval systems leaves much to be desired [1]. Image matching is an important issue in the analysis of the visual data. The precision of the image matching have played an important pole on the application such as three-dimensional modeling, data, pattern reorganization, panoramic reconstruction, super resolution, and phasic analysis [1, 2, and 3]. Achieving highly reliable matching results from a pair of images is the task that some of the most popular matching methods are trying to accomplish. However, none have been universally accepted. The methods for image matching can be broadly divided into area-based matching, feature-based matching, or a combination of area-based and feature-based methods.

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Although, the proposed method of extracting triangular shape regions is not new since other researchers proposed to use triangle regions [4], we extended triangles into parallelograms regions which have same invariance to affine distortion as triangle. Parallelograms segments are easier to handle and match than triangles. In order to match two parallelogram-shaped regions, one region is rectified w.r.t. the other region, then matching is conducted using normalized cross-correlation function.

In the following section, related work is presented. Sections III, IV, and V describe the proposed algorithm. Experimental results are shown in section VI. Conclusions and future work are presented in section VII.

II. Related Work

Comparative studies have been published assessing the performance of the image matching algorithms methods in several aspects [5][6].

In [7], Lowe demonstrated that detecting features invariant to image scaling, translation, rotation and partially invariant to illumination can be accomplished.

Mikolajczyk and Schmid [8] presented a method for detecting interest points invariant to scale and affine transformations. Their approach combines the Harris detector with the Laplacian-based scale selection first presented by Lowe [7]. In order to solve the problem of affine invariant transformation, the authors proposed a new feature detector that selects the points from a multi-scale representation.

In [9], Lowe presented the Scale Invariant Feature Transform (SIFT) algorithm. Other researchers tried to improve SIFT and eliminate the computational costs carried with Lowe‟ s implementations. Ke and Sukthankar were the first in presenting the “improved” version of SIFT‟ s descriptor: PCA-SIFT [10]. Then SURF was presented by [11]. SURF stands for Speeded-Up Robust Features and it is an algorithm aimed to re-build the strengths of the leading existing feature detectors and descriptors (i.e. SIFT and PCA-SIFT).

In [5] Babbar et al., presented comparative studies of image matching algorithms named: “Comparative Study of Image Matching Algorithms” was published in 2010. The authors conducted comparative analysis on the distinction between different matching “primitives” used for these algorithms. Also, Juan and Gwun [12] presented comparative studies that compared the performance of SIFT, PCA-SIFT and SURF for scale changes, rotation, blur, illumination changes and affine transformation. Other comparative studies on image matching algorithms can be found in [6].

In [1], the authors considered known algorithms for constructing feature vectors that reflect various image features, such as color, texture, and shape of the objects. In [13], authors presented an approach allowing semantic satellite image retrieval, describing the semantic image content and managing uncertain information. This algorithm is based on ontology model (ontological models merging and semantic strategic retrieval) which represents spatial knowledge in order to provide semantic understanding of image content. In [3], the authors introduced a matching algorithm that combines Harris detector with wavelet domain method. This uses the procedure of building a pyramid model on the remote sensing image.

In [2] the authors have used maximally stable extremal regions (MSER) algorithm and spectral clustering (SC) method for synthetic aperture radar (SAR) image segmentation. In [4] the authors proposed a region-level semantic mining approach for remote sensing image retrieval. The authors segmented images into several parts using an improved segmentation algorithm. In [14], the authors proposed a CBIR system that also retrieves images by clustering similar to CLUE (CLUE (CLUster based image retrieval) is a well-known CBIR technique retrieves the images by clustering approach). The proposed system combines all the features (shape, color, and texture) with some percentage of all features value for the purpose.

III. TRIANGLE-BASED SEGMENTS

Given an image, an efficient keypoint detector is needed in order to extract the important feature (key) points in the images. Next, each triplets can be considered as a triangle vertices {P1, P2, P3}, where Pi=[xi yi]; xi and yi are the coordinates of the vertices. Several keypoint detectors are found in the literature, however, Scale Invariant Feature Transform (SIFT) [9] is used in this paper because of its popularity and recognized performance over wide range of datasets.

The advantage of selecting the triangle-shaped segments for image matching is the invariant of triangles to affine transformation since triangles are mapped into triangles under such transformations. The computational complexity of n pairs of matched keypoints between two images is O(n3). In order to decrease the complexity of the search algorithm, a filtration method is used to eliminate keypoints that has low coarse-similarity with the reference keypoints.

IV. MATCHING ALGORITHM

After extracting the triangle-based regions from both images, the matching algorithm tries to find best match among all regions of the second image. This is done through two stages; in the first stage the filtration and coarse-matching is conducted, while in the second stage an exact matching is carried out.

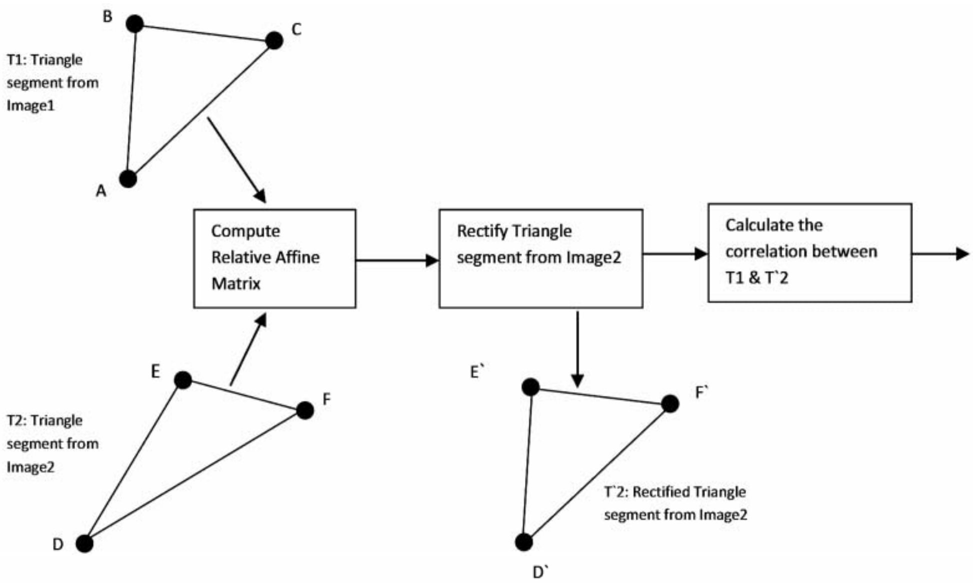

Fig. 1 Matching of Triangle-Based Segments

Fig. 1 shows the second stage of matching algorithm between two different regions. First, the algorithm computes the relative affine matrix between the two given segments in order to rectify one of the regions w.r.t. the other one, and then it calculates the similarity between the reference and rectified regions. Fig. 2 shows an example of Triangle-based region matching between two geometrically distorted Graffiti images.

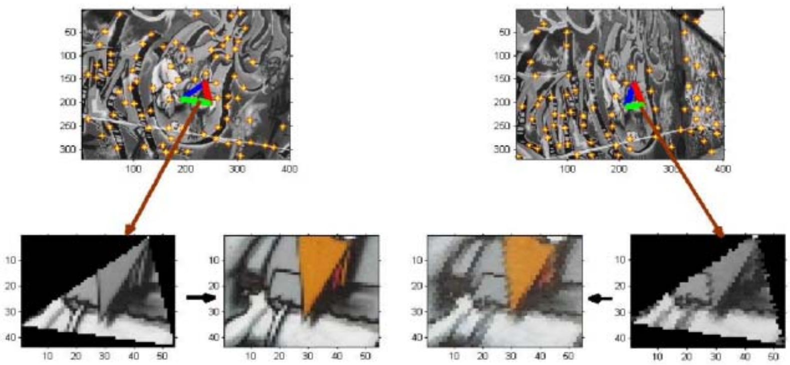

Fig. 2 An example of Triangle-based region matching between geometrically distorted Graffiti images

V. Parallelogram-Based Segments

One problem in triangular segments is that they are subject to noise and distortion around the edges and vertices (especially acute angles). Also, it is challenging to compute similarities between narrow (few pixels) regions. Therefore, these triangles are expanded into parallelogram-shaped regions. The extracted image segments inherit an important triangle property; the invariance to affine distortion. (A parallelogram can be considered as two adjacent triangles).

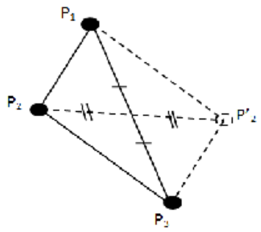

Fig. 3 The parallelogram region is found by calculating P'_2 from the triplet $\{P_1, P_2, P_3\}$

As seen in Fig. 3, the parallelogram is computed by finding the fourth vertex {P'2 } from the triangle triplet {P1, P2, P3}, where Pi=[xi yi]; xi and yi are the coordinates of the vertices. Therefore, the parallelogram region is now determined by the vertices {P1, P2, P3, P'2}. It should be noted that there are other possibilities for the fourth point; P'1 or P'3. In order to minimize comparisons, the fourth point of the parallelogram region of the first (reference) image is always the end point of the diagonal that bisect the largest edge of the triangle {P1P2P3}. For the second image and due to the probable affine distortion, all possible parallelograms are computed and compared to the reference one. The same matching process that has been used for triangle areas is also is used for parallelogram regions.

VI. Experimental Results

The proposed algorithm is tested using images of graffiti with 4 different views, magazine with object orientation from 0-60^o, and boat image with 6 different rotations and zooming. Fig. 4 shows samples of the images used in the experiment. The algorithm is implemented using Matlab 7.14©. All results are obtained using parallelogram regions since these regions are easier to handle than triangular regions with less noise distortion around vertices.

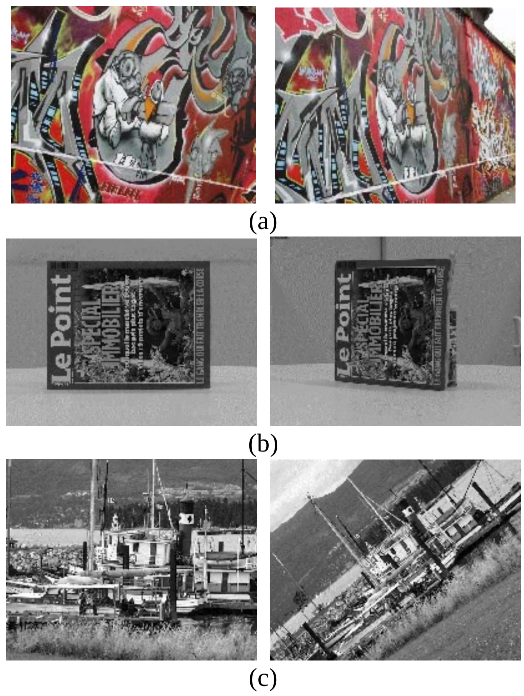

Fig. 4 Samples of Images used in Experiments: a) Grafitti, b) Magazine c) Boat

In order to evaluate the proposed method, first, SIFT is applied to each pair of images to get the correspondences between them. Also, Delaunay triangulation is used to obtain around 50 triangles in the first (reference) image. For each triangle segment, a parallelogram is extracted then the algorithm searches for best match in the second image (as shown in Fig. 5). The parameters of SIFT algorithm are adjusted so that around 50 triangle segments are obtained each reference image. The experimental results (Tables I, II, and III) show efficient and consistent results in finding matched regions for affine distorted image.

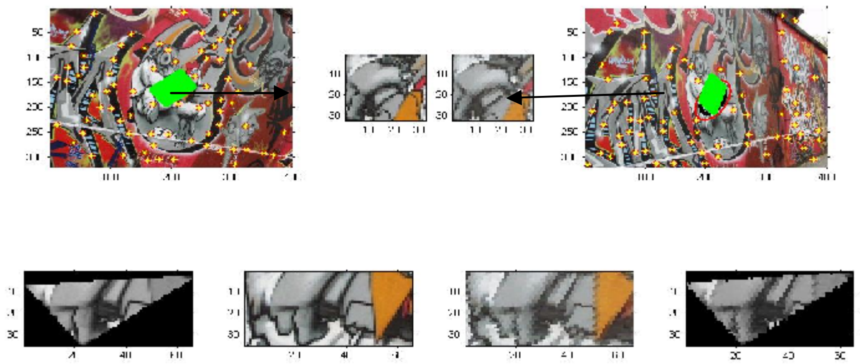

Fig. 5 Parallelogram-based region (Green) matching between geometrically distorted Grafitti Images

From the experiments conducted in this research, it has been noticed that the performance of the proposed segment extraction and matching is highly affected by the number of correct correspondences between images. SIFT failed to produce proper adjacent and correct correspondences in the 5th and 6th views of graffiti image and for magazine image with object rotations 70^{o} and 80^{o} at the given parameters. Therefore, this work will be extended in future by replacing the SIFT with a more robust keypoint detector such as Affine-SIFT (ASIFT) detector [15].or Non-Sampled Contourlet Transform (NSC) keypoint detector [16].

TABLE I
PRECISION SCORES FOR GRAFFITI IMAGES

Graffiti	***1 &2***	***1 &3***	***1 &4***
Precision %	100	95.65	68.08

TABLE II
PRECISION SCORES FOR MAGAZINE IMAGES

Magazine	***1 &2***	***1 &3***	***1 &4***	***1 &5***	***1 &6***	***1 &7***
Precision %	100	97	95.42	98	91.6	53.7

TABLE III
PRECISION SCORES FOR BOAT IMAGES

Boat	***1 &2***	***1 &3***	***1 &4***	***1 &5***	***1 &6***
Precision %	100	100	96	98.04	88.24

VII. CONCLUSIONS AND FUTURE WORK

In this paper, a method for matching image segments using triangle-based regions is presented. SIFT algorithm is used for obtaining triangular triplets which are used in calculating the fourth point in order to extract a parallelogram segment. The extracted image segments inherit an important triangle property; the invariance to affine distortion. In order to speed up calculations, the matching algorithm is implemented with two stages; coarse and fine matching. The experimental results show the promising efficiency and robustness of the proposed algorithm against the affine distortion. However, the proposed algorithm is highly affected by the keypoint detector (SIFT) used in the experiments. Therefore, SIFT will be replaced by a more robust keypoint detector such as Affine-SIFT (ASIFT) [15] or Non-Sampled Contourlet (NSC)-based key-point detector [16] for further enhancement to the matching performance.

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