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A Novel Algorithm for Pose and illumination Invariant Image Matching

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Abstract:

The challenges in local-feature-based image matching are variations of view and illumination. Many methods have been recently proposed to address these problems by using invariant feature detectors and distinctive descriptors. However, the matching performance is still unstable and inaccurate, particularly when large variation in view or illumination occurs. In this paper, we propose a view and illumination invariant image-matching method. We iteratively estimate the relationship of the relative view and illumination of the images, transform the view of one image to the other, and normalize their illumination for accurate matching.

Our method does not aim to increase the invariance of the detector but to improve the accuracy, stability, and reliability of the matching results. The performance of matching is significantly improved and is not affected by the changes of view and illumination in a valid range. The proposed method would fail when the initial view and illumination method fails, which gives us a new sight to evaluate the traditional detectors. We propose two novel indicators for detector evaluation, namely, valid angle and valid illumination, which reflect the maximum allowable change in view and illumination, respectively. Extensive experimental results show that our method improves the traditional detector significantly, even in large variations, and the two indicators are much more distinctive.

Introduction:

Image matching is a fundamental issue in computer vision. It has been widely used in tracking , image stitching , 3-D reconstruction , simultaneous localization and mapping (SLAM) systems , camera calibration , object classification, recognition, and so on. Image matching aim to find the correspondence between two images of the same scene or objects in different pose, illumination, and environment.

In this paper, we focus on local feature-based image matching. The challenges of this work reside in stable and invariant feature extraction from varying situations and robust matching. In image matching, key region or point of interest is often used as the local feature due to its stable performance in detection and description. A region feature is usually derived from a circle or ellipse with certain location and radius and is effective and efficient, compared with other types of features such as edges and contours. Therefore, region features are extensively used in real applications. Generally speaking, the framework of a region feature based image matching consists of three steps.

Detecting stable regions:

Interesting points are extracted from images, and the region of interest is the associated circular (or elliptical) region around the interesting point.Generally, researchers use corner (Harris, SUSAN, CSS , etc.) or center of silent region (SIFT, SURF , DoH, HLSIFD, etc.) as the interesting point since they are stable and easy to locate and describe. The radius of the region is determined by apriori setting (Harris corner) or the region scale (scale invariant features). The total number of features detected is the minimum number of the features extracted from the matched images.

Describing regions:

Color, structure, and texture are widely used to describe images in the recent literature. Descriptors with edge orientation information (SIFT and HOG) are also very popular since they are more robust to scale, blur, and rotation. Matching features. Local features from two images are first matched when they are the nearest pair. A handfulof distances can be used in practice, such as distance, distance, histogram intersection distance, and earth mover's distance .

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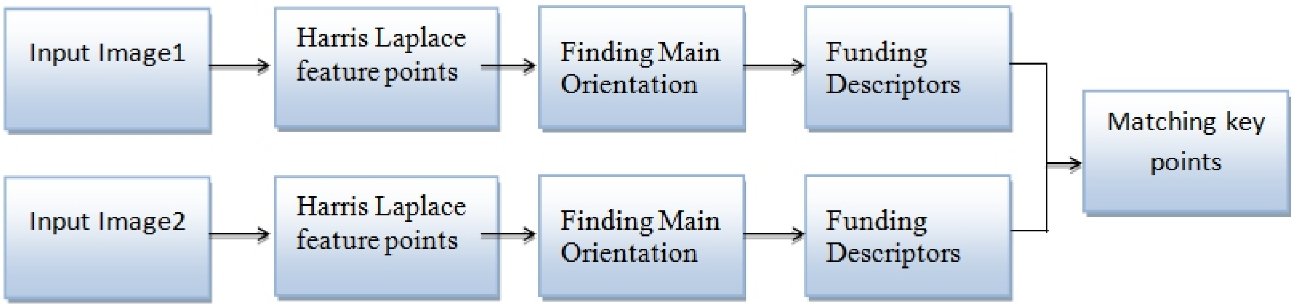
If the nearest distance is higher than k times (empirically) of the second nearest distance, the nearest matching pair will be removed. These are the very initial matching results. Then the priori hypothesis of the object transform filters the un-uniform transformed matches. In this paper, we simply use planar objects to show the effectiveness of the proposed method. For the multitransform problem, the proposed method could be also integrated. Random sample consensus (RANSAC),is used to select the uniform or multiple transformations set from all the matches.The three parts of the detect–describe–match (DDM) framework determine the performance of image matching. The first step is the basis of this framework. Unstable and variant features increase the difficulties of the next two steps. Researchers mostly focus on the first step for invariant feature extraction and have proposed many excellent detectors .

However, an important experience of a pervious work is that all the aforementioned feature detectors are not strictly invariant to the changes of view and illumination. The same interestingregions extracted from the matching images tend to be fewerand fewer when increasing the variation of view or illumination. For larger changes, there would be few invariant features that can be extracted from both images to be matched. This motivates us to think the essential difference of images with different view and illumination. Normally, a question need to be answered: whether an object in two images with different views and illumination looks like the same one, supposing there are two images with a large view change, as shown in Fig. 1. The two top images are the same object in different views. They are so different in appearance that they can be considered as two different objects. We do not attempt to find invariant local feature detectors as in a previous work but focus on a better framework for image matching.

Block Diagram:



Scale Invariant feature transform:

Image matching is a fundamental aspect of many problems in computer vision, including object or scene recognition, solving for 3D structure from multiple images, stereo correspondence, and motion tracking. This paper describes image features that have many properties that make them suitable for matching differing images of an object or scene. The features are invariant to image scaling and rotation, and partially invariant to change in illumination and 3D camera viewpoint. They are well localized in both the spatial and frequency domains, reducing the probability of disruption by occlusion, clutter, or noise. Large numbers of features can be extracted from typical images with efficient algorithms. In addition, the features are highly distinctive, which allows a single feature to be correctly matched with high probability against a large database of features, providing a basis for object and scene recognition.

The cost of extracting these features is minimized by taking a cascade filtering approach, in which the more expensive operations are applied only at locations that pass an initial test.Following are the major stages of computation used to generate the set of image features:

1.Scale-space extrema detection: The first stage of computation searches over all scalesand image locations. It is implemented efficiently by using a difference-of-Gaussianfunction to identify potential interest points that are invariant to scale and orientation.

2.Keypoint localization: At each candidate location, a detailed model is fit to determinelocation and scale. Keypoints are selected based on measures of their stability.

3.Orientation assignment: One or more orientations are assigned to each keypoint locationbased on local image gradient directions.

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All future operations are performedon image data that has been transformed relative to the assigned orientation, scale, andlocation for each feature, thereby providing invariance to these transformations.

4.Keypoint descriptor: The local image gradients are measured at the selected scalein the region around each keypoint. These are transformed into a representation thatallows for significant levels of local shape distortion and change in illumination.

This approach has been named the Scale Invariant Feature Transform (SIFT), as it transformsimage data into scale-invariant coordinates relative to local features.An important aspect of this approach is that it generates large numbers of features thatdensely cover the image over the full range of scales and locations.

A typical image of size 500x500 pixels will give rise to about 2000 stable features (although this number depends on both image content and choices for various parameters). The quantity of features is particularly important for object recognition, where the ability to detect small objects in cluttered backgrounds requires that at least 3 features be correctly matched from each object for reliable identification.

For image matching and recognition, SIFT features are first extracted from a set of referenceimages and stored in a database. A new image is matched by individually comparing each feature from the new image to this previous database and finding candidate matching features based on Euclidean distance of their feature vectors. This paper will discuss fast nearest-neighbor algorithms that can perform this computation rapidly against large databases.

The keypoint descriptors are highly distinctive, which allows a single feature to find itscorrect match with good probability in a large database of features. However, in a clutteredimage, many features from the background will not have any correct match in the database,giving rise to many false matches in addition to the correct ones. The correct matches can be filtered from the full set of matches by identifying subsets of keypoints that agree on the object and its location, scale, and orientation in the new image.

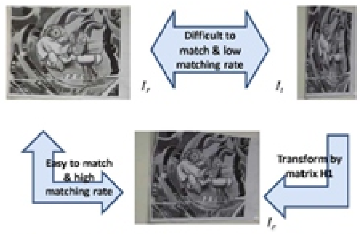

Fig. 1. Illustration of the proposed matching algorithm. I_r and I_t are the images to be matched. I_e is simulated from I_t by transformation T. I_r is difficult to match with I_t for the difference of view point and illumination, whereas I_e is easier to match with I_t since they are closer in the parameter space.

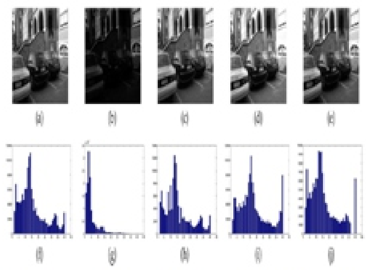

Fig. 2. Illustration of the histogram transformation. (a) The original image. (b) Darker image. (c) Transformed image from (b) according to the histogram of (a). (d) Brighter image. (e) Transformed image from (d) according to the histogram of (a). (f)–(j) The corresponding histograms of (a)–(e).

Discarding low-contrast keypoints:

To discard the keypoints with low contrast, the value of the second-order Taylor expansion is computed at the offset . If this value is less than , the candidate keypoint is discarded. Otherwise it is kept, with final location and scale , where is the original location of the keypoint at scale .

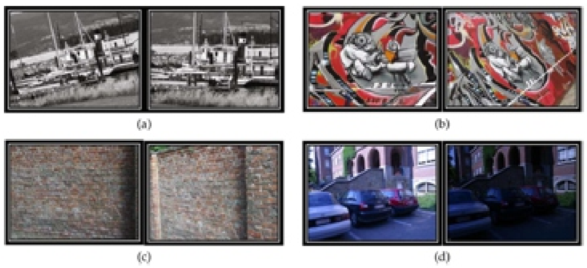

Fig:Group of photos used for comparision and transformation of the images.

Keypoint localization:

Scale-space extrema detection produces too many keypoint candidates, some of which are unstable. The next step in the algorithm is to perform a detailed fit to the nearby data for accurate location, scale, and ratio of principal curvatures. This information allows points to be rejected that have low contrast (and are therefore sensitive to noise) or are poorly localized along an edge.

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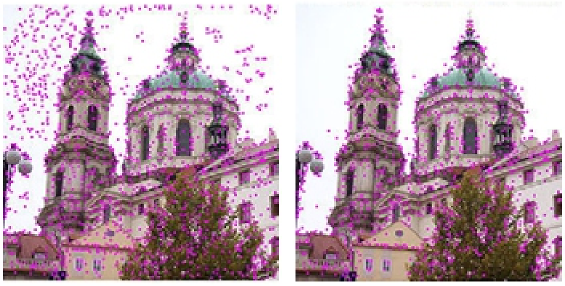


Fig:key point localization

Accurate keypoint localization:

Once a keypoint candidate has been found by comparing a pixel to its neighbors, the next step is to perform a detailed fit to the nearby data for location, scale, and ratio of principal curvatures. This information allows points to be rejected that have low contrast (and are therefore sensitive to noise) or are poorly localized along an edge.

The initial implementation of this approach (Lowe, 1999) simply located keypoints at the location and scale of the central sample point. However, recently Brown has developed a method (Brown and Lowe, 2002) for fitting a 3D quadratic function to the local sample points to determine the interpolated location of the maximum, and his experiments showed that this provides a substantial improvement to matching and stability.

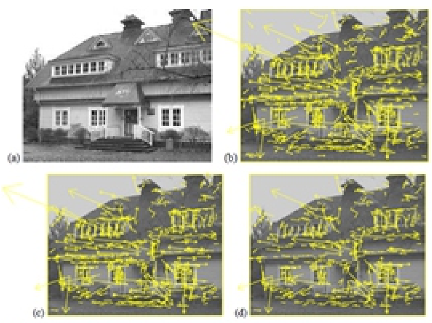
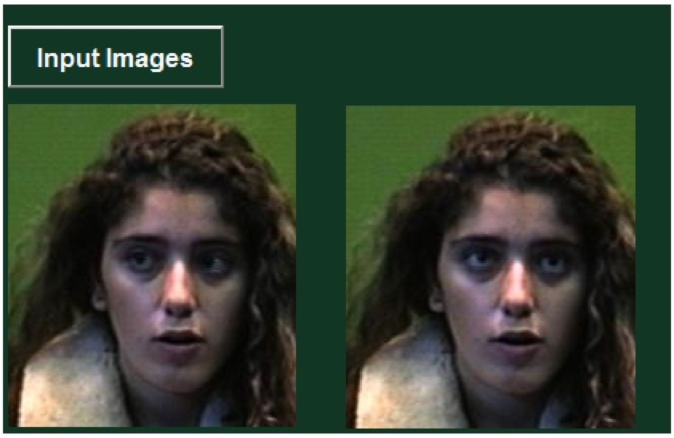
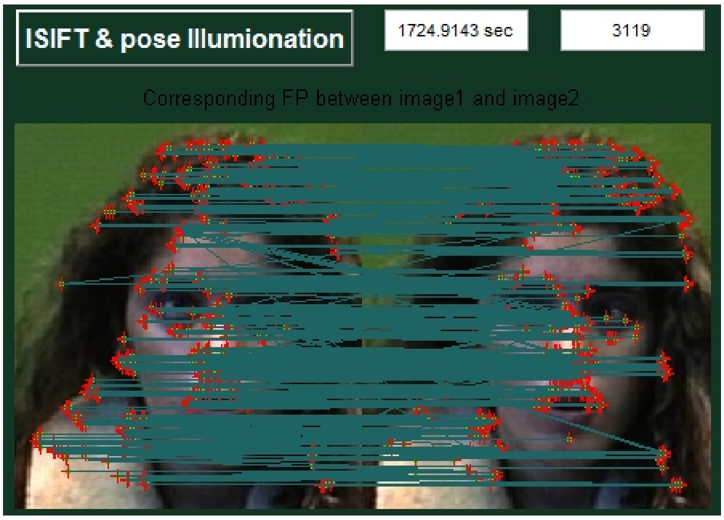


Figure 5: This figure shows the stages of keypoint selection. (a) The 233x189 pixel original image. (b) The initial 832 keypoints locations at maxima and minima of the difference-of-Gaussian function. Keypoints are displayed as vectors indicating scale, orientation, and location. (c) After applying a threshold on minimum contrast, 729 keypoints remain. (d) The final 536 keypoints that remain following an additional threshold on ratio of principal curvatures.

RESULT ANALYSIS:





CONCLUSION:

In this paper we have prop[osed an image matching novel algorithm for the iterative work for local feature detector ang matching algorthms. The performance of matching is significantly improved and is not affected by the changes of view and illumination in a valid range.

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REFERENCES:

[1] J. Shi and C. Tomasi, “Good features to track,” in Proc. Comput.Vis.Pattern Recognit., Jun. 1994, pp. 593–600.

[2] Y. Li, Y. Wang, W. Huang, and Z. Zhang, “Automatic image stitchingusing sift,” in Proc. Audio, Lang. Image Process., Jul. 2008, pp.568–571.

[3] R. Szeliski, “Image alignment and stitching: a tutorial,” Found. TrendsComput. Graph Vis. vol. 2, no. 1, pp. 1–104, 2006 [Online]. Available:http://dx.doi.org/10.1561/0600000009

[4] M. Brown and D. Lowe, “Unsupervised 3D object recognition and reconstructionin unordered datasets,” in Proc. Int. Conf. 3-D Digit. Imag.Model., Jun. 2005, pp. 56–63.

[5] A. Davison, W. Mayol, and D. Murray, “Real-time localization andmapping with wearable active vision,” in Proc. Int. Symp. Mixed AugmentedReality, 2003, pp. 18–27.

[6] B. Telle, M. J. Aldon, and N. Ramdani, “Camera calibration and 3dreconstruction using interval analysis,” in Proc. Int. Conf. Image Anal.Process., 2003, pp. 374–379.

[7] D. Lisin, M. Mattar,M. Blaschko, E. Learned-Miller, and M. Benfield,“Combining local and global image features for object class recognition,”in Proc. Comput. Vis. Pattern Recognit. Workshops, Jun. 2005,p. 47.

[8] C. Harris and M. Stephens, “A combined corner and edge detection,”in Proc. 4th Alvey Vis. Conf., 1988, pp. 147–151.

[9] S. M. Smith and J. M. Brady, “Susan—A new approach to low levelimage processing,” Int. J. Comput. Vis., vol. 23, no. 1, pp. 45–78, May1997.

[10] F. Mokhtarian and R. Suomela, “Robust image corner detectionthrough curvature scale space,” IEEE Trans. Pattern Anal. Mach.Intell., vol. 20, no. 12, pp. 1376–1381, Dec. 1998.

[11] D. G. Lowe, “Distinctive image features from scale-invariant keypoints,”Int. J. Comput. Vis., vol. 60, no. 2, pp. 91–110, Nov. 2004.

[12] H. Bay, A. Ess, T. Tuytelaars, and L. V. Gool, “Speeded-up robustfeatures (SURF),” Comput. Vis. Image Understand., vol. 110, no. 3,pp. 346–359, Jun. 2008.