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Citation for published version (APA):

Li, P., Farin, D. S., Klein Gunnewiek, R., & With, de, P. H. N. (2007). Descriptor-Free Smooth Feature-Point Matching for Images Separated by Small/Mid Baselines. In J. Blanc-Talon, & W. Philips (Eds.), *Proceedings of the 9th international conference on Advanced Concepts for Intelligent Vision Systems (ACIVS 2007) 28-31 August 2007, Delft, The Netherlands* (pp. 427-438). (Lecture Notes in Computer Science; Vol. 4678). Springer. https://doi.org/10.1007/978-3-540-74607-2_39

DOI:

[10.1007/978-3-540-74607-2_39](https://doi.org/10.1007/978-3-540-74607-2_39)

Document status and date:

Published: 01/01/2007

Document Version:

Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

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Descriptor-Free Smooth Feature-Point Matching for Images Separated by Small/Mid Baselines

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Abstract. Most existing feature-point matching algorithms rely on photometric region descriptors to distinct and match feature points in two images. In this paper, we propose an efficient feature-point matching algorithm for finding point correspondences between two uncalibrated images separated by small or mid camera baselines. The proposed algorithm does not rely on photometric descriptors for matching. Instead, only the motion smoothness constraint is used, which states that the correspondence vectors within a small neighborhood usually have similar directions and magnitudes. The correspondences of feature points in a neighborhood are collectively determined in such a way that the smoothness of the local correspondence field is maximized. The smoothness constraint is self-contained in the correspondence field and is robust to the camera motion, scene structure, illumination, etc. This makes the entire point-matching process texture-independent, descriptor-free and robust. The experimental results show that the proposed method performs much better than the intensity-based block-matching technique, even when the image contrast varies clearly across images.

1 Introduction

Tracking feature points along frames of a video sequence is useful in many applications such as image segmentation, structure reconstruction, depth creation for 3D-TV, object recognition, etc. The key step of feature-point tracking is to establish feature-point correspondences between two successive frames, which can be further divided into two sub-steps. First, detecting feature points/regions in two individual images. Second, establishing correspondences between the detected feature points. This paper focuses on the second step, with the assumption that the feature points are already detected in two images using the well-known Harris corner detector [1].

1.1 Related Work

Many feature-point matching algorithms have been proposed, and many of them are based on photometric descriptors to characterize and distinct the local

image regions. Local image regions can be described by the histogram of the pixel intensity, distribution of the intensity gradients [2], composition of the spatial frequencies, image derivatives [3,4], generalized moments [5], or other image properties. Two feature points are matched if their corresponding descriptors show high similarity. An evaluation of the state-of-the-art interest point detectors and region descriptors can be found in [6] and [7]. In the following, we summarize some of the well-known schemes that fall into this category.

Lowe [2] proposed a Scale-Invariant Feature Transform (SIFT) algorithm for feature-point matching or object recognition, which combines a scale-invariant region detector and a gradient-distribution-based descriptor. The descriptor is represented by a 128-dimensional vector that captures the distribution of the gradient directions (sub-sampled into 8 orientations and weighted by gradient magnitudes) in 16 location grids. The Gradient Location and Orientation Histogram (GLOH) algorithm proposed by K. Mikolajczyk and C. Schmid [7] extends the SIFT to consider more regions for computing the histogram, and was shown to outperform the SIFT. Recently, Herbert Bay *et al.* proposed a new rotation- and scale-invariant interest point detector and descriptor, called SURF (Speeded Up Robust Features) [8]. It is based on sums of 2D Haar wavelet responses and makes an efficient use of integral images. The algorithm was shown to have comparable or better performance, while obtaining a much faster execution than previously proposed schemes.

Another category of feature-point matching algorithms do not use region descriptors. In [9], a feature-point matching algorithm is proposed using the combination of the intensity-similarity constraint and geometric-similarity constraint. Feature correspondences are first detected using the correlation-based matching technique. The outliers are thereafter rejected by a few subsequent heuristic tests involving geometry, rigidity, and disparity. In [10], a point-matching method is proposed to globally match the feature points. The algorithm relaxes the huge combinatorial search domain into its convex-hull, which can be efficiently solved by concave programming. Any assumption can be used by the proposed method as a matching criterion, provided that the assumption can be translated into cost functions with continuous second derivatives. Intensity correlation has been demonstrated as a good criterion.

For feature-point tracking in a video sequence, the variation of the camera parameters (rotation, zoom, viewpoint) is relatively small. The correlation-based block matching technique is often used because of its computational efficiency. In this method, the similarity between two image patches in windows around two feature points is measured by aggregating measurements such as intensity, color, phase, etc., over the window. Two feature points are matched if the measurements show high correlation. The descriptor-based algorithms are more suitable for matching feature points between two widely separated views or object recognition. The high computational complexity of the high-dimension¹ descriptors makes these algorithms less efficient in this context. On the other hand, the

¹ To describe the local regions properly, the descriptors normally require dozens or even hundreds of dimensions [7].

block-matching algorithm is less robust due to the fact that only the local intensity similarity is used for point matching.

Geometric similarity² and intensity similarity are the two underlying principles of most feature-matching algorithms. Though both are widely used, it appears that the geometric similarity is more fundamental and stable than intensity similarity since intensities are more liable to change [9]. It is favorable to establish the feature correspondences using the geometric similarity alone.

1.2 Our Approach

Our approach concentrates on both the computational efficiency and robustness of feature-point matching algorithm, as well as the fundamental nature of the geometric similarity. Therefore, this paper proposes an efficient and robust point-matching algorithm that uses only the smoothness constraint, targeting at feature-point tracking along successive frames of uncalibrated video sequences.

In the proposed algorithm, the collected correspondences of feature points within a neighborhood are efficiently determined such that the smoothness of the correspondence field is maximized. Intensity information is not required for the matching. It is pursued that the proposed algorithm works well even when there is significant change of image contrast. Besides, due to the robustness and wide applicability of the smoothness constraint, the proposed algorithm works well even when the camera is subject to a moderate change of its parameters. Further, the proposed algorithm is also computationally efficient. As will be discussed in Section 3.1, the smoothness of the correspondence field is efficiently computed using a very simple metric.

Our experimental results on both synthetic and real images show that the proposed algorithm is able to detect a much higher number of feature-point correspondences with a higher quality than the correlation-based block-matching technique. Because correspondences of feature points within a neighborhood are collectively determined, the chance is lower for the erroneous two-frame correspondences to propagate among several frames. This increases the robustness of the feature-point tracking in video sequences.

2 Notations

Let $I = \{I_1, I_2, \dots, I_M\}$ and $J = \{J_1, J_2, \dots, J_N\}$ be two sets of feature points in two related images, containing M and N feature points, respectively. For any point I_i , we want to find its corresponding feature point J_j from its candidate set C_{I_i} , which, as shown in Fig. 1(b), is defined as all the points within a co-located rectangle in the second image. The dimension of the rectangle and density of the feature points determine the number of the points in the set.

² We consider the smoothness assumption related to the geometric constraint, because it is the rigidity of the scene geometry that gives the motion smoothness in the image. For example, a group of points on the surface of a rigid object usually move in similar direction and speed. This leads to smooth image motion.

Fig. 1. The set of feature points in neighborhood N_{I_i} in the first image and the set of candidate corresponding feature points C_{I_i} in the second image for feature point I_i

As illustrated by Fig. 1, the neighborhood N_{I_i} of feature point I_i is defined as a circular area around the point. The number of points within N_{I_i} depends on the radius of the circle and the density of the feature points. The displacement between I_i and I_j is represented by its Correspondence Vector (CV) $\mathbf{v}_{I_i}$. The candidate set C_{I_i} for I_i gives rise to a corresponding set of candidate correspondence vectors V_{I_i} . Determining the correspondence for I_i is equivalent to finding the corresponding point from C_{I_i} or finding the corresponding CV from V_{I_i} .

3 Matching Algorithm

We assume that correspondence vectors within a small neighborhood have similar directions and magnitudes, which is referred to as *local-translational-motion* (LTM) assumption in the remainder of the paper. CVs that satisfy this constraint are called *coherent*. In this section, the LTM assumption is translated into a coherence criterion for feature matching.

3.1 Coherence Metric

Given two coherent CVs $\mathbf{v}_i$ and $\mathbf{v}_j$, we require that both the difference d_{ij} between their magnitudes, and the angle deviation θ_{ij} between their directions, should be small, as illustrated in Fig. 2. Combining these two requirements, we obtain the following coherence metric:

$$d_{ij} < \|\mathbf{v}_i\| \times \sin(\varphi) = R, \quad (1)$$

where φ is the maximum allowed angle deviation between two CVs within a neighborhood, and R is a threshold based on the magnitude of the reference CV and φ , as illustrated in Fig. 2. The allowed degree of deviation φ specifies how similar two CVs should be in order to satisfy the coherence criterion. Difference d_{ij} is computed as:

$$d_{ij} = |\mathbf{v}_i - \mathbf{v}_j| = |x_{\mathbf{v}_i} - x_{\mathbf{v}_j}| + |y_{\mathbf{v}_i} - y_{\mathbf{v}_j}|. \quad (2)$$

Fig. 2. Two coherent CVs v_i and v_j within a neighborhood; vector v_i is the reference CV

Note that the smoothness assumption is more general than the LTM assumption, because it includes not only the translational motion but also other smooth motions caused by rotation, scaling, slanting depth, etc. The reason why our algorithm, which is based on the LTM assumption, works well for a wide range of scenarios (including images with evident rotation and scaling) is that the local correspondence field within a small neighborhood in most cases follows the translational-motion model well, regardless of the actual camera motion and scene structure.

3.2 Smoothness Computation

Given a reference CV $v_{I_i} \in V_{I_i}$, the smoothness of the correspondence field with respect to the reference vector within neighborhood N_{I_i} is measured as the ratio between the number of coherent CVs found in N_{I_i} and the number of the feature points in N_{I_i} . This ratio is denoted by $S(N_{I_i}, v_{I_i})$ and can be computed by:

$$S(N_{I_i}, v_{I_i}) = \frac{\sum_{I_k \in N_{I_i}} f_{I_k}(v_{I_i})}{n}, \quad (3)$$

where n is the number of feature points in N_{I_i} ; $f_{I_k}(v_{I_i})$ is a binary variable, indicating whether the most similar CV (smallest distance by Eq. (2)) of feature point I_k is coherent with the reference vector, which can be computed by:

$$f_{I_k}(v_{I_i}) = \begin{cases} 1 & d_{ik} < R \\ 0 & \text{else} \end{cases} \quad (4)$$

As stated by the smoothness assumption, the correspondence field within a neighborhood is smooth. This implies that $S(N_{I_i}, v_{I_i})$ should be as high as possible to have a smooth field. We compute $S(N_{I_i}, v_{I_i})$ for every $v_{I_i} \in V_{I_i}$. The maximum is considered as the smoothness of the field, and is computed by:

$$S_m(N_{I_i}) = \max_{v_{I_i} \in V_{I_i}} S(N_{I_i}, v_{I_i}). \quad (5)$$

With the above equation, the problem to determine the correspondences for feature points within N_{I_i} is converted into selecting a CV $v_{I_k} \in V_{I_k}$ for every $I_k \in N_{I_i}$ to have a maximum smoothness $S_m(N_{I_i})$ of the correspondence field.

True correspondences are found once we find that $S_m(N_{I_i})$ is larger than a given threshold. Note that once the vector $\mathbf{v}_{I_i}$ for I_i is selected, vector $\mathbf{v}_{I_k}$ for $I_k \in V_{I_k}$ is determined as well.

3.3 Steps to Compute Correspondences for Feature Points Within a Neighborhood

We summarize the steps to compute the correspondences for feature points within neighborhood N_{I_i} as follows:

- S1 Given a reference CV $\mathbf{v}_{I_i} \in V_{I_i}$, for every $I_k \in N_{I_i}$ ($k = 1, \dots, n$), find its most similar CV from V_{I_k} so that the distance d_{ik} by Eq. (2) is minimum.
- S2 Set the indicator variable $f_{I_k}(\mathbf{v}_{I_i})$ according to Eq. (4); compute the smoothness $S(N_{I_i}, \mathbf{v}_{I_i})$ of the correspondence field using Eq. (3).
- S3 Compute the maximum smoothness $S_m(N_{I_i})$ using Eq. (5); true correspondences are found if $S_m(N_{I_i})$ is higher than a given threshold.

3.4 Rationale of the Algorithm

The algorithm tries to find the CV that gives the maximum number of coherent CVs in a neighborhood. In this subsection, we explain why this maximum smoothness gives the correct correspondences with a high probability.

As explained in Section 3.1, the correspondence field within a neighborhood in most cases follows the LTM model well. Thus, we can expect that the smoothness with respect to the true CV is approximate to the repetition ratio of the feature points within the neighborhood³. That means, in the direction of the true CV, the smoothness is close to the repetition ratio. Due to the random pattern of the texture, along other candidate CVs from V_{I_i} , feature points appear randomly. The probability to find another set of coherent CVs that gives higher smoothness is thus low. Summarizing, the highest smoothness can be found, in most cases, only along the true CV. Once the highest smoothness (higher than a certain threshold) is detected, the true correspondences are found.

4 Experimental Results

The proposed algorithm is applied to both synthetic and real images for performance evaluation. To evaluate the quality of the detected correspondences, either the homography or the fundamental matrix is computed using RANSAC [11]. All correspondences that are inline to the homography or fundamental matrix are considered correct. We consider that a correspondence conforms to the homography or the fundamental matrix if the residual error d_r is smaller than one pixel, which is computed by:

³ The repetition ratio of feature points within a neighborhood is defined as ratio between the number of true point-to-point correspondences and the number of feature points in the neighborhood.

$$d_r = \begin{cases} [d(x', Fx) + d(x, F^T x')]/2, & \text{given } F \\ [d(x', Hx) + d(x, H^{-1} x')]/2, & \text{given } H. \end{cases} \quad (6)$$

Where, F is the fundamental matrix; H is the homography; (x, x') is a pair of matched points; $d(.,.)$ is the geometric distance between the point and the epipolar line given the F , or the euclidian distance between the two points given the H . The number and percentage of the correct matches are thereafter computed.

4.1 Experiments on Synthetic Images

First, we generate an 800×600 image with 1,000 randomly-distributed feature points. Second, the 1,000 feature points are rotated and translated with controlled rotation or translation parameters to generate the second image. Third, an equal number of randomly-distributed outliers are injected into both images to generate two corrupted images. The proposed algorithm is then applied to those two corrupted images to detect feature correspondences. The homography is computed using the RANSAC to evaluate the detected correspondences.

Fig. 3. #Correct matches obtained by the proposed algorithm

Fig. 3 shows the number and Fig. 4 shows the percentage of the correct correspondences obtained under different settings of *Degree of Deviation* (DoD), i.e., φ in Eq. (1), *Degree of Rotation* (DoR) and *Percentage of Injected Outliers* (PIO). In the figures, the *#Correct Matches* is the number of correct matches detected; the *Degree of Rotation* is the angle that the image rotates around its image center, which measures how strong the image motion deviates from translation; the *%Injected Outliers* is the percentage of outliers injected into both images, which can be considered as either the repetition ratio of the feature points or the noise level of the image; the *%Inliers* is the percentage of inliers to the homography.

As we see from Figs. 3 and 4, the DoR changes from 0 to 10 degrees, i.e., from pure translation to significant rotation (large deviation between two CVs). The

Fig. 4. Percentage of inliers to the homography

PIO changes from 0% to 75%, i.e., from repetition ratio of 100% (noise-free) to repetition ratio of 25% (seriously noisy). The DoD (φ) changes from 1° to 4° , i.e., from a small threshold to a large threshold by Eq. (2). In all experiments, the translation vector is kept constant as $(T_x, T_y) = (5, 10)$. Our experiments show that the magnitude of the translation has little effect on the performance.

Discussion. This section investigates the effect of the rotation, noise, DoD on the performance of the proposed algorithm. From Figs. 3 and 4, we obtain the following observations:

(1) The proposed algorithm is able to reliably detect the correspondences even when the image contains a large portion of injected outliers or when the image contains evident rotation. For example, when $PIO = 50\%$, $DoR = 4^\circ$, and $DoD = 2^\circ$, we found 989 correct matches out of 1000 ground-truths. Furthermore, 94.8% of the 1,043 detected correspondences are inline to the homography. The obtained CVs are shown in Fig. 5(b), where an evident rotation is observed.

(2) The performance drops when the rotation increases. As we discussed in Section 3.1, the proposed algorithm requires that the local correspondence field is more-or-less translational. With a high rotation, the deviation between two CVs is high. This may lead to a violation of the LTM assumption. Consequently, the performance of the proposed algorithm deteriorates, as can be observed from Figs. 3 and 4 when DoR increases above 5° .

(3) The noise has little effect on the performance when the rotation is small, but has an evident influence on the performance when the rotation is high. The reason is that a high deviation between two CVs, caused by a high rotation, makes it easier to find a false correspondence vector that gives a smaller difference by Eq. (2), especially when there are many outliers present.

(4) A large DoD is helpful when the rotation is high and the noise level is low. A high rotation means a high deviation between CVs. Increasing the DoD and thus the threshold R in Eq. (1) increases the chance for two true CVs to satisfy

Fig. 5. Results obtained by the proposed algorithm when $DoD = 2^\circ$, $DoR = 4^\circ$, and $PIO = 50\%$

the coherence criterion. On the other hand, if the noise level is high, a large threshold will make it easier for a false vector to satisfy the coherence criterion. This degrades the performance of the proposed algorithm.

4.2 Experiments on Real Images

We have applied the proposed algorithm to many image pairs from the *medusa* and *castle* sequences, which are used by [12] for structure reconstruction. We have also applied the algorithm to many self-recorded images. Since all experiments show similar results, only the results for two image pairs are presented in this section. The first pair (IP1) shows a small contrast change and the second pair (IP2) contains a large contrast change. The fundamental matrix is computed using detected correspondences to evaluate the performance. The homography is not applicable in this case. The results are then compared with those computed by the Block-Matching (BM) method. The proposed algorithm is referred to as Texture-Independent Featuring Matching (TIFM) in the following discussion.

The first row of Fig. 6 shows the correspondences obtained using the BM on IP1. By comparing Fig. 6(a) with Fig. 6(b), we see many spurious correspondences are detected by the BM. Table 1 shows the results obtained by the BM and the TIFM on IP1 and IP2. In the table, *OutOfDetcd* means the percentage of the feature correspondences that conform to the epipolar geometry; *OutOfTotal* means the percentage of the feature points for which the correct correspondences are found.

As we see from Table 1, for the BM-IP1, among the 1,332 correspondences detected out of 3,292 feature points, only 53% are found conforming to the epipolar geometry. Thus, we detect nearly⁴ 21% ($1,332/3,292 \times 53\%$) correct correspondences out of a total of 3,292 feature points.

Fig. 6(c) and Fig. 6(d) portray the correspondences obtained by the TIFM on IP1 before and after outlier removal. From the figures, only few spurious correspondences are observed. As we see from Table 1, for the TIFM-IP1, among the 1,609 correspondences detected out of 3,292 feature points, 97% conform to

⁴ Obviously, not all correspondences that comply to the epipolar geometry are correct.

Fig. 6. Correspondences obtained by the BM and the TIFM on IP1 and IP2; the correspondences are illustrated by the CVs superimposed on the first image of an image pair; outliers are removed using the epipolar constraint

Table 1. Results by the BM and the TIFM on IP1 and IP2

	BM-IP1	TIFM-IP1	BM-IP2	TIFM-IP2
Total fps	3,292	3,292	693	693
Detected fps	1,332	1,609	153	371
OutOfDetcd	53%	97%	54%	97%
OutOfTotal	21%	47%	12%	52%

the epipolar geometry. Thus, we detected nearly 47% correct correspondences out of 3,292 feature points.

Our second experiment is on IP2. The two images were taken at the same time. However, the contrast of the two images differs significantly because the images contain different portions of the bright sky, causing different internal camera parameters. Rows three and four of Fig. 6 show the results obtained by the BM and the TIFM on IP2, respectively. From Table 1 and Fig. 6, we see that the TIFM obtains much better results than the BM.

As seen from Table 1, the TIFM is robust to the change of image contrast. For IP1 showing a small contrast difference, correct correspondences are found for 47% of the total feature points. For IP2 with evident contrast change, the percentage of the correct correspondences is 52%. The percentage keeps at a constant level irrespective of the change of the contrast. In comparison, the percentage for the BM decreases from 21% for IP1 to 12% for IP2. Both are significantly lower than the percentages by the TIFM. The reasons of the contrast invariance of the TIFM are two-fold. First, the Harris corner detector is known to be robust to contrast change. Second, the TIFM does not rely on image texture for feature matching.

The proposed algorithm works under the following two conditions: (1) the local correspondence field within a small neighborhood follows the LTM model (certain degree of deviation allowed), and (2) the repetition ratio of the feature points is not too low. For images separated by wide camera baselines (with significant rotation, scaling, viewpoint change), the proposed algorithm may not work, because in those cases either the repetition ratio is too low or the LTM assumption is not valid. For future work, we will look at incorporating more constraints and extending the LTM assumption to a more general smoothness assumption.

5 Conclusion

In this paper, we have proposed a novel feature-point matching algorithm that uses only a self-contained smoothness constraint. The feature-point correspondences within a neighborhood are collectively determined such that the smoothness of the correspondence field is maximized. The proposed algorithm is descriptor-free and texture-independent. The performance of the algorithm is evaluated by experiments on both synthetic and real images. The experimental

results show that the proposed method performs much better than the intensity-based block-matching technique, in terms of both the number and the percentage of the correct matches. The algorithm is able to reliably detect the feature-point correspondences for images separated by small or moderate baselines, even when the image contrast varies substantially across two images.

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