Feature Point Matching with Matching Distribution

San Ratanasanya, Jumpol Polvichai, and Booncharoen Sirinaovakul

Department of Computer Engineering,
King Mongkut's University of Technology Thonburi, Bangkok, Thailand
hameroon@hotmail.com, jumpol@cpe.kmutt.ac.th,
boon@kmutt.ac.th

Abstract. Most of the feature point matching techniques considers only the number of matches. The higher number of matches is, the better results are. However, reliability and quality of the matching is addressed in a few techniques. So, finding the good matches of the pairs of points from the two given point sets is one of the main issue of feature point matching. This paper presents new approach to obtain reliable and good matches. The high quality of matching can be achieved when the matches are spread all over the entire point set. Therefore, we proposed to use the distribution of the matches to verify the quality of the matching. The preliminary results show that our proposed algorithm significantly outperform SIFT even when the results of SIFT are enhanced using RANSAC.

Keywords: Feature Point Matching, Image Registration, Image Retrieval, SIFT, RANSAC.

1 Introduction

Feature point matching is a very important process for applications that need to locate objects in images or databases such as robot navigation, tele-surgery, and image retrieval [1, 2, 3]. The feature points are derived from the images, called the reference and input image, of the same scene which may have been acquired at different times, from different viewpoints, and by different sensors. The goal of feature point matching is to geometrically align these two point sets. Automatic feature point matching algorithms are now used to initiate the better input for various complex tasks such as navigating robot, finding stereo correspondences, motion tracking, and recognizing object and scene.

There are many techniques to match feature points. All of them rely on location of points and/or other information. For instance, the techniques based on SIFT [4] or SIFT-based techniques such as SURF [5], ORB, BRIEF, and FREAK [6] use descriptor, a vector describes the distinctiveness of each feature computed by using neighborhood intensities of that feature points, to match the feature points. However, the distinctiveness of SIFT-based descriptors might not be distinct enough in some cases and results in ambiguous match. That is, one feature point can be matched with more than one feature points. Moreover, the geometric structures are used in more

H. Unger et al. (eds.), *Recent Advances in Information and Communication Technology 2015,*
Advances in Intelligent Systems and Computing 361, DOI: 10.1007/978-3-319-19024-2_2

recent techniques. The geometric structures are used to select a subset of points and match them to get better results. Additionally, a subset of matches can be selected according to some conditions, such as angular [7] and pairwise constraints [8], to get better matching results. A random selection can also be applied to improve the results [9]. Unfortunately, this approach cannot provide good matching results since the same pattern geometric structure might be found in any part of the images. It is hard to find the correct match of the same structure especially in the cases that the images are partially overlapped or do not have overlapped regions.

In this paper, we proposed a new algorithm to solve feature point matching problem. We treat feature point matching problem as a searching for the closet pair of points. The one-to-one relationship is used to find a reliable match by considering a distance between the pair of points. Moreover, we take distribution of the matches into account in order to make sure that the number of overall matches is reliable.

2 Literature Reviews

From the literatures, the techniques to tackle feature point matching can be classified into three groups [10]. The first category is to use only location of the points to find the best correspondences. The techniques in this group are simple but take high computational time since it needs exhaustive search throughout the search space to find the solution. However, they are sensitive to noise and cannot provide good results in some cases. The second group is to incorporate neighborhood information of each point to get the best correspondence. The techniques in this group seem to have more robust to noises than those of the first group since they use more information to find the solution. The state of the art technique in this category is SIFT. Although SIFT variations are also widely used with the comparable performance to SIFT, but they cannot outperform SIFT in every aspect [11]. However, their results are comparable. Some techniques get rid wrong match still need to be used in post processing to improve the solution. The techniques in third group are usually based on graph matching algorithms and use structural information of the point set to find the correspondences between the two point sets. These techniques seem to be better than those of the first two categories, but they require the most similar structure of the two point set for the best results [12].The principles of the techniques in each category are presented in the following section.

2.1 Location Information

The techniques in this group use only one piece of information that is location of the points. After the feature points are extracted from the images, the location of each point is used to determine the correspondences with the other point set. The framework is divided into four sub-tasks, namely, feature extraction, transformation space, search strategy, and similarity measure [13] as can be seen from the block diagram shown in Fig. 1.

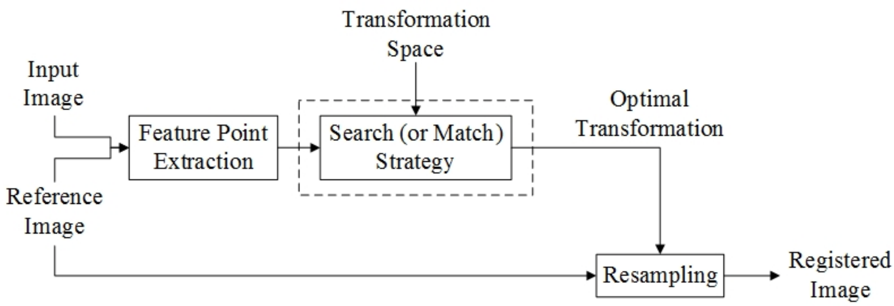


Fig. 1. Image Registration Block Diagram

A pair or a set of images is input to Feature Extraction sub-process. This sub-process will extract feature points from each image. These feature points represent the image itself with much smaller information, to cut off unnecessary computation and speed up the whole registration process, and are invariant to a specific class of transformation. Then, we decide which class of transformation is used to transform the input image. This assumption is set up in the Transformation Space sub-process. Also, we set up transformation width or range of transformation that the optimal transformation is in. Next, we search for or estimate the transformation within that range. There are several strategies for searching or estimation such as geometric branch and bound framework as proposed by [13]. So, we call this sub-process as Search Strategy. Finally, we can check whether the transformation is optimal by measuring the similarity between the reference and input image, after applying that transformation. The transformation that gives the best similarity will then be optimal transformation. This will be measured in the Similarity Measure sub-process using distance function such as Partial Hausdorff Distance.

Moreover, there is several works that apply optimization algorithm with the basic search. That is, searching for the best combination of transformation parameters such as rotation, scaling, and translation under the specific transformation. The optimization algorithm will then be applied to accelerate the search. For instance, Genetic algorithm and PSO are applied in [14, 15, 16].

Simplicity is the main advantage of the techniques in this group. Although it is computational intensive, any optimization algorithms could be used to accelerate the search. However, it may not robust to noises according to the definition of matched point.

2.2 Neighborhood Information

The techniques in this group are based on SIFT [4]. The framework of the techniques in this group is quite similar to that shown in Fig. 1 except the feature extraction and search strategy processes. In the feature extraction process, the feature points are extracted and their neighborhood information are used to build descriptor for each feature point. The details of how to extract feature point and create descriptor can be found in [4].

In the search strategy process, the matching of descriptors is performed instead of searching for the best transformation. The output of the descriptors matching is a set of corresponding feature points called correspondences. The correspondences are used to compute the optimal transformation between reference and input images. The techniques in this group have big advantage over those of the first group since they rely on local characteristics of feature points. They are more robust to noises which will result in more accurate mapping. Although using the local characteristics of feature points can sometimes lead to lots of false match, there are several algorithms to clear up these false matches such as RANSAC [17]. RANSAC was used in [9, 18] to improve the performance of SIFT-based feature point matching and the results are impressive.

Moreover, the feature points extracted by SIFT-based detector are high redundancy meaning that there are multiple features at the same location but not scale. The SIFT descriptors are build regarding to scaled local information of each feature point results in distinctive characteristic of each feature. The redundancy allows testing for best correlation of points more accurate. Unfortunately, it has a drawback. The redundancy makes it computationally intensive especially when there is enormous number of features. And the descriptors might lose their distinctiveness since it is based on intensity contrast which cannot be distinct if there are repetitive patterns in the image or there are areas that have similar contrast in the local neighborhood in the images.

2.3 Structural Information

From different perspective, feature point matching can be formulated in terms of graph matching. The feature extraction and search strategy processes in the feature point matching framework are also adopted for the techniques in this category.

After the feature points are extracted, they are treated like nodes in the graph. Then the structural information in terms of edges is added to represent the relation between each node in a graph. The search strategy can be done by graph matching which however is an NP-hard problem. The exact solution may not be found in reasonable time so approximation solution has to be found. Conventional graph matching approaches [19, 20] mainly focus on pairwise similarity between two correspondences such as distances among feature points. Most of them use Iterative Closet Point to minimize distance of set of points. Pairwise relations, however, are not enough to incorporate the information about the entire geometrical structure of features. To overcome the limitation of pairwise similarity, several researchers proposed techniques that applied graph theory, called graph matching, [21, 22] to get good matching results. However, graph matching still has two main issues. The first issue is that geometric constraints are required. Therefore, simulation of connection between edges and nodes must be tested iteratively to meet geometric constraints. Moreover, many techniques do not robust to outlier nodes. The second issue is that optimizing graph matching is difficult due to the nature of non-convex objective function of feature matching problem.

In summary, the main differences among the three groups are geometric constraints and local to global matching. In terms of overall performance, the SIFT-based techniques outperform the others because its density in both feature point and distinctive local descriptor. However, the local descriptors may lead to uncertain matching. On the other hand, if we can introduce local to global matching methods to the simplest group of feature matching, we can therefore get a low complexity technique that robust to noises and outlier so that it results in good feature matching performance.

3 Proposed Method

Considering a point set that has enormous number of points, the typical matching algorithm will be inefficient. The chances of mismatching results are high because there are too many ambiguous points to match. Not only ambiguity is introduced with algorithms in point matching but matching with neighborhood or structural information also ineffective in this case because there will be a lot of similar neighborhood or structural information if there are too many points. Moreover, in the case of symmetry object, the existing search strategy might not be able to tell the difference between the object under 0 and 180 degree of rotation. Therefore, we proposed another search algorithm that takes the distribution of the matches into account to tackle the aforementioned problem. This can be done by visualizing specific zone in the point set. The idea is that each point in the point set will be assigned to a zone or cluster, which is a quadrant in this work. The algorithm will do a search in quadrant-to-quadrant manner. Therefore, there will be 16 combination pairs of subset to be considered.

Considering the particular pair of cluster to be search, all the points from two point sets will be paired up and set as a center of transformation. Then the search aiming to get the maximum matching value will be processed by applying combinations of transformation parameters within the search interval. Matching value can be determined from the number of match pairs and the number of cluster that has at least one match as stated in the following equations.

$$\mathrm{MatchingValue} = \sum_{C} w_c * \sum_{C} \mathrm{match}_c \tag{1}$$

$$w_c = \begin{cases} 1, & \text{if there is at leat a match in cluster c} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Where C = {1,2,3, …, n}, n is number of cluster which equals to 4 in this work. match_c means number of matches in cluster c. w_c is a match coefficient of each cluster. The flowchart of this algorithm is shown in Fig. 2.

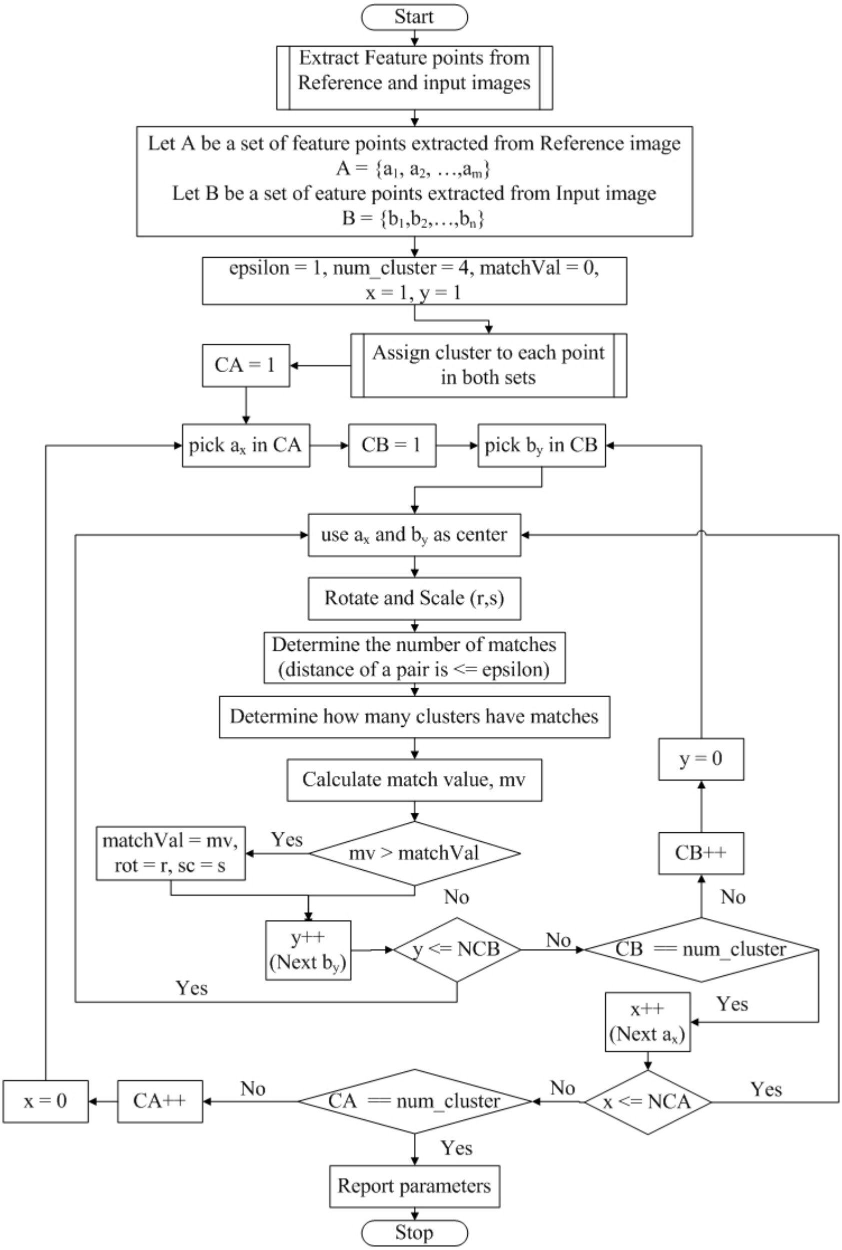


Fig. 2. The Flowchart of the Proposed Search Algorithm

4 Experiments and Discussions

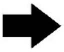
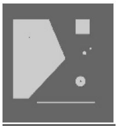
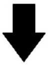
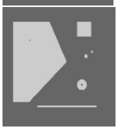
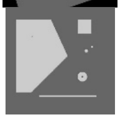
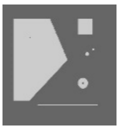
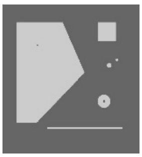
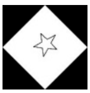
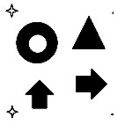
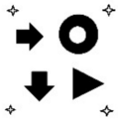
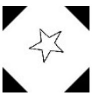
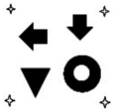
We investigate the performance of our algorithm in terms of accuracy. The experiment is done using simple images representing geometric shapes. The following subsections give details of the preliminary experiment.

4.1 Point Sets

The point sets used in our experiments are derived from the images having geometrical objects. The input images are the reference images that are transformed by known similar transformation. The reference and input images are shown in Table 1 and 2.

Table 1 showed the synthesis images that have only one object and multiple objects in the image. These images represent simple case of feature point matching problem. The transformations applied to the images are to simulate various ranges of similar transformation.

Table 1. Single Object Synthesis Images with the Transformation Applied

Case	Reference	Input	Transformation ([Rotation, Scale])	Case	Reference	Input	Transformation ([Rotation, Scale])
A1			[-90, 1.0]	B1			[18, 1.0]
A2			[180, 1.0]	B2			[0, 0.8]
S1			[180, 1.0]	B3			[0, 1.5]
S2			[-45, 0.7]	O1			[-90, 1.0]
S3			[-45, 1.0]	O2			[180, 1.0]

4.2 Experimental Settings and Measurements

In this work, we assumed similarity transformation and represent it by a 4-element vector, whose entries are the rotation r, the translation vector (tx,ty), and the scaling factor s. However, the translation vector can be omitted since our approaches have already cancelled this vector. Also, we assumed that the feature points are provided. In this paper, we compare our proposed algorithm with SIFT so the SIFT detector is used extract features to be fair comparison.

To measure which set of transformation parameters is the best, we use Euclidean distance to measure shortest distance among neighbor pairs and sum up to get an overall distance. On the other hand, we can compare the transformation parameters directly since we know the exact solution or ground truth. Moreover, we can use other similarity measure tool such as normal correlation to measure similarity of the point sets. For preliminary study, we simply measure the distance of the match pairs. The extensive review of performance evaluation for feature point matching based on local descriptors is presented in [11]. In this paper, we compare our proposed algorithm with SIFT since SIFT provides better performance in terms of matching feature point and robustness to transformations.

Considering high redundancy property of SIFT, there are high chances that there will be a lot of false matches. That is, many matched pairs of points are actually mismatched. The reliable match should have one-to-one relationship meaning that any particular point in one set should be matched to exactly one point from the other set. Therefore, RANSAC would be used to select the best reliable matches for SIFT. We called it SIFT+RANSAC. Moreover, the distance between a matched pair of points directly relates to the quality of that match. The longer distance the poorer match. Therefore, in this paper, we did not measure only number of reliable matches but also the distance of each match. The particular match will be considered as mismatch and will not be counted if the pair of points is far from each other more than a tolerance distance, which is set to 3 pixels. That is, we measure only the matches that are good and reliable.

4.3 Results on the Proposed Algorithm Search

The results are shown in Table 3. It shows that both techniques can find the matches in all cases. However, the number of reliable matches, the number of good matches, and the matching precision, of the solutions obtained from each technique are also presented.

From Table 3, it is obviously seen that the number of reliable match or one-to-one relationship of points obtained from both techniques are not much different exclude the last two cases, “O1” and “O2”. It is a nature of SIFT that has high redundancy of feature so the higher number of reliable match could be possible. Although the number of reliable matches obtained from both techniques are quite equal it can be obviously seen that the number of good matches are different. The proposed algorithm provides more good matches than SIFT+RANSAC. Additionally, our proposed algorithm has higher matching precision than SIFT+RANSAC. The value of matching precision also implies that SIFT+RANSAC has more false positive matches than our proposed algorithm. The higher number false positive matches the more ineffective performance to the applications that require feature point matching.

Table 2. The matching accuracy results of the preliminary experiments

Case	Number of Reliable Match Pairs		Number of Good Matches		Matching Precision	
	SIFT+ RANSAC	Proposed Algorithm	SIFT+ RANSAC	Proposed Algorithm	SIFT+ RANSAC	Proposed Algorithm
A1	26	19	6	11	23.08%	**57.89%**
A2	13	19	6	13	46.15%	**68.42%**
S1	22	19	7	17	31.82%	**89.47%**
S2	9	21	1	14	11.11%	**66.67%**
S3	12	21	3	12	25.00%	**57.14%**
B1	18	35	1	16	5.56%	**45.71%**
B2	28	35	5	14	17.86%	**40.00%**
B3	27	35	3	6	11.11%	**17.14%**
O1	131	43	39	31	29.77%	**72.09%**
O2	111	36	4	28	3.60%	**77.78%**

5 Conclusions

We have proposed feature point matching algorithm with three different perspectives from the most of the existing feature point matching algorithms. First, we omitted translation parameter from the search by setting a pair of points in consideration as origin points. Second, we not only measured the number of the matches based on Euclidean distance but also measured the spread of the matches by dividing the point sets into 4 areas and account for the matching distribution. Finally, neither neighborhood nor structural information was needed to provide more accurate mapping in our algorithm. We have done the preliminary experiment with synthesis images and compare the performance and accuracy with SIFT+RANSAC. The experimental results shows that the proposed algorithm outperform SIFT+RANSAC in terms of precision. In addition to investigate the performance of the proposed algorithm, we plan to test our algorithm with standard benchmark image data in the near future.

References

1. Tang, J., Shao, L., Zhen, X.: Robust point pattern matching based on spectral context. Pattern Recognition 47(3), 1469–1484 (2014)
2. Yongfang, G., Ming, Y., Yicai, S.: Study on an Improved Robust Algorithm for Feature Point Matching. Physics Procedia 33, 1810–1816 (2012)
3. Myronenko, A., Song, X.: Point set registration: Coherent Point drift. IEEE Transactions on Pattern Analysis and Machine Intelligence 32(2), 2262–2275 (2010)

4. Lowe, D.G.: Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision 60(2), 91–110 (2004)
5. Bay, H., Ess, A., Tuytelaars, T., Van Gool, L.: SURF: Speeded Up Robust Features. Computer Vision and Image Understanding (CVIU) 110(3), 346–359 (2008)
6. Bekele, D., Teutsch, M., Schuchert, T.: Evaluation of binary keypoint descriptors. In: Proceeding of the 20th IEEE International Conference on Image Processing, pp. 3652–3656 (2013)
7. Kim, J., Choi, O., Kweon, I.S.: Efficient feature tracking for scene recognition using angular and scale constraints. In: Proceeding of the 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 4086–4091 (2008)
8. Choi, O., Kweon, I.S.: Robust feature point matching by preserving local geometric consistency. Computer Vision and Image Understanding 113(6), 726–742 (2009)
9. Wang, Y., Huang, H., Dong, Z., Wu, M.: Modified RANSAC for sift-based in SAR image registration. Progress in Electromagnetics Research M 37, 73–82 (2014)
10. Yongfang, G., Ming, Y., Yicai, S.: Study on an Improved Robust Algorithm for Feature Point Matching. Physics Procedia 33, 1810–1816 (2012)
11. Mikolajczyk, K., Schmid, C.: A performance evaluation of local descriptors. IEEE Transactions on Pattern Analysis and Machine Intelligence 27(10), 1615–1630 (2005)
12. Tang, J., Shao, L., Jones, S.: Point Pattern Matching Based on Line Graph Spectral Context and Descriptor Embedding. In: IEEE Winter Conference on Applications of Computer Vision, pp. 17–22 (2014)
13. Mount, D.M., Netanyahu, N.S., Ratanasanya, S.: New approaches to robust, point-based image registration. In: Image Registration for Remote Sensing. Cambridge Publishing (March 2011)
14. Zhang, L., Xu, W., Chang, C.: Genetic algorithm for affine point pattern matching. Pattern Recognition Letters 24(1-3), 9–19 (2003)
15. Senthilnath, J., Omkar, S.N., Mani, V., Kalro, N.P., Diwakar, P.G.: Multi-objective Genetic Algorithm for efficient point matching in multi-sensor satellite image. In: Proceeding of the IEEE Geoscience and Remote Sensing Society, pp. 1761–1764 (2012)
16. Yin, P.Y.: Particle swarm optimization for point pattern matching. Journal of Visual Communication and Image Representation 17(1), 143–162 (2006)
17. Fischler, M.A., Bolles, R.C.: Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography. Communication of the ACM 24(6), 381–395 (1981)
18. Shi, G., Xu, X., Dai, Y.: SIFT Feature Point Matching Based on Improved RANSAC Algorithm. IHMSC 1, 474–477 (2013)
19. Cho, M., Lee, J., Lee, K.M.: Reweighted random walks for graph matching. In: Daniilidis, K., Maragos, P., Paragios, N. (eds.) ECCV 2010, Part V. LNCS, vol. 6315, pp. 492–505. Springer, Heidelberg (2010)
20. Leordeanu, M., Hebert, M., Sukthankar, R.: An integer projected fixed point method for graph matching and map inference. In: Proceeding of the 23rd Annual Conference on Neural Information Processing Systems (2009)
21. Chertok, M., Keller, Y.: Efficient high order matching. IEEE Transactions on Pattern Analysis and Machine Intelligence 32(12), 2205–2215 (2010)
22. Lee, J., Cho, M., Lee, K.M.: Hyper-graph Matching via Reweighted Random Walks. In: Proceeding of the 2011 IEEE Conference on Computer Vision and Pattern Recognition (2011)