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An Outlier Detection Method for Feature Point Matching Problem

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Abstract. *We present an efficient outlier detection method for finding consistent matching between two sets of feature points. We first define a kind of distance between each pair of candidate assignments which measures the compatibility between them. Using this distance measurement, correct assignments are generally compatible with each other and thus tend to form a cluster with high density. Our aim is to detect this correct assignment cluster by adapting an outlier detection method. We first present a new inlier scoring method, called Degree-Distance Inlier Scoring (DDIS), in which we integrate both degree and distance simultaneously based on kNN graph. Then we detect correct assignments and achieve point matching using DDIS and greedy algorithm. We call it as Outlier Detection Point Matching (ODPM). At last, we propose a more robust point matching algorithm by rendering ODPM in an iterative way. Experimental results on both synthetic and real-world data show the effectiveness the proposed method.*

Keywords: Feature matching; Outlier detection; Inlier score; kNN graph.

1. **Introduction.** Feature point matching is an important and fundamental problem in computer vision and pattern recognition area. It has been widely used in many computer vision problems such as stereo matching, image fusion, and shape recognition [1, 2, 3, 4, 5, 6]. The goal of feature point matching is to find a consistent correspondences between two sets of feature points.

There are many methods on solving feature point matching problem. One kind of the popular approaches is to use spectral techniques [3, 4, 5, 6, 7, 8], which aim to explore the spectrum of the adjacency matrix to find the matching solution. Some other methods such as relaxation, graduated assignment [9, 10, 11, 12, 13] and graphical models [14, 15, 15] have also been widely used in matching problem. These methods can find an effective solution for the matching problem. However, they usually have high computational complexity. Recently, pairwise constraints have been used to find the solution of the matching problem [17, 18, 19, 28]. These methods can handle large rate of outlier features and thus produce more robust matches with low complexity. Ng et al. [17] have presented a interest point matching method which uses spatial constraints and mean shift algorithm. Enqvist et al. [18] have proposed a graph vertex cover method to obtain correspondences based on pairwise constraints. Leordeanu and Hebert [19] have introduced a spectral technique to find the cluster formed by correct assignments from candidate assignment set. Generally, these pairwise constraint methods usually first define an affinity or distance between each pair of assignments. Then, they formulate the matching problem as a problem of finding a subset of assignments that maximizes the total pairwise compatibility (or minimizes the total pair wise distance). Although, mathematically, this kind of problem is NP-hard, these methods generally use some techniques to find an approximate solution. Inspired by these works, in this paper we propose a new pairwise constraint based point matching method by adapting an outlier detection technique [20, 21, 22, 23, 24, 25]. In the following, in order to discriminate the outlier points in outlier detection from the ones in feature sets, we denote the outlier points in the feature sets as outlier features.

As discussed in the works [17, 18, 19], in candidate assignment set, correct assignments are generally compatible with each other and thus likely to form a cluster with high density, while incorrect assignments are incompatible with them and thus can be regarded as outliers in candidate assignment set. Our aim in this paper is to obtain correct assignment cluster by adapting an outlier detection method. The main contributions are three aspects. (1) An new inlier scoring method, called Degree-Distance Inlier Scoring (DDIS), has been proposed. DDIS integrates both degree and distance simultaneously. (2) We introduce a correct assignment detection algorithm to achieve point matching based on DDIS and a greedy selection algorithm, which is called as Outlier Detection Point Matching (ODPM). (3) By rendering algorithm in an iterative way, a more robust matching algorithm (GODPM) has been proposed. Our ODPM method is most related to the work [28]. Compared with it, ODPM defines and uses a new inlier scoring method based on degree and distance measurements. Also, based on ODPM, we extend ODPM to GODPM and present a more robust and general matching method in this paper. Experimental evaluations on both synthetic and real-world matching tasks show the effectiveness of the proposed method.

2. **Problem Formulation.** Assume that two sets of features to be matched are Q and P. A corresponding mapping is a set O of candidate assignments (i, i'), where $i \in P$ and $i' \in Q$. In general, the size of O depends on the discrimination of the feature descriptors [17, 19, 27, 28]. For each assignment pair (a, b) in O, where $a = (i, i')$ and $b = (j, j')$, we can define a distance that measures how compatible the pairwise spatial relationship (e.g. Euclidean distance) of features (i', j') in Q is preserved by mapping them to features (i, j) in P. The smaller the distance is, the better this relative pairwise relationship can be preserved.

Using this distance measurement, for correct assignments $a = (i, i')$ and $b = (j, j')$, the pairwise relationship of features (i', j') in Q can be well preserved by mapping them to features (i, j) in P and thus has small distance between them. Therefore, all the correct assignments tend to form a cluster, i.e., subset with high density [19]. Incorrect assignments are generally incompatible with correct assignments and thus are weakly connected to this cluster [19]. These incorrect assignments can be regarded as outliers in candidate set O. Thus, the one-to-one feature matching between P and Q can then be found by searching a subset of O with high density. Our aim in this paper is to discover this subset by adapting an outlier detection method. In the following, we first present a new inlier scoring method based on kNN graph (DDIS). Then we use DDIS method to achieve point matching task.

3. **Inlier Scoring with Degree and Distance.** In this section, we give a new inlier scoring method, called Degree-Density Inlier Scoring (DDIS), by integrating both degree and distance based on kNN graph.

For dataset S, we first build a kNN graph in which every node represents the data point in S and the edge corresponds to pointer to neighbor data point [21]. Then, we define an *inlier score* (IS) for point a as

$$IS_{k,S}(a) = \alpha \frac{d_{in}(a)}{\max_{b \in S} d_{in}(b)} + (1-\alpha)\frac{1}{kdist(a)}, \tag{1}$$

where $d_{in}(a)$ is the *in-degree* of node a in kNN graph, and $kdist(a)$ is the distance from node a to its kth neighbor node [20, 22]. The parameter k is the number of outgoing edges in kNN graph. α is a positive weighting parameter. The above IS integrates both in-degree d_{in} and distance $kdist(a)$ simultaneously. Therefore, we can judge the inlier points (outlier points) based on the value of $IS_{k,S}(a)$, i.e., the larger (less) the value of $IS_{k,S}(a)$ is, the more possible point a is an inlier point (outlier point). Similarly, we can also define *outlier score* (OS) as

$$OS_{k,S}(a) = 1 - \frac{IS_{k,S}(a)}{\max_{b \in S} IS_{k,S}(b)}. \tag{2}$$

4. **Feature Point Matching using Outlier Detection.** In this section, we apply the above DDIS method to achieve feature point matching task. We first introduce a correct assignment detection technique based on DDIS and greedy algorithm and present a simple feature matching algorithm called outlier detection point matching (ODPM). Then, we propose a more general and robust matching algorithm (GODPM) by rendering ODPM algorithm in an iterative manner.

4.1. **ODPM algorithm.** We will use the above outlier detection method (DDIS) to detect correct assignments from candidate assignment set O. In order to do so, a kNN directed graph on set O is constructed firstly, in which every node represents the candidate assignment (i, i') and the edge corresponds to pointer to neighbor data point. Then, the inlier score for each node is calculated using Eq.(1). Similar to [19], the inlier score value ($IS_{k,O}(a)$) here can be interpreted as the correct confidence for assignment a. Thus, we can use a greedy selection method to select the correct assignment from O. This can be achieved by the following steps: (1) selecting the assignment a^* with the largest IS value. (2) Eliminating all other assignments that are conflict with a^*. This conflict is determined by the mapping constraints such as one-to-one or one-to-many mapping. (3) Selecting the next correct assignment as the one with the next highest IS value and continuously eliminating the assignments in conflict with the currently accepted assignments. (4) Repeating step (1)-(3) procedure until all assignments are determined. The overall algorithm is summarized as below.

4.2. **GODPM algorithm.** In ODPM, we judge the correct assignments based on the *in-degree* and *kdist* of kNN graph on candidate assignment set. However, in some cases incorrect assignments may account for a very large ratio of candidate assignment set O. In this case, there may exist some incorrect assignment points in O which can also have large IS value. These points may be determined as correct assignment points based on Step 4 and Step 5 in ODPM and lead to some errors. In the following, we call these incorrect assignment points as false correct assignments (FCA). However, different from the correct assignment points which are likely to form a cluster, FCAs establish links with the other correspondences only accidentally and they may only emerge when there exist high ratio of incorrect assignment points.

Algorithm 1 ODPM Algorithm

Input: Candidate assignment set O

Output: Correct assignment set S

1: Build a kNN directed graph on set O.
2: For each node a, calculate the inlier score $IS_{k,O}(a)$ using Eq.(1).
3: **while** O is not empty **do**
4: Find $a^* = argmax_{a \in O}(IS_{k,O}(a))$. If $IS_{k,O}(a^*) < \delta$, stop and output the correct assignment set S. Otherwise add point a^* to the set S and remove a^* from O.
5: Remove all potential assignments in conflict with $a^* = (i, i')$ from O. These are assignments of the form (i, k) and (q, i') for one-to-one mapping constraint.
6: **end while**

In order to eliminate the impact of the FCA, we render ODPM process to an iterative way. We start to remove some number of incorrect assignment points from original candidate assignment set O with smaller inlier score value to obtain the current candidate assignment set C_t. Next, we reconstruct kNN graph on C_t, and recalculate inlier score for each point using Eq.(1). We update current candidate assignment set and get C_{t+1} by removing the next some number of incorrect assignments with smaller inlier score value. We repeat this procedure until the current candidate assignment set contains *correct assignments*. Comparing to C_t, C_{t+1} contains less incorrect assignment points, and there exist less incorrect assignments that have large IS value. On the other hand, an incorrect assignment point with high inlier score (IS) value in C_t may have less IS value in C_{t+1}. Thus, false correct assignments are more difficult to form in the C_{t+1}. However, for the correct assignments, they can always keep having high IS value in both C_t and C_{t+1}. This can be shown in Fig.1 in next section. Based on this observation, we propose a more robust point matching method. We call this algorithm as general outlier detection point matching (GODPM). The detail of GODPM is summarized in Algorithm 2.

Algorithm 2 GODPM Algorithm

Input: Candidate assignment set O

Output: Correct assignment set S

1: Initialize current assignment candidate set C_0 as $C_0 = O$
2: **while** $R_t \nsubseteq S_t$ **do**
3: Compute S_t by running the algorithm ODPM on C_t
4: Compute R_t removing the assignments associated with the smallest N_t inlier score value from $C_t - S_t$
5: Update current assignment candidate to get C_{t+1} $(t = 0, 1, 2...)$ as
$$C_{t+1} = S_t \cup R_t$$
6: **end while**
7: Set $S = S_t$

The threshold N_t in Step 4 is selected to make C_{t+1} contains less incorrect assignment points than C_t. In this paper, N_t is computed by taking the integer of $0.2 \cdot |C_t - S_t|$.

5. Experiments.

We evaluate the robustness of our method on the task of finding correspondences between 2D sets of image feature points. Both in synthetic data and real-world experiments, we use the one-to-one mapping constraint, and the parameter α (Eq.(1)) in ODPM and GODPM is set to 0.5. We compare our methods with some alternative methods including spectral matching algorithm (SM) [19], graph based matching algorithm (GM) [5] and graph transformation matching algorithm (GTM) [27].

5.1. **Synthetic data experiments.** Our first experiment is based on synthetic 2D feature points data. Similar to the work [19], we have randomly generated data sets of 20 2D points Q. We obtain the corresponding 20 feature points in P by adding Gaussian noise $N(0, \sigma)$ to each point position from Q and then randomly rotating and translating the whole point set Q. The parameter σ controls the level of position deviation noises. We call this parameter as deformation level (DL). We define the distance between candidate assignments $a = (i, i')$ and $b = (j, j')$ as:

$$d(a,b) = \begin{cases} |d_{ij} - d_{i'j'}| & \text{if } i \neq i' \text{ and } j \neq j' \\ C & \text{otherwise,} \end{cases}$$

where d_{ij} is the Euclidean distance between the points i and j, and similar to $d_{i'j'}$. C is a large const. The parameter δ in ODPM is set to 0 here, because there is no outlying feature points in both Q and P. Figure 1 shows the inlier score (IS) variation curves for the correct assignment and false correct assignment (FCA) points. Here, we can note that the FCA can have higher IS values than the correct assignment at the beginning. However, the IS values for FCAs can not be retained in the iterative process and decrease fast as the iteration times increase (*red* curve) while correct assignments can keep high IS values in the whole iterative process of GOPDM (*blue* curve). This is the main observation for GODPM, as discussed in Section 4.2.

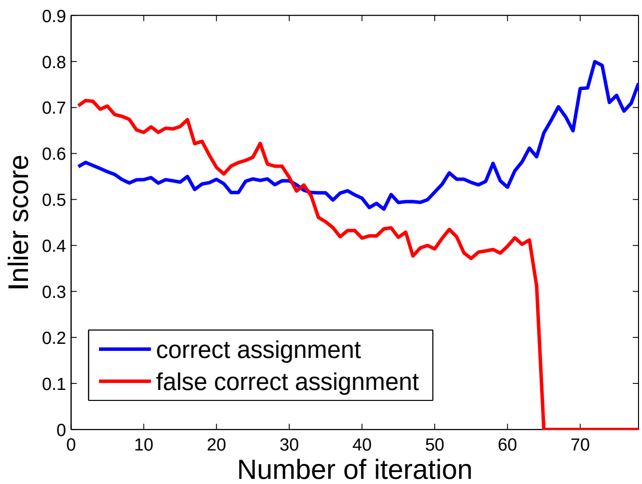


FIGURE 1. Inlier score variation curves for the correct assignment and false correct assignment points

In experiments, we use the correspondence ratio and actual matching score to evaluate different algorithms. Let S_{ca} be the correct assignment set obtained by the matching algorithm, we calculate the correspondence ratio as

$$\text{correspondence ratio} = \frac{\text{number of correct correspondences in } S_{ca}}{|S_{ca}|}. \tag{3}$$

Also, we define the actual matching score for S_{ca} as

$$MS = \sum_{a,b \in S_{ca}} d(a,b), \tag{4}$$

where $d(a, b)$ is the distance between assignment a and b. For each deformation level, we have generated 30 random data sets and then calculated the mean and standard deviation value of the correct correspondence ratio and actual matching score respectively. Figure 2 shows the performance curves of our methods (ODPM,GODPM) vs. SM and GM as we vary the deformation level σ from 1 to 20. Figure 2(a) and (b) show the mean and standard deviation curves of correspondence ratio respectively. Here we observe that when the deformation level is less than 15, the performance of the ODPM and SM degrades in a similar manner, which suggests that both SM and ODPM can find the similar correct assignment cluster in the candidate assignment set. However, when the deformation level exceeds 15, ODPM can return better matches than SM and GM. Also, GODPM clearly performs better and more robust than other three methods. Figure 2(c) and (d) show the mean and standard deviation curves of the matching score for different algorithms. As expected, comparing to the correspondence ratio curves, the matching score curves show the opposite trend, i.e., the higher the correspondence ratio, the less the actual matching score is. It demonstrates that our methods can find the cluster of correct assignment (correct assignment set) more accuracy than SM method.

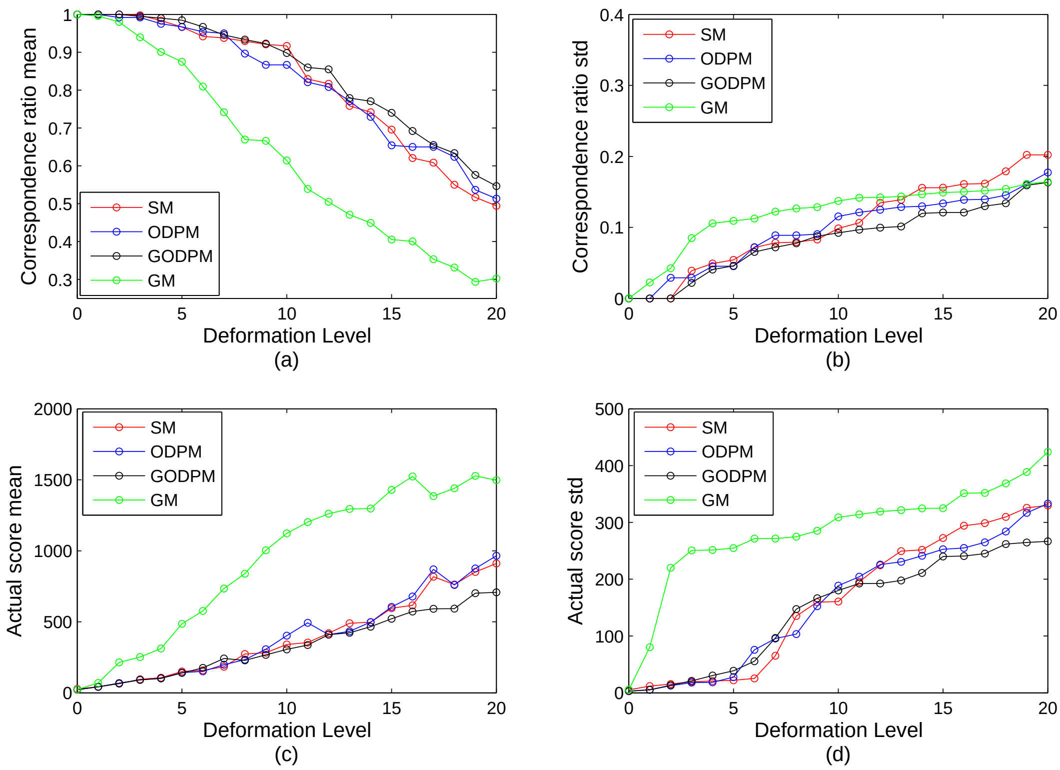


FIGURE 2. Comparison results on the synthetic data when there exist position deviation noises for the feature points in both Q and P. Top: Mean and standard derivation curves of the correspondence ratio. Bottom: Mean and standard derivation curves of the actual matching score

We also evaluate effect of our methods when there exist outlying feature points in both Q and P. Here we have added $20r$ outlying feature points in both Q and P at random positions respectively. The parameter r controls the number of outlying features in Q and P. We call this parameter as outlying level (OL). Figure 3 shows the mean and standard deviation curves of correspondence ratio. We can note that ODPM cannot have high average correspondence ratio as well as SM, but it can keep lower standard deviation

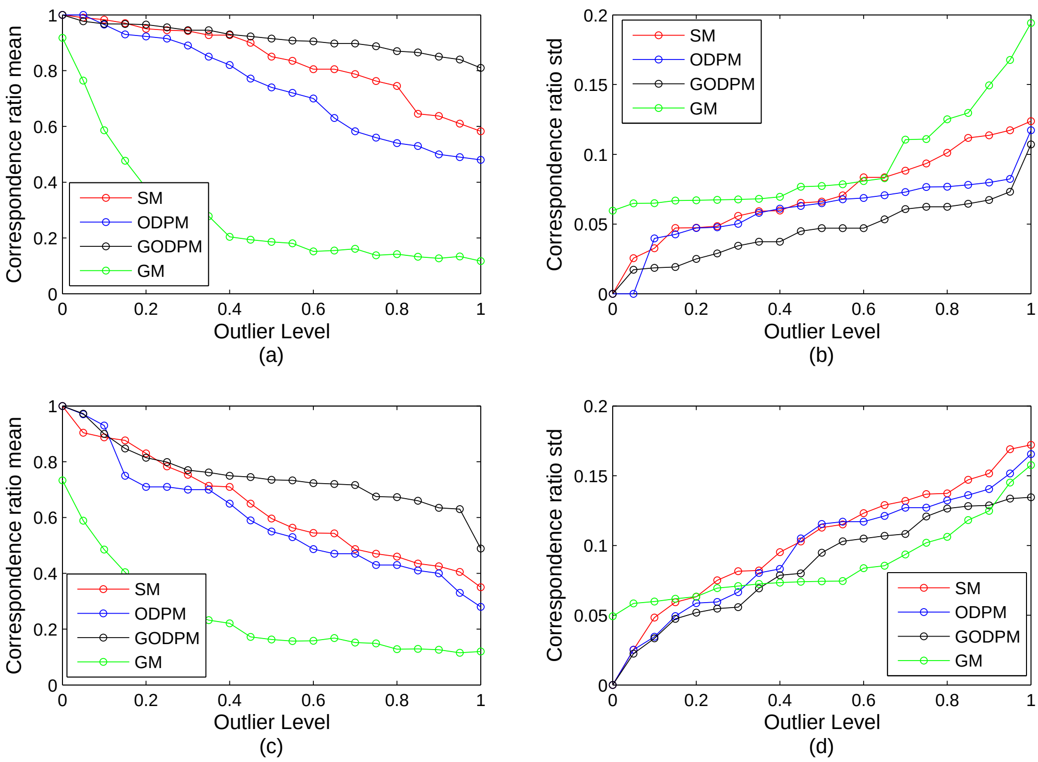


FIGURE 3. Comparison results on the synthetic data when there exist outlying feature points in both Q and P. Top: Mean and standard derivation curves of the correspondence ratio for the deformation level $\sigma = 4$. Bottom: Mean and standard derivation curves of the correspondence ratio for the deformation level $\sigma = 8$

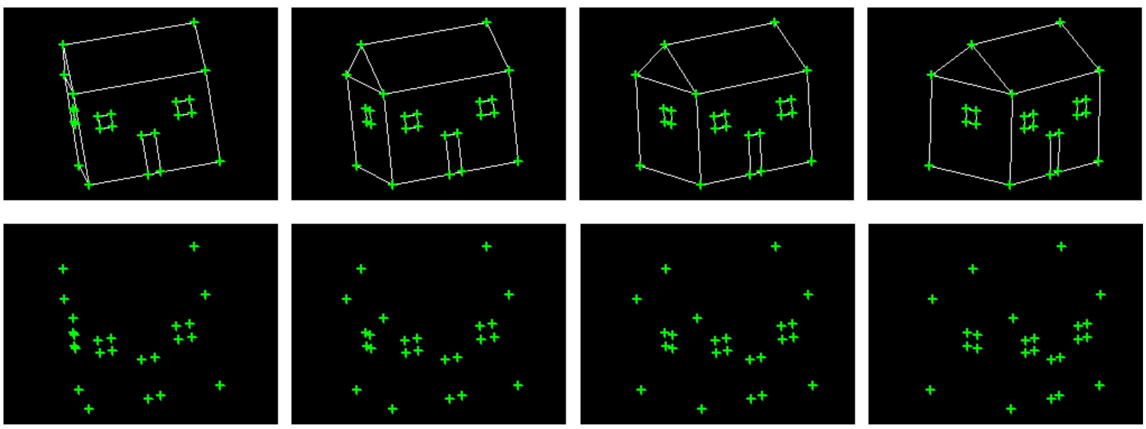


FIGURE 4. Synthetic house model sequence and associated feature points

value of correspondence ratio. This suggests that ODPM is more stable than SM. Also, GODPM can return considerably better matches than other three methods regardless of effectiveness and stability. It demonstrates that GODPM is more able to handle feature points matching task with large outlying feature points.

Our second synthetic experiment is based on synthetic house image data. This is a set of perspective views of a house as it rotates. Adjacent houses are obtained according to

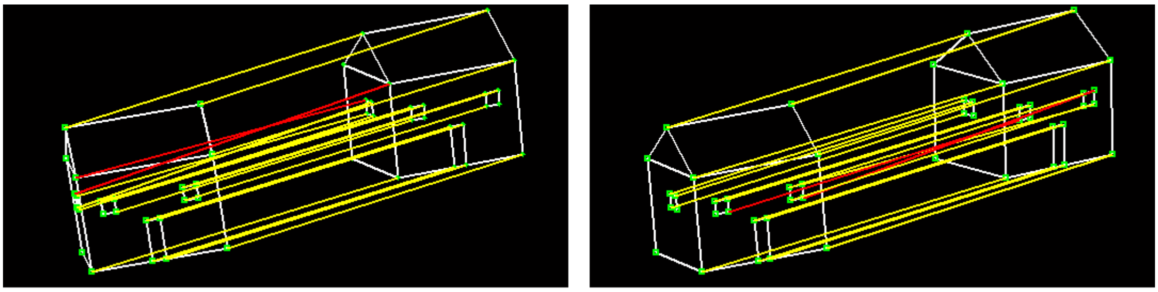


FIGURE 5. Correspondence results between synthetic houses (false correspondences are marked by red line). Left: Correspondences between the frame 1 and 25. Right: Correspondences between the frame 15 and 40

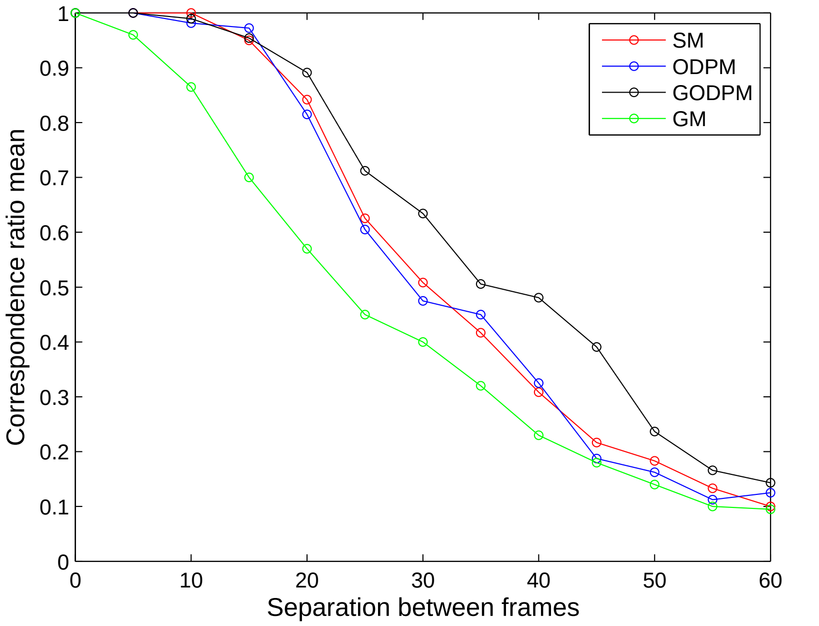


FIGURE 6. Summary of correspondence results for synthetic house data

rotation of 1°. There are 90 images in all and the sample images and associated points used in this study are shown in Fig. 4. We matched all images spaced by 5, 10, 15, ..., 55 and 60 frames and computed the average correspondence ratio. Since there are 90 images, the number of image pairs spaced by these amount of frames are 85, 80, 75, ...,30, respectively. Fig. 5 shows some matching results. The summary of the comparison matching results are shown in Fig. 6. We can note that the performance of the SM and ODPM algorithms degrades in a similar manner, but GODPM performs clearly better than other three methods.

5.2. **Real-world data experiment.** In this section, we perform some real world data experiments. We first use the CMU house sequence which contains 111 images of a toy house captured from moving viewpoints [15]. For each image, 30 landmark points were manually marked with known correspondences. We matched all images spaced by 5, 10, 15,..., 95 and 100 frames and computed the average correct correspondence ratio. Since there are 111 frames, the number of image pairs spaced by these amount of frames are respectively, 106, 101, 96,...,11. Figure 7 shows some examples. Some matching results are shown in Figure 8. Figure 9 summarizes the matching results. The average value is

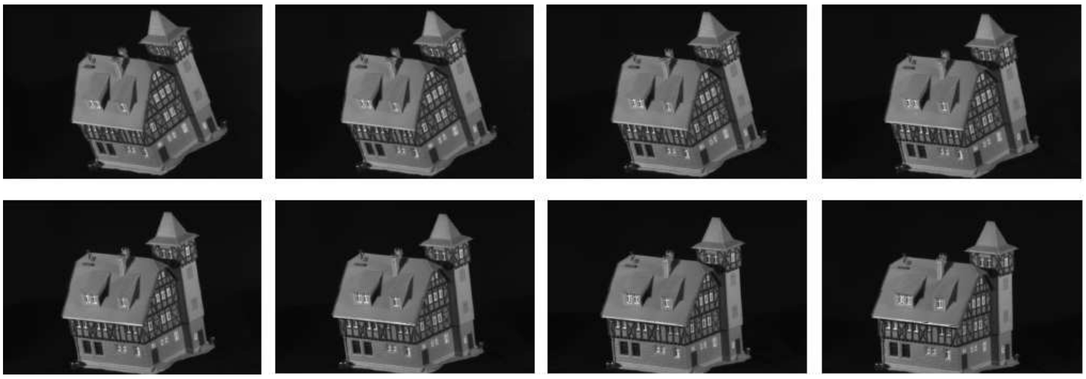
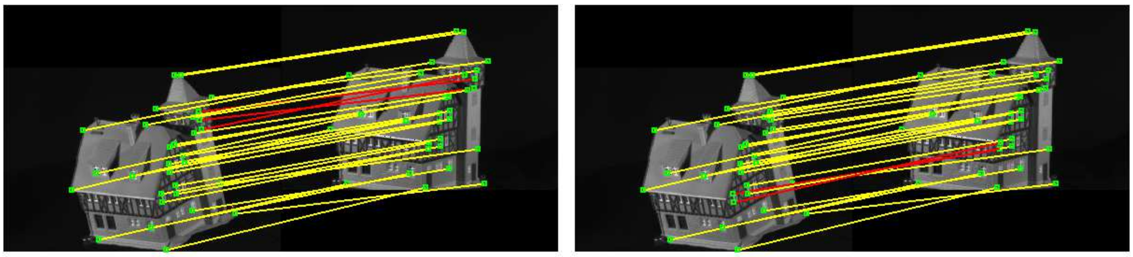


Figure 7. Images from the CMU house sequence (top row: frames 1, 11, ..., 31; bottom row: frames 41, 51, ..., 71)



(a) Result of ODPM matching (b) Result of GODPM matching

Figure 8. Correspondences between the frames 2 and the frames 72 (false correspondences are marked by red line)

taken over different spacings between image pairs in the frame sequence. Here we observe that, when the separation between frames is less than 60, ODPM performs better than SM and GM. Moreover, both ODPM and SM degrade abruptly once the separation exceeds 60, but GODPM can keep well performance. It shows that GODPM is more robust than other three methods.

In addition, we test the algorithms using images from the Zurich Building Image Database (ZuBud) [17]. Firstly, SIFT feature points and descriptors are extracted from images. Then, we construct an initial one-to-one matching between points of the two images. This can be done by computing Euclidean distances between SIFT feature descriptors for feature points. Each point in an image is matched to the smallest distance point of the other image. At last, we use our ODPM and GODPM algorithms to remove the erroneous correspondences. The parameter δ in ODPM (δ_{ODPM}) and GODPM (δ_{ODPM}) are determined as

$$\delta_{ODPM} = mean_{a \in O} IS_{k,O}(a) + std_{a \in O} IS_{k,O}(a), \tag{5}$$

and

$$\delta_{GODPM} = mean_{a \in O} IS_{k,O}(a), \tag{6}$$

respectively, where O is the original candidate assignment set. Since points are discriminative, we can define the distance between candidate assignments $a = (i, i')$ and $b = (j, j')$ as:

$$d(a, b) = \begin{cases} w(a, b) \cdot |d_{ij} - d_{i'j'}| & \text{if } i \neq i' \text{ and } j \neq j' \\ c & \text{otherwise,} \end{cases}$$

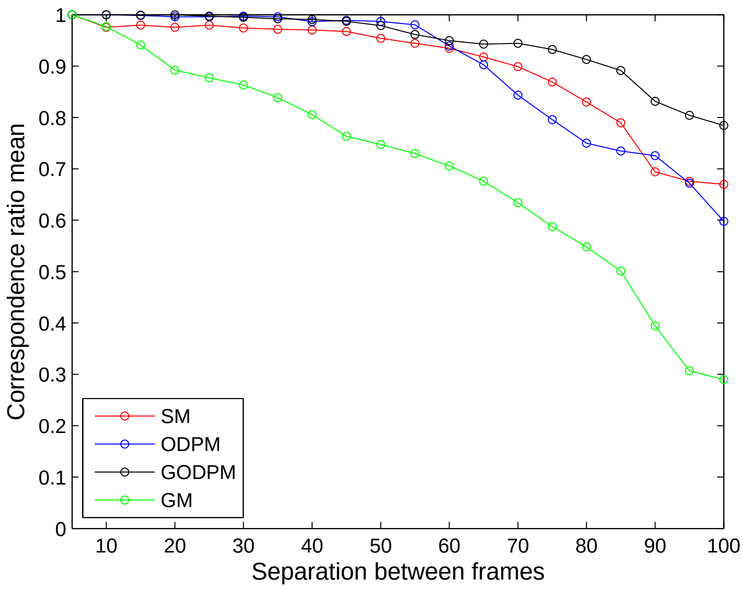


FIGURE 9. Summary of correspondence results for CMU image data

where $w(a,b)$ is the weight, and d_{ij} is the Euclidean distance between the points i and j, and similar to $d_{i'j'}$, c is a large constant. We calculate $w(a,b)$ as $w(a,b) = \|F_i - F_{i'}\|_F + \|F_j - F_{j'}\|_F$ in which F_k is the SIFT feature descriptor for the point k.

FIGURE 10. Comparison matching results for two pairs of building images (False matches are marked by red lines)

Some results are shown in Figure 10 (false matches are marked by red lines). Since the ground truth for actual correspondences is not available, we compare the results visually and mark the false matches by inspection.

Table 1. Matching results for 15 buildings in ZuBud database

	Spectral	GTM	ODPM	GODPM
Total matches	1896	1417	1854	2103
Positive matches	1743	1348	1726	1986
False matches	153	75	128	117
Correspondence ratio	0.919	0.951	0.931	0.944

From Figure 10 and Table 1, we observe that ODPM generally produces fewer false matches compared to spectral matching algorithm, along with higher correspondence ratio. Moreover, both GODPM and GTM can produce higher correspondence ratio compared to spectral and ODPM, especially, GODPM can produce more positive matches than other three methods.

6. **Conclusions.** This paper presents an efficient method for finding consistent correspondences between two sets of features. The main contribution is that we detect the correct assignments from candidate correspondences set by adapting an outlier detection method. In order to do this, we first propose an inlier scoring method based on degree and distance. Then, we recover correct assignments and achieve feature point matching based on the inlier score and greedy algorithm (ODPM). At last, we propose a more robust matching algorithm GODPM by rendering the ODPM to an iterative way. Experimental results on both synthetic and real world image data demonstrate that our method is robust to noise and outlying features.

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