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A graph matching algorithm based on filtering strategy of Bi-directional K-Nearest-Neighbors

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Abstract: In this paper, a novel graph matching algorithm, called Filtering Bi-directional K-Nearest-Neighbors Strategy (Filtering BiKNN Strategy) is presented to solve the pseudo isomorphic graph matching for remote sensing images with large affine transformation, similar patterns or from multisource sensors. BiKNN was proposed to describe the adjacent relationships of feature points. Filtering strategy is used to eliminate dubious matches of pseudo isomorphism for restrict constraints. Any BiKNN vertices of candidate outliers treated as outliers in latter iterations are rechecked with the expanded BiKNN respectively. Candidate outliers with stable graph structures are recovered to the residual sets. Three typical remote sensing images and twenty image pairs were utilized to evaluate the performance. Compared with random sample consensus (RANSAC), graphing transformation matching (GTM) and the proposed BiKNN matching, Filtering BiKNN Strategy can deal with pseudo isomorphism and obtain the highest recall and precision.

Key words: image registration; graph matching; remote sensing images; pseudo isomorphic
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基于双向邻域过滤策略的图形匹配类遥感图像配准算法

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摘要:针对遥感图像由于较大仿射变换关系、相似图案和多源性等导致图形匹配时出现伪同构现象,提出了一种基于双向邻域过滤策略的图形匹配方法.本方法采用双向邻域的图形特征描述子来表示特征点的邻域关系.当误配点的双向邻域任意顶点在后期迭代中被视为误配点时,将与匹配点集具有稳定双向邻域结构的点恢复至匹配点集,同时剔除伪同构中残留的误配点.通过与Random Sample Consensus (RANSAC)、Graphing Transformation Matching(GTM)算法以及提出的双向邻域匹配方式比较得出,基于双向邻域过滤策略的匹配方式能够处理空间顺序匹配时存在的伪同构问题,同时获得更高的召回率和匹配率.

关　键　词:图像配准;图形匹配;遥感图像;伪同构
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Introduction

Image registration is a crucial preprocessing technology for most image analysis, in which the respective information is integrated from various data sources. It has been widely used in remote sensing, computer vision and pattern recognition[1]. Feature matching is a crucial step of registration to determine a reliable correspondence of detected features between the images to be registered.

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Feature matching methods can be mainly classified into two categories: feature similarity-based methods[2-4] and spatial relation-based methods[5-7]. Feature similarity-based methods are sensitive to intensities from multisource images. Scale invariant feature transform (SIFT) [8] is the most remarkable descriptor, which is invariant to small affine transformation. However, remote sensing images are mainly taken from long-range and far distance, and the repetitive patterns and large transformations often make confuse for feature similarity-based matching. Spatial relations are stricter constraints to match feature points, and can be treated as a post-processing for non-rigid matching[12]. A classic approach is random sample consensus (RANSAC)[9], which is to estimate affine transformation parameters from the initial point matching sets, but it cannot deal with large proportion of outliers in initial sets. Graphing transformation matching (GTM)[10] relies on KNN graphs with the limitation of distances, but it does not work well when the pseudo isomorphic graph structures occur in the iterative process[2].

In this paper, we present a so called filtering strategy of bidirectional K-nearest-neighbors (BiKNN) graph matching algorithm, to describe the global information of corresponding point sets with bidirectional adjacent structures. It is designed based on the hypothesis that a feature point regarded as an outlier in previous iterations is invalid if there are outliers belonging to its BiKNN adjacent in latter iterations. With filtering BiKNN strategy, the mistakes of regarding inliers as outliers by most spatial order methods can be recovered. Simultaneously, outliers retained in BiKNN could be eliminated with the increasing proportion of inliers. Simulation results show that the proposed filtering BiKNN strategy can deal with the pseudo isomorphic graphs, and obtain highest recalls and precisions for typical remote sensing images as a post-processing matching, compared with RANSAC, GTM and BiKNN matching.

1 BiKNN matching for non-rigid registration

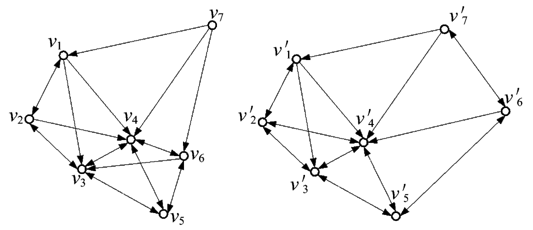
Suppose that feature points have been extracted from two affine transformed images respectively. This can be done by existing non-rigid methods, such as comparing the correlations of feature points' neighborhood or Euclidean distances between SIFT vectors. According to the analysis in Section I, there could be several incorrect matching pairs in the initial corresponding sets. The vertex of each initial matching pair can be described as $V_R = \{v_i\}$ and $V_T = \{v_i'\}$. BiKNN descriptor consists of two parts: The firstnearest points aroundis the forward K-nearest-neighbor, which is constructed as $Fknn_i$:

$$Fknn_i = \{v_{j_k} \mid v_{j_k} = \underset{j_k \in V_R, j_k \neq i}{\arg\min} \sum_{k=1}^{K} \| v_i - v_{j_k} \| \},\ \forall k \in \{1, 2, \cdots, K\} \quad . \quad (1)$$

The backward K-nearest-neighbor described as $Bknn_i$ and v_i belongs to K closest neighbors of any vertex in $Bknn_i$:

$$Bknn_i = \{v_j \mid V_i \in Fknn_i \mid \},\ \forall v_j \in V_R \quad . \quad (2)$$

A directed edge which starts from v_i to v_j exists when v_j is one of the K close neighbors of v_i. Considering graphs $G(V_R)$, $G'(V_T)$ respectively, V_R, V_T and BiKNN directed edges describe the adjacent relations more comprehensively than GTM. When corresponding vertices in V_R and V_T are matched in the strict sense, $G(V_R)$ and $G'(V_T)$ are presented as isomorphic graphs, no matter whether there is affine transform between them.



(a) $G(V_R)$ (b) $G'(V_T)$

Fig. 1 Example of BiKNN graphs, $K=3$
图 1 $K=3$ 时 BiKNN 图形示例

The difference of BiKNN indicates the isomerism of $G(V_R)$ and $G'(V_T)$ as shown in Fig. 1. $G(V_R)$ and $G'(V_T)$ are not exactly isomorphic because of the outliers v_6 and v'_6. $Fknn_i$, $Fknn_i'$ and $Bknn_i$, $Bknn_i'$ of vertices associated with them are not the same in most cases.

Defined as logical BiKNN matrices **FKNN** and **BKNN** represent the BiKNN connections of all vertices intuitively.

$$\mathbf{FKNN}[i,j]=\begin{Bmatrix}1, if & j\in Fknn_i\\0, if & j\notin Fknn_i\end{Bmatrix}$$
$$\mathbf{BKNN}[i,j]=\begin{Bmatrix}1, if & j\in Bknn_i\\0, if & j\notin Bknn_i\end{Bmatrix} \quad . \quad (3)$$

The difference of two graph structures can be obtained by **ΔFKNN** and **ΔBKNN**. It mainly measures whether the connections between the corresponding points of each graph are distinguished.

$$\mathbf{\Delta FKNN}[i,j]=\mathbf{FKNN}[i,j] \text{ xor } \mathbf{FKNN'}[i,j],$$
$$\mathbf{\Delta BKNN}[i,j]=\mathbf{BKNN}[i,j] \text{ xor } \mathbf{BKNN'}[i,j], \quad . \quad (4)$$

Candidate outliers $j^{outlier}$ could be selected with the following structural criterion (5).

$$j^{outlier}=\arg\max_{j=1,2,\cdots,N}\left\{\sum_{i=1}^{N}\mathbf{\Delta FKNN}[i,j]+\sum_{i=1}^{N}\mathbf{\Delta BKNN}[i,j]\right\}. \quad (5)$$

2 Problem formulation

The BiKNN matching relies on the hypothesis that inliers construct isomorphic graph structure, and that outliers which break the isomorphism can be distinguished from inliers by BiKNN connections. However, the above premise may fail in registering images when the initial matching sets are in the two ambiguous situations:

Situation 1. The corresponding outliers in two images have identical BiKNN, i. e.,

$$\sum_{j=1}^{N}\left(\mathbf{\Delta FKNN}[i^{outliers},j]+\mathbf{\Delta BKNN}[i^{outliers},j]\right)=0,$$
$$\exists\, i^{outliers}\in\{1,2,\ldots,N\} \quad . \quad (6)$$

Demonstrated in Fig. 2(a), outlier pairs (v_6, v'_6), (v_7, v'_7) cannot be removed by the same BiKNNs. This frequently occurs in the situation that the corresponding outliers have the similar spatial orders but their positions do not exactly satisfy affine transforms between two images.

Situation 2. Inliers surrounded by outliers are mistaken as outliers, since outliers make inliers with the most different BiKNN, i. e., $\exists\, i^{inliers}, i^{outliers}\in\{1, 2,\ldots,N\}$

$$\sum_{j=1}^{N}\left(\mathbf{\Delta FKNN}[i^{outliers},j]+\mathbf{\Delta BKNN}[i^{outliers},j]\right)$$
$$<\sum_{j=1}^{N}\left(\mathbf{\Delta FKNN}[i^{inliers},j]+\mathbf{\Delta BKNN}[i^{inliers},j]\right). \quad (7)$$

As presented in Fig. 2(b), inliers (v_5, v'_5), (v_6, v'_6) will be selected as outliers incorrectly. If there are a large proportion of outliers in local regions, BiKNN cannot reflect the similarity of graph structure for all vertices, especially the vertices connected with outliers. It's prone to remove inliers instead of outliers in some ambiguous situations.

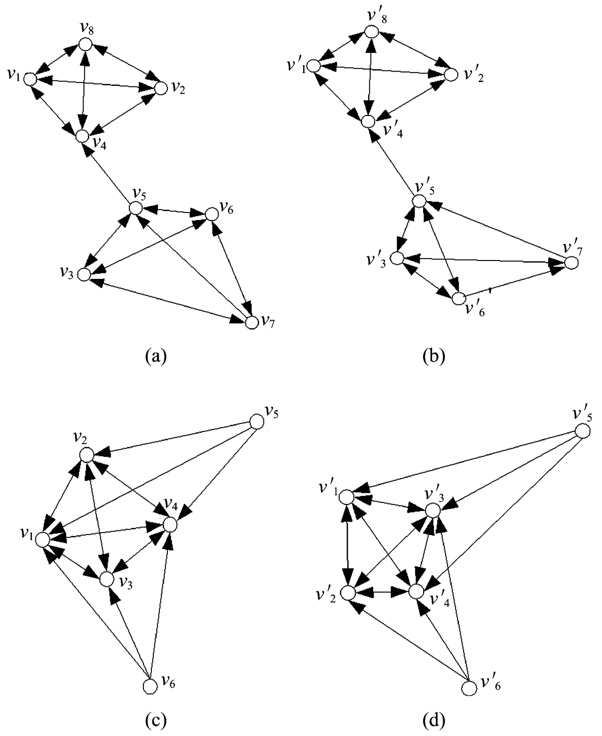


Fig. 2 Demonstration of ambiguous situations. (a) Inliers removed incorrectly (b) Outliers with identical BiKNN graphs
图2 误判情况演示(a)匹配点对误剔除(b)不匹配点对具有相同BiKNN图形

Situation 1 and 2 make BiKNN matching as a non-rigid method in image registration. The defects exist in most methods based on spatial orders or graph matching, such as GTM algorithm. To some extent, BiKNN describes the graph structure in greater details than GTM, so the two above situations occur less. However, it is also intolerable in rigid registration.

3 Filtering BiKNN matching strategy for optimization

The residual vertices sets of the fixed graphs can be denoted by $V_{residual}=\{v_{i residual}\}$ and $V'_{residual}=\{v'_{i residual}\}$. As analyzed in section III, candidate outliers selected by BiKNN matching algorithm cannot be removed arbitrarily. Likewise, there might be some stubborn outliers in the residual vertices set. Hence, a more restrict filtering BiKNN strategy is provided to overcome the defects in BiKNN matching by the following three steps.

Step 1. Checking candidate outliers.

The vertex $j^{c\_outlier}$ is treated as a candidate outlier due to the maximum BiKNN difference. Each vertex belongs to $Fknn^{jc\_outlier}$ or $Bknn^{jc\_outlier}$ has the contribution to make $j^{c\_outlier}$ as a candidate outlier. Along with the iterative process, more and more outliers are selected. If a vertex belonging to $Fknn^{jc\_outlier}$ or $Bknn^{jc\_outlier}$ is selected as a new outlier in latter iterations, the previous BiKNN of $j^{c\_outlier}$ may be changed. The assumption that $j^{c\_outlier}$ has the most different BiKNN will no longer exists. Therefore, whether $v_{jc\_outlier}$ is an outlier should be reconsidered, and all candidate outliers whose BiKNN points are found to be outliers in latter iterations should be checked in this step, i. e., $\forall j^{c\_outlier} \in V_{c\_outlier}$

$$(V_{check}, V'_{check}) = \{(v_{jc\_outlier}, v'_{jc\_outlier}) \mid (Fknn_{jc\_outlier} \cup Bknn_{jc\_outlier}) \cap V_{c\_outlier} \neq \Phi\} \quad . \quad (8)$$

Step 2. Recovering candidate outliers incorrectly removed in previous iterations.

The citation that $v_{jc\_outlier}$ is an outlier depends on the fact that it breaks the stabilization between $G(V_{residual})$ and $G'(V_{residual})$. The candidate outliers need to be checked from two new point sets, denoted by V_{check} and V'_{check}. Each vertex pair (i^{check}, i'^{check}) in V_{check} and V'_{check} is added into $(V_{residual}, V'_{residual})$, respectively, to re-construct their new BiKNN graphs. The two expanded BiKNN graphs have no difference with each other, if only (i^{check}, i'^{check}) are correctly matched. Hence, (i^{check}, i'^{check}) can be recovered to the residual point sets from the candidate outliers, if: $\forall j \in V_{resdual}$, $\forall i^{check} \in V_{check}$,

$$(V_{re\,cov\,er}, V'_{re\,cov\,er}) = \{(v_{i^{check}}, v'_{i^{check}}) \mid \Delta\mathbf{FKNN}[i^{check}, j] = \Delta\mathbf{BKNN}[i^{check}, j] = 0\} \quad . \quad (9)$$

Step 3. Deleting the outliers retained in residual sets with the updated residual sets.

The number of matching pairs increases when some candidate outliers have been recovered into $(V_{residual}, V'_{residual})$. The more matching points are in the input point sets, the more easily outliers in $(V_{residual}, V'_{residual})$ can be removed. So a new round of BiKNN iteration is implemented to delete the outliers retained in $(V_{residual}, V'_{residual})$ because of the pseudo isomorphic graphs. Filtering BiKNN strategy does not reach its end until there are no candidate outliers left to be recovered. Fig. 3 demonstrates the process of BiKNN and filtering BiKNN strategy.

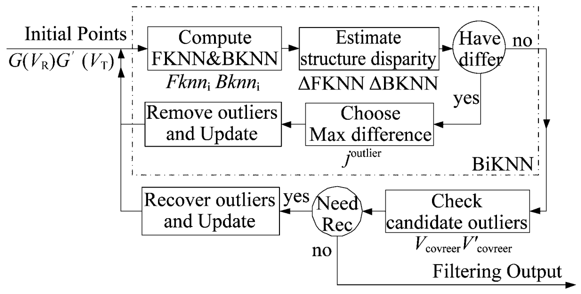


Fig. 3 Block diagram of BiKNN and filtering BiKNN strategy algorithms

图 3 BiKNN 和 Filtering BiKNN Strategy 算法框图

4 Experiments and analysis

In this section, we provide some experimental evaluations for filtering BiKNN strategy and BiKNN. To preclude other impacts on the performance analysis, the SIFT features are extracted for all demonstrations, and the initial matching is obtained by the Best-Bin-First (BBF) algorithm[11].

A. Process of BiKNN matching and filtering BiKNN strategy

Not all real isomorphic graph structures can be obtained by BiKNN matching in some rough scenarios as in Fig. 4. In Fig. 4(b), the bottom points are incorrect matches, so that final BiKNN graphs are pseudo isomorphic as shown in Fig. 4(d). The process of filtering BiKNN strategy is presented as in Fig. 4(e) ~ (g). As shown in Fig. 4(e), 12 potential inliers are added into residual point sets, and 3 of 12 are outliers. With the update of a large proportion of inliers and several outliers in Fig. 4(f), the graphs become isomerous. Therefore, the filtering BiKNN strategy can resume its iterations to delete retained outliers. Fig. 4(g) and (h) presents the stabilized results of the filtering BiKNN strategy. It proves that filtering BiKNN strategy is not only adopted to delete the stubborn outliers, but also to recover much more inliers on this occasion.

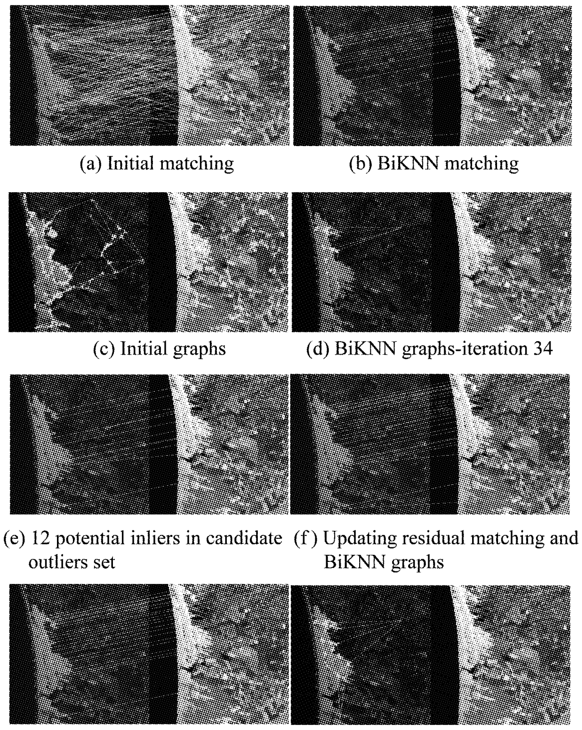
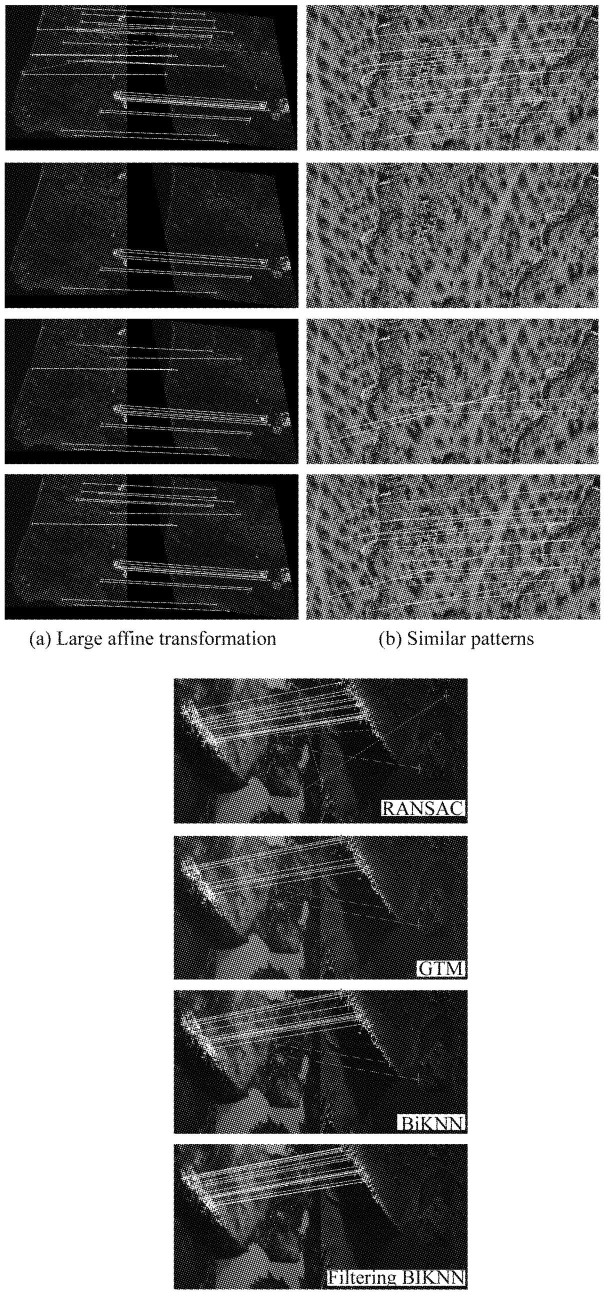

(a) Initial matching (b) BiKNN matching
(c) Initial graphs (d) BiKNN graphs-iteration 34
(e) 12 potential inliers in candidate outliers set (f) Updating residual matching and BiKNN graphs
(g) Filtering BiKNN matching iteration 34 (h) Filtering BiKNN strategy graphs

Fig. 4 Filtering strategy matching for BiKNN pseudo isomorphic of Landsat TM Band 3&5
图4 采用 Filtering Strategy 匹配 Landsat TM Band 3&5 伪同构图形

B. Comparison with Other Algorithms

Filtering BiKNN is compared with BiKNN and two other well-known algorithms, namely RANSAC and GTM. We split the image data into three thorny issues which occur frequently in remote sensing image registration: (1) large affine transformation; (2) similar patterns; (3) images from multisource remote sensors.

Figure 5 shows the matching comparison of three image pair types. The final graph structures of GTM, BiKNN and Filtering BiKNN are presented in Fig. 6, respectively. The performance of RANSAC is not as good as other three algorithms with the increase of outliers. Based on the result of BiKNN, more candidate outliers are recovered by filtering BiKNN strategy in the residual sets. Each graphs of filtering BiKNN strategy are real isomorphic. From the three issues demonstrated above, it is obvious that Filtering BiKNN strategy performs most effectively. Similarly, the combination of three issues compared by image sequence "Oriental Pearl". The testing sequence contains twenty image pairs (VIS & SWIR) with affine transformation (scale, rotation) and similar patterns.



(a) Large affine transformation (b) Similar patterns
(c) Multisource

Fig. 5 Matching results of three issues in remote sensing image registration with four algorithms
图5 采用四种算法匹配三种典型遥感图像的结果

Overall comparisons are given in Fig. 7. The Recall is defined as Recall = True Matches / Initial True Matches, and Precision defined as Precision = True Matches / (True matches + False matches). Filtering BiKNN strategy performs more effectively than the other

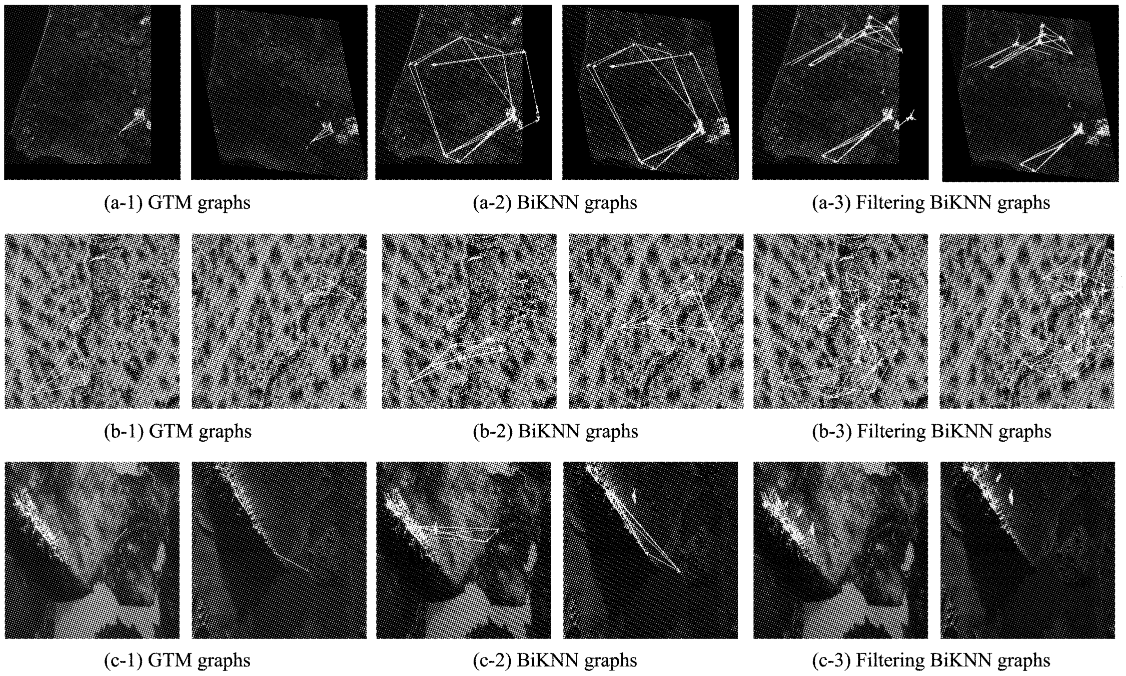


Fig. 6 Final graphs of three graph matching algorithms (a) large affine transformation (b) with similar patterns (c) multisource images

图 6 三种匹配算法最终匹配图形(a) 大仿射变换 (b) 相似图案 (c) 异源

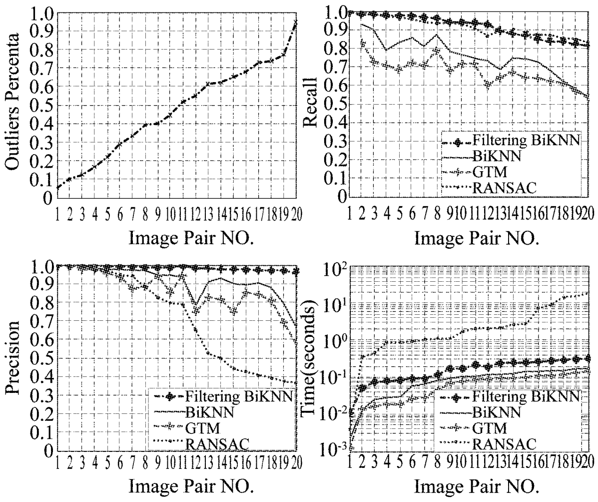


Fig. 7 Performance of four algorithms on "Orient Pearl" image sequence

图 7 四种算法处理"东方明珠"序列的效果

three algorithms in terms of recall and precision. The recall of RANSAC is better than GTM and BiKNN, while the precision of RANSAC is the worst of all. The reason is that RANSAC attaches more importance to identification of outliers than GTM and BiKNN. Besides, the outliers may influence the spatial order of GTM and BiKNN. Therefore, much more inliers might be mistaken as outliers. But with the growth of outliers, RANSAC performs worst in removing outliers, and spends more time on finding a correct matching set.

5 Conclusion

In this paper, we have proposed BiKNN matching and an improved graph matching strategy filtering BiKNN to eliminate the pseudo isomorphism of graph structures, and increase the proportion of inliers for ambiguous issues in remote sensing image registration. BiKNN with global adjacent relationships were constructed for initial corresponding vertices, and outliers were removed by distinguishing the graph structures. Filtering strategy was put forward to deal with the pseudo isomorphic graph structures by rechecking candidate outliers. Tested with three typical issues and twenty image pairs of their combinations, the filtering BiKNN strategy has demonstrated its effectiveness in dealing with remote sensing images with large affine transformation, similar patterns images and from multisource sensors. Compared with RANSAC, GTM and original BiKNN , filtering BiKNN has been evaluated to reach

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as high recall value as RANSAC with much less execution time, which is much better than GTM and BiKNN. Besides, the precision of filtering BiKNN strategy is the highest of all.

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