Iterative Global Similarity Points: A robust coarse-to-fine integration solution for pairwise 3D point cloud registration

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Highlights

(1) The global similarity of keypoints on the hybrid metric spaces of BSC feature and Euclidean distance, is used for the correspondence matching task to get a more robust result.

(2) The coarse-to-fine registration is implemented in an iterative and mutually reinforcing manner, so that a good initialization is not essential.

IGSP Framework

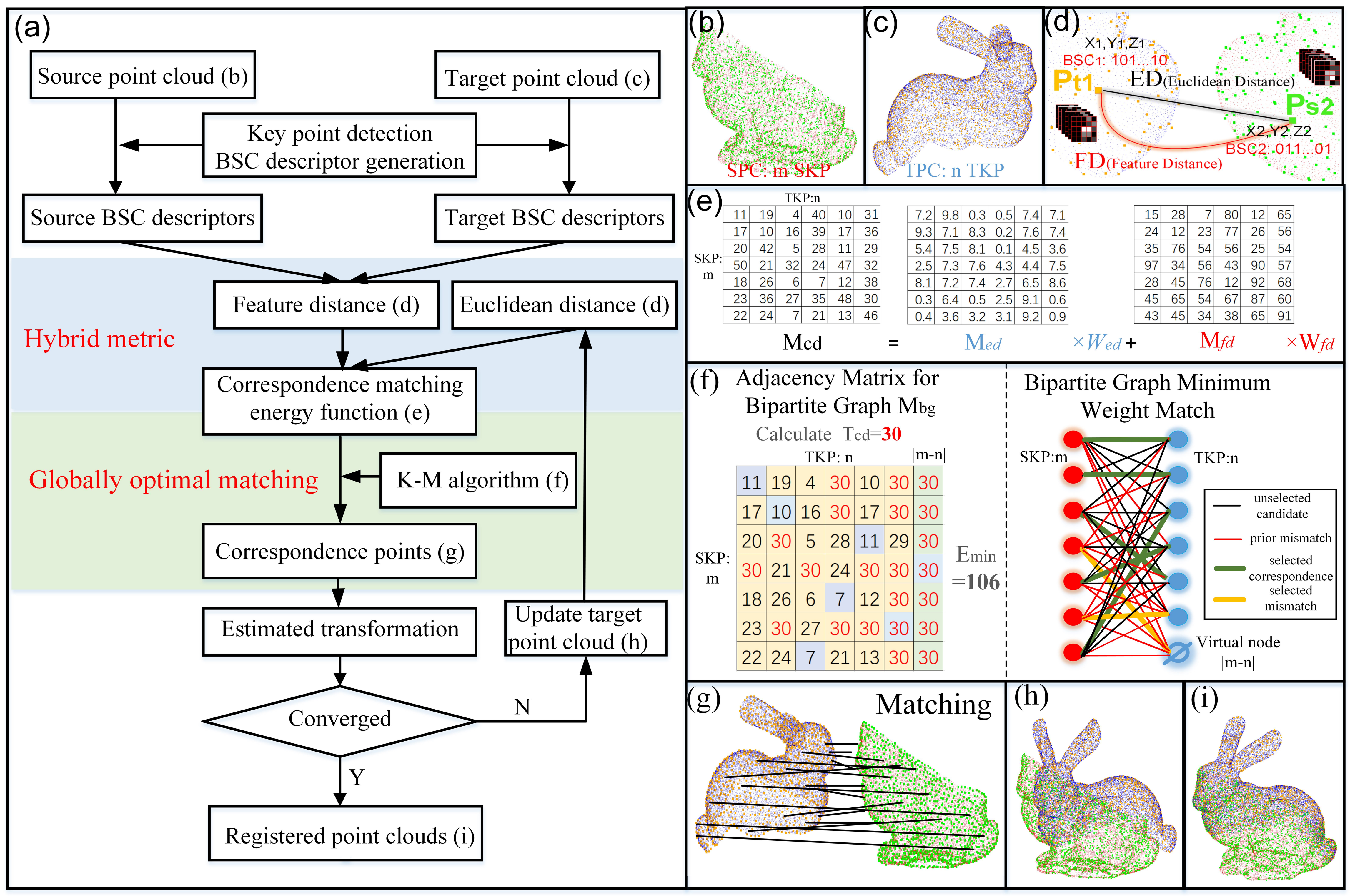

Figure 1. Overview of the proposed IGSP algorithm framework.

IGSP iteratively conducts globally optimal correspondences matching and transformation calculation, until the transformation is negligible. First, we detect the keypoints of point clouds and generate Binary Shape Context (BSC) descriptors to encode their local features. Then, we formulate the correspondence matching task as an energy function, which models the global similarity of keypoints on the hybrid metric space of BSC feature and Euclidean distance, as shown in Fig.1d-e. Next, we determine the globally optimal correspondences by optimizing the energy function using KM algorithm and then calculate the transformation based on them, as shown in Fig.1f-g. Finally, we refine the transformation between two point clouds by iteratively conducting optimal correspondences matching and transformation calculation to realize a coarse-to-fine registration under an unified framework, as shown in Fig.1h-i.

$$ED\left(p,q\right)=s_{ed}\|p-q\| \qquad FD\left(p,q\right)=HD\left(f_p,f_q\right) \tag{1}$$

$$\{M,\varphi\}^{*}=\underset{\{M,\varphi\}}{arg\min}E=\underbrace{W_p\,|\varphi|}_{penalty\_cost}+\underbrace{\sum_{p\in S,q\in T,\{p,q\}\in M}\left(\left(1-e^{-\frac{k}{m}}\right)ED\left(p,q\right)+e^{-\frac{k}{m}}FD\left(p,q\right)\right)}_{Data\_cost} \tag{2}$$

Comparison and Analysis

1.Experiment Platform. The experiments are implemented with a 16 GB RAM and an Intel Core i7-6700HQ 2.60GHz CPU. All algorithms are implemented in C++ with the help of PCL.

2.Comparison. Several pairwise point cloud registration methods (ICP, 3D-NDT, Super4PCS and feature matching with geometric consistency (FM+GC)) are selected for performance comparison using Stanford Bunny, TLS Park and TLS Indoor datasets.

3.Analysis. Table 1 lists the average registration errors and runtime of the compared methods on three datasets, in which / means the registration failed (the value is greater than 1000). ICP and 3D-NDT fail when good initial alignment or prior knowledge is not provided. Super4PCS has poor performance on point clouds with limited overlapping and too many similar structures, especially for the indoor corridor. IGSP outperforms the FM+GC since many correct matching keypoint pairs are also rejected by geometric consistency filter, which leads to a relatively low recall of keypoints matching. However, the time efficiency of IGSP is inferior to all the compared methods due to the iteration process and the O (n^3) time complexity of KM algorithm, which will be the main concern of our future work.

Table 1. Registration accuracy and time performance comparison.

Dataset	Method	e^r(mdeg)	e^t(mm)	T(s)
Stanford 30% overlapped	ICP	/	/	5.6
	3DNDT	/	/	**5.3**
	Super4PCS	74.21	0.17	10.5
	FM+GC	758.23	2.59	8.9
	IGSP	**9.89**	**0.02**	11.3
Park 65% overlapped	ICP	/	/	9.4
	3DNDT	/	/	**8.1**
	Super4PCS	205.14	187.65	38.0
	FM+GC	184.56	414.61	35.2
	IGSP	**93.74**	**85.12**	81.6
Indoor 70% overlapped	ICP	/	/	6.2
	3DNDT	/	/	**6.0**
	Super4PCS	209.85	/	47.1
	FM+GC	486.15	431.90	29.8
	IGSP	**100.42**	**25.53**	61.1

Experiment Result

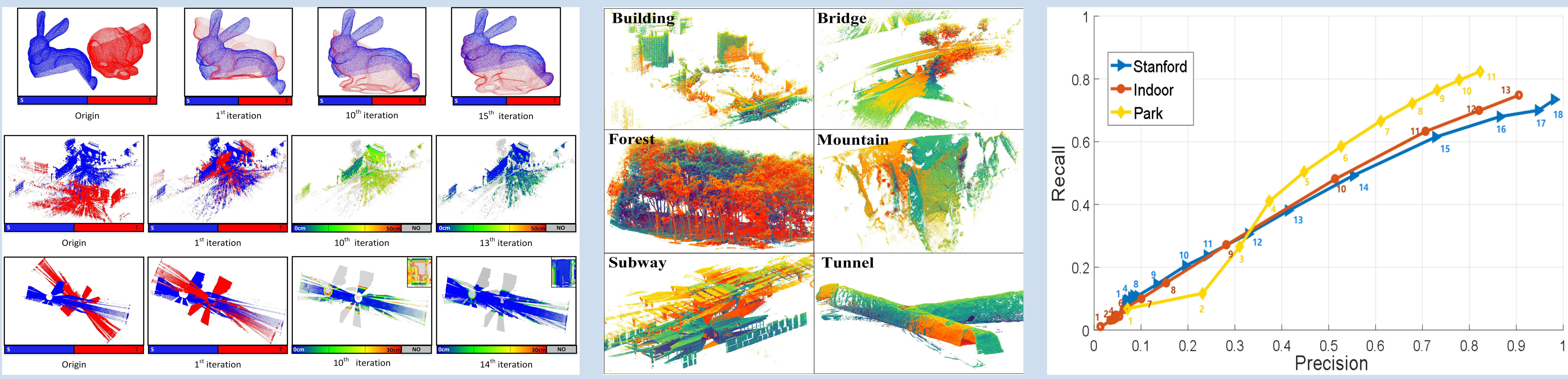

Figure 2. Left:Registration result of Stanford Bunny, TLS Park and TLS Indoor datasets during the iterative process. Middle:Registration result of other challenging real-world datasets. Right:PR-Curve during iterative process on different Datasets

Fig.2 Left shows different phases of registration results using IGSP method on three datasets respectively. As seen in these figures,by IGSP method, the point cloud pairs are iteratively converged from coarse to fine and get registered successfully. To further test the robustness, the algorithm is applied on other challenging real-world datasets, as shown in Fig.2 Middle. These results show that the proposed IGSP method performs well for various scenes, including those with repetitive, symmetric, noisy and incomplete structures, which are quite challenging for previous methods. Fig.2 Right shows the precision-recall curve during IGSP's iterative process, in which each point represents a temporal correspondence result. Since the global optimal correspondences are applied in each iteration, both the precision and recall of the correspondence increase through the process and finally exceed 0.75 on all three datasets, thus resulting in excellent registration performance.