Improved Techniques for Multi-view Registration with Motion Averaging

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Abstract

Recently, motion averaging has been introduced as an effective means to solve multi-view registration problem. This approach utilizes the Lie-algebras to implement the averaging of many relative motions, each of which corresponds to the registration result of the scan pair involved in multi-view registration. Accordingly, a key question is how to obtain accurate registration between two partially overlapping scans. This paper presents a method to estimate the overlapping percentage between each scan pair involved in multi-view registration. What's more, it applies the trimmed iterative closest point (TrICP) algorithm to obtain accurate relative motions for the scan pairs including high overlapping percentage. Besides, it introduces the parallel computation to increase the efficiency of multi-view registration. Experimental results carried out with public data sets illustrate its superiority over previous approaches.

1. Introduction

Multi-view registration is a fundamental and difficult issue in computer vision due to its wide application in 3D model reconstruction. The development of scanning technology makes it possible to generate accurate and dense range scans of real objects or scenarios. As a scenario or object cannot be scanned in its entirety from a single viewpoint, it is required to acquire range scans from multiple viewpoints for covering the entire object or scenario. Accordingly, each range scan has its own reference frame and they should be registered into a co-ordinate system and turn to be an integrated model. Thus, multi-view registration is the prerequisite for model reconstruction.

For the registration problem, the most popular solution is the iterative closest point (ICP) algorithm [3], which can achieve the rigid registration for its good accuracy and fast speed. However, this basic approach can only obtain good registration of absolutely overlapping scans. Consequently, Chetverikov et al. [5] proposed the trimmed ICP (TrICP) algorithm, which introduces an overlapping parameter into a least-square (LS) function to automatically discard outliers and can achieve accurate registration of partially overlapping rang scans. Since the original TrICP algorithm is time-consuming, Phillips et al. [10] presented an improved TrICP algorithm with much faster speed. Although these approaches may obtain good registration results, they are widely known to be susceptible to local minima. To obtain the desired global minimum, genetic algorithm (GA) [9, 15] and the particle filter [11] had been adopted to search optimal solution for registration problem.

Compared with pair-wise registration problem, multi-view registration is somewhat more difficult due to its huge amount of registration parameters. In [4], Chen and Medioni proposed the primary approach for multi-view registration. It repeatedly registers two scans and integrates them into one scan until all the scans are integrated into the whole model. However, this approach can suffer from the problem that errors accumulate in each individual registration step and can lead to poor integration as the model grows. Therefore, Bergevin [2] proposed an improved multi-view registration approach, which can simultaneously consider all the scans and solve the multi-view registration problem by the ICP algorithm. For one point of each scan, this approach should establish the correspondence to each other scans, so it is time-consuming. Subsequently, the improved method is proposed based on a segmentation of the sampled points in an optimized set of z-buffers [1]. This multi-z-buffer technique provides a 3D space partitioning which greatly accelerates the establishment of the point-to-point correspondence between overlapping surfaces. However, this approach is difficult to deal with non-overlapping regions due to the adoption of the ICP algorithm. Besides, the multi-view registration problem can also be viewed as the optimization over the graph of adjacent scans. These approaches [12, 13] cast the multi-view registration problem into a diffusion of rigid transformations over the graph of adjacent scans. They only transfer the registration errors between coordinate frames but do not update the correspondences through registration process. Moreover, Fantoni [6] et al. proposed a completely automatic approach for regis-

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tration of multiple range scans by extracting and describing the key-points from scan data. However, it is difficult to extract the key-points from rang scans without any extra information.

Recently, Govindu and Pooja [7] proposed an extension of the ICP algorithm that simultaneously registers multiple 3D scans. As the ICP algorithm fails to exploit the redundant information available in multiple scans, this approach exploits the information redundancy in a set of range scans by using the averaging of relative motions. Although this approach is very effective, its accuracy should be further improved due to the adoption of ICP algorithm for relative motions estimation between partially overlapping scans. More recently, Zhu et al. [14] proposed a coarse-to-fine approach for multi-view registration. In this approach, each scan should be sequentially registered to a coarse model reconstructed by other registered scans. By applying the TrICP algorithm, it can obtain good multi-view registration results for each scan, which can then be immediately utilized to refine the coarse model for registration of other scans. Since the TrICP algorithm is applied to registration, its accuracy is satisfactory, yet it may fail into local minima due to the poor initial parameters.

Accordingly, this paper extends the approach presented in [7] and proposes some improved techniques for multi-view registration by motion averaging algorithm. The main differences between the previous work [7] and this one are described as follows: (1) It presents a method to estimate the overlapping percentage between scan pair involved in multi-view registration. (2) For the scan pair containing high overlapping percentage, the TrICP algorithm is applied to calculate the accurate transformation between two scans. (3) Parallel computation is introduced to reduce the runtime of the proposed approach. All these three technique can improve the performance of multi-view registration. The first technique can increase the robustness of multi-view registration, the second technique can lead to accurate multi-view registration and the third technique can reduce the runtime of multi-view registration.

The remainder of this paper is organized as follows. In Section 2, the pair-wise registration algorithm is briefly reviewed. Section 3 presents the proposed approach for registration of multi-view registration. Following that is section 4, in which the proposed approach is tested and evaluated on some public data sets. Finally, some conclusions are drawn in Section 5.

2. Pair-wise Registration

In general, the scan pair involved in multi-view registration are partially overlapping or even non-overlapping. Accordingly, the application of the original ICP algorithm is unable to obtain accurate registration results. Suppose there are two partially overlapping range scans, a data shape $P \triangleq \{\vec{p}_a\}_{a=1}^{N_p}$ and a model shape $Q \triangleq \{\vec{q}_b\}_{b=1}^{N_q}$. Denote ξ, $\mathbf{R} \in \mathbb{R}^{3\times3}$, $\vec{t} \in \mathbb{R}^3$ as the overlapping percentage, 3D rotation matrix and translation vector, respectively. The goal of partially overlapping registration is to find the optimal transformation $(\mathbf{R}, \vec{t})$ with which P is registered to be in the best alignment with Q. This problem can be formulated as follows:

$$\begin{aligned} &\min_{\xi,\mathbf{R},\vec{t}} \left(\frac{1}{|P_\xi|\xi^{1+\lambda}} \sum_{\vec{p}_a \in P_\xi} \left\| \mathbf{R}\vec{p}_a + \vec{t} - \vec{q}_{c(a)} \right\|_2^2 \right) \\ &\text{s.t.} \quad \mathbf{R}^T\mathbf{R}{=}\mathbf{I}_3, \quad \det(\mathbf{R}) = 1 \\ &\qquad \xi \in [\xi_{\min}, 1], \; P_\xi \subseteq P, \quad |P_\xi| = \xi\,|P| \end{aligned} \tag{1}$$

where $\vec{q}_{c(a)}$ denotes the correspondence of the $\vec{p}_a$ in model shape, λ is a preset parameter, $|\cdot|$ denotes the cardinality of a set and P_ξ represents the overlapping part of data shape to model shape.

Actually, Eq. (1) can be solved by the trimmed ICP algorithm, which achieves partially overlapping registration in the manner that the ICP algorithm does by iterations. Given the initial transformation $(\mathbf{R}_0, \vec{t}_0)$, three steps are included in each iteration:

(1) Based on the previous transformation $(\mathbf{R}_{k-1}, \vec{t}_{k-1})$, assign the correspondence between two scans:

$$c_k(a) = \mathop{\arg\min}_{b\in\{1,2,..,N_q\}} \left\| \mathbf{R}_{k-1}\vec{p}_a + \vec{t}_{k-1} - \vec{q}_b \right\|_2 \tag{2}$$

(2) Update the current overlapping percentage ξ_k and its corresponding subset P_{ξ_k}:

$$(\xi_k, P_{\xi_k}) = \mathop{\arg\min}_{\xi_{\min}<\xi\leq1} \frac{\sum_{\vec{p}_a\in P_\xi} \left\| \mathbf{R}_{k-1}\vec{p}_a + \vec{t}_{k-1} - \vec{q}_{c_k(a)} \right\|_2^2}{|P_\xi|\,\xi^{1+\lambda}} \tag{3}$$

(3) Calculate the kth transformation:

$$(\mathbf{R}_k, \vec{t}_k) = \mathop{\arg\min}_{\xi,\mathbf{R},\vec{t}} \sum_{\vec{p}_a\in P_{\xi_k}} \left\| \mathbf{R}\vec{p}_a + \vec{t} - \vec{q}_{c_k(a)} \right\|_2^2 \tag{4}$$

Obviously, the optimal transformation can be obtained by repeating these three steps until some convergence criteria are satisfied. To achieve robust registration, the overlapping percentage ξ should be larger than ξ_{min}. Usually, $\xi_{\min} = 0.35$ can give a guarantee of good registration in many practical applications.

3. Registration of Multi-view Range Scans

According to [7], the motion for scans registration has the form:

$$\mathbf{M} = \begin{bmatrix} \mathbf{R} & \vec{t} \\ \mathbf{O} & 1 \end{bmatrix} \tag{5}$$

where $\mathbf{M} \in SE(3)$, $\mathbf{R} \in SO(3)$ and $\mathbf{O} = [0, 0, 0]$. Generally, there are two kinds of motions involved in the multi-view registration: the global motion and the relative motion,

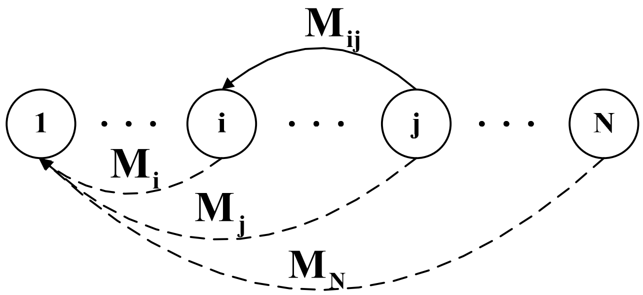

Figure 1. The set of range scans involved in multi-view registration, where $\mathbf{M}_{ij}$ indicates the relative motion from scan j to scan i and $\mathbf{M}_{global} = \{\mathbf{I}, \mathbf{M}_2, \ldots, \mathbf{M}_N\}$ denotes the global motion being estimated.

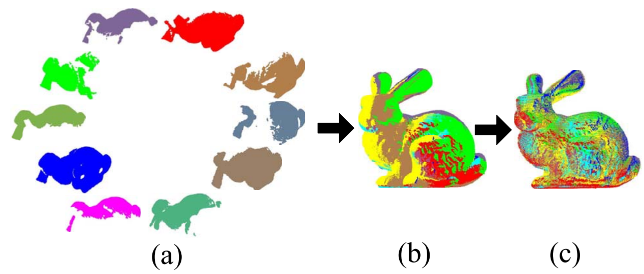

Figure 2. Two steps of multi-view registration, different color denotes different rang scans. (a) Range scans acquired from different viewpoints; (b) The coarse model obtained by initial global motions; (c) The refine model obtained by multi-view registration.

and their relationship can be depicted in Fig. 1. Define $\mathbf{M}_i$ as the motion from ith scan's coordinate to the reference frame. Without lose of generality, the coordinate of the first scan can be set as the reference frame. Suppose there are N range scans, the goal of multi-view registration is to obtain the accurate global motions $\mathbf{M}_{global} = \{\mathbf{I}, \mathbf{M}_2, \ldots, \mathbf{M}_N\}$, and the integrated global model can be denoted as:

$$P_{global} = \{P_1,\, \mathbf{M}_2 \oplus P_2,\, \ldots,\, \mathbf{M}_N \oplus P_N\} \tag{6}$$

where $\mathbf{M}_i \oplus P_i \triangleq \{\mathbf{R}_i \vec{p}_a + \vec{t}_i\}_{a=1}^{N_i}$.

Fig. 2 displays the general steps of multi-view registration. As Fig. 2 illustrates, the first step of multi-view registration is to obtain the initial global motions. Given the results of sequential registration $\{\mathbf{M}_{i-1,i}\}_{i=2}^{N}$ for the adjacent scan pairs, the initial global motion $\mathbf{M}^0_{global}$ can be calculated as follows:

$$\mathbf{M}^0_i = \mathbf{M}^0_{i-1}\mathbf{M}_{i-1,i} \tag{7}$$

3.1. Recovery of relative motions

Before the implementation of pair-wise registration, the initial relative motion of one scan pair should be recovered and viewed as the initial parameters for the TrICP algorithm.

Given the initial global motion $\mathbf{M}^0_{global}$, it is easy to recover the initial motion for pair-wise registration as follows:

$$\mathbf{M}^0_{ij} = (\mathbf{M}^0_i)^{-1}\mathbf{M}^0_j \tag{8}$$

where the ith scan denotes the model shape and the jth scan indicates the data shape.

For the scan pair including high overlapping percentage $(\xi_{ij} > \xi_{thr})$, the TrICP algorithm can be applied to obtain the registration results $\mathbf{M}_{ij}$, which can be viewed as the relative motion for this scan pair.

3.2. Estimation of the overlapping percentage

To obtain robust and accurate relative motion, the TrICP algorithm can only applied to these scan pairs, which include high overlapping percentage. Hence, it is necessary to estimate the overlapping percentage before applying the TrICP algorithm.

For each point in the ith scan P_i, it can search $(N-1)$ nearest neighbors from each other scans P_j $(j \neq i)$ involved in multi-view registration and the distances can be preserved for subsequent processing. Based on the preserved distance, it is easy to sort all the point pairs by their distances in the ascending order. Each time, a pair of sorted points can be added to compute the corresponding value of objective function $\psi(\xi)$ denoted by Eq. (1). By traveling all the sorted point pairs, it is easy to obtain the minimum value $\psi_{min}(\xi)$, which corresponds the optimal overlapping percentage ξ_i. Then, the distance d_i of the $\lfloor \xi_i(N-1)N_i \rfloor$th point pair can be viewed as threshold, which can be utilized to decide the overlapping percentage ξ_{ij} between the scan pair (P_i, P_j). For the scan pair (P_i, P_j), N_j point pairs can be obtained by solving Eq. (2). Suppose there are $N_j^{'}$ point pairs, whose distance is shorter than the threshold d_i, then the overlapping percentage of scan P_j to scan P_i can be calculated as follows:

$$\xi_{ij} = \frac{N_j^{'}}{N_j} \tag{9}$$

Given the threshold ξ_{thr}, it is easy to make the decision to ignore the scan pairs including low overlapping percentage.

3.3. Motion averaging algorithm

After the estimation of overlapping percentage, it can find several pairs of scans, which have high overlapping percentage. If there are n pairs of scans satisfy the condition $\xi_{ij} > \xi_{thr}$, then the corresponding relative motions $\{\mathbf{M}_{ij1}, \mathbf{M}_{ij2}, \ldots, \mathbf{M}_{ijn}\}$ can be acquired by application of the TrICP algorithm.

According to [7], motion averaging algorithm is an effective approach to deal with multi-view registration. Given the initial global motion $\mathbf{M}^0_{global}$ and the n relative motions $\{\mathbf{M}_{ij1}, \mathbf{M}_{ij2}, \ldots, \mathbf{M}_{ijn}\}$, it can achieve multi-view registration by iterations and obtain the corresponding global motions $\mathbf{M}_{global} = \{\mathbf{I}, \mathbf{M}_2, ..., \mathbf{M}_N\}$. In each iteration, the following five steps are included:

(1) Get the difference between the relative motion $\mathbf{M}_{ij}$ and the initial relative motion $\mathbf{M}_{ij}^0$ obtained from Eq. (8):

$$\Delta\mathbf{M}_{ij} = \mathbf{M}_i^0 \mathbf{M}_{ij} (\mathbf{M}_j^0)^{-1} \tag{10}$$

(2) Transform these difference from Lie group $\mathbf{M}$ to Lie algebra $\mathbf{m}$:

$$\Delta\mathbf{m}_{ij} = log(\Delta\mathbf{M}_{ij}) \tag{11}$$

(3) Averaging the difference in Lie algebra:

$$\Delta\mathbf{v}_{ij} = vec(\Delta\mathbf{m}_{ij}) \tag{12}$$

$$\Delta\Im = \mathbf{D}^\dagger \Delta\mathbf{V}_{ij} \tag{13}$$

where Lie algebra $\mathbf{m}$ is a skew-symmetric matrix and $\Delta\mathbf{v}_{ij}$ is a columnwise vector with six elements extracts from $\Delta\mathbf{m}_{ij}$. Besides, $\mathbf{D}_{ij} = [\,..., -\mathbf{I}_{6\times6}, ..., \mathbf{I}_{6\times6}, ...\,]$ is a matrix with 6 rows and $6 \times N$ columns, where $-\mathbf{I}_{6\times6}$ appears at the $(6 \times i)$th column and $\mathbf{I}_{6\times6}$ appears at the $(6 \times j)$th column. $\Delta\mathbf{V}_{ij} = [\Delta\mathbf{v}_{ij1}, \Delta\mathbf{v}_{ij2}, ..., \Delta\mathbf{v}_{ijn}]^T$, $\mathbf{D} = [\mathbf{D}_{ij1}, \mathbf{D}_{ij2}, ..., \mathbf{D}_{ijn}]^T$ and $\mathbf{D}^\dagger$ is the pseudo-inverse of $\mathbf{D}$.

(4) Transform the averaging from Lie algebra to Lie group and refine the global motion:

$$\Delta\mathbf{m}_k = cev(\Delta\mathbf{v}_k) \tag{14}$$

$$\forall k \in [2, N],\ \mathbf{M}_k = e^{\Delta\mathbf{m}_k}\mathbf{M}_k \tag{15}$$

where $\Delta\Im = [\Delta\mathbf{v}_1, ..., \Delta\mathbf{v}_k, ..., \Delta\mathbf{v}_N]^T$ and $cev(\cdot)$ represents the recovery of the corresponding Lie algebra matrix $\Delta\mathbf{m}_k$ from the columnwise vector $\Delta\mathbf{v}_k$.

(5) Set $\mathbf{M}_{global}^0 = \mathbf{M}_{global}$, repeat steps $(1) \sim (4)$ until $\|\Delta\Im\| < \varepsilon$, where ε is a preset constant.

3.4. Algorithm implementation

Given the results of sequential registration $\{\mathbf{M}_{i-1,i}\}_{i=2}^N$ for the adjacent scan pairs, the proposed multi-view registration approach can be reasonably outlined as follows:

(1) Get the initial global motion $\mathbf{M}_{global}^0$ from $\{\mathbf{M}_{i-1,i}\}_{i=2}^N$ according to Eq. (7);

(2) Based on the proposed EOP (estimation of overlapping percentage) method, pick out several scan pairs, which satisfy $\xi_{ij} \geqslant \xi_{thr}$; then obtain their relative motions $\{\mathbf{M}_{ij1}, \mathbf{M}_{ij2}, ..., \mathbf{M}_{ijn}\}$ by the application of the TrICP algorithm;

(3) Utilize motion averaging algorithm to refine the global motion $\mathbf{M}_{global} : \{\mathbf{I}, \mathbf{M}_2, ..., \mathbf{M}_N\}$;

(4) Denote σ as a small positive number, set $\mathbf{M}_{global}^0$=$\mathbf{M}_{global}$ and repeat steps (2) $\sim$ (3) utill the number of iteration reaches the maximum value K or $(\frac{1}{(N-1)}\sum_{i=2}^n \left\|\mathbf{R}_i - \mathbf{R}_i^0\right\|_F) \leqslant \sigma$.

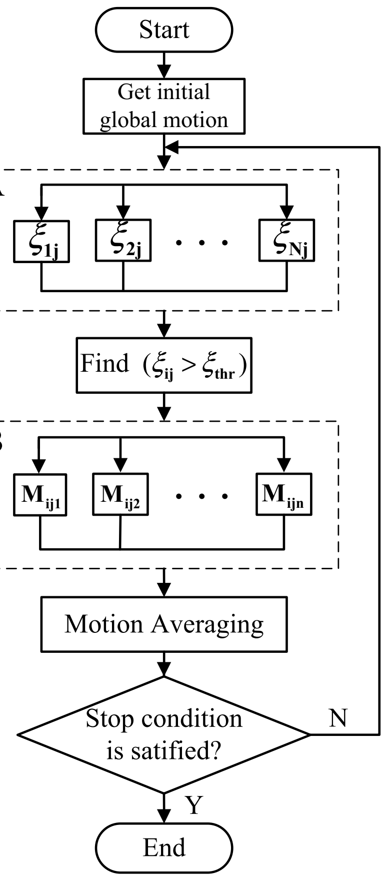

Figure 3. The diagram of the proposed approach, where the frame A represents the estimation of overlapping percentages and the frame B denotes the application of TrICP algorithm.

Subsequently, the diagram of the proposed approach can be displayed in Fig. 3. As shown in Fig. 3, the overlapping percentage of one scan to other scans can be estimated simultaneously and the application of the TrICP algorithm to each scan pair is independent. As these two parts are required to build correspondence among scans, they are time consuming. Hence, parallel computation can be applied to reduce the runtime of the proposed approach in multi-core computers. Since the Matlab software provides the tool for parallel computation, it is easy to implement the parallel computation for the proposed approach in Matlab.

4. Experimental Results

To verify its superior performance, the proposed approach was compared to the motion average ICP algorithm [7] and the coarse-to-fine TrICP approach [14], which are abbreviated as MAICP and CFTrICP. Experiments were tested on three datasets from the Stanford repository [8], where the Bunny, Dragon and Happy Buddha include 10, 15, 15 range scans, respectively. As each of these three data sets contains a huge number of points, the multi-view registration is time-consuming. In order to save time, the testing data sets are sampled from the raw data sets with the sampling frequency set to be 8. During experiments, parameters are set as follows: $\lambda = 2$, $\xi_{min} = 0.35$, $\xi_{thr} = 0.5$, $\varepsilon = 10^{-3}$, $\sigma = 4.5(N-1) \times 10^{-4}$, $K = 30$. All the competed approaches adopted nearest-neighbor search method based on $k-d$ tree to assign the correspondences and were implemented in Matlab. Experiments were performed on a double-Core 3.10GHZ computer with 4 GB of memory except the experiment of parallel computation.

4.1. Parallel computation

To verify the efficiency of parallel computation, the proposed approach was carried out in two modes: (1) Sequential computation (SC); (2) Parallel computation (PC). And it was tested on Stanford Bunny, Dragon and Happy Buddha, respectively. Before experiment, the noise was added to the initial parameters obtained by Eq. (7). Experiment was performed on two computers: a double-Core 3.10GHZ computer with 4 GB of memory and a four-core 3.40GHZ computer with 16 GB of memory. During experiment, the runtime of every data set was recorded for each mode. To eliminate randomness, 50 Monte Carlo (MC) trials were carried out with respect to three data sets for two modes of the proposed approach. For comparison of the results between different computers, the average runtime of sequential computation can be normalized and the percentage of average runtime between these two modes is displayed in Fig. 4.

As shown in Fig. 4, the adoption of parallel computation can reduce the runtime of the proposed approach for multi-view registration and its efficiency can be further improved with the number of cores increased in the computer.

4.2. Efficiency and accuracy

Since all these three approaches require the initial global motions, it only needs to compare the runtime in multi-view registration step. For comparison of different approaches, the objective function presented in [14] is adopted as the error criterion for accuracy evaluation of multi-view registration results. During experiment, the same noise is added to the initial registration parameters obtained by Eq. (7). Accordingly, three approaches can be applied to register multi-view range scans. Table 1 records the runtime and objective function value of the final registration result for all these competed approaches. To view the results in a more intuitive way, Fig. 5 displays the registration results of three data sets for different approaches in the form of cross-section.

As shown in Table 1 and Fig. 5, the proposed approach can obtain the most efficient and accurate multi-view registration result among these competed approaches. Since

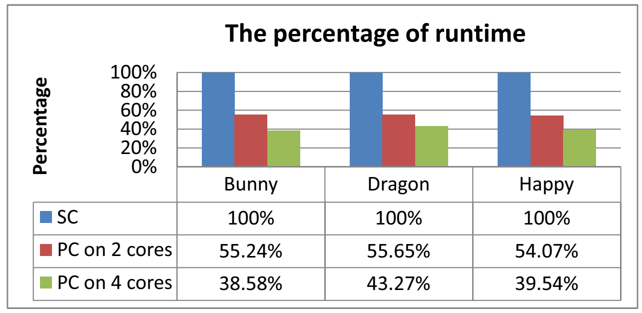

Figure 4. The comparison of runtime between the parallel computation (PC) and the sequential computation(SC).

CFTrICP minimizes the objective function presented in [14] to achieve multi-view registration, it is reasonable to obtain accurate results. Compared to MAICP, the proposed approach improves the registration performance by the three following techniques: (1) The EOP method is introduced to roughly estimate the overlapping percentage, which can help us to discard some scan pairs including low overlapping percentage. (2) Parallel computation is adopted to replace the sequential computation. (3) For the scan pair including high overlapping percentage, the ICP algorithm is replaced by the TrICP algorithm to obtain accurate relative motions. Both the first and second techniques can accelerate the multi-view registration, the third one can improve the accuracy of the proposed approach. Therefore, the proposed approach has good performance for multi-view registration on efficiency and accuracy.

4.3. Robustness

To verify the robustness of the proposed approach, all competed approaches were tested on Stanford Bunny with varied initial parameters, which can be obtained by adding the uniform noises to the initial rotation obtained by Eq. (7). To eliminate randomness, 50 MC trials were carried out with respect to three noise levels for all competed approaches. Table 2 depicts the mean value and standard deviation of objective function, the mean runtime for these approaches. To compare the robustness in a more intuitive way, Fig. 6 displays the objective function value of the registration results for all competed approaches in each MC trial.

As shown in Table 2 and Fig. 6, the proposed approach can obtain the most efficient, accurate and robust registration results under varied noise levels. To achieve multi-view registration, CFTrICP should adjust all the registration parameters simultaneously, which can make it easy to trap into local minima. Hence, the robustness of CFTrICP is poor especial for the high noise levels. Since MAICP adopts the ICP algorithm to calculate relative motions between the scan pair including non-overlapping regions, it is

Table 1. Performance comparison among different approaches for different shapes

	Bunny		Dragon		Happy Buddha	
	Obj	T(min)	Obj	T(min)	Obj	T(min)
MAICP [7]	0.8533	5.0333	0.5152	4.1986	0.1821	25.6729
CFTrICP [14]	0.7112	2.6530	0.4116	1.9533	0.1376	6.9097
Ours	0.6329	0.9235	0.4095	1.1205	0.1344	3.8964

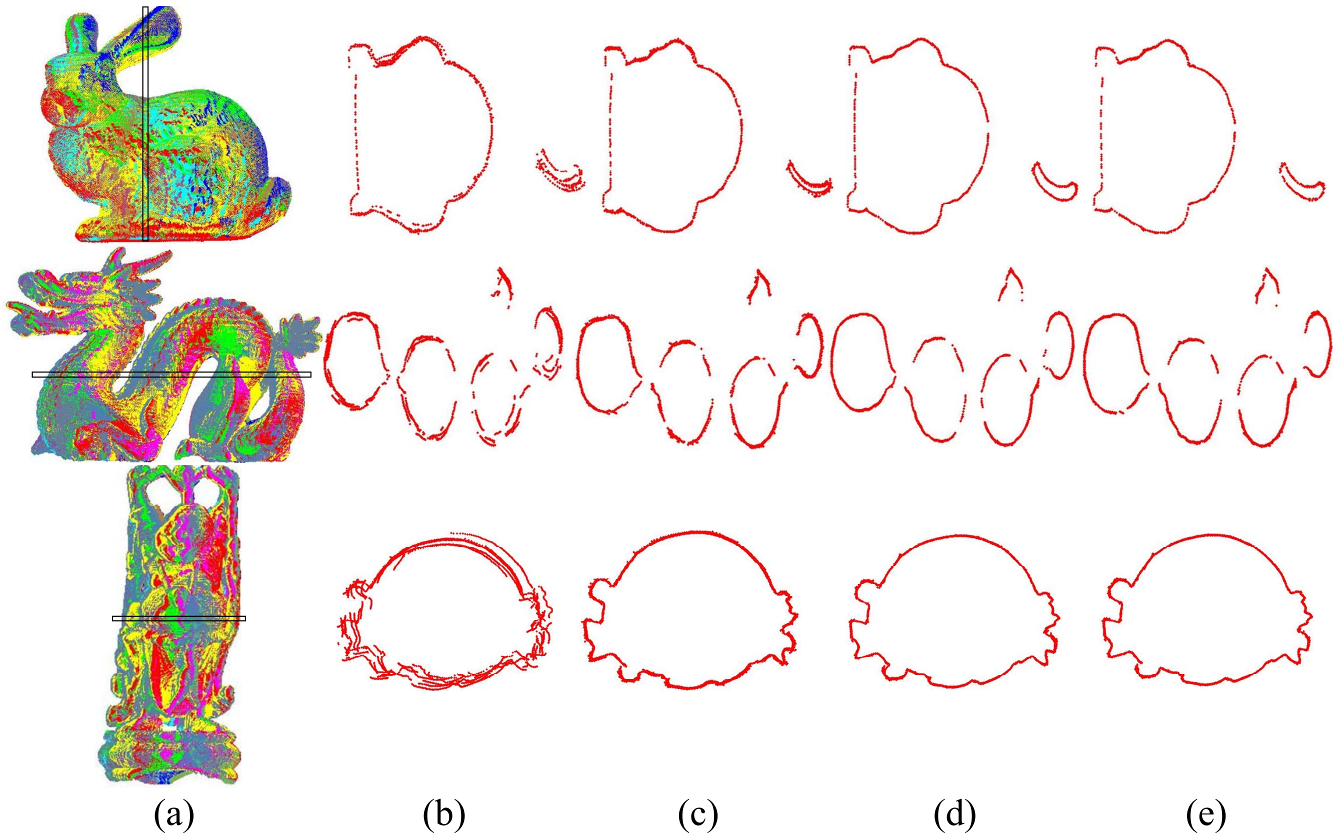

Figure 5. Cross-section of multi-view registration results for three competed approaches. From the first to third rows are Stanford Bunny, Dragon, and Happy Buddha, respectively. (a) The 3D model obtained by the proposed approach; (b) Cross-section of the initial model; (c) Cross-section of MAICP; (d) Cross-section of CFTrICP; (e) Cross-Section of our approach.

unable to obtain accurate and robust relative motions, which can lead to bad multi-view registration. While, the proposed approach can estimate the overlapping percentage between each scan pair and apply the TrICP algorithm to calculate accurate relative motions for the scan pair including high overlapping percentage. Therefore, it can obtain the most robust multi-view registration results by further adopting the motion average method proposed in [7] .

5. Conclusion

This paper proposes the improved techniques for multi-view registration with motion averaging. By considering non-overlapping regions, it presents a method for estimation the overlapping percentage between each scan pair, which can help us to pick out the scan pairs with high overlapping percentage. For these scan pairs, the TrICP algorithm can be utilized to obtain accurate relative motions. Subsequently, the motion averaging algorithm can be applied to these relative motions for registration of multi-view range scans. Since it is time-consuming to estimate the overlapping percentages and apply the TrICP algorithm, the adoption of parallel computation can dramatically reduce the runtime of multi-view registration. Experimental results demonstrate that the proposed approach can achieve the registration for multi-view range scans with good performance in efficiency, accuracy and robustness.

Although we have achieved good results of rigid registration of multi-view range scans, there are still many degrees

Table 2. Performance comparison of three approaches under varied noise levels

	[-0.02,0.02]rad			[-0.04,0.04]rad			[-0.06,0.06]rad		
	Obj.		T(min)	Obj.		T(min)	Obj.		T(min)
	Mean	Std.	Mean	Mean	Std.	Mean	Mean	Std.	Mean
MAICP [7]	0.8532	0.0002	5.4050	0.9164	0.4474	5.2097	1.4980	1.6478	5.0499
CFTrICP [14]	0.7127	0.0017	2.0368	0.7651	0.1302	2.3165	0.7915	0.1691	2.8180
Ours	0.6329	0.0002	0.9685	0.6330	0.0003	1.0174	0.6330	0.0003	1.1271

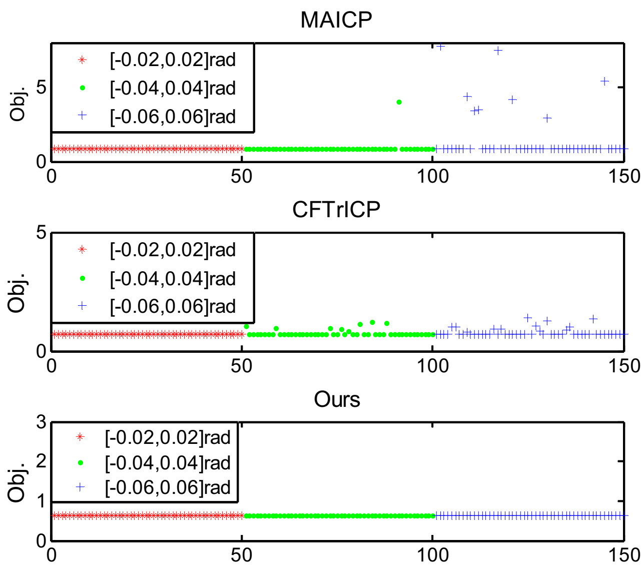

Figure 6. The objective function value of the registration results for the competed approaches in each MC trial.

of freedom that could be explored, such as the extension of this approach to the non-rigid registration of multi-view range scans.

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