Global Hybrid Registration for 3D Constructed Surfaces using Ray-casting and Improved Self Adaptive Differential Evolution Algorithm

Tao Ngoc Linh[1], Tam Bui[1] and Hasegawa Hiroshi[2]
[1]*Deparment of Functional Control Systems, Graduate School of Engineering and Science, Shibaura Institute of Technology, Saitama 337-8570, Japan*
[2]*Department of Machinery and Control System, College of Systems Engineering and Science, Shibaura Institute of Technology, Saitama 337-8570, Japan*

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Abstract: As a fundamental task in computer vision, registration has been a solution for many application such as: world modeling, part inspection and manufacturing, object recognition, pose estimation, robotic navigation, and reverse engineering. Given two images, the aim is to find the best possible homogenous transformation movement resulting in a more completed view of objects or scenarios. The paper presents a novel algorithm of registering structured pointcloud surfaces by using a fast ray-casting based closest point method intergrated with a new developed global optimization method Improve Self Adaptive Differential Evolution (ISADE). Ray-casting based L_2 error calculation method enables the algorithm to find the local minima error effectively while ISADE exploits the searching boundary to find the global minima. The new algorithm is evaluated on structured images captured by a Kinect camera to show the superior in quality and robustness of ISADE over state-of-the-art searching method and accuracy of the new method over a well known registration algorithm, KinectFusion.

1 INTRODUCTION

The introduction of commercial depth sensing devices such as Microsoft Kinect, Asus Xtion, etc has shifted robotics, computer vision research areas from 2D based imaging and laser scanning toward 3D based depth scenes of environment processing. As a physical object or scenario can not be completely captured with a single image, different images from different time and positions need to be aligned into a more completed view of the senario, the process of alignment is called registration. Registration algorithms estimate the movement of the camera through calculating the transformation that optimally maps two point clouds. Various applications such as 3D object scanning, 3D mapping, 3D localization use registration algorithms as backbone algorithms. According to how many views or images of the objects are processed at the same time, registration strategies are divided into multi-view registration (for all views case) and pair-wise registration (for two views case). Our paper focus on the pair-wise registration of constructed range images taken by 3D cameras. As a consequence, starting from two views, i.e., the model and the data, the objective of our registration process is to find the best homogeneous transformation that, when applied to the data, aligns it with the model in a common coordinate system.

Iterative Closest Point (ICP)(1) and its variants such as non-linear ICP, generalized ICP and non-rigid ICP have been always indispensable tools in registration tasks. ICP's concept and implementation are easy to understand. ICP uses L_2 error estimated from pairwise point-clouds to derive a transformation which draws them closer to each other. Registration process finishes after many iterations of minimizing error and results in a homogeneous transformation.

However, ICP-class algorithms alone cannot solve problems for general registration tasks since they require a further assumption in which a initial near-optimal pose transformation is necessary for right convergences. Otherwise, the registration process would likely converge to local optimal solutions instead of the global optimal or near global optimal one. This result cannot be overcome merely by iteration procedure. In some mesh and point-cloud edi-

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tor softwares such as Meshlab (2), registering tool for range data is available. It requires manually data pre-alignment from users before ICP comes into use.

To overcome the shortage of ICP-class methods, in general, registration processes are generally divided into two steps: coarse transformation or initialization and fine transformation. If two point-clouds are close enough, the first step could be omitted. Otherwise, the problem remains a big challenge for researchers. Coarse transformation, pre-alignment estimation or initialization solving has two approaches: local and global. Local methods use local descriptors (or signatures) such as PFH(3) and SIFT(4) which encode local shape variation in neighborhood points. If points with those descriptors appear in both registering point-clouds, initialization movement could be estimated by using sample consensus algorithms such as RANSAC (5). The problem of local approaches is that those signatures are not always guarantied to appear on both registering point-clouds. On the other hand, global approaches take every points into account such as Go-ICP (6) and SAICP(7). The biggest problem of those methods is computation cost in finding the corresponding points in point-clouds. If there are big number of point in point-clouds, the computation cost is going large. However, thanks to new algorithms especially heuristic optimal searching methods as well as the increasing in computer speed especially with parallel computing with multi-core CPU processor and Graphic Computation Unit (GPU)(8) it is possible to find solutions of global approaches of registration problem. After estimating coarse transformation, ICP algorithm is an efficient tool to find the fine transformation.

This paper proposes a new global registration method for 3D constructed images without need of good initializing. It is called Global Hybrid Registration for 3D Constructed Surface Using Ray-casting and ISADE (12). As other global registration methods, our method requires no local descriptors on works directly on raw scan surfaces. The method uses ray-casting based method for local minima searching together with ISADE as a search engine to find the global minima without using fine registration. Our method rapidly produces results at high rate convergence of the global optimization solution.

2 THREE DIMENSION REGISTRATION

This part summaries some approaches for global range image registration task up to date. SVD, PCA (13) are integrated together with ICP as classical methods and global searching algorithms are integrated with ICP as in the most current methods.

2.1 ICP Algorithm

SVD and PCA have been used to find coarse transformation together with ICP as the fine transformation estimating tool. Original version of ICP algorithm relies on L_2 error to derive the transformation including rotation and translation. To register two point-clouds $X = \{x_i\}, \{i = 1,2,3,...,m\}$ (model point-cloud) and $Y = \{y_j\}, \{j = 1,2,3,...,n\}$ (data point-clouds), where x_i and $y_j \in R^3$ are point coordinates of points in point-cloud. ICP algorithm arms to find rotation $\mathbf{R} \in SO^3$ and translation $\mathbf{t} \in R^3$, which minimize L_2 type error as in Equation 1:

$$\mathbf{E}(\mathbf{R},\mathbf{t}) = \sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{e_i}(\mathbf{R},\mathbf{t}) = \sum_{\mathbf{i=1}}^{\mathbf{n}} |\mathbf{R}\mathbf{x_i} + \mathbf{t} - \mathbf{y_{j^*}}| \quad (1)$$

where $\mathbf{R}$ and $\mathbf{t}$ are rotation and translation matrix, $\mathbf{y_{j^*}}$ is the corresponding point of $\mathbf{x_i}$ denoted for its closest point in data point-cloud Y. There are some ICP variants which rely on different categories to define closest points. Point-to-point and Point-to-plane are two popular examples. Equation 2 is used to search for closest point by Point-to-point category.

$$\mathbf{j}^* = \underset{\mathbf{j}\in\{\mathbf{1},\ldots,\mathbf{n}\}}{\text{argmin}} ||\mathbf{R}\mathbf{x_i} + \mathbf{t} - \mathbf{y_j}|| \quad (2)$$

The iteration process is as following to archives the final transformation:

1. Compute the closest model points for each data point as (2).
2. Compute the transformation $\mathbf{R}$ and $\mathbf{t}$ based on the error from (1).
3. Apply $\mathbf{R}$ and $\mathbf{t}$ to the data point-clouds.
4. Repeat step 1, 2, 3 until error as (1) smaller then a set tolerant or the procedure reaches its max iteration.

Step by step, ICP draws the data point-cloud closer to model point-cloud and the process stops at local minima. There are some variants of ICP algorithm based on different methods to calculate the transformation from error $\mathbf{E}(\mathbf{R},\mathbf{t})$ and error itself as in LMICP (14) and SICP (15).

2.2 Global Hybrid Searching Algorithm

ICP algorithms are superior for registering close or pre-aligned point-cloud data, otherwise, it often converges wrongly. Global searching algorithms are solution to solve this problem since they are able to find

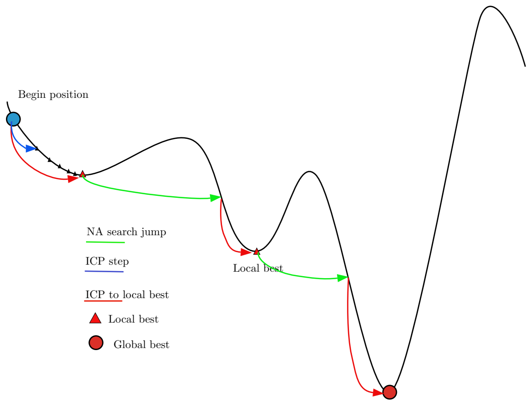

Figure 1: global searching algorithm with ICP integrated.

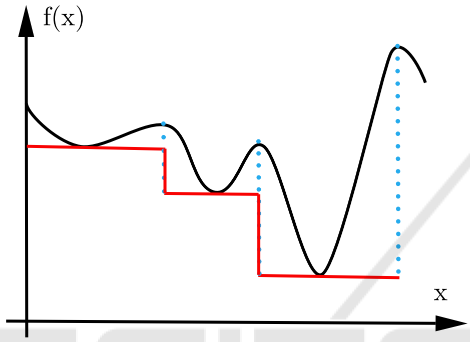

Figure 2: Example of flatten objective function after icp in red color where original function is in black.

the global minima instead of local one. To make the task of global searching algorithm less difficult, ICP are often applied to flatten the searching space. Figure 1 and Figure 2 show how ICP works as a objective function flattening tool. By using ICP, a complex fitness function in black turns into simpler one in red color. And with such a much more flatten fitness function, global searching method find a global minima more effectively.

The integration work well in case of point-cloud data with small point number. For large data case, ICP becomes slow and impossible for applying into real time applications. Our method integrates new global searching algorithm ISADE which works well in complicated fitness function without flattening process and fast error calculation method based on ray-casting corresponding searching algorithm which accelerates registration procedure to high speed.

3 METHOD OVERVIEW

3.1 Methodology Approach

The biggest disadvantage of ICP based registration methods in calculating cost function is runtime. In KinectFusion (16), a real-time scene reconstruction algorithm, ICP is used as a only method for registering two continuous frames. The method requires a powerful Graphic Card to fasten calculations and reduce runtime. However, in global registration algorithms with thousand times of error function calculation more than ICP through many iterations and populations, to make the algorithm can run real-time, we need a faster error calculation method. The proposed algorithm takes the advantage of fast error calculating by using ray-casting based corresponding point searching to applied for a new optimization algorithm ISADE with a purpose of getting a faster and global optimal convergence guaranty.

3.2 Ray-casting Closest Point

ICP-class algorithms often uses kd-tree(17) structure to speed up the process of finding j^* in Equation 2. The order of kd-tree searching closest algorithm is $O(log(n))$ where n is number of searching point set. Figure 3 shows an example of corresponding points of the data point-cloud in the model one.

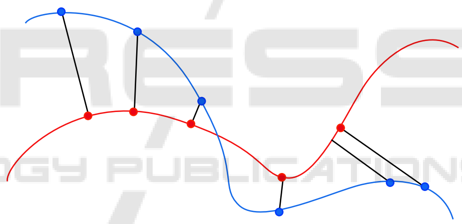

Figure 3: closest corresponding point defined in original ICP algorithm.

Since depth image or point cloud data are often obtained from 3D range camera in which the data could be consider as an 2D gray image G where value of each pixel show the depth of the point.

$$\mathbf{z_{i,j}} = \mathbf{G_{i,j}} \tag{3}$$

where $z_{i,j}$ is depth of image at pixel i,j.

Equations 4 is to convert from depth image and real 3D depth data $\{x,y,z\}$.

$$\mathbf{x_{i,j}} = (\mathbf{i} - \mathbf{cx})\mathbf{G_{i,j}}/\mathbf{fx} \tag{4a}$$

$$\mathbf{y_{i,j}} = (\mathbf{j} - \mathbf{cy})\mathbf{G_{i,j}}/\mathbf{fy} \tag{4b}$$

$$\mathbf{z_{i,j}} = \mathbf{G_{i,j}} \tag{4c}$$

where fx, fy, cx, cy are intrinsics of the depth camera. In conversion, pixel position and structured expression of a point x,y,z can be calculated as equation 5.

$$\mathbf{G_{i,j}} = \mathbf{z_{i,j}} \tag{5a}$$

$$\mathbf{i} = \mathbf{round}(\mathbf{cx} + \mathbf{x_{i,j}} * \mathbf{fx}/\mathbf{G_{i,j}}) \tag{5b}$$

$$\mathbf{j} = \mathbf{round}(\mathbf{cy} + \mathbf{y_{i,j}} * \mathbf{fy}/\mathbf{G_{i,j}}) \tag{5c}$$

Equations 5 is to calculate i,j of data points which are also i,j of corresponding point in model point-clouds. The idea of the method is showed as Figure 4 which reminds the ray-casting process in computer vision.

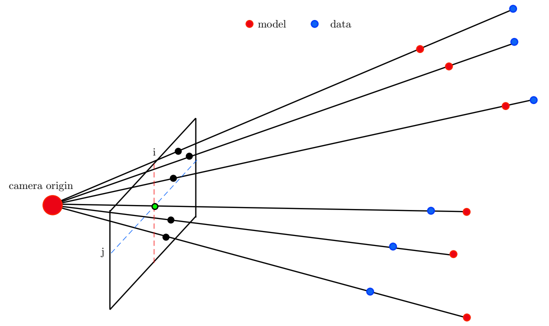

Figure 4: Ray-casting method for searching corresponding point.

3.3 Objective Function

The fitness function need to provide an error score that is minimized when the best transformation matrix are applied. The paper uses fitness function as Equation 6.

$$\mathbf{F}(\mathbf{R},\mathbf{t}) = \mathbf{f}(\mathbf{n})\frac{\mathbf{1}}{\mathbf{n}^2}\sum_{\mathbf{i}=\mathbf{1}}^{\mathbf{n}}(\mathbf{R}\mathbf{x_i} + \mathbf{t} - \mathbf{y_{j^*}})^2 \tag{6}$$

where $f(n)$ is a function of inlier point number, n, dependence. n is the number of inlier points in the data point-cloud.

The error function should be smaller in bigger number of inlier point. Since that, searching algorithm would get rid of the case in which cost function is small for only small inlier points. Function $f(n)$ is calculated as in Equation 7.

$$\mathbf{f}(n) = \left\{ \begin{array}{ccc} \infty & \multirow{2}{*}{if} & n < N/10 \\ 1 - n/N & & n \geqslant N/10 \end{array} \right\} \tag{7}$$

where N is number of points in the data point-cloud.

3.4 ISADE

Differential evolution (DE) is an optimization technique originally proposed by Storn and Price (18). It is categorized into evolution algorithm group which is characterized by operators of mutation and crossover. In DE, two important coefficients which play key rolls to decide the correction and speed of convergence are scaling factor F and crossover rate C_r. Another important parameter in DE, population size NP remains a user-assigned value to cope with problem complexity. ISADE not only adaptively changes those three coefficients but also integrates different mutation schemes to take advantages of them.

3.4.1 Adaptive Learning Strategies Selection

In their paper of ISADE, Tam Bui et al. randomly chose three mutation schemes which are $DE/best/1/bin$, $DE/best/2/bin$ and $DE/randtobest/1/bin$. Among DE's schemes, $DE/best/1/bin$ and $DE/best/2/bin$ are known for good convergence property and "DE/rand to best/1/bin" is known for good diversity. The probability of applying those strategies are equal equally assigned at with values $p_1 = p_2 = p_3 = 1/3$. Equations 8 show the formula of chosen schemes.

$$DE/best/1: V_{i,j}^G = X_{best,j}^G + F(X_{r1,j}^G - X_{r2,j}^G) \tag{8a}$$

$$DE/best/2: V_{i,j}^G = X_{best,j}^G + F(X_{r1,j}^G - X_{r2,j}^G) + F(X_{r3,j}^G - X_{r4,j}^G) \tag{8b}$$

$$DE/randtobest/1: V_{i,j}^G = X_{best,j}^G + F(X_{best,j}^G - X_{r2,j}^G) + F(X_{r2,j}^G - X_{r3,j}^G) \tag{8c}$$

3.4.2 Adaptive Scaling Factor

In APGA/VNC appoach proposed by S.Tooyama and H.Hasegawa (19), scaling factor changes according to iteration as sigmoid function as in Equation 9.

$$F_i = \frac{1}{1 + exp(\alpha * \frac{i - NP/2}{NP})} \tag{9}$$

ISADE give addition scaling F_i^{mean} as in Equation 10.

$$F_i^{mean} = F_{min} + (F_{max} - F_{min})(\frac{i_{max} - i}{i_{max}})^{n_{iter}} \tag{10}$$

where

$$n_{iter} = n_{min} + (n_{max} - n_{min})(\frac{i}{i_{max}}) \tag{11}$$

F_i in Equation 9 is modified as in Equation 12.

$$F_i = \frac{F_i + F_i^{mean}}{2} \tag{12}$$

Now scaling factor is set to be high in first iterations and after certain generations it become smaller for proper exploitation.

3.4.3 Crossver Control Parameter

ISADE algorithm is able to detect whether hight values of C_r are useful and if a rotationally invariant crossover is required. A minimum base for C_r around its median value is incorporated to avoid stagnation around a single value. The control parameter C_r is assigned as Equation 13.

$$C_r^{i+1} = \left\{ \begin{array}{cc} rand_2 & if rand_1 \leqslant \tau \\ C_r^i & otherwise \end{array} \right\} \quad (13)$$

where $rand_1$ and $rand_2$ are random values $\in [0,1]$, τ presents probability to adjust C_r. C_r is adjusted as in Equation 14.

$$C_r^i = \left\{ \begin{array}{cc} C_{r_{min}} & C_{r_{min}} \leqslant C_r^{i+1} \leqslant C_{r_{medium}} \\ C_{r_{max}} & C_{r_{medium}} \leqslant C_r^{i+1} \leqslant C_{r_{max}} \end{array} \right\} \quad (14)$$

where $C_{r_{min}}$, $C_{r_{medium}}$, $C_{r_{max}}$ denote low value, median value and high value of crossover parameter respectively. As in (12), we take $\tau = 0.1$, $C_{r_{min}} = 0.05$, $C_{r_{medium}} = 0.50$, $C_{r_{max}} = 0.95$.

All above ideas and theories are implemented as in flowchart in Figure 5.

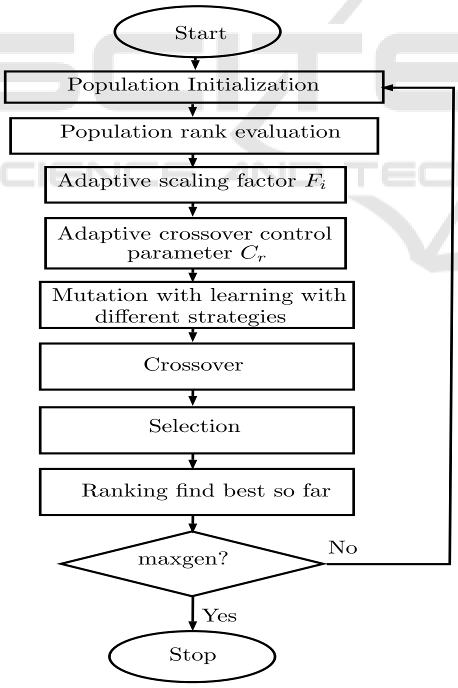

Figure 5: ISADE implementation process.

3.5 A New Combination Method

From initial position matrix, using ICP with one iteration to gain a slightly better rotation and translation matrix. The algorithm recalculates the error as in Equation 6 and uses it in ISADE searching algorithm. Flowchart in Figure 6 shows implementation of the whole algorithm.

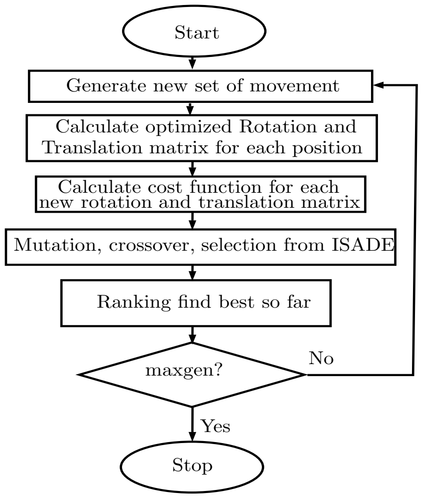

Figure 6: Registration with ISADE and Ray-casting.

4 EXPERIMENT AND RESULTS

This section arms at presenting a number of experimental results to study how robust and accurate of ISADE results in comparison to other Global searching algorithm in using the same ray-casting based error function as well as comparison of result from new algorithm to KinecFusion in term of accuracy.

1) De Falco et al's proposal (DE), Differential Evolution as a viable tool for satellite image registration (20).

2) Valsecchi et al.'s proposal (GA), An Image Registration Approach using Genetic Algorithms (11).

3) Talbi et al.'s proposal (PSO), Particle Swarm Optimization for Image Processing (10).

4) Luck et al.'s proposal (SA), registration of range data using a hybrid simulated annealing and iterative closest point algorithm (7).

The proposed algorithm is implemented in C++ and compiled with GNU/g++ tool.

In order to perform a fair comparison between different optimization tools, in all methods, maximum iteration is set to 100 with population of 25 for each iteration. As SAICP is not a multi agent methods, its maximum iteration is set to 2500.

4.1 Range Image Dataset

Our experiments carry out number of pair-wise

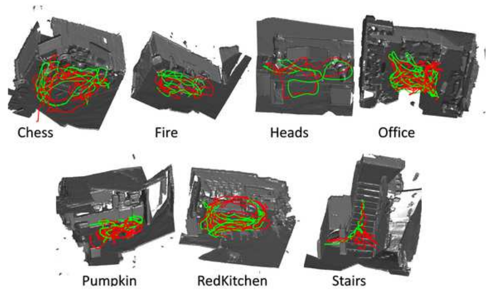

Figure 7: RGB-D 7 scenes Dataset for experiments.

registration task using well-known Depth data taken from Kinect Microsoft Camera downloaded from website of Microsoft Research http://research.microsoft.com/en-us/projects/7-scenes/. Specifically, Figure 7 shows all scenes: Chess, Fire, Heads, Office, Pumpkin, RedKitchen, Stairs.

Those png format depth images are sub-sampled into smaller solution of 128×96 which is 5 times smaller than original solution of 640×480 in each dimension. The reason for using smaller number of points dataset is to archive considerable suitable runtime while accuracy remains unchanged.

4.2 KinectFusion Error from Camera Transpose

Accompany with depth datasets, 7 scenes database gives us camera homogeneous transposes at each frame calculated from Kinect-Fusion algorithm. Using those transpose, we could calculate transformation matrix between two scene as Equations 15.

$$T_i^j = T_i^{-1} * T_j \tag{15a}$$

$$T_i^j = \left[\begin{array}{ccc|c} & R_i^j & & t_i^j \\ 0 & 0 & 0 & 1 \end{array} \right] \tag{15b}$$

where T_i^j is transformation matrix to move frame j to align with frame i, T_i and T_j are homogeneous transpose matrix for camera at frame i and j respectively, R_i^j, t_i^j are rotation and translation matrix of T_i^j.

R_i^j, t_i^j are applied into ray-casting error calculation methods for two frames as in Equation 6 to draw errors of KinectFusion algorithm for the next comparison step.

4.3 Parameter Settings

In each methods 30 runs were executed with two registration depth images are at distance of 20 frames in the sequence. The searching space is set so rotation and translation limitation at $[-2\pi/10, 2\pi/10]$ and $[-0.3, 0.3]$ separately. All methods are run on a PC of Intel core I7-4790 CPU 3.60 GHz $\times$ 8 processor and 8 GB of RAM memory.

4.4 Comparision between Different Algorithms

ISADE searching algorithm results are compared with other algorithms' results in three categories including convergent rate, mean and standard deviation which are shown in Table 1.

Table 1: Results of different algorithms for 7 scenes.

Scene name	Algorithm	CvR (%)	Mean	St. dev.
Chess	ISADE	100	0.0695	0.0107
ref: 0.2483	DE	100	0.0752	0.0144
	GA	0	1.8018	0.6643
	PSO	10	0.6753	0.4502
	SA	6.6667	0.9413	0.7171
Fire	ISADE	100	0.0230	8.8565e-04
ref: 0.2431	DE	100	0.0290	2.5576e-04
	GA	0	0.7740	0.2300
	PSO	20	0.3497	0.2826
	SA	6.6667	0.3306	0.2679
Heads	ISADE	100	0.0024	3.5903e-05
ref: 2.9907	DE	100	0.0027	0.0048
	GA	100	0.3080	0.1349
	PSO	100	0.0824	0.0836
	SA	73.3333	0.4494	0.3385
Office	ISADE	100	0.0358	8.4689e-05
ref: 0.6294	DE	100	0.0371	8.2449e-04
	GA	100	0.8577	0.3445
	PSO	100	0.2819	0.3702
	SA	33.3333	0.5526	0.5851
Pumpkin	ISADE	100	0.0407	0.0071
ref: 0.111361	DE	100	0.0489	0.0127
	GA	0	1.1097	0.4057
	PSO	6.6667	0.3779	0.3330
	SA	0	6.6667	0.6984
RedKitchen	ISADE	100	0.0315	0.0049
ref: 0.0984	DE	93.3333	0.0473	0.0239
	GA	0	1.4215	0.6508
	PSO	0	0.4863	0.3829
	SA	10	0.3021	0.2898
Stairs	ISADE	100	0.0056	5.6268e-06
ref: 0.0156	DE	100	0.0062	0.0014
	GA	0	0.9413	0.3373
	PSO	0	0.2441	0.2435
	SA	3.3333	0.4808	0.6281

KinectFusion error or reference value is considered as correct convergence. In Table 1, convergence rate (CvR) means percentage of algorithms results smaller than reference value.

Proposed algorithm and DE are superior than other methods in every categories. ISADE are better than DE in almost cases only in the Fire scene standard deviation of ISADE method larger than DE method's.

The proposed method are qualified in all tested scenes with convergence value are always smaller than reference value. This can be explained by accumulating error by using ICP algorithm from frame to frame. As using ICP continuously from frame to frame in Kinect Fusion algorithm error would be accumulated and become large. The final transformation matrix becomes less accurate than which gained from direct registration method using only two frame.

Figure 8 shows four scenes registration results using ISADE integrated algorithms including: Fire, Head, Office, Stairs. Model pointsets are in red and data pointsets are in grey color.

4.5 Runtime

For the data of 128×96 resolution, average running time for the proposed method are shown in Table 2.

The results show the average time for registration at around 8 second. Two registering frames are at distance of 20 frames. That means the rate of registering equivalence at rate of 2.5 fps (frames per second). To make algorithm run at real-time rate of 20fps, the speed need to be increased by 8 times. This is possible if we exploit all core of 8-core-processors not mention using GPU.

Table 2: Average runtime (in second) on different scenes.

Chess	Fire	Heads	Office	Pumpkin	RedKitchen	Stairs
7.5053	5.8596	8.0114	7.4527	5.9005	6.0466	7.8627

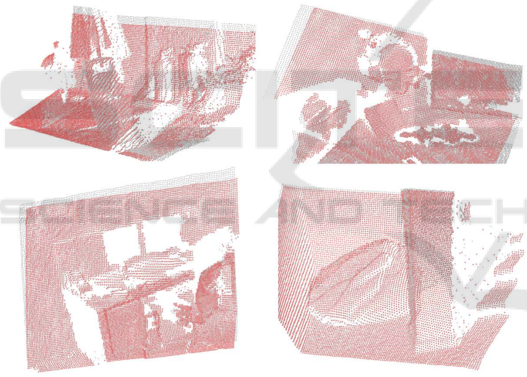

Figure 8: Registration output example.

5 DISCUSSION AND CONCLUSION

Image registration has been a very active research area. Recently, the approach of using evolutionary algorithms (EAs), especially new methods, proved their potential of tackling image registration problem based on their robustness and accuracy on searching for global optimal. With EAs algorithm as searching tools, it is not necessary to have good initials to avoid local minima and converge to near-global minima solutions. To do that, EAs algorithms need tuning carefully to gain best results.

We proposed the new registration algorithm by integrating a new self-adaptive optimization algorithm (ISADE) into a fast closest point searching method to tackle well-known challenging task of computer vision area. In the experiments, the results show that ISADE is able to find a robust and accurate transformation matrix of camera movement.

What is more important, accuracy and robustness results has been obtained in comparison with other state-of-the-art evolution based algorithms. ISADE shows its superior than GA, PSO, SA in searching for global minima solution. In comparision with DE, ISADE also show its much better in almost tested scenes. The robustness and accuracy is tested and proved in real 3D scenes captured by Microsoft Kinect camera.

In term of running time, by using fast searching closest point methods, proposed algorithms are considered fast in our sense. It shows potential of applying in real-time application if using parallel programing technique with multi-core processors.

In future work, ISADE algorithm can be implemented in parallel in GPU (Graphic Processor Unit) which can help algorithm reduces runtime to prove real-time implement possibility in 3D reconstruction, 3D mapping and 3D localization.

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