Silhouette-based Three Dimensional Image Registration Using CMA-ES with Joint Scheme of Partial Restart and Variable Fixing

Takuto Shigenobu,
Takuya Ushinohama
Kagoshima University
Kagoshima, Japan
sc114021@ibe.kagoshima-u.ac.jp

Hiroshi Kawasaki
Kyushu University
Fukuoka, Japan
kawasaki@ait.kyushu-u.ac.jp

Satoshi Ono
Kagoshima University
Kagoshima, Japan
ono@ibe.kagoshima-u.ac.jp

ABSTRACT

This paper proposes a three-dimensional (3D) entire shape reconstruction method that performs simultaneous 3D registration of multiple depth images obtained from multiple viewpoints. With the combination of a silhouette-based objective function and evolutionary computation algorithms, the proposed method realizes the entire shape reconstruction from small number (two or three) of depth images, which do not involve enough overlapping regions for other 3D registration methods. In particular, this paper proposes a CMA-ES algorithm with regional intensification techniques (CMA-ES$_{\mathrm{PR+VF}}$) to speed up the registration process. Experimental results show that the proposed CMA-ES$_{\mathrm{PR+VF}}$ achieved a speedup that is at most 18 times faster than self-adaptive differential evolution.

CCS CONCEPTS

• **Mathematics of computing** → **Evolutionary algorithms**; • **Computing methodologies** → **Reconstruction**; **Matching**;

KEYWORDS

3D image registration, global registration, ICP, CMA-ES, differential evolution

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1 INTRODUCTION

Recently, 3D shape measurement techniques have made significant progress, and they have been widely used in various fields such as self-driving, production automation, medical, educational, digital archiving and entertainment fields. To acquire 3D shapes of real-world objects, range scanners are used. However, the 3D scanners can capture only one side of the object. Therefore, multiple depth images should be captured from different viewpoints and aligned to recover the entire shape of the object. This process of geometrically aligning the depth images is called *registration*. Although many studies have been devoted to global registration, general and robust algorithm has not been established yet.

To reconstruct an object's entire shape from such a few scan, silhouette-based approach has been proposed [3]. The combination of the silhouette-based cost and self-adaptive differential evolution (jDE) [1] enables the reconstruction from at least three scans. However, this method requires much computational cost because jDE required large population size to avoid local optima.

To tackle this issue, this paper proposes a high-speed simultaneous global registration method based on Covariance Matrix Adaptation Evolution Strategy (CMA-ES) with a joint scheme of partial restart and variable fixing, (CMA-ES$_{\mathrm{PR+VF}}$). which supports CMA-ES on globally multimodal functions. Experiments have shown that the proposed CMA-ES$_{\mathrm{PR+VF}}$ found global optimum up to 18 times faster than jDE-based previous method.

2 THE PROPOSED METHOD

2.1 Basic idea

The drawback of the silhouette-based objective function [3] is its multimodality. [3] adopts self-adaptive differential evolution (jDE) [1], which finds global optimum even when the target fitness function involves many local optima while carefully narrowing down promising areas of the variable space. However, it slowly converges and requires many function evaluations. Therefore, this paper proposes a CMA-ES-based algorithm that is designed specific to 3D entire shape reconstruction, i.e., simultaneouls registration for two or more 3D images. Because CMA-ES generally requires much smaller population size than DEs, improvement of convergence speed can be expected. Furthermore, by considering

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the problem structure and property, the proposed method introduces joint scheme of partial restart and variable fixing.

2.2 Overview of proposed CMA-ES$_{\mathrm{PR+VF}}$

The proposed CMA-ES$_{\mathrm{PR+VF}}$ is designed based on [2] and introduces a couple of mechanisms to enhance search exploitation. At every $P_{stagnation}$ generation, CMA-ES$_{\mathrm{PR+VF}}$ checks if the optimization got *stagnated*, which is judged by the following equation:

$$\frac{F(\boldsymbol{x}_{recent\_best})}{F(\boldsymbol{x}^{(prev)}_{recent\_best})} \geq T_{local} \tag{1}$$

where $\boldsymbol{x}_{recent\_best}$ and $\boldsymbol{x}^{(prev)}_{recent\_best}$ denote the recent best solution obtained since the last time when eq. (1) is satisfied and previous recent best solution. When the search is regarded as stagnated, partial restart and variable fixing is applied first, and then variable range reduction is applied.

2.3 Joint scheme of partial reset and variable fixing

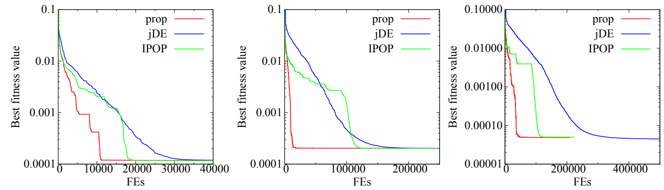
When the search is regarded as stagnated, CMA-ES$_{\mathrm{PR+VF}}$ evaluates a subfitness function, i.e., how each image is matched to a reference image. Then, values of variables for i-th image is fixed when $f_i^{(p)}/f_{worst}^{(p)}$ is lower than a threshold T_{fix}, where $f_i^{(p)}$ is the subfitness of i-th image and $f_{worst}^{(p)}$ is the worst subfitness function value of $N-1$ images. The fixation continues until the next stagnation judgement and will be cancelled when the above condition would not be satisfied. When calculating subfitness functions, best subsolutions in archive are updated if better subsolutions are found.

If variables are fixed too long, a risk arises that the search cannot escape from local minima. Therefore, CMA-ES$_{\mathrm{PR+VF}}$ releases one image fixation when the fixation situation has not been changed during $T_{release}$ cycles and the global best has not been updated. To avoid fixing the same image instantly in the next cycle, the image cannot be fixed again until other image is fixed or all images are released.

2.4 Simple local search scheme by variable range reduction

CMA-ES$_{\mathrm{PR+VF}}$ shifts to local search by reducing the variable ranges when variables of $N-2$ depth images were fixed in the previous cycle and variables of all images are released in the current cycle. The above condition is checked after subsolution fixation process is finished. If the above condition is satisfied, the covariance matrix is reconfigured so that diagonal components correspoinding to the target variables have $S_{ls}\sigma^{(0)}$ ($0 < S_{ls} < 1$), and mean vector $\boldsymbol{m}$ is also reset by a solution consisting of best subsolutions in the archive.

Even when the above condition is not satisfied but some variables are partially restarted, variable ranges for translation parameters are reduced, i,e., part of the covariance matrix corresponding to them are reinitialized with $S_{tr}\sigma^{(0)}$.



(a) 2 images (b) 3 images (c) 4 images

Figure 1: Transitions on best fitness values.

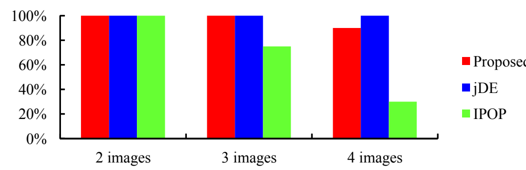


Figure 2: Comparison on success rates.

3 EVALUATION

The proposed CMA-ES with regional intensification techniques was compared with jDE that was successfully produced good registration results and IPOP-CMA-ES that is one of the representative models of CMA-ES with restart strategy. In the proposed CMA-ES$_{\mathrm{PR+VF}}$, control parameters are configured as follows: λ and μ were set to 8 and 4, $P_{stagnation}$, T_{local}, T_{fix}, $T_{release}$, $P_{exploitation}$, S_{ls} and S_{tr} were set to 30, 0.99, 0.3, 3, 3, 0.1, and 0.2, respectively.

The tested problem instance, Stanford Bunny, involve two, three or four depth images to be aligned. In problem instances involving two images, the two images that were measured with the angle difference of 180°. In the problems involving three or four images, the angle intervals between scans were 120° and 90°, respectively. Figure 1 shows the averaged fitness transitions of the best solutions over success cases of 20 runs, and Figure 2 shows the success rates. CMA-ES$_{\mathrm{PR+VF}}$ successfully reduced FEs to 1/7 to 1/18 of that of jDE, while maintaining the success rate.

4 CONCLUSION

This paper proposed a rigid registration method that achieves 3D shape reconstruction of an entire volume from just two or three depth images. The proposed CMA-ES$_{\mathrm{PR+VF}}$ successfully reduced the function evaluations.

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