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Fast Free-form Surface Registration by A New Genetic Algorithm

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Abstract

Robust and fast free-form surface registration can find applications in various areas such as object recognition and 3D model reconstruction. Given range images taken from different views of an object, the object model can be constructed, in principle by surface registration and integration of these images if an accurate, robust and fast solution for surface registration algorithm is available. The surface registration problem can be formulated as a high dimensional optimization problem. In this paper, we describe a new GA surface registration algorithm using an adaptive mutation for model construction and image registration. Our work shows that the performance of a GA surface registration algorithm greatly depends on its speed in evaluating the fitness function. After incorporating a fast algorithm to evaluate the fitness function, the process becomes fast and robust. The method can be used for registering intensity image too. Some experiments to demonstrate the value of the proposed system on model integration and image matching are reported.

1. Introduction

A range image of a 3D object usually lacks data points hidden behind the object or those are out of the field of view of the sensor. It is usually difficult to measure the whole surface of an object at one time. Thus it is necessary to acquire multiple views by moving (rotation and translation) the sensor around the object or by moving the object in front of a fixed sensor. Even though the motion is controlled, it may not be so accurate as the range measurements. Therefore, registration among the free-form surfaces is necessary in order to form the complete object [1].

Many registration algorithms have been developed in recent years. They could be divided into two main dasses: (1) ICP (Iterative Closest Point) algorithm [2, 8] and (2) Correspondence matching [3]. Besl and McKay [8] proposed the iterative closest point (ICP) algorithm, which estimated a set of rigid motion parameters that registered a data shape to a model shape. This method works well if all data point has a corresponding point in the model. However, its performance is greatly affected by noise and occlusion, especially when we apply it to multiple range image registration. Masuda et al [2] proposed a more robust method for registering a pair of dense range images, which was an integration of the ICP algorithm with random sampling and the least median of squares (LMS) estimator which can tolerate the presence of outliers of up to theoretically, 50%.

Yamany and Farag [3, 6, 7] proposed an alternative algorithm, which first computed the surface signatures from the images, which are surface curvature information, seen from each point in the images. Matching signatures of two surfaces then enabled recovery of the transformation parameters between these surfaces. They proposed to use template matching to compare the signature images.

While the ICP-based algorithm is sometimes effective, a good initial guess is essential to find the correct solution. If the initial guess is far from the actual solution, incorrect solution or mismatching will be in result. In correspondence matching approach, correspondences are established by matching features extracted from the images. However, since no unique feature can be defined for all 3D objects, correspondence matching becomes highly application dependent. Even if we permit, through a very time-consuming process, the correspondences are marked by the user, automatic surface registration would not be possible.

Registration of two free-form surfaces can be cast as a search or an optimization problem. This leads to a 6 dimensional optimization problem with many local extrema. Most of the existing optimization algorithms can only be applied on differentiable objective functions. They are also only good on objective functions with several optimal points and, this kind of optimization methods would most likely fail, when no initial guess of the location of the global optimum is given.

The surface registration problem we address is as follows. Given two surface measurement images of an object from different viewing locations, such as those obtained from a range sensor or from some 3D re-construction processes, we aim at finding the transformation between these images. These two images can be merged by mapping one set on top of the other with the estimated transformation such that occluded parts of one image can be recovered from the other. We propose to solve this problem using genetic algorithms[4]. Its effectiveness has been critically evaluated using the synthesized data. The developed genetic algorithm is found to be fast, accurate, and robust. For example, registering two dense range images of 10,000 sample points each with about 70% overlaps in content only need 30 seconds to find the solution in a PC with Pentium III 450MHz processor. The re-constructed model using the proposed surface integration algorithm has less than 1% error compared to the original one.

The remaining of this paper is organized as follows. Section 2 describes our GA formulation, and how they are applied to solve the surface registration problem. Several experiment results are shown in Section 3 to demonstrate the effectiveness of the proposed GA free-form surface registration and model re-construction. Error sensitivity of the developed system in constructing object model with synthesized data is also included in this section. Application of the developed system to image registration is discussed in Section 4. Finally, the paper is concluded in Section 5.

2. Genetic Algorithms

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics [5]. A possible solution is represented as a chromosome in a string structure with each element representing one parameter in the solution. A collection of possible solutions (chromosomes) then forms a generation, which produces another generation through a search process. The search process adopts "the fittest survives" rule after a structured yet randomized information exchange within the existing generation to yield a new generation. For the genetic algorithms to be successful, how to formulate the chromosome and fitness function is very important. The genetic algorithms will have better convergence behavior if the fitness function is generally continuous and the chromosome with the optimal fitness value corresponds with the target solution. In the following, formulations of the chromosomes and the fitness function for surface registration are described. We also define a new adaptive mutation operator which is more effective than the traditional one.

2.1 Gene and Chromosome

Since the geometric relation (transformation) between two surfaces can be defined by six parameters, They defined as a chromosome. Each parameter corresponds to one of the genes in the chromosome:

Translation Gene	*Rotation Gene*
T_x: Translate on x axis	α: Rotate about x axis
T_y: Translate on y axis	β: Rotate about y axis
T_z: Translate on z axis	θ: Rotate about z axis

T_x, T_y and T_z are the translation genes and, ***a, b, q*** are the rotation genes. They form a chromosome, which represents the relation (3D transformation matrix) between two free-form surfaces, i.e the data points in two images are related by the mapping, T where T = R_x R_y R_z S and R_x, R_y, R_z are the rotation matrixes about x, y and z axis with angles α, β and θ respectively and S is the translation matrix with distances T_x T_y and T_z on x, y and z axis respectively.

2.2 Fitness Function

A genetic algorithm uses a fitness function to determine the performance of each artificially created chromosome, therefore the fitness function should measure the registration quality the matching error caused by each chromosome. Since the Euclidean distance between each correspondence pair tends to zero as two 3D surfaces are registered, the GA should try to find a chromosome with the minimum Euclidean distance between each correspondence pair.

However, unless the final transformation is determined, the true correspondence pairs are not known. Hence, the "best possible" correspondence is used instead, to measure the fitness of a given chromosome, *T*. Given a set of points $\{P_i\}$ in S_1 (size N_1) and $\{Q_j\}$ in S_2 (size N_2), the point CP_i in S_2 is defined as the "best possible" correspondence of P_i under the transformation T, such that the Euclidean distance, E_i between CP_i and $T(P_i)$ is the minimum among all points in S_2. This is the best possible correspondence because any other correspondence should yield higher matching error.

Since the two given free-form surfaces may not totally overlap each other, some points on surface S_1 may have no correspondence on surface S_2 even the identified transformation is correct. Therefore, if all E_i are considered, the fitness of the solution may not tend to zero as no correspondence can be found for some points. Therefore we adopt the median of E_i as the fitness measurement instead of the average Euclidean distance E_i, to avoid the effects by outliners (points at the non-overlapped region) of up to 50%. So for a chromosome representing a transformation T, the corresponding fitness measurement is $F(T)$ and is defined as:

$F(T) = Median(E_i)$ for $1 \le i \le N_1$
where $E_i = |T(P) - CP_i|$
and $CP_i = Q_k$ such that
$|Q_k - T(P_i)| \le |Q_j - T(P_i)|$ for all j where $1 \le j \le N_2$

Evaluation of fitness function described above requires a search on the closest point from a data set given an input data point. The corresponding searching time will be very long and becomes a major obstacle in utilizing the GA approach for practical surface registration applications. A fast nearest-neighbor searching algorithm will greatly enhance the performance of a GA surface registration process because the search is required for each sample point for every chromosome in a generation. After incorporating a fast search algorithm[9], the developed surface registration algorithm was speeded up significantly. It is approximately 30 times faster than just using a simple binary search algorithm [10] and, without any search, 1000 times faster. Now the algorithm becomes fast and robust. Its value can be demonstrated in the following sections.

2.3 Reproduction

The process to generate a new set of possible solutions from the current set is the reproduction stage in a genetic algorithm. Cross-over and Mutation are the standard operators used for this purpose. In our formulation, however, the genes are represented in real values. Therefore each gene in a chromosome will be accumulated with a small value instead of changing from 0 to 1 or 1 to 0 for a binary gene during the mutation stage [11]. The value to be accumulated is generated randomly within the range [-MV, +MV]. While the maximum accumulated value (MV) has been generally kept constant, we propose to vary this value according to the fitness of the target chromosome. If the fitness value is large, the chromosome is far away from the optima point. Hence, a far jump is needed to get to a better chromosome and we let MV be a larger value. Conversely, only small movement is needed and MV is set to be a small value. Therefore, maximum allowed movement of the translation genes is set to $FIT(T_i) / sqrt(3)$.

3. Surface Registration and Integration

In below, results illustrating the performance of the proposed system for free-form surfaces matching through model construction are described. In particular, we investigate the performance of the proposed system with input images containing various levels of noise using synthesized data. The results with real image are also given.

3.1 Model Integration

A complete set of images of an object has been downloaded from [13]. The input images are shown in Fig. 1(a). After model construction, new images can be obtained from the model. Four such views from the merged model are shown in Fig. 1(b). The corresponding construction process took 4 minutes on a PC with Pentium III 450 MHz CPU. The results show that the proposed surface registration process appears to be effective and fast. However, it is important to measure the modeling accuracy for practical applications. Thus the error sensitivity of the proposed process is evaluated next.

3.2 Error Sensitivity

In this experiment, four depth images corresponding to range images taken from different directions were generated from a computer model of "foot-bone" obtained from [12]. Noise of different levels has been added to the generated images. A complete model was constructed by integrating these images. These input images are shown in the first row in Fig. 2. Below are the surface images of the constructed model viewed at four arbitrary directions. During registration, 300 points were chosen randomly from one of the input images. The whole model construction process took 5 minutes on a PC with Pentium III 450 MHz CPU, and the corresponding error varied from 0.5% to 1% and were tabulated against noise levels in Table 1.

Gaussian noise level (s)	Modeling error
0.255	0.4215%
0.5	0.582%
1.25	0.721%

Table 1 Modeling error by images with added noise (error for noise-free inputs is 0.016%)

4. Image Registration

Application of the developed system for surface registration ignored information such as texture on each surface point. The genetic algorithms described in Section 2 can be modified to include matching of such information on each surface point. This additional information could be useful to reduce transformation ambiguity and hence, to speed up the registration process. In this section, we take the intensity obtained from a surface point as the additional information available. A 2D image can be considered as a 2D projection of a scene. Then given two images for registration, we let one be the model image, corresponding to a planar object. The image to be registered is the 2D projection of such planar object viewed at another direction. With such formulation, image registration becomes finding the required view transformation. Hence image registration can be accomplished by adopting the surface registration described above with little modification on the formulation of chromosome. The experimental results show that such an approach is effective and the developed image registration algorithm can even be used to locate and recognize deformed objects. In below, the necessary modifications of the genetic algorithm developed for surface registration are first described and the results then follow.

4.1 Gene and Chromosome

The view transformation has to be described by seven parameters instead of six to account for the possible change in scale. T_x, T_y and T_I are the translation genes, *a*, *b*, *q* are the rotation genes and *l* is the scaling gene. They form a chromosome, which represents the relation (3D-transformation matrix) between two images. For the data point in the model image with coordinates x, y and intensity value I, and its image is x', y', and I', then they are related by the mapping:

$$[x' \ y' \ I' \ 1] = [x \ y \ 0 \ 1] \, R_x \, R_y \, R_z \, P + [0 \ 0 \ I \ 1] \, S$$

where P is the orthogonal projection matrix.

4.2 Results

In below, results illustrating the performance of the developed image registration process for image matching are described.

Experiment 4.2.1: Image Registration

The intensity images of a personal computer, Fig. 3(a), and 3(b) were taken from nearly the same viewpoint, with more than 85% overlap. Figure 3(c) was obtained by mapping Fig. 3(a) on top of Fig. 3(b) with the estimated transformation using the proposed algorithm. A relative clear picture in Fig. 3(c) showed that the registration result is satisfactory. To cut down the processing time, 100 out of 16384 points were selected from Fig. 3(a) randomly for registration. By setting the population size to 120 chromosomes, the computation time required to determine the transformation was about 18 seconds for 48 generations on a Pentium III 450MHz PC platform.

Experiment 4.2.2: Object Location and Recognition

Fig. 4(a) and Fig. 4(b) show a doll captured at larger difference in viewing angles from the images in Fig. 4. After registration, the angle differences are found to be 24, 15, 0 degrees around x, y, and z axes respectively. Again Fig. 4(c) shows the overlapped views. Fig. 4(c) was also quite clear indicating good registration. As in other experiments, 100 points have been selected from Fig. 4(a) for registration and the population size was set to 120, the developed systems then took 58 generations and 22 seconds to obtain the solution.

Experiment 4.2.3: Location and Recognition of Deformed Objects

In this experiment, two intensity images of a person with different expressions shown in Fig. 5 were registered. The overlapping view in Fig. 5(c) was somehow blurred as would be expected for a deformed object. Again 100 points have been chosen randomly from one of the input images for registration and the process took 11 seconds.

5. Conclusion

This paper described a robust system for free-form surface registration, based on a modified Genetic Algorithm using a new adaptive mutation process which was found to be more efficient than the traditional mutation. To speed up the process, random sampling of the input images and adopting a fast search method for evaluating the fitness function were found necessary. The steps of the algorithm are: 1) random sampling one of the given surfaces, 2) computing the transformation with the genetic algorithm.

Two major advantages of developed system are: 1) it does not depend on a good initial guess, nor require prior information on correspondences or feature points given by the users, 2) it is fast. The results on model re-construction show that the developed system is robust and the corresponding modeling error is acceptable. In addition, we have tested the system with a large number of models and its performance was found to be insensitive to the internal parameters set for our system. For example, all the experiment results reported in this paper were obtained using the same set of internal parameters without tuning. Moreover, the proposed system is very efficient. Merging a model with 4 views only took 5 minutes on a PC with Pentium III 450 MHz CPU while rough image registration only requires less than 30 seconds. Therefore real time implementation will be possible with faster processing platform.

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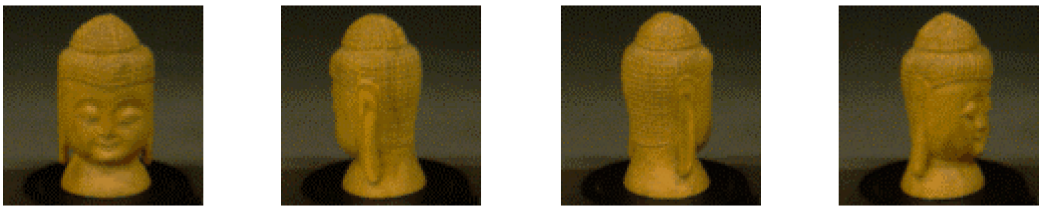
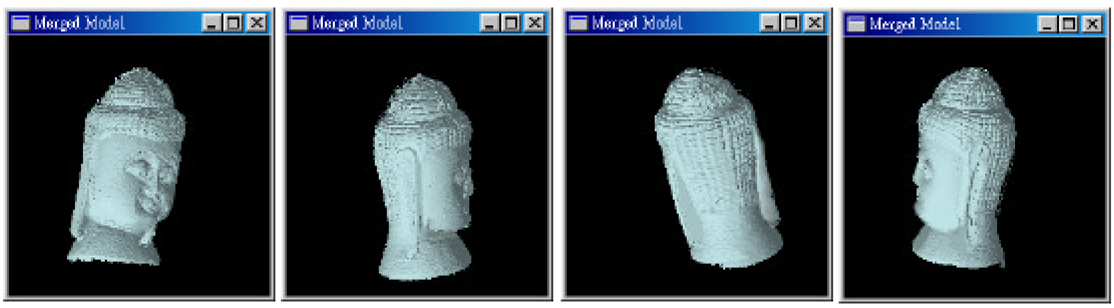


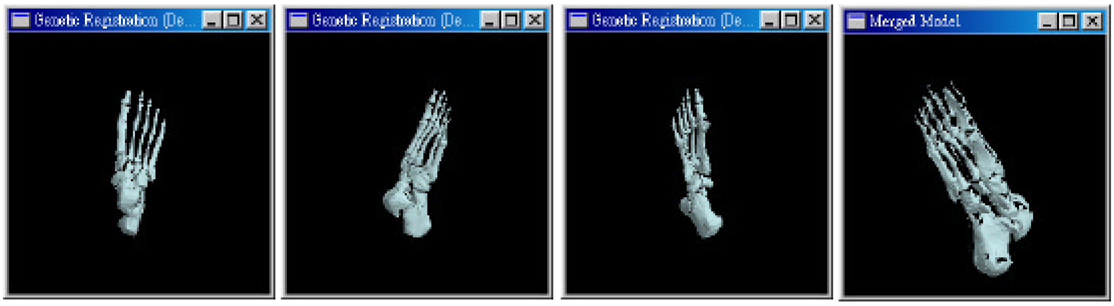
Input image 1 Input image 2 Input image 3 Input image 4

Figure 1(a) Input images of an object.

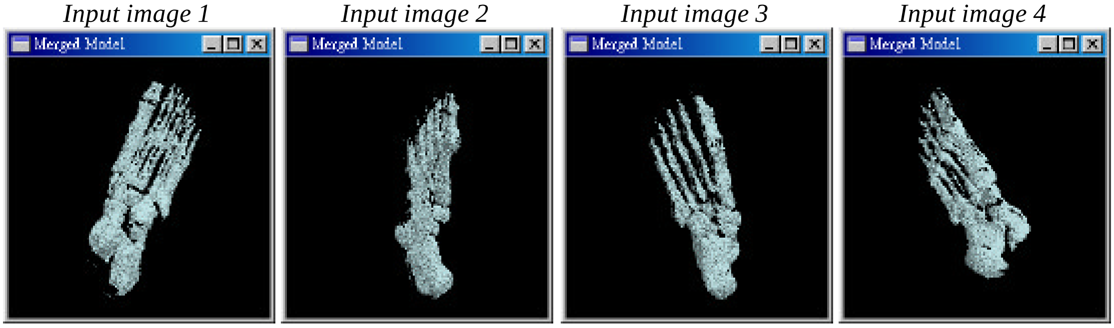


Merge Model at view 1 Merge Model at view 2 Merge Model at view 3 Merge Model at view 4

Fig. 1(b) Synthesized views from the model constructed from the range images



Input image 1 *Input image 2* *Input image 3* *Input image 4*



Merge Model at view 1 *Merge Model at view 2* *Merge Model at view 3* *Merge Model at view 4*

Fig. 2 Experiment results for merging noise-added images of a foot-bone computer model

Figure 3(a)

Figure 3(b)

Figure 3(c)

Figure 4(a)

Figure 4(b)

Figure 4(c)

Figure 5(a)

Figure 5(b)

Figure 5(c)