THE ANNALS OF "DUNAREA DE JOS"UNIVERSITY OF GALATI
FASCICLE XIV MECHANICAL ENGINEERING, ISSN 1224-5615
2005

OPTIMIZATION OF POINT CLOUDS REGISTRATION BY MEANS OF A HYBRID ALGORITHM

Assist. Prof G. Mansour, Prof. S. Mitsi,
Prof. K.-D. Bouzakis, Dipl.-Eng. D. Sagris,
Dipl-Eng. E. Varitis
Laboratory for Machine Tools and Manufacturing Engineering,
Mechanical Engineering Department, Aristoteles University of Thessaloniki, Greece

ABSTRACT

An important area in Reverse Engineering applications is the combination of multiple scans of a 3D product to model the object. Moreover the registration refinement of multiple range images is a crucial step in multi-view 3D modeling. In the present paper a hybrid optimization method is developed to align point clouds, without any user-applied initial alignment. The proposed method combines a genetic algorithm with a quasi-Newton algorithm and furthermore a constraints handling method is involved. Several free-form point clouds are used to verify the accuracy and the reliability of the proposed method and two characteristic examples are presented.

1. Introduction

Nowadays Reverse Engineering (RE) is a popular method of object modeling. RE is performed through a scanning procedure, which aims to obtain a point cloud. The most common difficulty in this process is to register into one part, various views of the same object, which have been obtained by a 3D scanning device (Coordinate Measurement Machine-CMM, laser scan, light sectioning).

The most common applications where the registration method takes place are the modeling of an object through the combination of multiple point clouds and in the inspection process of a CAD model [1]. Since laser scanners have a limited field of view, in order to obtain a complete representation and modeling of an object it is necessary to collect data from several different locations that must be transformed into a common reference coordinate system. The point clouds are necessary to have a common area. In the inspection process of a CAD model the object is measured with a measuring device, such as CMM, and the acquired point cloud is compared with the CAD model of the same object. The CAD model, which represents the original object, is located in a different position with respect to the reference coordinate system than the 3D data point. For the success of shape inspection, the problem is to find the transformation that aligns the point cloud to the CAD model. This method gives the ability to provide 3D CAD-to-part verification with complete and accurate analysis.

The automatic and semi-automatic registration procedures used in currently available commercial software are not robust and often lead to incoherent results. Many registration algorithms have been developed in recent years. The concept of the registration of two point clouds is the following. For two point clouds as input data that are usually called the model cloud and the data cloud, in a common coordinate system, the target of the registration algorithm is to find a homogeneous transformation matrix that optimally merges these two point clouds. Bels and McKay proposed the Iterative Closest Point (ICP) algorithm [2], where the rigid transformation between two scans is iteratively refined directly using corresponding points extracted after each refinement step. Several improvements have been proposed to this approach [3,4], but all the ICP algorithms require an initial estimation of the rough transformation between the two point clouds and easily fall into local minima. Furthermore, the rate of ICP algorithms convergence depends on the choice of the corresponding point-pairs and the primitive location of the point clouds. Chen and Medioni [5] proposed a point-to-surface algorithm, which is more accurate than the ICP algorithm, but also requires a expensive computational task [6]. Some genetic algorithms (GA) have been proposed for the registration of the point clouds. For example Chow [7] developed a dynamic GA where a new genetic operator was proposed.

In the present paper a hybrid optimization method [8,9] is developed to solve the automatic point clouds registration problem. The developed algorithm combines a genetic algorithm [10] with a hill climbing method (Quasi-Newton algorithm) [11] and furthermore a constraints handling method is involved. The usage of random numbers in genetic algorithms to produce the individuals of each generation, gives the ability to explore the whole space around the model cloud to find the best alignment position of the data cloud. With the aid of a simple genetic algorithm an initial approximate solution is found and with the Quasi-Newton optimization method this solution is guided to an optimum one. During the procedure, using a method of constraints handling, the variables limits are reduced to accelerate the optimization procedure. Although the objective function is non-differentiable the successive application of the genetic algorithm and of the gradient-based algorithm avoids the degradation of the performance of the proposed method in searching for the global minimum. The proposed algorithm works successfully for common boundary areas of point clouds. The reliability, the accuracy and the speed of the proposed method are tested through several numerical applications of various objects. Two of these applications are presented in this paper.

2. Registration of Point Clouds Data

The point clouds registration approach is described for a couple of point clouds. For more point clouds, each step's registration result can be combined with one new cloud. Lets set $M = [m_1, m_2, \ldots, m_n]$ and $D = [d_1, d_2, \ldots, d_k]$ the two point clouds in IR^3, called model cloud and data cloud respectively, expressed in a common fixed Cartesian coordinate system. The data cloud can be moved while the model cloud is kept fixed. The goal of the registration algorithm is to find a homogeneous transformation matrix T that best aligns the data cloud D with the model cloud M. The transformation matrix T is applied to data points in order to calculate the distance between points of the data and model clouds. For every point $T(d_j)$ (j=1,...k) of data cloud is calculated the minimum distance until all the points of the model cloud m_i (i=1,...,n). Therefore, the point clouds registration can be formulated as an optimization problem, where the objective function takes into account the minimum distances of respective points of data cloud and model cloud, with respect to the transformation matrix T.

The objective function, which is minimized, can be described by:

$$F=\sum_{i=1}^{k}\left|m_i^*-T(d_i)\right|,\ k<n \tag{1}$$

where m_i^* is the model point closest of $T(d_i)$ data point.

The transformation matrix T used in equation (1), contains six parameters: the translation on x,y,z-axis and the rotation angles Roll-(α), Pitch-(β), Yaw-(γ) about x,y and z-axis respectively [12].

The variables vector is,

$$\vec{V}=[x \quad y \quad z \quad \alpha \quad \beta \quad \gamma]^t=$$

$$=[v_1 \quad v_2 \quad v_3 \quad v_4 \quad v_5 \quad v_6]^t$$

with variables bounds

$v_{imin}<v_i<v_{imax}$, i=1,...,6.

The x, y and z bounds are related to the data and model geometry and the orientations angles (α, β, γ) bounds are (0, 2π).

From the minimization of the objective function, the values of these unknown parameters occur.

The objective function (1) is non-differentiable and application of a gradient-based optimization algorithm degrades the performances in searching for the global minimum. In order to avoid these problems, in this paper a new algorithm is proposed, which is presented in the next section.

3. Proposed Algorithm

The described mathematical problem is solved with a hybrid method that combines a genetic algorithm (GA), a quasi-Newton algorithm (QNA) and a constraints handling method (CHM). In order to reduce the computational time, a uniformed points reduction of the point clouds is established. Moreover the center of mass of data cloud is transferred to the center of mass of model cloud to be able to reduce the bounds of each positional variable (xyz).

The basic steps of the proposed algorithm are illustrated in Figure 1. The input data for the algorithm are the two point clouds coordinates, the variables bounds and the algorithm parameters. In these parameters are included the initial parameters of the GA such as the population size, the crossover rate, the mutation rate, etc. and the number of the GA, QNA, and CHM loops. Using the equation (1) the fitness function is defined, which is used in all the following steps of the algorithm.

In the first loop (L_1) of the proposed algorithm, starting populations are randomly generated to set variables values, which are used to calculate the fitness function value. Genetic algorithm

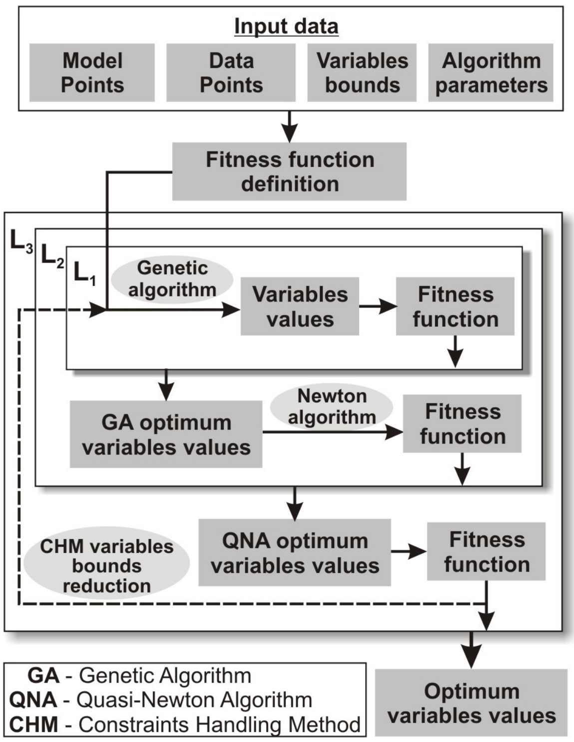

Fig. 1: Developed algorithm flowchart diagram

considering this starting population uses selection, crossover and mutation procedures to create new generations. The new generations converges towards a minimum that is not necessarily the global one. After some repetitions, the minimum value is selected as final value of the genetic algorithm (output of loop L_1). The minimum value of the fitness function defines the GA optimum variables values as output of first loop (L_1). These optimum variables values are inserted in the QNA as an initial variables vector guess. The QNA modifies the values of this vector using a finite-difference gradient method in a way that the fitness function is minimized. Through this 'hill climbing' method a new fitness value is obtained. This loop (L_2) is applied several predefined times, including the repetition of loop L_1, in order to locate several local minimums using the GA and approach the global one using the QNA. The minimum calculated value of the fitness function in second loop (L_2) defines as output the QNA optimum variables values. Afterwards these output variables values are used in the third loop (L_3) to reduce the bounds of each variable, about this optimum selected one. The optimum calculated value of each variable in i-1 step is defined as a center for the current area of the step i. This area is reduced around the optimum one, by a percentage defined by the user. This procedure is illustrated in Figure 2. The third loop (L_3) is applied a few predefined times in order to accelerate the process through the reduction of the variables bound, but not lower than a user defined critical value. The minimum calculated value of the fitness function defines the optimum obtained variables value of the third (L_3), which represent as well the optimum variables values of the proposed algorithm. These variables define the optimum homogeneous transformation matrix and the optimal location of the data point cloud. Although the fitness function is non-differentiable, the successive applications of the genetic algorithm and of the gradient-based algorithm lead to a better value of the fitness function, to a decrease of the generations

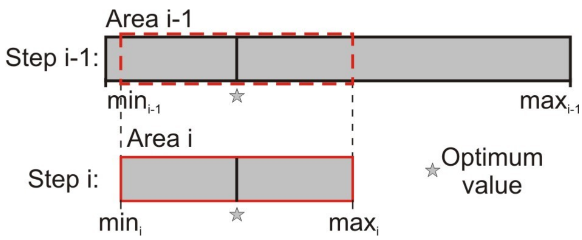

Fig. 2: Variable bounds reduction, using CHM

number and computational time than the ones with only genetic algorithm.

4. Applications of the proposed algorithm

The proposed algorithm is applied in two categories of point clouds. The first category investigates the case of point clouds with same boundaries and different holes in their surfaces (Figure 3). This figure illustrates a turbines wing, which was scanned using a Coordinate Measurement Machine. The second category (see Figure 4) investigates the case of registration of a CAD model and a point cloud of the same object. The statue is called Eusy and the scanning device is a CMM. The initial number of points of the model and data clouds, the percentage of reduction and the final number of points that is used in these applications are presented in Table 1.

The parameters involved in all tests, mainly in GA procedure, are the same and selected as optimums through many applied tests: population of individuals=50, cross probability=70%, mutation probability=7% and the reduction of variables range in CHM=50%. All the other algorithm parameters such as the number of GAs in loop L_1, the number of QNAs in loop L_2 and the number of CHMs in loop L_3 are presented in Table 2. The loops number of GA, QNA and CHM are selected in a way that the solutions of both cases are accurate and quick enough simultaneously.

The proposed algorithm is compared with a classic GA to verify the capacity and the reliability of the hybrid method. In Figure 5 is illustrated the fitness function value versus the generation number in the hybrid and a classic GA method. In both examples the fitness function value of hybrid algorithm converges in

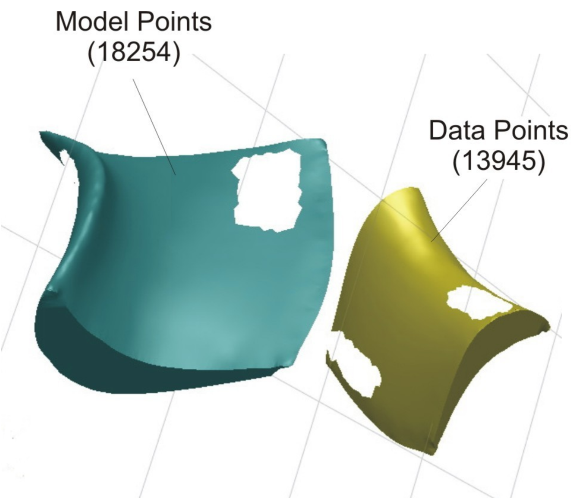

Fig. 3: Initial position of point clouds with the same boundaries and different holes

better solution in sorter time. For the hybrid method, in the example of the wing, the final

Exam-ples	Initial Points		Reduction %		Finally	
	Model	Data	Model	Data	Model	Data
Wing	18 254	13 945	90.154	97.899	1 797	293
Eusy	33 983	25 992	94.509	98.692	1 866	340

Table 1: Points number before and after the reduction

Exam-ple	Parameters			Hybrid method	
	Number of loops			Compu-tational time	Fitness value
	GAs (S1)	QNAs (S2)	CHMs (S3)		
Wing	1	20	1	0:03:06	3.21E-03
Eusy	1	8	1	0:01:16	6.77E-04

Table 2: Parameters of two numerical examples and the corresponding results of the hybrid method

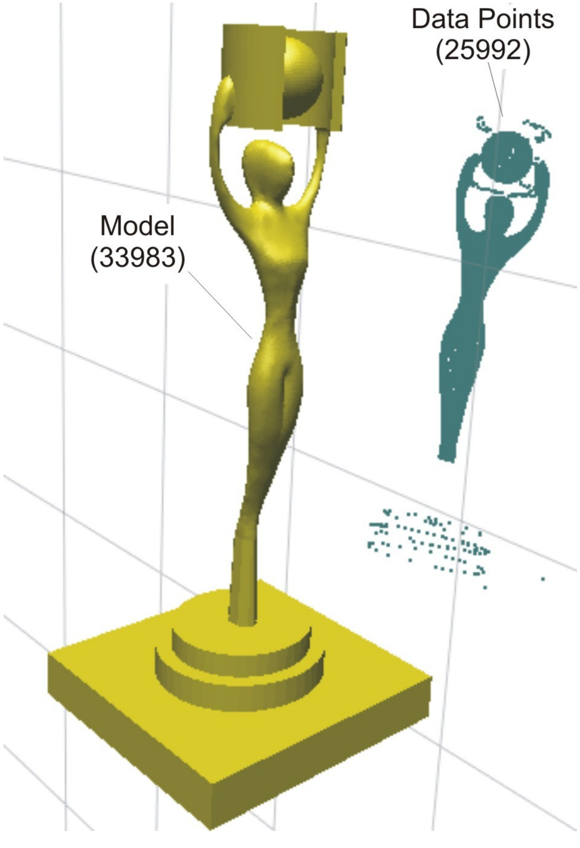

Fig. 4: Initial position of a CAD model and a point cloud

alignment result was obtained after 3 generations. Additionally, in the Eusy statue the final alignment result was obtained after 16 generations. For the classic GA, in the example of the Eusy and wing, the fitness function converges in higher value after 550 and 700 generations respectively. The fitness function value, the generation number and the computational time are presented in Table 2 and

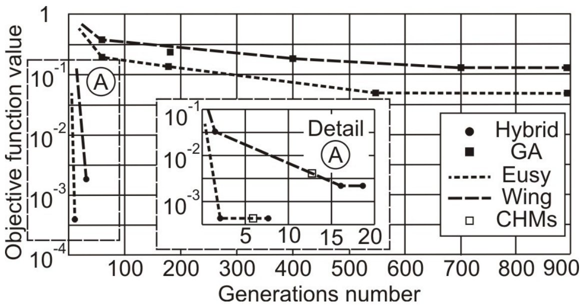

Fig. 5: Minimum objective function value versus generation's number of both examples

Table 3. The proposed hybrid method needs less computational time than the classic GA algorithm.

The registration process is also tested with commercial RE software. The automatic algorithm that is provided in this software is based on ICP algorithm and it failed to align the point clouds for all the above examples, when the point clouds were on their initial positions. When an initial manually applied approach is used, this ICP algorithm obtains an acceptable solution. Furthermore an acceptable solution can be obtained with the three points method, which is also a non-automatic procedure against the proposed one.

Example	Parameters			GA method	
	Number of loops			Computational time	Fitness value
	GAs (S1)	QNAs (S2)	CHMs (S3)		
Wing	900	-	-	0:15:16	1.26E-01
Eusy	900	-	-	0:06:23	5.60E-02

Table 3: Parameters of two numerical examples and the corresponding results of the genetic method

The registration that has been achieved with the proposed algorithm for the first category of same boundary objects and different holes is shown in Figure 6, where the positional deviation is also displayed. The maximum distance in the case of the wing is 1.104mm and the average distance 0.02mm. In the category of a point cloud and a CAD model, as illustrated in Figure 7, the maximum distance is 0.240mm and the average is 0.005mm.

5. Conclusions

In the present paper a hybrid algorithm for registration of point clouds is developed. The method combines a genetic algorithm with a hill climbing method (quasi-Newton algorithm) and furthermore a constraints handling method is involved. Experimental results show that the automatic proposed approach behaves much better, with higher accuracy, in comparison to common algorithms that require users' interaction. The alignment capability and the computational time are not affected by the initial positions of model and data point clouds. The algorithm leads to high accuracy results for each possible distance between the two point clouds, with a stable behavior.

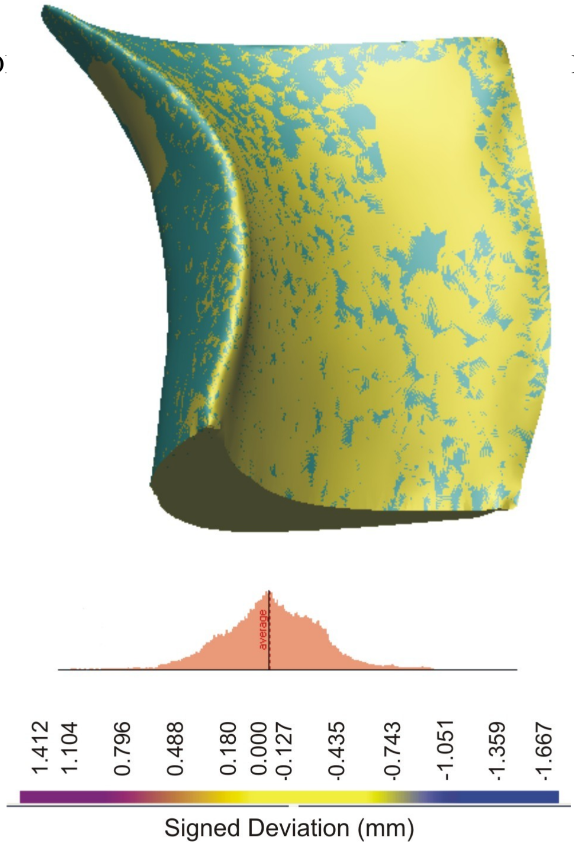

Fig. 6: Two point clouds deviation after the automatic registration process of the wing

References

[1] **Pottmann H., Leopoldseder S., and Hofer M.**, *Simultaneous registration of multiple views of a 3D object,* Int. Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS), volume XXXIV, Part 3A, (2002), pp.265-270.

[2] **Bels P.J. and McKay N. D.**, *A method for registration of 3D shapes*, IEEE Trans. Pattern Anal. and Mach. Intell, 14 (1992), pp.329-256.

[3] **Zhang Z.**, *Iterative point matching for registration of free-form curves and surfaces,* Int. Journal of Computer Vision, 13 (1994), pp.119-152.

[4] **Trucco E., Fusiello A. and Roberto V.**, *Robust motion and correspondence of noisy 3-D point sets with missing data,* Pattern Recognition Letters, 20/9 (1999), pp.889-898.

[5] **Chen Y. and Medioni G.**, *Object modeling by registration of multiple range images,* Image Vision Comput. 10 (1992), pp.145-155.

[6] **Soon-Yong Park, Murali Subbarao,** *An accurate and fast point-to-plane registration technique,* Pattern Recognition Letters, 24(16) (2003), pp.2967-2976.

[7] **Chow C. K., Tsui H. T. and Lee T.,** *Surface registration using a dynamic genetic algorithm,* Pattern Recognition, 37 (2004), pp.105-117.

[8] **Sagris D., Mitsi S., Bouzakis K.-D. and Mansour G.,** *Geometric design optimization of spatial RR robot manipulator using a hybrid algorithm,* Acta Technica Napocensis, 47, vol. II, (2004), pp.717-722.

[9] **Sagris D., Mitsi S., Bouzakis K.-D. and Mansour G.,** *5-DOF robot base location optimization using a hybrid algorithm,* Mecatronica, 1 (2004), pp.76-81.

[10] **Coley D.,** *An Introduction to Genetic Algorithms for Scientists and Engineers,* World Scientific Press, 1999.

[11] IMSL, *Fortran subroutines for mathematical applications*, Visual Numerics, 1997.

[12] **Emiris D.,** *Robotics*, Anosis Press, Athens, 1999, pp.138-161 (Greek).

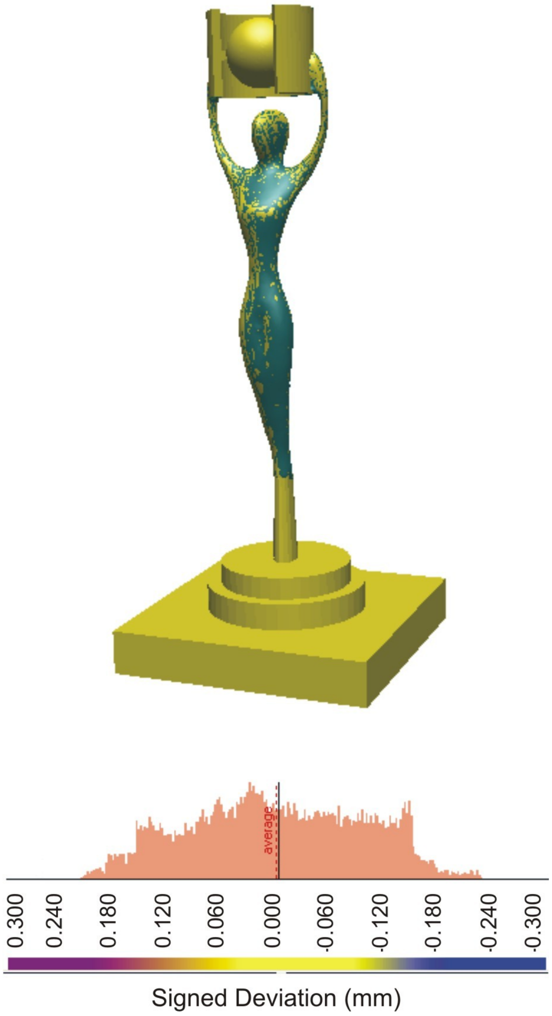

Fig. 7: Two point clouds deviation after the automatic registration process of EUSY statue