RESEARCHING FOR THE SAMPLING METHOD ON CMM

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ABSTRACT: *Accurate dimensional inspection and error analysis of free-form surfaces requires accurate registration of the component in hand. Registration of surfaces defined as non-uniform rational B-splines (NURBS) has been realized through an implementation of the iterative closest point method (ICP). The paper presents performance analysis of the ICP registration method using Monte Carlo simulation. A large number of simulations were performed on an example of a precision engineering component, an aero-engine turbine blade, which was judged to possess a useful combination of geometric characteristics such that the results of the analysis had generic significance. Data sets were obtained through CAD (computer aided design)-based inspection. Confidence intervals for estimated transformation parameters, maximum error between a measured point and the nominal surface (which is extremely important for inspection) mean error and several other performance criteria are presented. The influence of shape, number of measured points, measurement noise and some less obvious, but not less important, factors affecting confidence intervals are identified through statistical analysis.*

Keywords: *accurate dimensional inspection, ICP registration.*

1. INTRODUCTION

Accurate registration of free-form surfaces is an importantrequirement in many branches of the manufacturing industry. The requirement arises at several stages in the product life cycle such as inspection during product and manufacturing process development, inspection in production, and also in the repair of broken or worn out parts. A common feature of these components is the absence of clearly defined reference points. The prime examples are components produced using forming processes (casting, forging, pressing), such as aero-engine compressor and turbine blades, car body panels and others. Inspection of free-form surfaces requires measurement of a large number of points such that the actual surface may be characterized in full (**1**). This may be performed using one of a number of available contact or non-contact measurement sensors (**2**). In such situations the adoption of CAD (computer aided design)-oriented inspection is widely seen as the appropriate inspection methodology (**3**, **4**). In the cases when the free-form component possesses no clear reference features, the CAD-oriented inspection is based on software best-fitting between the CAD model and the measured points as the required registration technique.

Fully analytical evaluation of the performance is extremely difficult, if not impossible, owing to the complexity of the problem. Under these circumstances, Monte Carlo simulation (**10**) was undertaken as an alternative to an analytical evaluation of the LS fitting performance. This is a method of statistical trials, based on the principle of simulating a statistical experiment by computational techniques, and recording the numerical characteristics obtained from this experiment. The solution of numerical problems by this method is closer to physical experiments than to classical computational methods.The implementation involved a number of important improvements in the computational speed which were mainly realized in relation to the manipulation of model geometry.

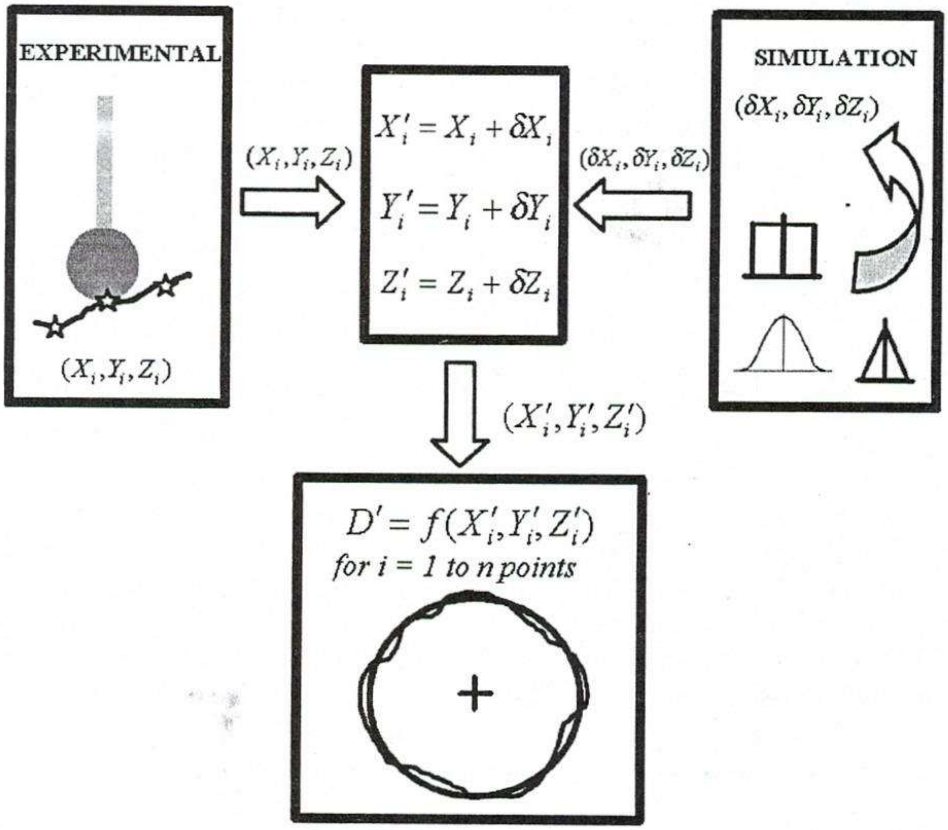

Figure 1. Graphic about Sampling method on CMM with the simulation

2. ITERATIVE CLOSEST POINT (ICP) PERFORMANCE ANALYSIS USING MONTE CARLO SIMULATION

The Monte Carlo simulations were conducted with the aim of investigating ICP performance in terms of several criteria that are considered to be of importance in inspection related applications. These criteria are:

(a) mean square error (MSE),

(b) maximum error (important for inspection),

(c) average error,

(d) confidence in the transformation parameter estimates,

(e) number of iterations required to achieve given accuracy.

The simulations analysed the dependence of these performance measures with respect to the following factors:

(a) number of random measurements on the object,

(b) measurement noise (assumed to be Gaussian with known standard deviation, j),

(c) initial misalignment (three-dimensional translation and rotation),

(d) fineness of approximation of the NURBS model.

2.1 Effect of initial misalignment

In this study it was important to conduct simulations such that the effects of different noise values and different numbers of measured points were analysed 'under the same circumstances', since there was only a finite set of simulation runs and a finite number of randomly generated measured points in each case. Thus in order to ensure *statistical reliability* (**10**) of the results, the same set of randomly generated initial positions was used in examining each combination of the measurement noise and the number of points.

With the different measurement noise and the different number of points in each experiment, the fitting error of the ICP method was analysed, this being the difference between the true transformation parameters (introduced as initial misalignment) and the estimated transformation. This difference also has its own probability distribution because of the randomness of the measurement noise and of the initial misalignment. It is common practice to summarize such a distribution in the form of *confidence limits*. In accordance with reference (**20**), the confidence statement for the case of the mean value estimate m of a random variable x is given by

$$\bar{x} - \frac{st_{\alpha/2}}{N} \le \mu < \bar{x} + \frac{st_{\alpha/2}}{N} \qquad (1)$$

where

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \text{ is the sample mean} \qquad (2)$$

$$s^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(\bar{x} - x_i\right)^2 \text{ is the unbiased sample variance} \qquad (3)$$

N = sample size

$t_{\alpha/2}$ is found from the Student t-statistic tables

2.2 Random number distributions

All of Monte Carlo Simulaitons is based on generating random numbers from distribution in range of 0 to 1.

Pseudo random number u_i in accordance with uniform distribution, it is obtainable from series of positive integer x_i , by following expression:

$$u_i = \frac{x_i}{m} \qquad (4)$$

where m = maximum integer that its magnitude is definited by used limit of computation.

A series of dandom numbers could be assumed by relation:

$$x_{i+1} = (ax_i + b)\mathrm{mod}(m) \qquad (5)$$

where x_{i+1} is remanent number, as $ax_i + b$ divide by m; a, b are positive integers that aligned interval 0 to m-1

If n_i is called integer of rate $\dfrac{ax_i + b}{m}$, means:

$$n_i = \mathrm{int}\,eger\left(\frac{ax_i + b}{m}\right) \qquad (6)$$

Therefore, achieve remanent number x_{i+1}, definited by expression:

$$x_{i+1} = ax_i + b - mn_i \quad (7)$$

For the arbitrary standard distribution, how to generate sample values?

Assumed t that has random variable in standard X, with mean value m_x, and standard deviation S_x. Basic relation between X and standard variable coefficient as:

$$X = m_x + zS_x \quad (8)$$

Assume that a sample value known z_i, this proceduce is used to generate correspondence value x_i:

$$x_i = m_{xi} + z_i S_{xi} \quad (9)$$

From input random variables were obtained, we can definite output random y_i through the critical situation function $Y = g(x)$, then definite the mean value and the unbiased sample variance through the expressions (2-3)

2.3 Least squares fitting

LS fitting can be defined as follows (**4**):

Given 3D data in a sensor co-ordinate system, which describes a data shape that may correspond to a model shape, and given a model shape in a model co-ordinate system in a different geometric representation, estimate the optimal rotation and translation that aligns the model shape and the data shape minimizing the distance between the shapes and thereby allowing determination of the equivalence of the shape via a mean-square distance metric.

Based on the above definition the cost function to be minimized in LS fitting is the model-part distance, which can be expressed as

$$F = \sum_{i=1}^{N} (q_i - R_i.p_i - T)^2 \quad (10)$$

where

$\boldsymbol{T}$ =3 × 1 translation vector

R 3 × 3 rotation matrix

p_i =*i*th measurement point

q_i =corresponding point on the model

The fitting procedure involves exclusion of two distinct steps in a loop, namely:

(a) evaluation of the corresponding point set $\{q\}$ on the model and

(b) calculation of the required translation $\boldsymbol{T}$ and rotation **R** and their application on the measured data set.

The critical step in the procedure is to establish the points on the model that correspond to the measured points. It has been shown (**4**) that by using the closest points on the model as the corresponding points, it is possible to construct an iterative LS fitting algorithm that would always converge to a local minimum. This is the basis of the ICP algorithm as the principal registration method.

3. MONTE CARLO SIMULATION EXPERIMENT

Data sets were obtained by performing simulation of CADbased inspection. Because of the large number of data sets required, it was decided to conduct all trials on the basis of a single real object, which was carefully chosen to contain various geometric characteristics that would be representative of different situations. The object used was a circular cylinder with approximate dimensions of d = 23.351 mm, height z = 36 mm. The reasons for its selection are summarized as follows:

(a) Definite to measured direction according to two directions:

1) Along z axis, divide Object into twelve measured intervals, distance 3 mm,

2) Each of measured intervals (xy plane), divide twelve points, 30^0 rotation for each point.

(b) CAD model defined as NURBS

(c) poor geometric determinacy along the stacking axis (z axis)

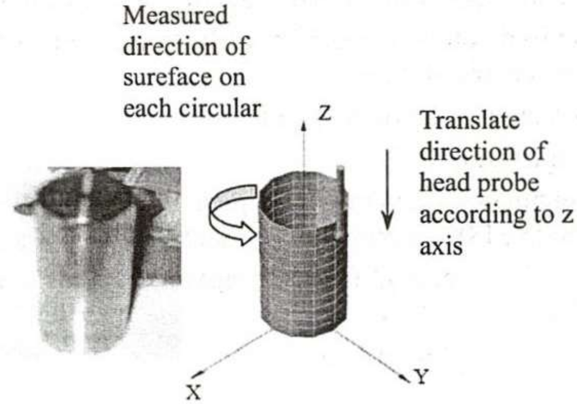

Figure 2. Show a circular cylinder measurement on Mitutoyo ***CRYSTA-PLUS M540*** CMM

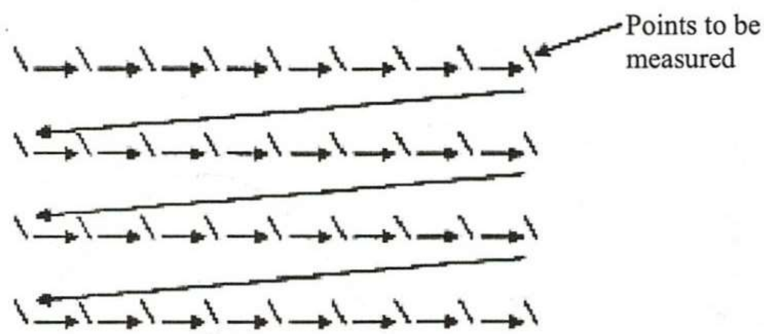

Figure 3. Show measured directions on circular cylinder

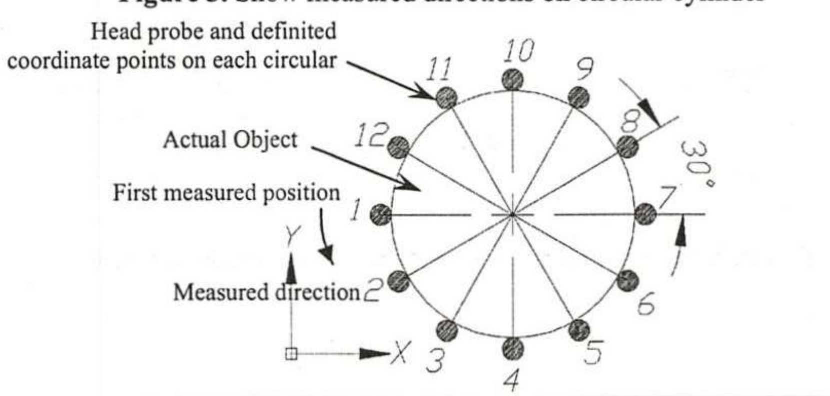

Figure 4. Show measured method on each circular of object

The investigation took the form of measuring a section of a cylinder perpendicular to its axis of symmetry

Table 1. Measured Data on each circular of Object, with heigh z = 36 mm

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
Xi	-11.434	-9.904	-5.71	0	5.725	9.92	11.438	9.898	5.708	-0.001	-5.72	-9.906
Yi	-0.001	-5.694	-9.891	-11.422	-9.904	-5.718	-0.01	5.703	9.889	11.424	9.898	5.72
Zi	36	35.999	36	36	36	36	35.999	35.999	36	36	36	36

The simulations were conducted through a number of experiments. Each experiment involved 100 simulations by executing the following loop:

1. Compute N random points on the surface, N = 12.

2. Add Gaussian noise with known statistic $\sigma = \pm 2$ mm to each point.

3. Apply random rotation $\pm\ 0.3^0$about lines parallel to the coordinates axes and passing through the object centre of mass.

4. Apply random translation along all axes.

5. Perform registration.

6. Subtract estimated transformation parameters from the (known) true values and record result, together with MSE, maximum error and number of steps.

Using Monte Carlo method for each measured point with 100 simulations through follow constraint conditions:

$$y = x \tan \alpha \tag{11}$$

$$x^2 + (y + dy)^2 = (R + r)^2 \tag{12}$$

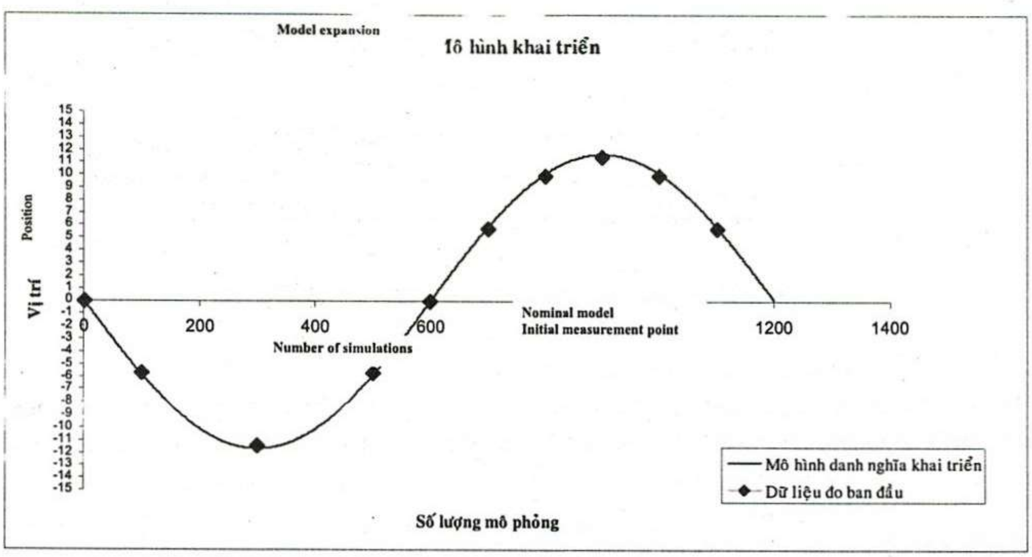

Figure 5. Show measurement point meshes on circular cylinder

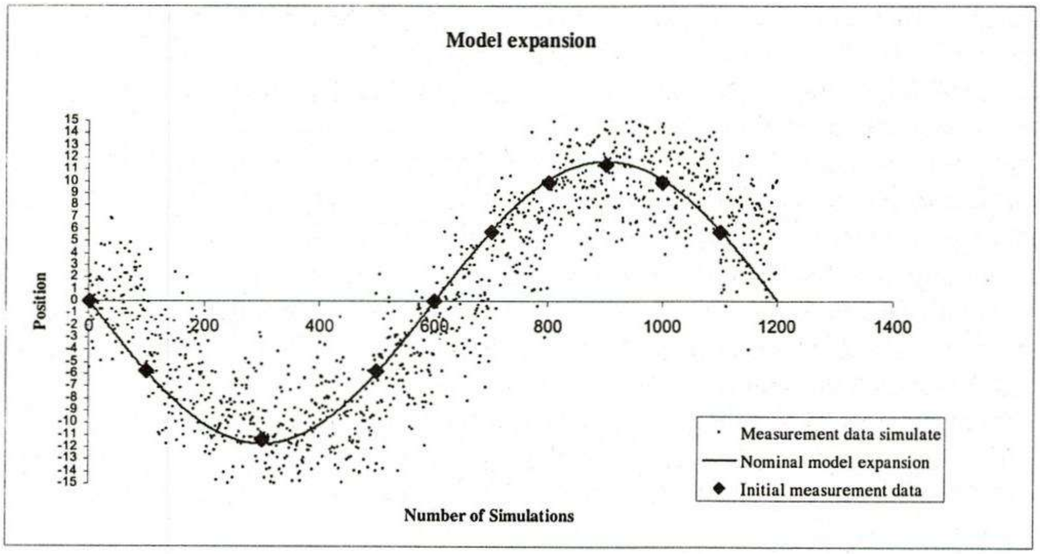

Figure 6. Monte Carlo simulation result with N = 100 for each point

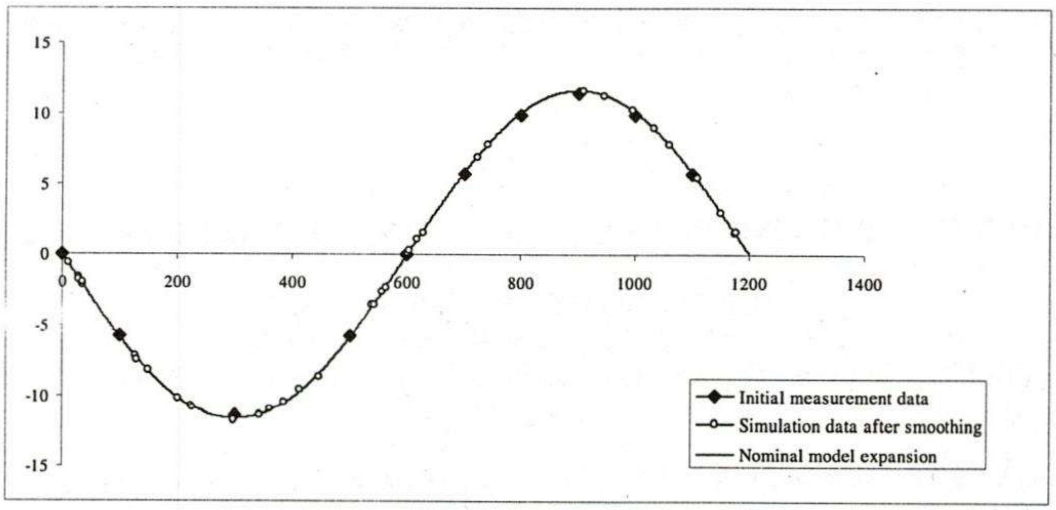

Figure 7. Simulation data after smoothing result

4. RESULT EVALUATE

Base on the result in fig.7, we can't characterize full of circular cylinder with only 12 initial measurement points. Simulating at each measurement point helps us to characterize full of circular cylinder with 0.03 mm error.

5. CONCLUSIONS

This paper is concerned with accurate registration as demanded by the purposes of dimensional inspection of free-form surfaces. Registration of surfaces defined as NURBS was implemented using the ICP method, as a realization of LS fitting. The influence of a number of important factors was analysed, one of the most important ones for inspection purposes being the measurement noise.

Quality of fit was measured using confidence in the transformation parameter estimates. The results clearly show that in the presence of measurement noise, as is always the case in practice, confidence improves with an increased number of measured points. This is an important result for inspection, which confirms the intuitive reasoning that measuring a very large number of points with lower accuracy can provide better results than measuring a very small number of points with higher accuracy. This has important implications when evaluating different measurement technologies for a given application.

The investigation has also confirmed that accurate registration requires a large number of iteration steps. This was the main incentive for maximizing the computational efficiency of each iteration and the adoption of dual representation of the NURBS model has significantly improved the overall computing time. Importantly, the results have also shown that beyond a certain point, increased fineness of approximation brings diminishing benefits, while the computation time increases linearly with the number of approximating points. The cut-off point was found to correspond to the fineness that adheres to the object thickness criterion, which must be satisfied.

Finally, in the absence of readily available analytical techniques, Monte Carlo simulation was shown to be a good tool for assessing the registration performance in a given situation. The simulation process described in the paper can be readily performed, in full or in part, to produce definitive results about registration of any given object using any given measurement sensor.

NGHIÊN CỨU PHƯƠNG PHÁP LẤY MẪU TRÊN MÁY ĐO TỌA ĐỘ (CMM)

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TÓM TẮT: *Kiểm tra độ chính xác kích thước và phân tích sai số bề mặt tự do yêu cầu phải đăng ký độ chính xác của chi tiết. Việc đăng ký bề mặt NURBS xác định, thực sự thông qua quá trình thực hiện phương pháp lặp điểm lân cận. Nội dung bài báo là sử dụng phương pháp mô phỏng Monte Carlo trong việc đăng ký. Một số lượng lớn mô phỏng được biểu diễn mà kết quả phân tích có ý nghĩa chung. Tập hợp dữ liệu thu được thông qua việc kiểm tra dựa trên nền tảng mô hình CAD. Độ tin cậy đối với tham số chuyển vị được ước lượng, cũng như thực hiện tính toán sai số lớn nhất giữa điểm đo và bề mặt danh nghĩa (rất quan trọng trong việc kiểm tra), sai số trung bình và nhiều loại tiêu chuẩn khác. Ảnh hưởng của hình dạng, số điểm đo, nhiễu đo và một số nhân tố khác không rõ ràng, nhưng không kém quan trọng, những nhân tố ảnh hưởng đến độ tin cậy đều xác định thông qua quá trình phân tích thống kê.*

Từ khoá: *registration, inspection, Monte Carlo simulation, free-form surfaces, NURBS.*

REFERENCES

[1]. **Jain, R.** and **Jain, A.** Report on Range Image Understanding Workshop, held in East Lansing, Michigan, 21–23 March 1988. *Machine Vision and Applications*, No. 2, 1989, pp. 45–60 (Springer-Verlag, New York).

[2]. **Newman, T. S.** and **Jain, A. K.** A survey of automated visual inspection. *Comp. Vision Image Understanding*, March 1995, **61**(2), 231–262.

[3]. **Besl, P. J.** *Surfaces in Range Image Understanding*, 1988 (Springer-Verlag, New York).

[4]. **Besl, P. J.** and **McKay, N. D.** A method for registration of 3-d shapes. *IEEE Trans. Patt. Ann. Mach. Intell.*, February 1992, **14**(2), 239–255.

[5]. **Menq, C. H., Yau, H. T.** and **Lai, G. Y.** Automated precision measurement of surface profile in CAD-directed inspection. *IEEE Trans. Robotics Automn*, April 1992, **8**(2), 268–278.

[6]. **Haralick, R. M., Joo, H., Lee, C., Zhuang, X., Vaidya, V. G.** and **Kim, M. B.** Pose estimation from corresponding point data. *Machine Vision for Inspection and Measurement*, 1989 (H. Freeman, New York Academic).

[7]. **Pennec, X.** and **Thirion, J.-P.** Validation of 3-D registration methods based on points and frames. In Fifth International Conference on *Computer Vision*, Cambridge, Massachusetts, 1995, pp. 557–562 (IEEE, Piscataway, New Jersey).

[8]. **Eggert, D. W., Lorusso, A.** and **Fisher, R. B.** Estimating 3-D rigid body transformations: a comparison of four major algorithms. *Mach. Vision and Applic.*, 1997, **9**(5/6), 272–290.

[9]. **Stoddart, A. J., Lemke, S., Hilton, A.** and **Renn, T.** Estimating pose uncertainty for surface registration. In British Machine Vision Conference, Edinburgh, Scotland, 1996.

[10]. **Shreider, Y. A.** Method of Statistical Testing–Monte Carlo Method, 1994 (Elsevier, Oxford).

[11]. **Lin, Z. C., Lee, H.** and **Huang, T. S.** Finding 3-D point correspondences in motion estimation. In Eighth International Conference on *Pattern Recognition*, 1986, pp. 303–305 (IEEE, New York).

[12]. **Assoc. Prof. Dr Nguyen Huu Loc.** Mechanical System of Design and Analysis. The Publisher for Science and Technology. October, 2005.