Lasers in Eng., Vol. 37, pp. 345–355
Reprints available directly from the publisher
Photocopying permitted by license only

Simulation of Lidar Target Orientation Estimation Based on Point Clouds Model Matching

Y. WANG[1,2,*], F. WANG[1], T-F. WANG[1] AND J-J. XIE[1]

[1]*State Key Laboratory of Laser Interaction with Matter, Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences, Changchun 130033, Jilin Province, China*
[2]*University of the Chinese Academy of Sciences, Beijing 100049, China*

Thee-dimensional (3-D) laser active imaging technology is widely used in military and civilian applications for its advantages of high energy density, coherence and directionality. 3-D pose estimation using laser array imaging system involves finding the rotation and translation between image point clouds and model point clouds. Owing to limitations such as detector technology and other factors, it is difficult to achieve high-resolution 3-D laser imaging systems. This article introduces a laser array imaging simulation method, and the pose estimation process is simulated. In the simulation, different range and spatial resolutions of the imaging system are discussed to analyse the influence of these imaging system factors on the accuracy of 3-D pose estimation. The results show that for a target size of $4 \times 4 \times 6\,\mathrm{m}^3$, the accuracy of orientation estimation could be 0.10° when the ranging resolution of the system is 0.35 m. For a ranging resolution of 1.50 m and spatial resolution of 0.15 m, the accuracy of orientation estimation could be 0.50°. The simulation results further show that the impact of the range resolution on the accuracy of pose estimation is greater than that of the spatial resolution. We can, therefore, reduce the spatial resolution and increase the range resolution of the imaging system to improve the accuracy of the pose estimation for certain special cases. The results of this analysis could be used in the design of systems with different needs, which makes the design more efficient in terms of the use of resources. The simulation method and analysis can be used in other applications, such as point clouds registration and lidar target recognition based on point clouds-model matching.

Keywords: *Lidar, three-dimensional (3-D) laser imaging, simulation, iterative closest point (ICP) algorithm, target orientation estimation, point clouds registration, accuracy of orientation estimation*

*Corresponding author: Tel: +86 (0)375 610 9038; E-mail: wyciomp@163.com

1 INTRODUCTION

Three-dimensional (3-D) orientation of lidar target is a very important technique index in military and space applications. It is much more important to know the exact character of the target. In many applications, it is necessary to determine the pose of objects whose precise surface geometry is unknown. Automatic pose estimation of objects in a 3-D scene is an important prerequisite for a number of robotic, security, and defence applications, including grasping and manipulating of manufactured parts, autonomous navigation and obstacle avoidance, as well as aim point selection and tracking for fire control and missile guidance.

The traditional method to determine the pose of the target is to put a fixed gyroscope or GPS pose sensor on the target; however, we cannot put these sensors on unknown targets, which makes this method less useful in many special applications and so some other methods are used in more applications. The pose estimation method based on projection image is also widely used in many applications [1], but compared with the projection images method, which came from the 3-D image, the 3-D point clouds obtained from the 3-D image laser system includes the range information of the target, and is also resistant to yardstick, illumination, and transmission. Pose estimation using 3-D point cloud is much more accurate than the two-dimensional pose estimation method.

Determining the pose and orientation of the object requires matching the image data to object models. The method of principal component analysis (PCA) [2, 3], characterization of irregularly shaped bodies [4] and the rectangle estimation method [5, 6] are used to estimate pose of the target. The PCA method is to analyse the component of the three main directions, and the pose estimation result is calculated by the point clouds distribution of the three main directions. The characterization of irregularly shaped bodies method is calculating the pose of the target by analysing the Eigenvalue of the point cloud. The rectangle estimation method is to put the target point cloud on the three coordinate planes and calculate the pose of the target using the least rectangle. These three methods, however, are all sensitive to the shelter of the point cloud; that is to say, when the point cloud has shelter, the performance of the methods is reduced. For these shortcomings, we estimate pose of the target by using the iterative closest point (ICP) algorithm; the range resolution and spatial resolution requirements of target pose estimation based on the ICP method are simulated and discussed in this paper.

2 POSE ESTIMATION BASED ON THE ITERATIVE CLOSEST POINT (ICP) ALGORITHM

The ICP algorithm concurrently proposed by Besl and McKay [7] is an excellent method for the registration of free form curves and surfaces when the transformation between model and scene is small. The method handles the full six degrees of freedom and only requires a procedure to find the closest point on a geometric entity to a given point. One important application of this method is to register sensed data from unfixed rigid objects with an ideal geometric model prior to shape inspection.

In this paper we use the ICP algorithm to determine the orientation of the target; during the matching process, we can obtain the matrix of the transformation. From this matrix, we can determine the rotation and translation information, and finally we can also obtain the pose information of the target. For a given model shape and a sensed data shape that represents a major portion of the model, the shape can be registered in minutes by testing one initial translation and a relatively small set of rotations to allow for the given level of model complexity.

For a given model point cloud P and sensed data Q, the two point clouds are in the same coordinate system. The sensed point cloud is obtained from the model point cloud after it undergoes a transformation. After matching P and Q we can obtain the relationship of P and Q:

$$P^{'} = R(\alpha,\beta,\gamma)\times P + t(t_x,t_y,t_z) \tag{1}$$

where the function $R(\alpha,\beta,\gamma)$ denotes the rotation matrix; $t(t_x,t_y,t_z)$ denotes the transform matrix; α, β and γ denote the angle of converse rotation of the three coordinate axes; and t_x, t_y and t_z are transform matrices of the three coordinate axes. So, with these definitions the transform matrix can be written as

$$R(\alpha,\beta,\gamma) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos(\alpha) & -\sin(\alpha) \\ 0 & \sin(\alpha) & \cos(\alpha) \end{pmatrix} \begin{pmatrix} \cos(\beta) & 0 & \sin(\beta) \\ 0 & 1 & 0 \\ -\sin(\beta) & 0 & \cos(\beta) \end{pmatrix} \begin{pmatrix} \cos(\gamma) & -\sin(\gamma) & 0 \\ \sin(\gamma) & \cos(\gamma) & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{2}$$

For different Euler angles and different translation, we can obtain different rotation and transform matrices. When we use this method to determine the pose information of the target, the rotation is all the information we need.

3 LIDAR IMAGING SIMULATION

The process of 3-D lidar imaging is that the 3-D image system emits a laser array to the surface of target. After reflection off the surface of the target, the laser returns to the receiving system, then the timing system can calculate the time between emission and reception of each laser beam; therefore, the range information of the target, as well as the pose orientation, can be obtained from the point cloud.

Using the 3-D imaging principle above, in the simulation, we use the laser beam to cross the target to simulate the 3-D imaging process. The laser beam can be defined as an emanative beam towards the target, and point of intersection between the beeline and the surface of the target is the coordinate of the surface point. In the actual operating environment, the laser is not a strict beeline, and the laser cannot reach back surface of the target. However, in this simulation method the beeline can get to the back surface of the target, so we must wipe off the back point of the target. Meanwhile, in the simulation we will add the gauss noise on the direction of the image system.

Figure 1 is the point cloud image under the condition of the system range resolution of 1.50 m, and the emit laser array is 40×40. The target is the Hubble Space Telescope (HST) model download from the NASA website with size of $4 \times 4 \times 6\,\mathrm{m}^3$, which is 1 km from the imaging system. All the simulation is carried out by using MATLAB.

4 SIMULATION OF POSE ESTIMATION

With the image data and model data, we can simulate the pose estimation process based on the ICP algorithm. The process is:

(i) For P with $N_{original}$ points we can turn the model data in some coordinate axis with an angle of $\theta_{original}$;
(ii) In the imaging direction, we can obtain Q of N_{data} points and add the gauss noise of mean value 0 and variance σ from the ranging system;
(iii) $R(\alpha,\beta,\gamma)$ and $t(t_x,t_y,t_z)$ can be obtained after matching P and Q with the ICP algorithm. The rotation angle can be calculated using $R(\alpha,\beta,\gamma)$; and

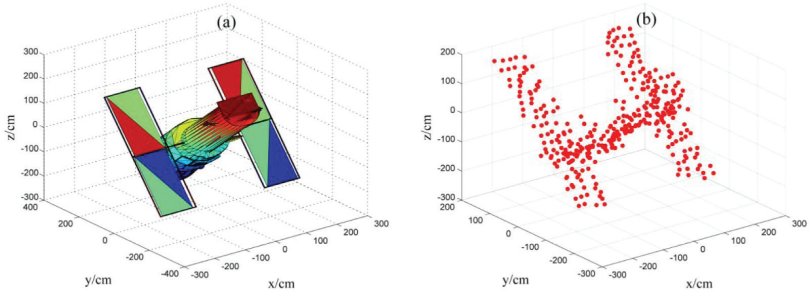

FIGURE 1
Images of (a) the real target 3-D image and (b) the sensed 3-D point cloud.

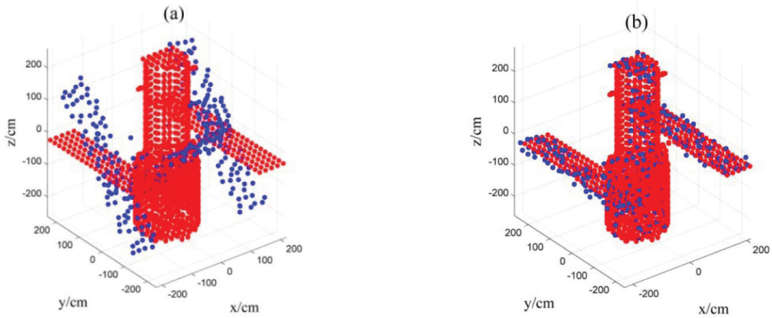

FIGURE 2
Model cloud and data cloud (a) before and (b) after registration.

(iv) Change the parameters and repeat the process before. In this way we can get the variation of the angle $\theta_{calculate}$ and using this we can know the effect of these parameters on the pose estimation.

Figure 2 shows the model and sensed data point clouds before and after matching after the target is rotated through an angle of 50.00°. From Figure 2 we can see after using the ICP algorithm, the sensed data point cloud matches the model data very well. We can calculate the rotation angle with the rotation matrix. The angle deviation of the calculation is 0.32°. The simulation shows that the ICP algorithm can be used to estimate the pose of the target very well.

5 ANALYSIS OF THE RESULTS OBTAINED FROM THE SIMULATION

5.1 Effect of range resolution

The target data point cloud is inverted from range information of the surface of the target; however, in the imaging process, the range information is affected by the range system, which will affect the point cloud image achieved. For different range resolution, the pose estimation result varies. Using these simulation methods we can simulate the 3-D process for the condition where the target is 1 km away and without other factors, when the timing resolution is 1 ns and the range resolution is $data_{noise}$=0.15 m. When the timing resolution is 10 ns, the range resolution is 1.50 m. We will simulate the pose estimation process in the two conditions, and the variation of the angle is shown in Figure 3. From the pose angle variation shown in Figure 3 we can determine that when the range resolution is 1.50 m, the mean pose angle calculated with the ICP algorithm after the simulations is 9.30^{o}, and variance of the pose angle is 0.41°. When the range resolution is

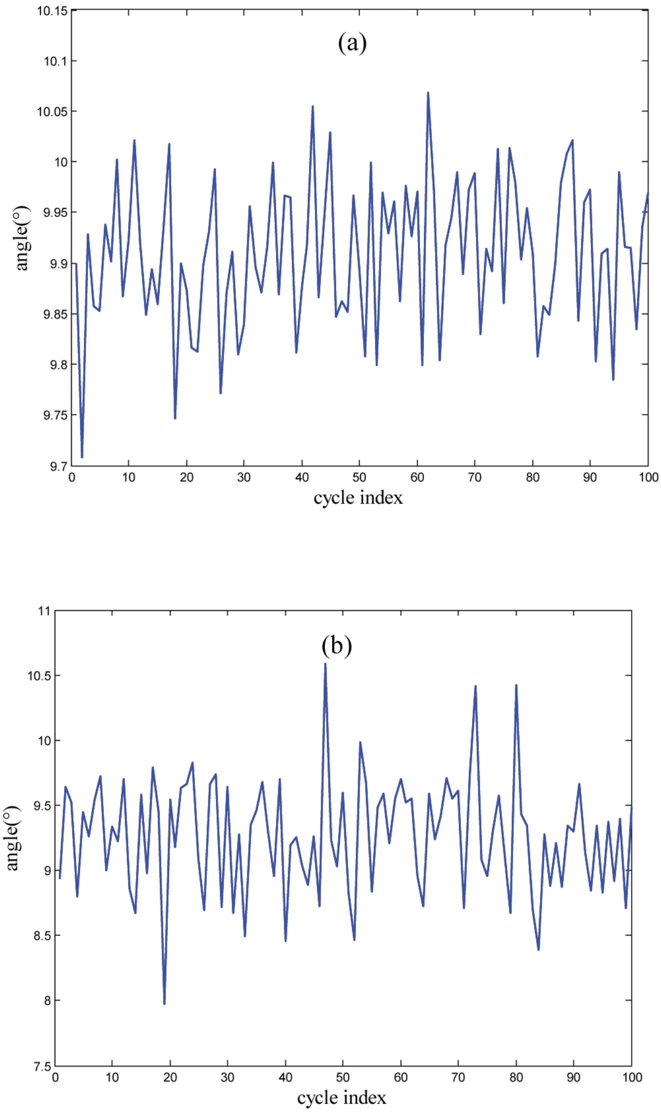

FIGURE 3
Graphs showing the orientation estimation variation under ranging resolution of (a) 0.15 m and (b) 1.50 m resolution.

0.15 m, the mean value of the pose angle is 9.90° and its variance is 0.04°. From the simulation result, we can see that the pose estimation is much more accurate with lower fluctuation when the range resolution is higher.

After changing the range resolution and repeating the process above, we can obtain the pose estimation result for different range resolutions. The mean value and the variance of the pose angle for ICP algorithm with different resolutions

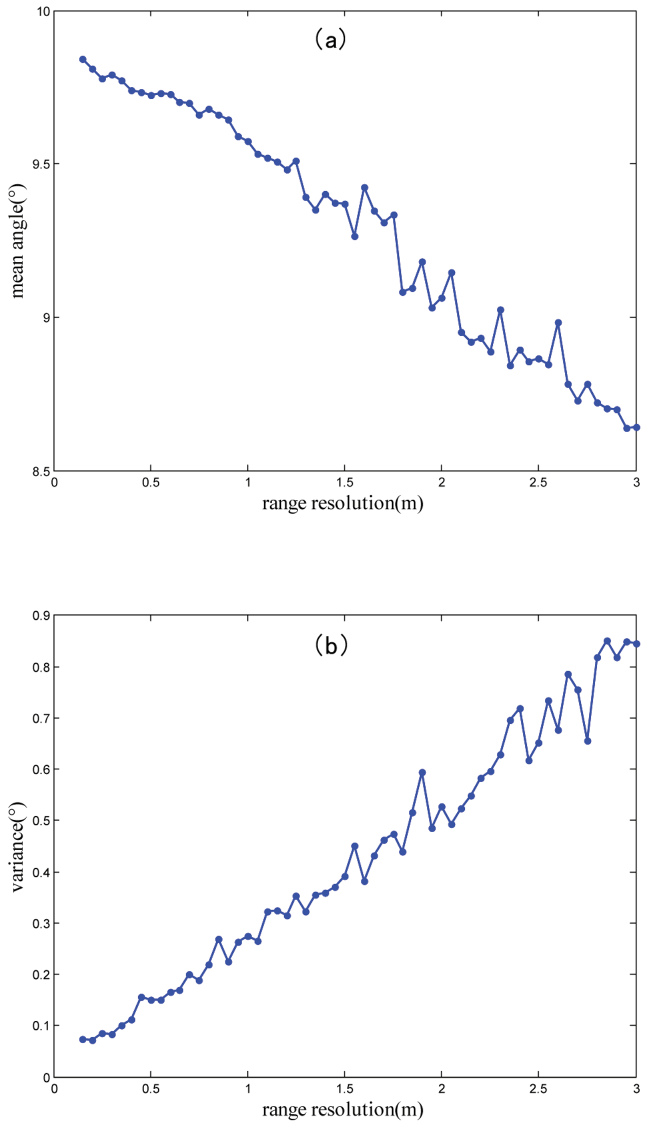

FIGURE 4
Graphs showing (a) the mean and (b) the variance of attitude angle variation with the distance resolution.

from 0.15 to 3.00 m is shown in Figure 4. From the variation curve in Figure 4 we can see that pose estimation result is 0.10° for the range resolution 0.35 m, and with the range resolution of 0.20 m, the pose estimation result is 0.50°. From the result we can see when the range resolution is decreased, the pose estimated by the three dimension point cloud is less accurate and the variance is higher. This is because when the range resolution of the system is decreased, the range information obtained from the ranging system is also inaccurate; the result of pose estimation is worse for the inaccurate range information; however, in the actual 3-D imaging condition, we cannot repeat the process several times. The simulation results show that by using higher range resolution we can obtain more accurate pose estimation results. We can also design the imaging system reasonably based on different conditions, which will decrease resource waste.

5.2 Effect of system space resolution on the pose estimation

The space resolution of the target point cloud will influence the information of the target point cloud. The space resolution is related to the number of points in the point cloud. Therefore, for the limit of the system detector technique, circuit of the system and transmit equipment, the imaging point cloud we get from the system cannot be very high. Therefore, we should know the effect of the space resolution on the pose estimation to better design the system. To know this relationship we should change the space resolution to simulate its effect on the pose estimation.

When the laser array can cover the whole target, with a 40×40 laser array and a space resolution of 0.15 m, for the 20×20 laser array to the target with the space resolution of 0.30 m. For the range resolution of 0.15 m, the pose estimation result is shown in Figure 5. The space resolution of the target point cloud are 0.15 and 0.30 m, the pose variances are 0.04 and 0.13° over 100 calculations. We can see that when the space resolution ranges from 0.15 m 0.30 m, the variance of the pose angle increases.

For different space resolution of the point cloud, the effect of the space on the pose estimation is shown in Figure 6. In Figure 6, we can see that as the space resolution decreases, the pose error estimated by the ICP algorithm is increases. For the range resolution of 1.50 m and space resolution of 0.15 m, the variance of the pose estimation result is 0.50°. For the target rotation of 10.00°, the situation above can be used to estimate the pose of the target very well.

5.3 Effect of the initial position

When the target is in space we cannot know what position the target should be before imaging, so the effect of position of the target in the sky on the pose estimation should be simulated. For different positions, the effect of the position on the pose estimation is shown in Figure 7.

From Figure 7 we can see that when the pose angle of the target is blow 55.00°, the pose estimation result calculated by using ICP algorithm is useful. The effect of the pose angle in the sky is small on the pose estimation; however, when the pose angle of the target is over 55.00°, the effect is obvious that the pose estimation result is far from the real value. This is because that the ICP algorithm is a greedy method; when matching the two point clouds, the matching result can only guarantee that the result is best in the local value. This implies that the result is related to the pose of the target. When the pose

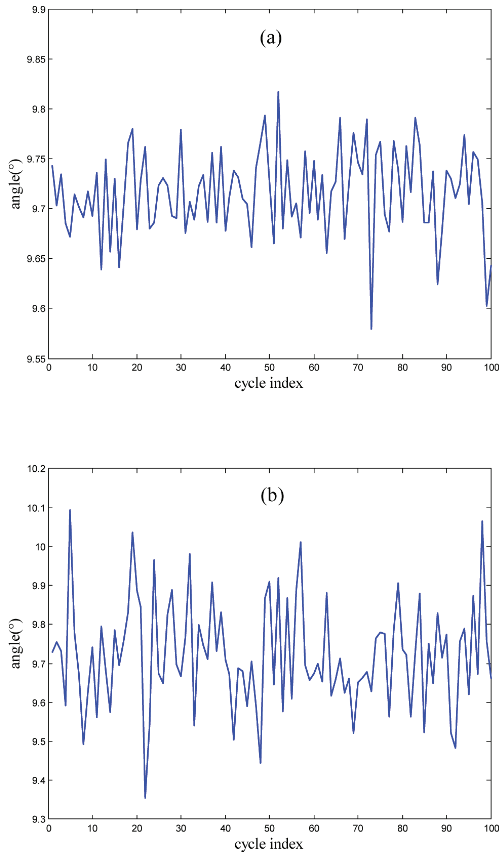

FIGURE 5
Graphs showing the orientation estimation variations under spatial resolution of (a) 0.15 m and (b) 0.30 m.

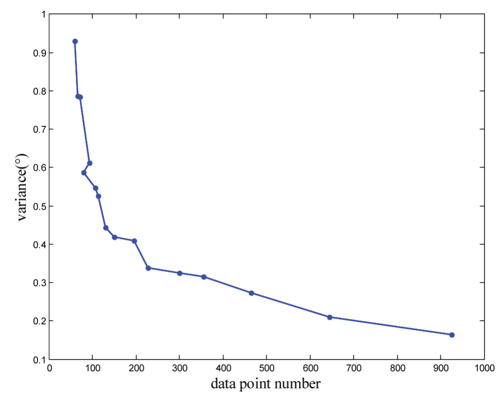

FIGURE 6
Graph showing the variance of attitude angle variation with the effect of spatial resolution.

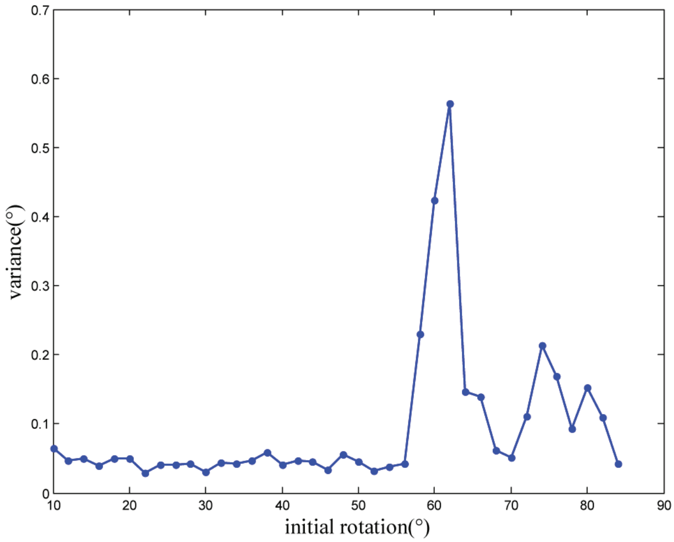

FIGURE 7
Graph showing the variance of attitude angle with different initial position.

of the target is high, the result of the method is not the best. We cannot, therefore, use this method to estimate the pose of the target when the pose of the target is far from the model. We should use some coarse method to optimize the initial position of the target before using the ICP algorithm.

6 CONCLUSIONS

We have simulated the process of the three-dimensional (3-D) imaging to the target, and analysed the effect of factors including range resolution, space resolution, and initial position on the pose estimation. The results showed that for a target size of $4 \times 4 \times 6\,\mathrm{m}^3$, when the range resolution of the system is 0.35 m, the space resolution is 0.20 m, and the initial pose angle is 10.00°, we can achieve a precision of 0.10°. For the range resolution of 1.50 m and space resolution of 1.50 m, we can get the pose precision of 0.50°. From the result, we can see that the range resolution has a much stronger effect on the pose estimation than does the space resolution. In the application we can reduce spatial resolution and increase the range resolution of the imaging system to improve the accuracy of the pose estimation for certain special cases. The results of this analysis could be used in the design of systems with different needs, which makes the design more efficient in terms of the use of resources; however, owing to the limitations of the iterative closest point (ICP) algorithm, the pose cannot be calculated in certain conditions. In future implementations, we should use some coarse registration method to matching the two point clouds before using the ICP method to complete the pose estimation.

NOMENCLATURE

$data_{noise}$	The range resolution of the ranging system (m)
N_{data}	Point number of the imaging data point cloud
$N_{original}$	Point number of the model point cloud
P	Model data point cloud
Q	Sensed data point cloud
t_x	Transform matrices of the x-axes
t_y	Transform matrices of the y-axes
t_z	Transform matrices of the z-axes

Greek symbols

α	Angle of converse rotation of the x axes
β	Angle of converse rotation of the y axes
γ	Angle of converse rotation of the z axes
$\theta_{calculate}$	Pose angle result of the after the pose estimation (^{o})
$\theta_{original}$	The real pose angle of the imaging data point cloud (^{o})
σ	Variance of the gauss noise of the ranging system

REFERENCES

[1] Zhao J., Ahalt S.C. and Stribling B.E. Three-dimensional orientation vector estimation from satellite imagery. *Proceedings of the SPIE* **2755** (1996), 472–483.

[2] Yang Y., Lin H. and Zhang Y. Content-based 3-D model retrieval: A survey. *IEEE Transactions on Systems, Man and Cybernetics - Part C: Applications and Reviews* **37**(6) (2007), 1081–1099.

[3] Tangelder J.W.H. and Veltkamp R.C. A survey of content based 3D shape retrieval methods. *Multimedia Tools and Applications* 39(3) (2008), 441–471.

[4] Zhu D.Q. and Chu C.C. Characterization of irregularly shaped bodies. *Proceedings of the SPIE* **2466** (1995), 17–22.

[5] Gronwall C., Gustafsson F. and Millnert M. Ground target recognition using rectangle estimation. *IEEE Transactions on Image Processing* **15**(11) (2006) 3401–3408.

[6] Felip R.L, Binefa X. and Diaz-Caro J. Discerning objects from ground and target pose estimation in ladar data using robust statistics. *The 13th IEEE International Conference on Image Processing (ICIP 2006)*. 8–11 October 2006, Atlanta, GA., USA. **4244**, pp. 2109–2112.

[7] Besl P.J. and Mckay N.D. A method for registration of 3-D shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **14**(2) (1992), 239–256.