# 3-D Modeling from Range Images with Integrated Registration

P. Payeur
*Vision, Imaging, Video and Audio Research Laboratory*
*School of Information Technology and Engineering*
*University of Ottawa*
*Ottawa, Ontario, Canada*
*ppayeur@site.uottawa.ca*

## Abstract

***3-D modeling of cluttered environments for semi-autonomous robotic systems implies that the position and the orientation of the sensor is determined for each viewpoint from which measurements are collected. Often the registration estimation is performed offline or with the help of external tracking devices. In this paper, we propose to integrate an efficient range data-based registration estimation technique with a probabilistic occupancy modeling scheme which both make use of the same data set to estimate registration and to build 3-D virtual representations of complex scenes. The resulting models are to be used for collision avoidance as well as for interaction with human operators who have to validate operations and guide data acquisition. The impact of the registration estimation technique on the quality of the models is examined in the context of telerobotic applications under operator's supervision.***

## 1. Introduction

Modeling 3-D environments finds numerous applications in virtual reality and robotics. Especially, the ability to represent occupied and free spaces is a critical issue in robot path planning with collision avoidance. Powerful modeling techniques using occupancy grids have been developed that estimate the occupancy state of a recursively subdivided 3-D volume directly from passive [10] or active range measurements [14] without the need for feature extraction. Such occupancy grids provide a useful tool for collisions detection but also for interaction with human operators who can take advantage of such a virtual representation of the scene for task validation and decision making. These functions are an important part of most semi-autonomous robotic systems currently used.

Obtaining virtual representations of 3-D environments from range measurements requires that data are collected from many different viewpoints. This requirement results from the complexity of objects to be modeled, from the limited field of view of sensors and from occlusions that occur between objects. However, the relative geometrical transformations that exist between the sensor positions from which measurements are collected need to be estimated. The widely known registration problem consists of determining the geometric relationship that exists between different views provided by the sensor. Even though the sensor pose can be estimated from external means such as magnetic trackers or passive robotic arms, these apparatus are expensive and suffer from important limitations on their operational range.

On the other hand, various computer vision techniques have been studied to deal with the registration problem but no extensive and definitive solution has been found yet. Many variations to the widely known iterative closest point (ICP) algorithm [1] have been introduced to match characteristic point sets [3, 11], curves, meshes [2, 6] or parametric surfaces [9]. Some of them use both range and intensity data, also provided by most range sensors, to improve their selection of control points that are to be matched [8, 13]. These algorithms generally provide good results but the search for characteristic curves or surfaces is very complex and time consuming. As most of the approaches look for high precision estimates, they invest large computing efforts in building complex intermediate representations of the scene to allow precise matching between characteristics extracted for these models. It seems therefore appropriate to examine if such a high precision is really necessary on the registration parameters for various fields of application such as telerobotics and path planning with collision avoidance.

A new 6 degrees-of-freedom registration technique has recently been proposed that relies on the raw measurements provided by a single line range sensor to build a compact surface map that is used to estimate three rotation angles and

0-7803-7635-8/02/$17.00  

three translation parameters between pairs of successive views [4, 5]. The compactness of the surface map significantly reduces computing time and therefore makes the technique suitable for on-line modeling by progressive refinement as a continous estimation of registration parameters is then required. This registration technique has demonstrated that it can estimate the 6 parameters of a geometrical transformation between two viewpoints with an error of less than 2% of the actual values.

The current research work considers the integrating this registration technique in the modeling stage of a telerobotic system currently under development for telesurveillance and telemaintenance. In the proposed approach, the raw range measurements that are used for computing a probabilistic occupancy grid are also used for registration estimation purpose. As these measurements have to be collected for modeling, there is no need for supplementary equipment dedicated to the registration process.

In this paper, we discuss the integration of the range data-based registration estimation technique in a 3-D space modeling framework and examine how the resulting models are influenced by the approximative registration estimates. The following sections present an overview of the occupancy modeling scheme and of the compact surface-based registration technique. Experimental results are then analyzed and the impact of registration on models is discussed.

## 2. Modeling scheme

The modeling strategy used to build 3-D occupancy models using range measurements is an extension of a technique introduced by Elfes for planar navigation maps in mobile robotics [7]. The extended version uses a closed-form approximation of the characteristic occupancy probability distribution function (OPDF) that was obtained in Elfes' approach [12]. When applied directly on range measurements, this approximated OPDF allows a direct computation of the occupancy probability $P(\rho, \theta)$ for a given cell in an occupancy grid while taking into account the Gaussian noise characteristics of the sensor.

$$P(\rho, \theta) = \frac{1}{2}\left(1 + e^{-\left(\frac{2((\rho - \bar{\rho}) + 2\sigma_\rho)}{\sigma_\rho} + \frac{(\theta - \bar{\theta})^2}{\sigma_\theta^2}\right)}\right) + \frac{3}{20}e^{-\left(\frac{(\rho - \bar{\rho})^2}{\sigma_\rho^2} + \frac{(\theta - \bar{\theta})^2}{\sigma_\theta^2}\right)} \quad (1)$$

where $(\sigma_\rho^2, \sigma_\theta^2)$ are the variances characterizing the sensor along each axis and $(\bar{\rho}, \bar{\theta})$ are the polar coordinates of the measurement provided by the sensor. The coefficients have been tuned on an experimental basis in order to reproduce the typical behavior of the Elfes' function computed with conditional probabilities while minimizing the model saturation.

A Bayesian merge is applied to combine probabilities when a given point of the environment is sampled more than once.

$$P[state(C_i) = occupied | P_1, P_2] = \frac{P_1 P_2}{P_1 P_2 + (1 - P_1)(1 - P_2)} \quad (2)$$

where $P_1$ and $P_2$ are the respective occupancy probabilities estimated for a given occupancy grid cell, $C_i$. As a result, the occupancy probability in the occupancy grid experiences a progressive evolution from the unknown state ($P(\rho, \theta)=0.5$) to a fully occupied state ($P(\rho, \theta)=1.0$) or to an empty state ($P(\rho, \theta)=0.0$) as supplementary consistent measurements are introduced in the model. Figure 1 illustrates the evolution of the occupancy probability distribution function in both directions as repetitive measurements are collected on a same point in space.

As a single line range sensor is used to collect measurements around a central viewpoint, the occupancy grid resulting from the application of eq. (1) is temporarily stored as a polar grid. Such a grid is obtained for each viewpoint visited by the sensor as shown in figure 2. In order to build the desired cubic model of the scene that will contain the entire set of probability distributions, these local polar grids must be merged into one global Cartesian occupancy grid of cubic shape. The merge of information relies on a search for intersections between cubic cells and polar cells while taking advantage of the multiresolution and recursive structure of the occupancy grid to avoid useless volume matching where no data had been gathered as shown in figure 3. Starting at the coarsest level of resolution of the Cartesian occupancy grid, the search is performed in a recursive and descending order in the cubic occupancy grid. When intersections are found, a merge between the occupancy probabilities contained in the respective grids is performed using Bayes theorem, eq. (2).

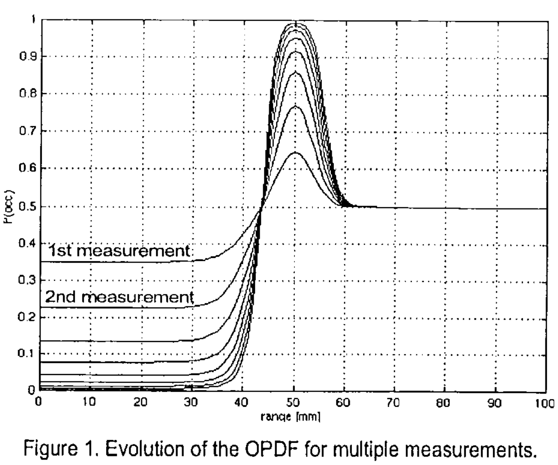



Figure 1. Evolution of the OPDF for multiple measurements.

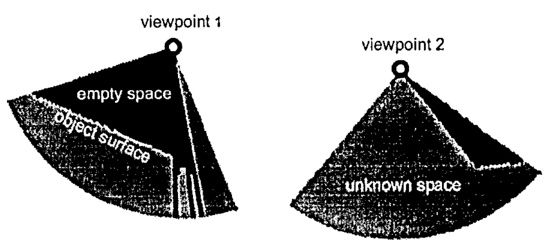



Figure 2. Set of spherical probabilistic occupancy grids.

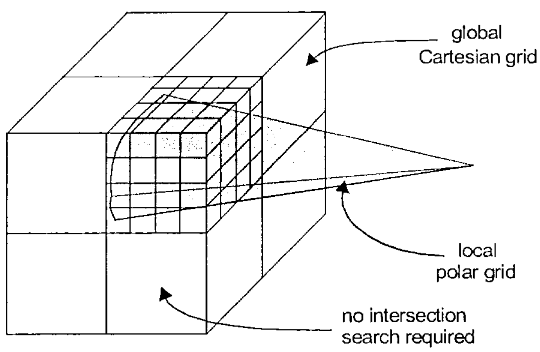



Figure 3. Intersection between spherical and cubic grids.

## 3. Integrated surface-based registration

The goal of the registration technique that has been developed in this work is to take advantage of the already available range measurements to estimate the change in position and orientation of the sensor between two successive viewpoints [4]. This way, no supplementary measurements need to be collected and no external devices are required thus keeping the necessary setup to a minimum and increasing its flexibility. Assuming that the model is to be built with respect to a reference frame that corresponds to the first viewpoint visited by the sensor, it is then possible to obtain an estimate of the relative position and orientation of the sensor in successive viewpoints. As these geometrical transformations can be estimated, it becomes possible to merge raw measurements in a coherent way when computing the 3-D occupancy virtual representation.

Another characteristic of the proposed registration estimation technique is its relative simplicity in comparison other approaches that rely on sophisticated features [2, 13]. Here, simple planar patches are defined to create a very compact surface representation for each set of range profiles (one for each viewpoint). Rather than manipulating thousands of point coordinates, only a small number of normal vectors and centroid points associated with each patch need to be considered. This results in a significant reduction of the computing time for registration estimation. This aspect is critical as most 3-D models used in robotic applications must be computed on-line and frequently updated to keep track of the evolution of the environment. Therefore, new viewpoints are continuously visited or revisited to provide up-to-date measurements.

The first step of the registration estimation process consists of segmenting each range profile to locate linear sections and to approximate them with straight line segments. These line segments provide an efficient way to merge neighbor profiles that show similar shapes into planar patches of various sizes. The normal vectors and the areas of these patches are then used to encode the surface representation as a modified Gauss sphere as shown in figure 4, where the length of a vector, $\vec{n}_i$, corresponds to the area of the corresponding patch.

Given two sets of scan lines respectively associated with two different viewpoints and encoded as Gauss spheres, rotation parameters are estimated by determining the appropriate rotation angles that make similar vectors on the respective spheres to overlap. The estimation of rotation is based on three non-degenerated sets of matching normal vectors, $\vec{n}_i$ and $\vec{n}_i'$, respectively extracted from the two compact representations of surfaces associated with two viewpoints between which a rotation, $R$, exists: $\vec{n}_1 = R\vec{n}_1'$, $\vec{n}_2 = R\vec{n}_2'$ and $\vec{n}_3 = R\vec{n}_3'$. The parameters of the rotation matrix can be estimated by solving the following set of equations for the $R_{rowi}$ vector:

$$\begin{bmatrix} [\vec{n}_1] \\ [\vec{n}_2] \\ [\vec{n}_3] \end{bmatrix} = \begin{bmatrix} [\vec{n}_1'] & 0 & 0 & [\vec{n}_2'] & 0 & 0 & [\vec{n}_3'] & 0 & 0 \\ 0 & [\vec{n}_1'] & 0 & 0 & [\vec{n}_2'] & 0 & 0 & [\vec{n}_3'] & 0 \\ 0 & 0 & [\vec{n}_1'] & 0 & 0 & [\vec{n}_2'] & 0 & 0 & [\vec{n}_3'] \end{bmatrix}^T \begin{bmatrix} [R_{row1}] \\ [R_{row2}] \\ [R_{row3}] \end{bmatrix} \quad (3)$$

where $[\alpha]$ are 3x1 vectors.

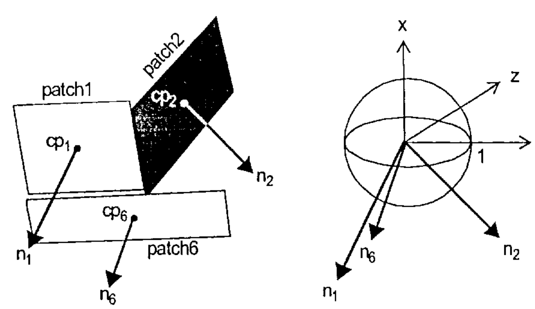



Figure 4. Compact representation of a surface.

Applying the resulting orthogonal rotation matrix to all other normal vectors in one Gauss sphere representation results in the overlap of these vectors on those of the other Gauss sphere associated with the second viewpoint.

Finally, the translation parameters associated with the two sets of scan lines, and therefore with the displacement of the sensor between viewpoints are estimated by computing the necessary shift of the patch centroids, $cp_i$, to make corresponding planar patches to match. The translation parameters are estimated as the translation along the reference axes between centroids associated with each surface patch. As many surface patches need to be matched, a good estimate of the translation parameters, $T$, is the weighted average (with respect to the area of patches) of the necessary displacement along each axis to superpose two different sets of center points:

$$T = \frac{1}{N}\sum_{i=1}^{N} Rcp_i' - cp_i \tag{4}$$

where $R$ is the rotation matrix previously estimated, $cp_i$ and $cp_i'$ are the corresponding centroids of the $i^{\text{th}}$ matched planar surfaces.

As many patches in the surface description might share the same orientation, the correct translation parameters are considered to those with a maximum number of correspondences, thus increasing the approach robustness.

## 4. Modeling with raw range data-based registration estimates

In order to evaluate the validity of the registration estimation technique, it has been applied to various sets of data collected with a range sensor from different viewpoints and 3-D models have been built for these scenes using the registration parameters provided by the estimator to define the displacement in position and orientation of the sensor between viewpoints. This section presents some experimental results that have been obtained following the integraton of the proposed registration and modeling schemes. The quality of the resulting models is compared with that of models of the same scene but built from the same range data with the exact registration information. The impact of the proposed approximative but efficient registration technique is estimated in terms of the model degradation originating from registration imprecisions.

The first experimental set consists of a typical computer setup illustrated in figure 5. This setup has been previously used to validate performances of the range data-based registration technique [4]. The raw data collected with a Jupiter range finder from three successive viewpoints have been initially processed to extract the geometrical transformation between each pair of viewpoints. Next, the same range measurements have been used with the 3-D probabilistic modeler along with the estimated registration parameters in order to create a virtual representation of the computer scene. The resulting model is presented in figure 6b from a front and a top perspective and compared with the corresponding model (figure 6a) built from the same set of range measurements but using exact registration parameters. Gray levels correspond to the probability of occupancy of each cell. The models shown are incomplete as only three viewpoints have been visited and do not allow a full coverage of such a complex scene.

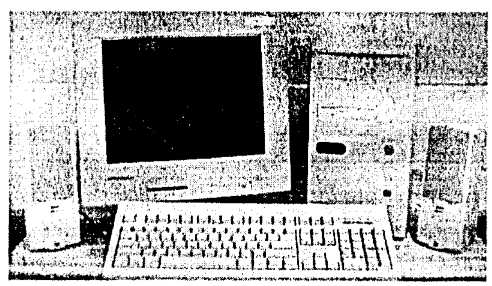
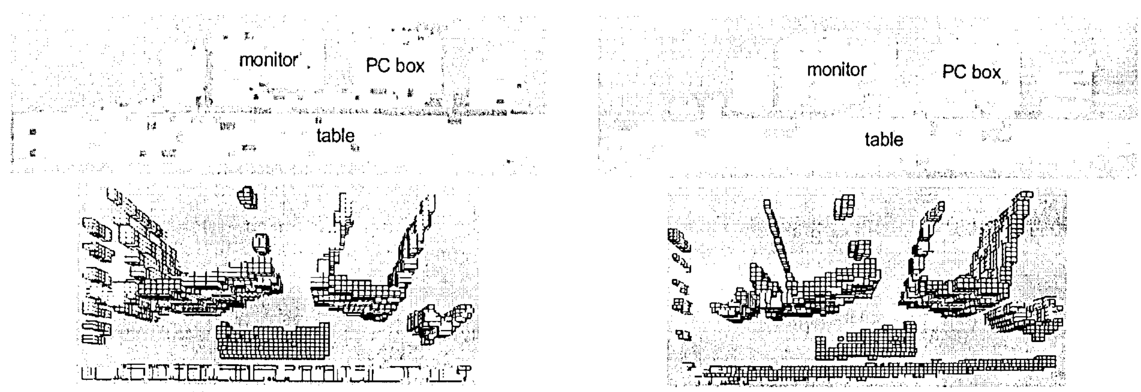


Figure 5. Scene of a computer setup.




a) With exact registration

b) With estimated registration from raw range data

Figure 6. Probabilistic models of the computer setup (front and top views).

A second set of experimental range measurements collected on a scene composed of the extremity of a pole in an electricity distribution network (figure 7) has been used to validate the registration approach. Here, the objective is to build a model of the structure of the pole in order to perform remote robotic tasks on a live electricity distribution network. Collision avoidance and localization of specific parts are then critical issues to prevent damages to the robotic system as well as to the pole structure.

As these tasks usually have to be performed in outdoor environments and within a relatively short period of time, it is not realistic to use sophisticated registration techniques to estimate the displacement of the sensor between viewpoints as this would constraint the operator and the equipment to remain in the same location for many hours before range data can be collected, placed in registration and combined in a 3-D virtual representation. Data collection and 3-D modeling being relatively efficient, the sensor pose estimation process remains the bottleneck in such applications. Therefore, an efficient, even though approximative, registration technique reveals to be of great interest. Figure 8a shows a probabilistic representation of the electricity pole scene for exact registration values while figure 8b illustrates the same scene modeled with the integrated range data-based registration approach. In this example, the raw range data have been generated from a range sensor simulator.

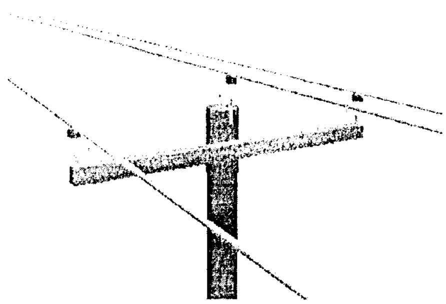
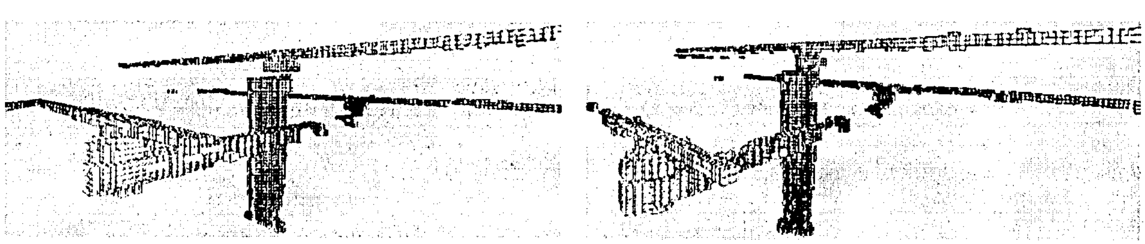


Figure 7. Top of an electricity distribution pole.

In both cases, we observe that the probabilistic model does not experience significant degradation in terms of the space occupied by the objects. For instance, in the first experimental setup the boundaries between occupied and empty space around the computer box, the monitor and the speaker are preserved. As a result, a path planner would not have difficulties finding empty space to make a robot circulate and avoid collisions. The same conclusion can be derived from the electricity distribution pole even though the size of the modeled area is significantly larger.

In terms of the probability of occupancy, we might notice a slight variation in the maximum probabilities. That is when an exact registration is performed the reinforcement process that results from the evolutive occupancy probability distribution function shown in figure 1 tends to associate a higher occupancy probability to the cells located on the surface of the objects. These cells then appear as brighter regions in figures 7 and 8. This phenomena is explained by the fact that are larger number of coherent measurements are assigned to the exact same cell during the modeling phase. If small registration errors occur, these measurements that should have been associated with a given cell in the occupancy grid might now be merged with neighbor ones. However, the fact that a probabilistic occupancy model is used allows to deal with such small uncertainties on the sensor position and orientation by automatically adjusting the occupancy probability for each cell of the grid. Such an adaptation would not be possible with discrete modeling approaches that only allow totally empty or totally occupied cells.

As the proposed registration and modeling schemes are dedicated to semi-autonomous robotic control, the resulting models should allow a path planner to select a safe way for the robot to move. They should also ensure reliable collision detection between objects and robotic equipment. This modeling technique is not dedicated to produce visually appealing representations. The experiments presented here demonstrate that the proposed compact surface-based registration technique provides a sufficient accuracy for 3-D modeling in the context of robot control. The fact that a full set of six registration parameters between two groups of about 300 scan lines can be estimated within a few seconds allows



a) With exact registration b) With estimated registration from raw range data

Figure 8. Probabilistic models of the electricity distribution pole.

autonomous 3-D modeling in applications where time is a critical issue. Up to now, most of the existing registration techniques require longer computation times thus preventing any use in live telerobotic systems where tasks are usually performed under the supervision of a human operator.

To control fine interactions between the robot end effector and objects in the scene, the proposed registration and modeling techniques can be used as the initial stage of a refinement process. The estimated registration parameters can then become the seeds of a matching algorithm to accelerate convergence between a limited set of features while the probabilistic modeling procedure can proceed with supplementary recursive subdivisions to generate a higher resolution occupancy grid.

# 5. Conclusion

The experimental results of 3-D modeling presented here demonstrate an approximative raw data and surface-based registration estimation technique allows to build 3-D occupancy models of a sufficient quality for robotic path planning and collision avoidance in a progressive refinement process where computing time is a critical issue. The occupancy models are not significantly degraded by the use of this approximative registration estimator as the characteristics of the occupancy probability distribution function allow to merge the uncertainty on the camera pose along with the noise model of the sensor. We can then conclude that the previously proposed registration estimation approach is adequate for numerous robotic applications where computing time is a critical issue. Moreover, as the same data set is used both for registration and for modeling, the proposed solution minimizes the number of data that need to be collected and merged. Meanwhile, the cost of the setup can be kept to a minimum as no external tracking devices are required. On the other hand, the resulting models are also of sufficient quality for a human operator to perform selection of optimal viewpoints to direct the range sensor towards the most critical regions that need to be scanned in order to increase the completeness of the representation or to refine some specific areas for fine interaction. The registration and the modeling processes can then be merged together to facilitate and speed up the building of a virtual representation which is required in various field of robotics.

# 6. References


[1] P. Besl, N. McKay, "A Method of Registration of 3-D Shapes", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no 2, Feb. 1992, pp. 239-256.

[2] R. Bergevin, D. Laurendeau, D. Poussart, "Registering Range Views of Multipart Objects", *Computer Vision and Image Understanding*, vol. 61, no 1, 1995, pp. 1-16.

[3] Y. Chen, G. Medioni, "Object Modeling by Registration of Multiple Range Images", *Image and Vision Computing*, vol. 10, no 3, 1992, pp. 145-155.

[4] C. Chen, P. Payeur, "Scan-Based Registration of Range Measurements", in *Proceedings of the IEEE Instrumentation and Measurement Technology Conference*, Anchorage, AK, May 2002, pp. 19-24.

[5] C. Chen, *Registration of Range Measurements with Compact Surface Representation*, M.Sc. thesis, University of Ottawa, Ottawa, ON, 2002.

[6] C. S. Chua, "3D Free-Form Surface Registration and Object Recognition", *International Journal of Computer Vision*, vol. 17, 1996, pp. 77-99.

[7] A. Elfes, *Occupancy Grids: A Probabilistic Framework for Robot Perception and Navigation*, Ph.D. thesis, Carnegie Mellon University, Pittsburgh, PA, 1989.

[8] M. K. Elstrom, P. W. Smith, "Stereo-Based Registration of Multi-Sensor Imagery for Enhanced Visualization of Remote Environments", in *Proceedings of the IEEE International Conference on Robotics and Automation*, Detroit, May 1999.

[9] D. F. Huber, "Automatic 3D Modeling Using Range Images Obtained from Unknown Viewpoints", in *Proceedings of the IEEE International Conference on 3-D Digital Imaging and Modeling*, Los Alamitos, CA, May 2001, pp. 153-160.

[10] T. Kanade, A. Yoshida, K. Oda, H. Kano, M. Tanaka, "A Stereo Machine for Video-Rate Dense Depth Mapping and its New Applications", in *Proceedings of the IEEE 15th Computer Vision and Pattern Recognition Conference*, San Francisco, CA, 1996.

[11] T. Masuda, N. Yokoya, "A Robust Method for Registration and Segmentation of Multiple Range Images", *Computer Vision and Image Understanding*, vol. 61, no 3, 1995, pp. 295-307.

[12] P. Payeur, C. M. Gosselin, D. Laurendeau, "Range Data Merging for Probabilistic Octree Modeling of 3-D Workspaces", in *Proceedings of the IEEE International Conference on Robotics and Automation*, vol. 4, Leuven, Belgium, May 1998, pp. 3071-3078.

[13] G. Roth, "Registering Two Overlapping Range Images", in *Proceedings of the 2nd International Conference on Recent Advances in 3-D Digital Imaging and Modeling*, Ottawa, Canada, 1999, pp. 191-200.

[14] M. Rioux, "Laser Rangefinders Based on Synchronized Scanning", *Applied Optics*, 23:3837-3844, 1985.