

# Improving Plane Extraction from 3D Data by Fusing Laser Data and Vision

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**Abstract**—The problem of extracting three-dimensional structures from data acquired with mobile robots has received considerable attention over the past years. Robots that are able to perceive their three-dimensional environment are envisioned to more robustly perform tasks like navigation, rescue, and manipulation. In this paper we present an approach that simultaneously uses color and range information to cluster 3d points into planar structures. Our current system also is able to calibrate the camera and the laser based on the remission values provided by the range scanner and the brightness of the pixels in the image. It has been implemented on a mobile robot equipped with a manipulator that carries a range scanner and a camera for acquiring colored range scans. Several experiments carried out on real data and in simulations demonstrate that our approach yields highly accurate results also in comparison with previous approaches.

## I. INTRODUCTION

To have an accurate three-dimensional model of the environment has been found to be an important precondition for various tasks such as rescue, manipulation and also obstacle avoidance. Furthermore, three-dimensional models also play a crucial role in the computer games industry. Over the past years, the topic of learning three-dimensional representations has received considerable attention including systems for acquiring city models [1], reconstruction of pieces of art [2], or other objects [3].

Most of the work presented so far operates mainly on single modalities like cameras [4], [5] or lasers [6], [7] to acquire 3d data. In combination both modalities have mostly been used to map color or texture information to the resulting models [6], [7], [8]. In this paper we present an approach to integrate vision and range information to learn accurate planar approximations to range data. The key idea of our algorithm is to simultaneously cluster the 3d points into planes based on both their position and their color. As a result, our algorithm learns more accurate models especially in situations in which planes have uniform colors. For scenarios, in which all planes have the same average color, our algorithm corresponds to the plane clustering approach presented in our previous work [9].

To realize the advantages of a color-based plane extraction algorithm consider a situation in which the robot scans a desk with several colored objects on top of it. Without any color information, the robot will encounter a high data association uncertainty for the 3d points at the border between the table top and the objects. In such a situation, the color information can reduce the ambiguity in the data association so that the resulting plane parameters are more accurate.

In order to achieve the color-based clustering of range data into planes, the camera and the range scanner need to be calibrated. Without accurate calibration, we would assign wrong colors to the data points which then in turn would decrease the performance of the clustering process. To calibrate the laser and the camera, our system automatically computes the corresponding parameters by comparing the image data with the remission values provided by the laser range scanner.

This paper is organized as follows. In the following section we describe our approach for clustering data points into planes using range and color information. In Section III we describe our algorithm to calibrate the laser range finder and the camera based on color information and the remission values from the laser. Section IV presents our approach to extract colored planes from the range data. In Section V we then present experimental results obtained from simulated and real data sets.

## II. RELATED WORK

In the past, cameras were the main source of information to acquire 3D point estimates by matching correspondences between images. Nowadays, more and more groups are using range scanners for acquiring three-dimensional models. For example, range scanners have been used to extract architectural objects, such as buildings [8], indoor environments [7] and even cities [1]. Additionally, several authors have studied the problem of creating high-resolution models of pieces of art like the Michelangelo statue [2] or from excavation sites [3]. In these approaches the major focus lies on the question of data acquisition and registration of the individual

scans. Color information is typically mapped onto the resulting models after creating the three-dimensional structures.

To create models several scans have to be fused, and hence the scanning device has to be moved. Two different scenarios are possible now: Either the position of the scanner is known and the problem is solved, or the scanner position has to be estimated, which is what commonly is called *registration*. There has been some work on incorporating color information during the registration, such as the color ICP [4] or by incorporating illuminance and gradient information [5]. Both of these approaches estimate the registration from images only.

In this paper, we propose an approach to extract planar structures from range data by fusing color information with the laser data. The problem of extracting planes from range data has previously been considered by Liu et al. [6] as well as Martin and Thrun [10], who apply the EM algorithm for clustering the range data into planar structures. This approach recently has been extended by Triebel et al. [9] who use a hierarchical model to additionally consider main directions of the planes. In the work proposed here we also use the hierarchical model for plane extraction but additionally consider the color of the individual data points. This way we can more reliably distinguish between data points belonging to a plane and data points belonging to objects close to the planar structure.

To the best of our knowledge, the problem of integrating 3D laser data with color information during the extraction of structure has not been studied in depth. Several approaches use the camera information only for mapping textures onto already extracted models [6], [1], [3], [2]. An attempt to actually combine laser and vision information is the work carried out by Yoshida and Saito [11] who use texture information around each scan point to select corresponding points for the registration of two scans.

The algorithm described in this paper differs from the techniques described above in that it simultaneously uses both the laser data and the vision for the extraction of planes. It is an extension of our previous work [9] and uses a hierarchical version of the popular expectation maximization (EM) algorithm.

### III. CALIBRATION

To be able to fuse color information with laser data the scanner and the camera have to be calibrated simultaneously, i.e., we have to estimate the mapping of scan points to camera images. Under the assumption that  $\mathbf{h}$  specifies the vector of intrinsic parameters of the camera, the external parameters we are interested in are the three Euler angles  $\varphi$ ,  $\vartheta$ , and  $\psi$  and the translation  $\mathbf{t} = (t_x, t_y, t_z)^T$ .

In principle, there are several ways to calibrate the camera and the laser. One approach might be to extract features from both modalities and to estimate these six parameters so as

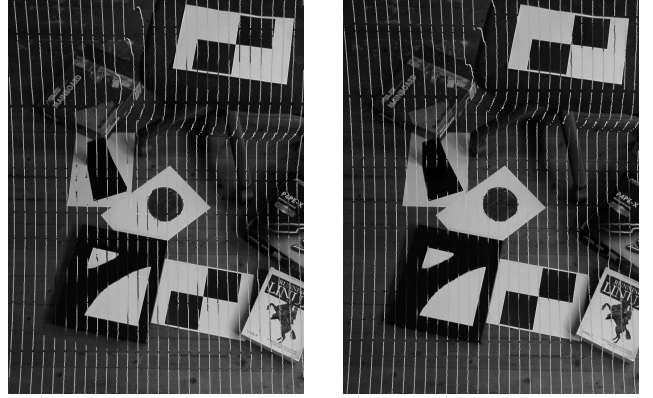


Fig. 1. The intensity values from a camera image with the collected remission data superimposed. The horizontal scan resolution was 1 degree. The vertical resolution depends on the speed of the tilting joints and lies usually around 0.2 degrees. **Left:** Raw estimates have been used for the extrinsic parameters in the mapping function. We can see that the remission values do not match the image intensities in many areas. **Right:** Result after calibration. The errors in the mapping have been drastically reduced, for example in the region of the black circle.

to best align the extracted features. For example, Pervölz et al. [7] use a checker board to find the correspondence between the corners in the image and the 3D position from the board. Liu and Stamos [12] extract lines from remission scans and the intensity images to match regions. In our system we apply a featureless approach. Empirical studies have shown that the remission value (the strength of the reflected laser-beam, also called reflectance value) and the illuminance from the camera are correlated. Typically, dark areas tend to give lower remission values than bright ones (see also the work by Lamond and Watson [13]). This correlation is not strong since the remission values also depend on the type of the material that reflects the beam. A bright, non-reflecting material may have a lower remission value than a dark highly reflecting one.

If we denote the remission value of a scan point as  $\rho$  and the RGB color vector of a given pixel as  $\mathbf{c} = (r, g, b)$ , we can define the distance between  $\rho$  and  $\mathbf{c}$  as follows:

$$d(\rho, \mathbf{c}) = \left| \frac{r + g + b}{3} - \rho \right|. \quad (1)$$

Let  $f(\mathbf{s}_n; \varphi, \vartheta, \psi, \mathbf{t}, \mathbf{h})$  be the non-linear mapping of a scan-point  $\mathbf{s}_n \in \mathbb{R}^3$  to a point  $\mathbf{y}_n \in \mathbb{R}^2$  in the image plane. The overall distance between an image  $I$  and a complete scan  $S = \{(\mathbf{s}_n, \rho_n) \mid n = 1, \dots, N\}$  consisting of  $N$  scan points is then calculated as:

$$d(I, S)^2 = \sum_{n=1}^N d(\rho_n, \mathcal{I}(\mathbf{y}_n))^2, \quad (2)$$

where  $\mathbf{y}_n = f(\mathbf{s}_n; \varphi, \vartheta, \psi, \mathbf{t}, \mathbf{h})$  and  $\mathcal{I}(\mathbf{y}_n)$  is the intensity of the image at position  $\mathbf{y}_n$ . In the case that  $\mathbf{y}_n$  is outside the image borders, we use the expected distance between remission and

intensity values. To minimize (2), we use the Levenberg-Marquardt method [14], which combines steepest descent with the Newton method.

Since the calibration does not require any special objects or special features it can be carried out for every scan, this way improving the calibration parameters over time. As already mentioned above, the calibration may fail if the correlation with the illuminance and the remission values is not strong enough. To detect calibration failures, we specify a bounding box around the current estimate. If any parameter value lies outside the allowed interval the calibration is considered to have failed and the previous calibration values are used.

#### IV. EXTRACTION OF COLOR PLANES

##### A. The Probabilistic Model

Suppose we are given a set  $\{\mathbf{s}_n\}$  of  $N$  scan points. After calibration between camera and scanner we can assign a color vector  $\mathbf{c}_n$  to each  $\mathbf{s}_n$ . In the following, we will denote the pair  $(\mathbf{s}_n, \mathbf{c}_n)$  as the *measurement*  $\mathbf{z}_n$ . The set of all measurements will be denoted by  $Z$ . The goal now is to cluster these measurements into a set  $\Theta = \{\theta_m\}$  of  $M$  planes and, simultaneously, to cluster the planes into  $K$  main directions  $\Phi = \{\phi_k\}$ . As in standard EM formulation, we define a set  $A = \{\alpha_{nm}\}$  of correspondence variables between measurements and planes, and likewise a set  $B = \{\beta_{mk}\}$  of correspondences between planes and main directions. The correspondences  $\alpha_{nm}$  and  $\beta_{mk}$  are represented as binary variables. For example,  $\alpha_{nm} = 1$  means that measurement  $\mathbf{z}_n$  is assigned to plane  $\theta_m$ .

In addition to the approach presented in [9], we assume in this paper a *surface color*  $\bar{\mathbf{c}}_m$  assigned to each plane  $\theta_m$ . This means that  $\theta_m$  is represented as a 3-tuple  $(\mathbf{n}_m, d_m, \bar{\mathbf{c}}_m)$  consisting of the normal vector  $\mathbf{n}_m$ , the distance  $d_m$  to the origin and the color  $\bar{\mathbf{c}}_m$ . All three parameters will be estimated during the maximum likelihood estimation process, together with the main directions  $\phi_k$ . Here,  $\phi_k$  is represented as a unit vector in  $\mathbb{R}^3$ .

In order to calculate the probability that a measurement corresponds to a plane, we first need to define an appropriate distance measure. In our application, where color information is added to planes and scan points, this distance measure consists of a *geometrical* part  $d_1$  and a *visual* part  $d_2$ :

$$d_1(\mathbf{z}_n, \theta_m) = \mathbf{s}_n \cdot \mathbf{n}_m - d_m \quad (3)$$

$$d_2(\mathbf{z}_n, \theta_m) = \|\mathbf{c}_n - \bar{\mathbf{c}}_m\|. \quad (4)$$

If we assume that both the geometrical and the visual assignments between scan points and planes underlie a Gaussian error with variances  $\sigma_1$  and  $\sigma_2$  respectively, we can write:

$$p(\mathbf{z}_n | \theta_m) = \eta \exp\left\{-\frac{1}{2}\left(\frac{d_1(\mathbf{z}_n, \theta_m)^2}{\sigma_1^2} + \frac{d_2(\mathbf{z}_n, \theta_m)^2}{\sigma_2^2}\right)\right\} \quad (5)$$

Here,  $\eta = (2\pi\sigma_1\sigma_2)^{-1}$  is the normalization factor that stems from the two independent Gaussian distributions. In our

maximum likelihood estimation process described below this constant has no influence in the maximization step, so that we can neglect it in the following.

If we incorporate the correspondence variables  $\alpha_{nm}$ , assuming that they are uniformly distributed, we obtain

$$p(Z, A | \Theta) \propto \exp\left\{-\frac{1}{2} \sum_n \sum_m \alpha_{nm} \left(\frac{d_1(\mathbf{z}_n, \theta_m)^2}{\sigma_1^2} + \frac{d_2(\mathbf{z}_n, \theta_m)^2}{\sigma_2^2}\right)\right\}. \quad (6)$$

Similarly, we define a distance measure  $d_3$  between planes and main directions

$$d_3(\theta_m, \phi_k) = \sqrt{1 - (\mathbf{n}_m \cdot \phi_k)^2} \quad (7)$$

and use this quantity to compute the probability of a set  $\Theta$  of planes and the correspondences  $B$  for a given set  $\Phi$  of main directions in the following way:

$$p(\Theta, B | \Phi) \propto \exp\left\{-\frac{1}{2} \sum_m \sum_k \beta_{mk} \frac{d_3(\theta_m, \phi_k)^2}{\sigma_3^2}\right\} \quad (8)$$

Again, we assume a Gaussian error with variance  $\sigma_3$ . Using the independence of the variables, the joint posterior can be calculated as [15]

$$\begin{aligned} p(A, B, \Phi, \Theta, Z) &\propto p(Z | A, \Theta)p(\Theta | B, \Phi) \\ &\propto p(Z, A | \Theta)p(\Theta, B | \Phi). \end{aligned} \quad (9)$$

##### B. Expectation Maximization (EM)

To maximize the likelihood of the data  $Z$  the EM algorithm is applied. EM iteratively maximizes the expected log likelihood of the data and the model. That is, in each iteration step  $i$  we take the current estimate of the model parameters  $(\Theta^{[i]}, \Phi^{[i]})$  to compute a new model  $(\Theta^{[i+1]}, \Phi^{[i+1]})$  that maximizes the logarithm of the overall likelihood

$$\begin{aligned} (\Theta^{[i+1]}, \Phi^{[i+1]}) &= \\ \arg \max_{(\Theta, \Phi)} E_{AB}[\log p(A, B, \Phi, \Theta, Z) | \Theta^{[i]}, \Phi^{[i]}]. \end{aligned} \quad (10)$$

If we insert (6) and (8) into (9) and the result into (10) we obtain

$$\begin{aligned} (\Theta^{[i+1]}, \Phi^{[i+1]}) &= \arg \max_{(\Theta, \Phi)} \\ &- \sum_{nm} E[\alpha_{nm} | \Theta^{[i]}] \left(\frac{d_1(\mathbf{z}_n, \theta_m)^2}{\sigma_1^2} + \frac{d_2(\mathbf{z}_n, \theta_m)^2}{\sigma_2^2}\right) \\ &- \sum_{mk} E[\beta_{mk} | \Phi^{[i]}] \frac{d_3(\theta_m, \phi_k)^2}{\sigma_3^2}. \end{aligned} \quad (11)$$

Here we used the fact that the expectation operator is linear and that it needs to be computed only over all possible values for the hidden variables  $\alpha_{nm}$  and  $\beta_{mk}$ .



Fig. 2. The mobile robot Zora used for the experiments described in this paper. The robot carries a color CCD camera and SICK LMS range scanner mounted on top of a 4DOF AMTEC arm for flexible colored 3d scanning.

In the E-step the expectations  $E[\alpha_{nm} | \Theta]$  and  $E[\beta_{mk} | \Phi]$  need to be computed. Taking into account that  $\alpha_{nm}$  and  $\beta_{mk}$  are binary, we can write

$$\begin{aligned} E[\alpha_{nm} | \Theta] &= \frac{p(\alpha_{nm} | \mathbf{z}_n, \Theta)}{p(\mathbf{z}_n | \Theta)} \\ &= \frac{p(\mathbf{z}_n | \alpha_{nm}, \Theta)p(\alpha_{nm} | \Theta)}{p(\mathbf{z}_n | \Theta)} \\ &= \frac{\exp\left\{-\frac{1}{2}\left(\frac{d_1(\mathbf{z}_n, \theta_m)^2}{\sigma_1^2} + \frac{d_2(\mathbf{z}_n, \theta_m)^2}{\sigma_2^2}\right)\right\}}{\sum_j \exp\left\{-\frac{1}{2}\left(\frac{d_1(\mathbf{z}_n, \theta_j)^2}{\sigma_1^2} + \frac{d_2(\mathbf{z}_n, \theta_j)^2}{\sigma_2^2}\right)\right\}}. \end{aligned}$$

In a similar way we can calculate  $E[\beta_{mk} | \Phi]$ .

In the M-Step we compute the new model parameters  $\Theta$  and  $\Phi$  so that the log likelihood function in Equation (11) is maximized. To determine the geometric parameters we apply the Fletcher-Reeves conjugate gradient algorithm. The visual parameters are calculated as the mean of the color vectors  $\mathbf{c}_n$  weighted by their assignment probabilities.

### C. Estimating the Model Complexity

To determine the appropriate number  $M$  of planes and  $K$  of main directions we apply the Bayesian Information Criterion (BIC)

$$BIC = -2L + (6M + 2K) \ln(N). \quad (12)$$

Here  $L$  is the logarithm of the overall likelihood. The goal is to find a model with the smallest BIC value. Whenever we introduce a new plane, we draw a point from  $Z$ , with a probability proportional to the average distance

$$\sum_{m=1}^M d_1(\mathbf{z}_n, \theta_m) + d_2(\mathbf{z}_n, \theta_m) \quad (13)$$

from the current model. Thus, points which do not have proper explanation according to the current model are selected with higher probability. Note that we also take into



Fig. 3. Data recorded with the mobile robot Zora in a corridor environment at CS Department in Freiburg. The whole data set, which consists of 2,159,137 points has been registered using the ICP algorithm. Note the highly accurate color labeling of the individual 3d points, which is due to our calibration algorithm.

account the plane colors in this function. Thus, points whose color differs from that of a neighboring plane are also selected with high likelihood.

## V. EXPERIMENTAL RESULTS

The algorithm described above has been implemented and intensively tested using data collected with our mobile robot Zora (see Figure 2). Zora is a B21r robot equipped with a 4DOF AMTEC manipulator which carries a SICK LMS range scanner. In addition it carries a camera so that we can acquire color information for the individual three-dimensional range data. To carry out the experiments described below, we relied on an accurate calibration obtained with the algorithm presented in Section III. The goal of the experiments described below is to demonstrate that our algorithm can reliably extract planar models from colored range data. We also illustrate that the combination of range and color information yields more accurate results than can be obtained with previous approaches relying solely on range data.

### A. Real World Experiment

The first experiment described in this section has been carried out in a 20m long and 2m wide corridor of building 78 at the University of Freiburg. This corridor contains four doors, from which one is blue and the other three are yellow. The data set consists of 72 scans, which were taken at eight different positions each approximately 2m apart. The need for taking 9 scans at each position is due to the limited opening angle camera. To register the individual scans we applied the iterative closest point (ICP) [16] algorithm. After the alignment we only stored those 3d-points for which color

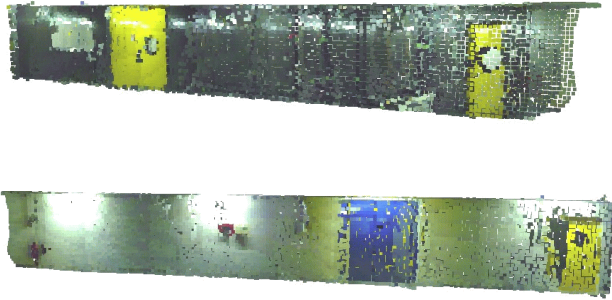


Fig. 4. Front and back-side view of the corridor data shown in Figure 3.

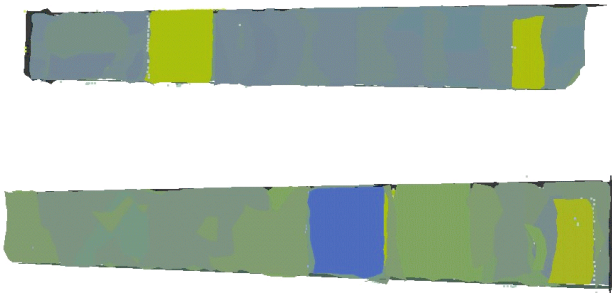


Fig. 5. The corridor after plane extraction (front- and back-side). Note that the doors have nicely been extracted although their displacement relative to the wall is between 6 and 25cm only.

information was available. We furthermore sample the model down to reduce its complexity.

Figure 3 shows a three-dimensional visualization of the corresponding data. In this figure the view-point of the camera lies inside the corridor. Two virtual views from the outside are depicted in Figure 4. Note that the resulting data pose high challenges for color-based plane extraction. Many surfaces in this corridor are rather shiny, so that many data points have wrong colors. For example, there were several reflections of doors and lights in data points belonging to the floor, the ceiling, and the walls.

Figure 5 depicts the model obtained with our color-based plane extraction algorithm. Shown are two side-views corresponding to the two views shown in Figure 4. As can be seen from the figure the four doors, which have an indentation of 6, 14, 23, and 25cm from the four walls, have correctly been extracted from the range data. Note that this model shows yellowish planes close to the blue door. These planes have been added due to the reflections of the yellow door on the other side of this corridor. Furthermore, our current algorithm to extract polygons from the data cannot handle



Fig. 6. A blue jacket lying on a desk. Photograph of the scene (left) and 3D scan acquired with Zora (right)

holes in surfaces so that the round windows in the doors are not visible in the resulting model.

We additionally carried out a series of experiments with a plane clustering algorithm that does not utilize the color information. Thereby we tried to identify the optimal value for the geometric variance parameter  $\sigma_1$  so that EM learns a model with individual planes for all four doors. In all our experiments we could not find such a value. Whereas too small values for  $\sigma_1$  result in a huge number of planes, whereas larger values for  $\sigma_1$  yield models with appropriately many planes but typically with one or even more doors missing.

### B. Quantitative Comparison to Non-Color-Based Clustering

The second experiment is designed to illustrate that our color-based plane clustering approach yields more accurate results than an approach relying on range data only. In this particular experiment we placed a blue jacket on top of a desk and generated one scan with Zora. The corresponding situation in combination with the acquired scan is depicted in Figure 6. Additionally we scanned the table without the jacket from which we determined an accurate estimate of the parameters of the table top. The errors in the height of the plane reduces from 5.9cm for the non-color-based approach to 1.3cm. Simultaneously our algorithm reduces the angular deviation from 4.4 degrees to 3.1 degrees.

### C. Simulation Experiments

To evaluate the performance of our algorithm with respect to the ground truth, we created an artificial 3d environment which allows us to simulate colored three-dimensional range scans. The scene used for the experiment described here is depicted in Figure 7. It represents a room with several planar structures of different colors, sizes, and orientations. The planar structures used for the quantitative evaluation are also labeled in this figure.

Table I shows the angular deviations of the plane normals from the ground truth for eight different planes. Note that the planes  $\theta_2$ ,  $\theta_3$ , and  $\theta_5$  have not been found without taking

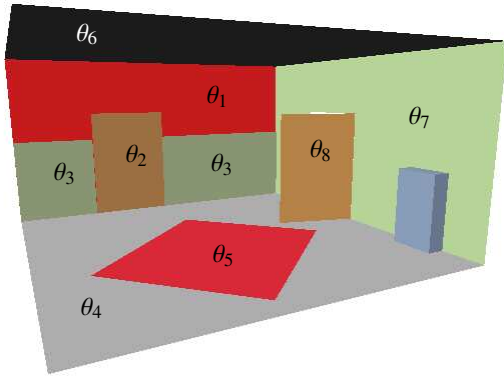


Fig. 7. Artificial environment used for simulation experiments.

TABLE I  
ANGULAR DEVIATIONS FROM THE GROUND TRUTH IN DEGREES

Plane	non-color based	color based
$\theta_1$	1.97	0.25
$\theta_2$	—	0.54
$\theta_3$	—	0.49
$\theta_4$	0.13	0.11
$\theta_5$	—	0.12
$\theta_6$	0.15	0.08
$\theta_7$	0.28	0.25
$\theta_8$	0.22	0.06

into account the color information. For all other planes the estimates obtained with our color-based approach were closer to the ground truth. Without the color information the EM cannot distinguish between data points belonging to different objects. For example, the surface of the carpet lies slightly above the floor. The standard approach cannot distinguish between the two point sets and usually clusters them into a single plane. Our color-based algorithm, however, generates two different planes with more accurate parameters. Whereas the height of the plane for the floor deviates from the ground truth only by 2mm, the error in the height of the plane corresponding to the carpet is zero. The non-color-based version, in contrast, generates only one plane with a distance of 5mm to both objects. Here the height difference was determined as the distance of the plane to the center of the rectangle corresponding to the floor.

## VI. CONCLUSIONS

In this paper we presented an approach to fuse color and range information for the extraction of planar structures from three-dimensional data. Our approach simultaneously takes into account the geometric properties and the associated colors of the scan points when clustering the data into planes. As a result we obtain more accurate approximations of range data by planes. We also presented an approach to automatically calibrate the camera-laser-system. This is

achieved by matching the intensities in the camera image with the remission information from the laser range scanner. The improvement of fusing both color and 3D information to extract plane have been shown in various experiments, both using real and simulated data. The results shows that by incorporating color information, more accurate planar models are obtained, especially in situations in which planes have small offsets or when objects are close to the planar structures.

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## REFERENCES

- [1] C. Früh and A. Zakhor, "An automated method for large-scale, ground-based city model acquisition," *International Journal of Computer Vision*, vol. 60, pp. 5–24, October 2004.
- [2] M. Levoy, K. Pulli, B. Curless, S. Rusinkiewicz, D. Koller, L. Pereira, M. Ginzton, S. Anderson, J. Davis, J. Ginsberg, J. Shade, and D. Fulk, "The digital michelangelo project: 3D scanning of large statues," in *Siggraph 2000, Computer Graphics Proceedings*.
- [3] P. D. Lyons, M. Rioux, and R. T. Patterson, "Application of a three-dimensional color laser scanner to paleontology: an interactive model of a juvenile tylosaurus sp. basisphenoid-basioccipital," in *Palaeontologia Electronica*, vol. 3, 2000.
- [4] A. Johnson and S. B. Kang, "Registration and integration of textured 3-d data," Cambridge Research Lab, Tech. Rep. CRL96/4, 1996.
- [5] S. Weik, "Registration of 3-d partial surface models using luminance and depth information," in *International Conference on Recent Advances in 3-D Digital Imaging and Modeling (3DIM '97)*, May 1997.
- [6] Y. Liu, R. Emery, D. Chakrabarti, W. Burgard, and S. Thrun, "Using EM to learn 3D models of indoor environments with mobile robots," in *Proc. 18th International Conf. on Machine Learning*. Morgan Kaufmann, San Francisco, CA, 2001, pp. 329–336.
- [7] K. Pervölz, A. Nüchter, H. Surmann, and J. Hertzberg, "Automatic reconstruction of colored 3d models," in *Proc. Robotik 2004*, 2004.
- [8] P. Allen, I. Stamos, A. Gueorguiev, E. Gold, and P. Blaeer, "Avenue: Automated site modeling in urban environments," in *Proc. of 3rd Conference on Digital Imaging and Modeling in Quebec City, Canada*, May 2001, pp. 357–364.
- [9] R. Triebel, W. Burgard, and F. Dellaert, "Using hierarchical EM to extract planes from 3d range scans," in *Proc. of the International Conference on Robotics and Automation (ICRA)*, 2005, to appear.
- [10] C. Martin and S. Thrun, "Online acquisition of compact volumetric maps with mobile robots," in *Proc. of the International Conference on Robotics and Automation (ICRA)*, 2002.
- [11] K. Yoshida and H. Saito, "Registration of range images using texture of high-resolution color images," in *IAPR Workshop on Machine Vision Application (MVA02)*, December 2002.
- [12] L. Liu and I. Stamos, "Automatic 3d to 2d registration for the photorealistic rendering of urban scenes," 2005, submitted.
- [13] B. Lamond and G. Watson, "Hybrid rendering - a new integration of photogrammetry and laser scanning for image based rendering," in *Proc. of Theory and Practice of Computer Graphics (TPCG)*, 2004.
- [14] D. Marquardt, "Algorithm for least-square estimation of non-linear parameters," *Journal of the SIAM*, vol. 11, pp. 431–441, 1963.
- [15] D. Anguelov, R. Biswas, D. Koller, B. Limketkai, S. Sanner, and S. Thrun, "Learning hierarchical object maps of non-stationary environments with mobile robots," in *Proc. of the 17th Annual Conference on Uncertainty in AI (UAI)*, 2002.
- [16] P. Besl and N. McKay, "A method for registration of 3-d shapes," in *IEEE Trans. on Pattern Analysis and Machine Intelligence (PAMI)*, 1992.