Increasing the precision of reconstructed 3D model of indoor robot environment by elimination of problematic points [1]

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Abstract: In the process of reconstructing the 3D environment from the point cloud acquired from 3D laser the main objective is to obtain the model that is as precise as possible. Reconstruction algorithms greatly rely on the input data precision. Unfortunately, the point clouds regularly contains points that are problematic for the reconstruction. They are mostly associated with the reflection of laser beams off the semi–transparent surfaces, e.g. windows. This paper proposes the method for eliminating such points based on K–means clustering in order to increase the accuracy of the reconstructed 3D model.

Keywords: 3D modeling, surface reconstruction, point cloud, clustering, visualization

1. INTRODUCTION

In recent years a lot of work has been done to improve the virtual model of environment in general. When it comes to indoor environment 3D models the precision and interactivity are required in order to provide good user experience.

Laser scans of the indoor environment are mainly represented by point clouds (RIEGL Laser Measurement Systems, 2010; 3dtk Webpage, 2012). However, this is not the best way of representation of virtual model of environment. People working with virtual models either for analyses of inspection encounter major problems if it's represented by point cloud. This lies in the fact that people tend to perceive better surfaces (or meshes) without holes, therefore the point cloud just doesn't have the required *resolution* for the human eye (Yan et al., 2008).

This paper deals with the problem of precision in reconstruction of 3D model of indoor environment. The main requirement for the reconstructed model is to precisely presents the indoor environment, i.e. walls must be flat with right dimensions, furniture and people must be recognizable in the model etc. Several factors influence precision of the model (Oude Elberink and Vosselman, 2011; Crosilla et al., 2002):

- Uncertainties in the laser scanning due to non–stationarity of the mobile platform, laser scanner and the environment
- Points that are recorded by scanning the semi–transparent surfaces

The first factor that influences precision is inherent and mostly dealt with during the process of acquiring the point cloud of indoor environment (Borrmann et al., 2008; Thrun et al., 1997). This partially eliminates the problem that uncertainties and false registration cause in the reconstruction process. The second factor cannot be eliminated during the process of acquiring the data and requires post–processing.

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Up to our knowledge no method for eliminating the problematic points, recorded by scanning the semi–transparent surfaces, in order to raise the point cloud density and the reconstructed model's overall accuracy is presented.

In this paper we introduce the procedure for removing the problematic points contained in the point cloud due to scanning of the transparent and the semi–transparent surfaces. Section 2 analyses this problem and proposes the procedure we further explain in section 3. Finally, the results of the procedure are presented in section 4 and we compare the reconstructed model precision before and after eliminating the problematic points. Section 5 concludes the paper.

2. ANALYSIS OF THE PROBLEM

In this section we will analyse the problem of the problematic points in the recorded point cloud. As stated before, these points mainly appear when laser beam reflects off a semi–transparent surfaces. Due to physical properties of light and such medium one part of the light beam will pass through the surface and another part will reflect back to the laser scanner. In this situation we assume that the light energy absorbed by such surface is negligible.

Typical situation with described phenomenon is represented in Figure 1. As it is presented in the image, valid data is marked with green rectangle while invalid data with red rectangle. This is due to light beam reflecting off a semi–transparent surface, in this case a window marked with red on the second image. Desirable outcome is the removal of points marked with red rectangle while the ones marked with green will be considered during the reconstruction of 3D model.

In the next section we will describe the methodology applied for the given task of the removal of problematic and undesirable points in the point cloud in terms of the model reconstruction.

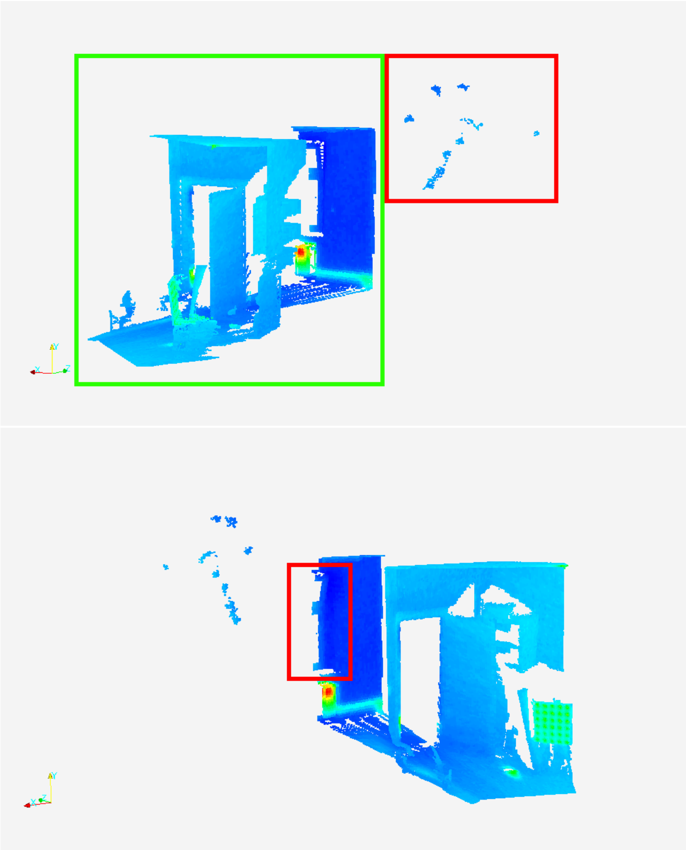

Fig. 1. Point cloud of a scene with window as semi–transparent surface and artifacts behind window acquired by laser scanner; Green rectangle represents valid data while red rectangle represents invalid; Window is marked with red rectangle on the second image

3. METHODOLOGY

In this section we will present the simple methodology for the removal of the undesirable points in the point cloud. This is a typical point cloud segmentation problem where we need to segment the point cloud into several smaller parts. Several methods dealing with the problem of point cloud segmentation emerged in recent years. In the paper (Golovinskiy and Funkhouser, 2009) author describes the method based on local connectivity to successfully segment the objects from the point cloud. (Dorninger and Nothegger, 2004) presents a method for segmentation of buildings using the decomposition into planes and distance measurement. Other papers use constrained surface normals estimation based methods for point cloud segmentation (Castillo and Zhao, 2009; Rabbani et al., 2006).

This task is somewhat easier as we can only base our segmentation on the connectivity of the point cloud without applying extensive procedure. We base this on the assumption that valid points and invalid points will be somewhat distant from each other. This eliminates the need for time and resource consuming segmentation algorithms.

To accomplish this task we propose the method of K–means clustering for the point cloud segmentation in order to eliminate the points problematic for the reconstruction of 3D model.

Algorithm 1 K–Means clustering pseudo code

Require: Input 3D point cloud
Initialize: Set K means to random values
repeat
  Assignment: Assign every point to a nearest cluster center
  Update: The model parameters, the means, are adjusted to match the sample means of the data points that they are responsible for according to equation 2
until the assignments don't change

3.1 K–means clustering

The K–means algorithm is an algorithm for putting N data points in an I–dimensional space into K clusters. Each cluster is parameterized by a vector $\mathbf{m}^{(k)}$ called its mean.

The algorithm starts by initializing the K means $\mathbf{m}^{(k)}$ to some random value (although other implementations don't use random numbers for initial values). Then we repeat two iterations. In the *Assignment step* each point is assigned to its nearest mean by calculating the Euclidean distance between the cluster center and the given point:

$$\hat{\mathbf{k}}^{(n)} = \underset{k}{argmin}\left\{d\left(\mathbf{m}^{(k)}, \mathbf{x}^{(n)}\right)\right\} \quad (1)$$

We denote our guess for the cluster $\mathbf{k}^{(n)}$ that the point $\mathbf{x}^{(n)}$ belongs to by $\hat{\mathbf{k}}^{(n)}$. An alternative, equivalent representation of this assignment of points to clusters is given by *responsibilities*, which are indicator variables $\mathbf{r}_k^{(n)}$. In the assignment step, we set $\mathbf{r}_k^{(n)}$ to one if mean k is the closest mean to datapoint $\mathbf{x}^{(n)}$; otherwise $\mathbf{r}_k^{(n)}$ is zero (Mackay, 2003).

In the *update step* we calculate the new means to be the centroid of the observations in the cluster. This is done by:

$$\mathbf{m}^{(k)} = \frac{\sum_n \mathbf{r}_k^{(n)} \mathbf{x}^{(n)}}{R^{(k)}} \quad (2)$$

where $R^{(k)}$ is the total *responsibility* of mean k:

$$R^{(k)} = \sum_n \mathbf{r}_k^{(n)} \quad (3)$$

Pseudo code of K–means clustering algorithm is given in Algorithm 1.

This is the description of the algorithm for segmenting the point cloud in order to eliminate the undesirable points. In the next section we present the results of the segmentation of the point cloud as well as the improved model reconstruction results.

4. RESULTS

In this section we will present the results of the process of elimination of the points problematic for the reconstruction of 3D model of indoor environment. After presenting results we will also discuss the implication the procedure has on the actual 3D model reconstruction.

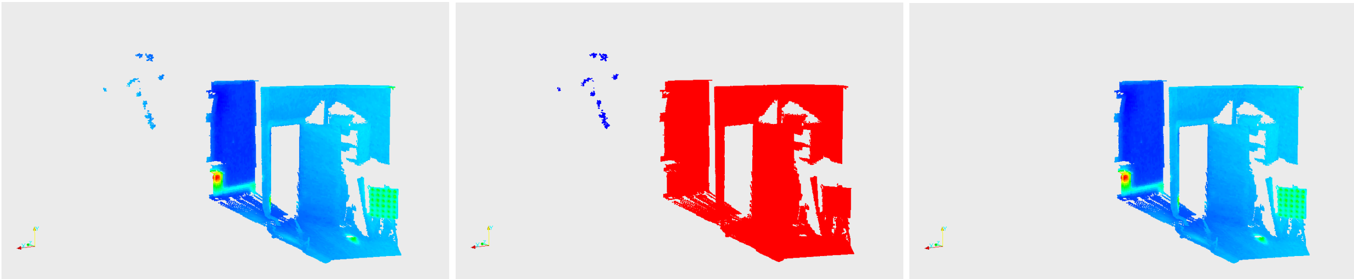

Fig. 2. Three images represent the same scene as in section 2; First image is the original point cloud; Second image shows points divided into two clusters one with valid points and one with problematic points; Third image shows the resulting point cloud after the removal of the points marked with blue on the second image

4.1 Elimination of problematic points

In the figure 2 we present the results of point cloud segmentation with the objective to eliminate the points that cause problems in the 3D model reconstruction.

This scene is represented by a point cloud containing 552,479 points in 3D space with added temperature scalar value acquired by a thermal imaging camera. Bounding box has dimensions of $267 \times 396 \times 1630$ cm which gives a volume of $172, 343, 160$ cm^3.

After running the algorithm, the output point cloud contains 551,692 points in 3D space. The dimensions of the bounding box that bounds these points are $267 \times 310 \times 550$ cm. The volume is now down to $45, 523, 500$ cm^3. This means that the data valid for 3D model reconstruction is contained in only 26% of the original data volume.

The most important parameter for the reconstruction algorithm (based on Gaussian iso–values estimation and Marching Cubes Algorithm (Osmankovic and Velagic, 2012)) is the number of points per unit volume (density). After segmenting the point cloud into two distinct clusters and eliminating the problematic points the density is 0.12118 $points/cm^3$ which is a 37.86875 times increase from the original density of 0.0032 $points/cm^3$.

We've run this algorithm on 10 different scenes and the results are similar. The increase in density of the point cloud varies from few times to 140 times, average increase of around 35. This will provide more precise model outputs from 3D model reconstruction procedure since the density is much greater. This is due to the nature of the problem of reconstruction (digital–to–analogue data conversion) which requires more oversampled environment data in order to raise the precision of the output model of that environment.

The performance of the proposed algorithm is satisfactory. As presented in (Kanungo et al., 2002) the algorithm has the time complexity of $O\left(m \cdot log(m)\right)$ where m is the number of points in the point cloud. This implementation of K–Means Clustering Algorithm is one of the fastest known implementation (Kanungo et al., 2002). The results we obtained are consistent to the results presented in the before mentioned paper and are satisfactory in terms of constraints on automated 3D model reconstruction of indoor environment.

4.2 Reconstruction results

We now present the results of the 3D model reconstruction of indoor environment after the point cloud post–processing with objective to eliminate the undesirable points that affect the precision of the reconstructed model.

In Figure 3 we present the reconstructed 3D model of indoor environment in the case when using the original point cloud and when the problematic points are removed.

It can be observed that by removing the problematic points the model precision is drastically improved. Furniture are now well defined in the 3D model without any noticeable distortion that is by-product of reconstruction algorithm if the density of the point cloud is low. In Figure 5 the qualitative comparison by visual expertise can be achieved. It can be observed that by removing the problematic points higher precision is achieved compared to the model reconstructed from the original point cloud. This is, as mentioned before, achieved by increasing the point cloud density.Bounding box size of the point cloud after filtering is drastically reduced as presented in 4.

Quantitatively, the differences between points in the original point cloud and corresponding points in the reconstructed model go up to 10 cm. However, by removing the problematic points these differences are less than 1 cm.

5. CONCLUSION

In this paper we presented one method to improve the overall precision and performance of the 3D model reconstruction of an indoor environment. The proposed method removes the points from the recorded point cloud acquired by laser scanner which increases the density of the point cloud. Consequently, this improved precision of the 3D model reconstruction as well as the performance. This creates more truthful representation of the environment which also decreases the size of the virtual model. It increases overall interactivity and user experience when inspecting the model or data analysis. For future work, we plan on investigating the effects of choosing different types of sensors that produce point clouds especially ones with depth–view camera, e.g. Microsoft Kinect. Although with much smaller range, this type of sensor can be useful in dealing with small scaled models specifically furniture with glass elements etc. The implementation of algorithms is done using C++ programming language and *open–source* VTK (*Visualization Toolkit*) for the visualization. The scenes were recorded using the a Riegl VZ-400 laser scanner and optris PI160 thermal camera mounted on top of the scanner placed on Irma3D mobile platform. More information can be found on (Project Webpage, 2012).

REFERENCES

3dtk Webpage (2012). 3dtk. `http://slam6d.`

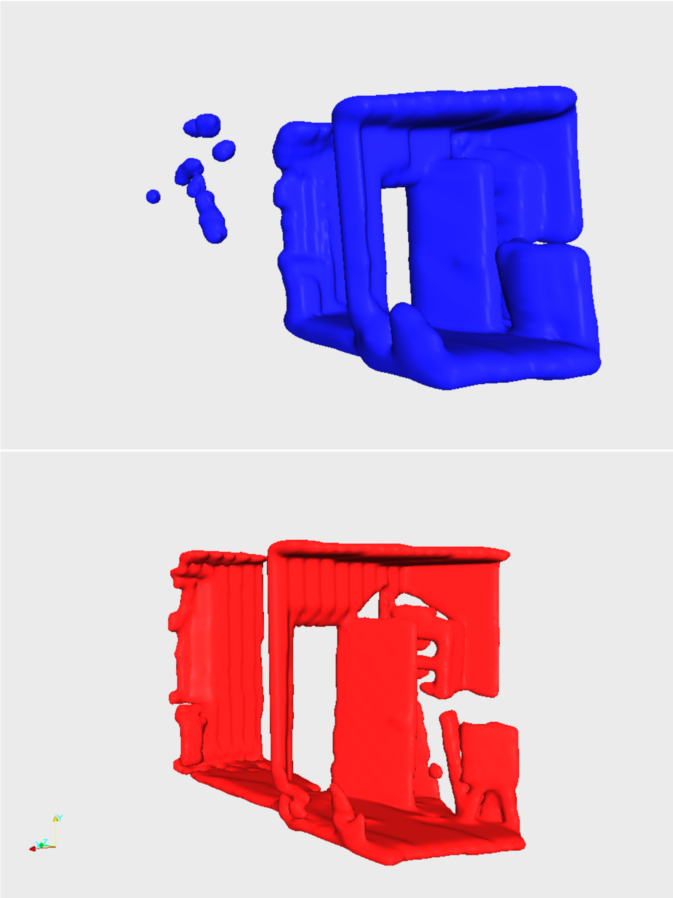

Fig. 3. Two images represent the reconstructed 3D model obtained by laser scanning; First image is the model reconstructed from the original point cloud; Second image is the model reconstructed from the point cloud without problematic points

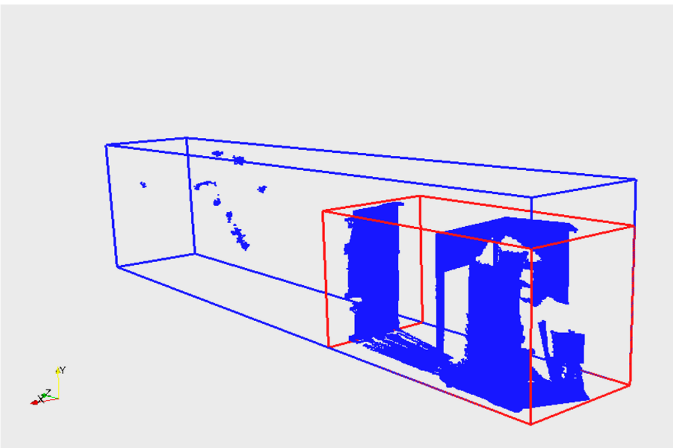

Fig. 4. Bounding box of the original point cloud (blue) and the bounding box of the filtered point cloud (red)

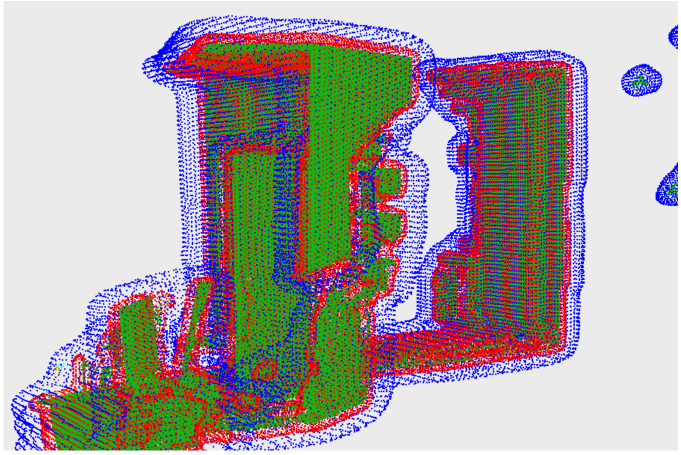

Fig. 5. Comparison between the original point cloud and the point clouds obtained by discretization of the reconstructed model in the case of the reconstruction from the original point cloud and the point cloud with no problematic points; Green points are original point cloud, blue points are reconstructed model from the original point cloud and red from the point cloud with no problematic points

`sourceforge.com`.

Borrmann, D., Elseberg, J., Lingemann, K., Nüchter, A., and Hertzberg, J. (2008). Globally Consistent 3D Mapping with Scan Matching. *Journal of Robotics and Autonomous Systems*, 56(2), 130–142.

Castillo, E. and Zhao, H. (2009). Point cloud segmentation via constrained nonlinear least squares surface normal estimates. *Computational Geometry*.

Crosilla, F., Beinat, A., Visintini, D., Fico, B., and Sossai, E. (2002). Likelihood and accuracy analyses of 3d building models from airborne laser data. *Building*.

Dorninger, P. and Nothegger, C. (2004). 3d segmentation of unstructured point clouds for building modelling. *Building*, 36(3/W49A), 191–196.

Golovinskiy, A. and Funkhouser, T. (2009). Min-cut based segmentation of point clouds. In *IEEE Workshop on Search in 3D and Video (S3DV) at ICCV*.

Inc., K. (2004). *The VTK User's Guide, Version 4.4*. Kitware Inc.

Kanungo, T., Mount, D.M., Netanyahu, N.S., Piatko, C.D., Silverman, R., and Wu, A.Y. (2002). An efficient k-means clustering algorithm: Analysis and implementation. *IEEE Trans. Pattern Anal. Mach. Intell.*, 24, 881–892. doi:10.1109/TPAMI.2002.1017616.

Mackay, D.J.C. (2003). *Information theory, inference, and learning algorithms*. Cambridge University Press, Cambridge.

Osmankovic, D. and Velagic, J. (2012). Reconstructing the 3d thermal model of indoor environment from unorganized data set acquired by 3d laser scans and thermal imaging camera. In *IEEE Multi-Conference on Systems and Control (submitted to)*.

Oude Elberink, S. and Vosselman, G. (2011). Quality analysis on 3d building models reconstructed from airborne laser scanning data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(2), 157–165.

Project Webpage (2012). Project ThermalMapper. `http://www.faculty.jacobs-university.de/anuechter/thermalmapper.html`.

Rabbani, T., Van Den Heuvel, F., and Vosselmann, G. (2006). Segmentation of point clouds using smoothness constraint. *International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences*, 36(5), 1–6.

RIEGL Laser Measurement Systems (2010). `http://www.riegl.com`.

Schroeder, W., Martin, K., and Lorensen, B. (1997). *The Visualization Toolkit: An Object-Oriented Approach to 3-D Graphics (2nd Edition)*. Prentice Hall.

Thrun, S., Burgard, W., and Fox, D. (1997). A Probabilistic Approach to Concurrent Mapping and Localization for Mobile Robots. *Machine Learning and Autonomous Robots*, 31(5), 1 – 25.

Yan, Z., Hu, L., Chen, H., and Lu, F. (2008). Computer vision syndrome: A widely spreading but largely unknown epidemic among computer users. *Comput. Hum. Behav.*, 24(5), 2026–2042. doi:10.1016/j.chb.2007.09.004. URL http://dx.doi.org/10.1016/j.chb.2007.09.004.