

Segmentation of Large Point-Clouds Using Recursive Local PCA

E. Funk, D. Griebßbach, D. Baumbach, I. Ernst, A. Boerner, S. Zuev
Deutsches Zentrum für Luft und Raumfahrt, Berlin, Germany

Abstract—We present a segmentation method for 3D point clouds, resulting from a stereo camera. Given an unsorted list of points the algorithm splits the data recursively until some quality level is achieved. In the second and the last step we use a min-cut method in order to summarize similar plane-clusters from a global point of view. The method does not require any prior knowledge about the scene and was tested in complex indoor environments.

I. INTRODUCTION

Especially in the field of mobile robotics the perception of the environment using range-sensors like a stereo camera [3] became feasible for small mobile robots.

However, in order to be able to use the acquired data of $5e^6$ points per second, one is required to reduce and to interpret parts of the point cloud as objects. This makes it necessary to split the points into clusters, which can be post processed in order to extract further information.

Some previous works like [1] presented methods for segmentation of objects restricted a specific environment: Tools placed on a table. Golovinskiy presented in [2] a combination of initial base-plane removal and a min-cut method for clustering of outdoor scenes. The results look quite promising and demonstrate the capability of spectral clustering methods, which we also adopted.

Here we present segmentation of 3D points acquired by the *Integrated Positioning System (IPS)* [3] (see fig. 1). The clustering method is based on Einbeck's proposed *local and recursive PCA*¹ approach [4]. The main idea is to perform linear deviation of the data into smaller segments and to continue the analysis on them locally. One of the advantages is that we are able to perform clustering on measurements in any given dimension. The resulting principal planes or lines (depending on the user choice) do not require any prior knowledge about the environment and allow further general analysis. In the following section we describe the algorithm more in detail and present two results from a corridor and an office environment.

II. RECURSIVE LOCAL PCA

In this section we describe the local recursive PCA-clustering algorithm. At first we give a short introduction of the general PCA analysis. In the second step we present the main recursive algorithm.



Fig. 1. Integrated Positioning System developed by DLR Berlin. Using a stereo camera and an IMU as sensors, the system delivers accurate movement trajectory with dense 3D points.

A. General PCA

Given a dataset $\mathbf{X} = (\mathbf{x}_1, \dots, \mathbf{x}_n)^T$, $\mathbf{x}_i \in \mathbb{R}^p$ the principal components provide a sequence of best linear approximations to it. Let Σ be the empirical covariance matrix of \mathbf{X} , then the principal components are given by the eigen decomposition $\Sigma = \mathbf{V}\Lambda\mathbf{V}^T$, where $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$ is a diagonal matrix containing the ordered eigenvalues of Σ , with $\lambda_1 \geq \dots \geq \lambda_p$ and \mathbf{V} is an orthogonal matrix. The columns of $\mathbf{V} = (\mathbf{v}_1, \dots, \mathbf{v}_p)$ are the eigenvectors of Σ . The first eigenvector \mathbf{v}_1 leads to maximization of the dataset projections: $\mathbf{X}\mathbf{v}$. The second eigenvector \mathbf{v}_2 maximizes the projections orthogonal to \mathbf{v}_1 .

Having sampled points from a plane, one receives \mathbf{v}_1 and \mathbf{v}_2 lying on the plane and \mathbf{v}_3 as its normal vector. If the plane samples are exact planar, the 3rd eigenvalue λ_3 will be zero. Otherwise it increases. Using these considerations one can easily analyze the planarity of a point cloud.

B. Recursive PCA

Starting with a single partition it is split up into two new partitions. The decision to split the data is verified by the *relative planarity check* suggested by [4]:

$$\frac{\sum_{i=1}^2 \lambda_i^{(0)}}{\sum_{i=1}^3 \lambda_i^{(0)}} < \left(\frac{n_1 \sum_{i=1}^2 \lambda_i^{(1)}}{n_0 \sum_{i=1}^3 \lambda_i^{(1)}} + \frac{n_2 \sum_{i=1}^2 \lambda_i^{(2)}}{n_0 \sum_{i=1}^3 \lambda_i^{(2)}} \right), \quad (1)$$

where n_q is the amount of points in the q -th partition and $\lambda_i^{(q)}$ is the i -th eigenvalue of the partition q .

¹Principal Component Analysis

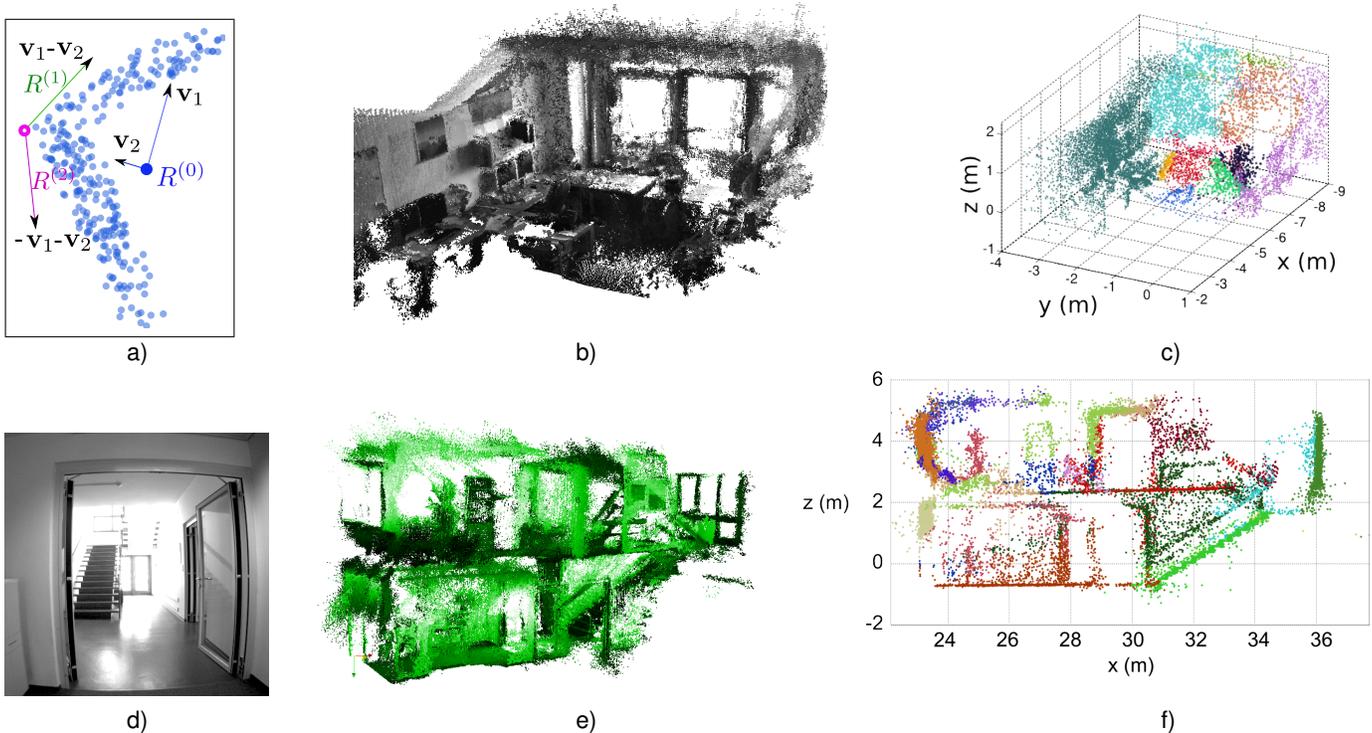


Fig. 2. a) On splitting a cluster into two new partitions, the new centers are moved along the second eigenvector \mathbf{v}_2 . The new principal eigenvector results from a linear combination of \mathbf{v}_1 and \mathbf{v}_2 . b) Shaded unfiltered point cloud from an office, acquired by the IPS [3] system. c) Clustered (down sampled) office-point cloud containing principal planar point groups. d) A photograph of a corridor leading upstairs. e) Colored, unfiltered point cloud from the photographed corridor. f) Most of the planar objects like stairs and walls were summarized successfully to single clusters.

Algorithm: Recursive PCA

- 0) Start with a single partition $R^{(0)}$ containing all points in \mathbf{X} .
- 1) Split the data into two new partitions $R^{(1)}$ and $R^{(2)}$.
- 2) Test whether the split improves the approximation of \mathbf{X} by two planes.
- 3) If the split was accepted:
 - a) Iterate a few times between:
 - Reassigning the points to clusters using a distance measure considering the euclidean distance to the plane's surface and to its center along the plane.
 - Plane calculation according to section II-B.
 - b) Start at 1) with $R^{(0)} = R^{(1)}$ and $R^{(0)} = R^{(2)}$.

After the recursive process is finished, we fuse the planar partitions using a simple spectral clustering method similar to [2]. The final number of clusters is estimated over the eigenvectors of the affinity matrix using the *Bayesian Information Criterion* (BIC) [5]. The success of the algorithm is quite sensitive to the split method, mentioned in step 1). Here we used a split decision, which behaves best on corner-like point sets (see. figure 2.a).

III. RESULTS

The figure 2 shows two sampled complex scenes using the IPS. Most planar clusters contain small objects like monitors or

plants and do not allow to detect them directly. Depending on the application, this might be an issue, which can be resolved by processing only one or two frames, where the target objects appear more obvious.

IV. FURTHER STEPS

Receiving a set of planar clusters we aim to perform further nonlinear analysis in order to recognize and track (moving) objects, recognize places and performing semantic scene analysis. In addition, we will evaluate the clustering method on samples from outdoor scenes, where we expect even lower processing times due to simpler scene structures.

REFERENCES

- [1] D. Holz, R. Schnabel, D. Droschel, J. Stückler, and S. Behnke, "Towards Semantic Scene Analysis with Time-of-Flight Cameras," in *Proceedings of the 14th RoboCup International Symposium*, Singapore, June 2010.
- [2] A. Golovinskiy, V. G. Kim, and T. Funkhouser, "Shape-based recognition of 3D point clouds in urban environments," *International Conference on Computer Vision (ICCV)*, Sep. 2009.
- [3] I. E. S. D. Griebach, A. Boerner, "Real-time dense stereo mapping for multi-sensor navigation," *ISPRS*, 2010.
- [4] E. L. Einbeck J and B.-J. C, "Brepresenting complex data using localized principal components with application to astronomical data," *Lecture Notes in Computational Science and Engineering* 58, 2008.
- [5] C. M. Bishop, *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Springer, 2007.