Robust Segmentation for Multiple Planar Surface Extraction in Laser Scanning 3D Point Cloud Data

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Abstract

This paper investigates the segmentation of multiple planar surfaces from 3D point clouds. A Principle Component Analysis (PCA) based covariance technique is used for segmentation which is one of the most popular approaches in point cloud processing. It is well known that PCA is very sensitive to outliers and does not give reliable estimates for segmentation. We propose a statistically robust segmentation algorithm using a fast-minimum covariance determinant based robust PCA approach to get the local covariance statistics. This results in more reliable, robust and accurate segmentation. The application of the proposed method to simulated and terrestrial laser scanning point cloud datasets gives good results for multiple planar surface extraction and shows significantly better performance than PCA based methods. The algorithm has the potential for non-planar complex surface reconstruction.

1. Introduction

Object recognition and modeling by surface reconstruction (classification, segmentation and fitting) in laser scanning 3D point cloud data has been considered an important branch of computer vision, pattern recognition and reverse engineering [2, 3, 5, 7]. Segmentation is the process of separating the most similar surface points into single feature surfaces. It is a basic step for surface reconstruction and so for 3D modeling. Segmentation in point cloud data is difficult because the points are usually unorganized, incomplete, noisy, sparse, have inconsistent point density, and in addition the surface shape can be arbitrary with sharp features. The segmentation methods can be categorized into three: border based [5], region based [3] and hybrid [15]. In the border based approach, the boundary and edge points are first identified and then the extracted border points are used to segment the surface according to different saliency features (e.g. normal and curvature) while region based approaches use local neighborhood properties to seek the homogeneity within a specific feature or find variation among the features, and merge the spatially close points. Region based methods are more robust to noise than edge based ones [7] when using global information. Region based methods can result in over or under segmentation and the region border can be hard to locate. They are also sensitive to the choice of the initial seed points. Hybrid methods can overcome the limitations of both these methods [7].

Local surface neighborhood based saliency features are used for segmentation. Principal Component Analysis (PCA) has been used rigorously for studying surfaces and to find local saliencies [1, 9]. Since PCA is sensitive to outliers, the saliency features based on PCA are not robust and results can be erroneous. To minimize the outlier effects on the estimates, this paper uses a robust PCA approach [6] based on robust location and covariance estimators from the Fast-Minimum Covariance Determinant (FMCD) [12]. The FMCD is beneficial because of its high resistance to outliers and computationally efficiency. We propose a segmentation algorithm that can classify the edge, boundary and surface points (surfels), and segment multiple planes efficiently in 3D point cloud data. The proposed algorithm is a hybrid robust one, so it is able to localize region border and edge points accurately, efficiently handles over or under segmentation and reduces outlier effects for the whole process.

Section 2 contains the relevant principles, Section 3 proposes the algorithm and in Section 4, experiments are performed to prove the efficiency of the algorithm followed by conclusions in Section 5.

2. PCA, local covariance statistics and robust PCA

Principal Components (PCs) are the small number of linear combinations of the original variables that rank the variability in the data through the variances, and produce the corresponding orthogonal directions using the eigenvectors of the covariance matrix, **C**. A ranked PC explains a part of the variance not expressed by previous PCs. PCA minimizes the variance from the data by subtracting the mean from the related variables and then performs singular value decomposition on that **C**, to find the required PCs.

The saliency features are based on covariance techniques of local neighborhoods [2, 9]. The **C** for a point $\mathbf{p}_i = (x_i, y_i, z_i)$ ($p_i \in P \in R^3$; a point in a 3D cloud **P**) with k neighbours $\boldsymbol{N}_{pi}$ is defined as:

$$\mathbf{C}_{3\times3} = \frac{1}{k}\sum_{i=1}^{k}(\mathbf{p}_i - \overline{\mathbf{p}})(\mathbf{p}_i - \overline{\mathbf{p}})^T, \quad \overline{\mathbf{p}} = \frac{1}{k}\sum_{i=1}^{k}\mathbf{p}_i, \qquad (1)$$

where $\overline{\mathbf{p}}$ is the centroid of $\boldsymbol{N}_{pi}$. The C can define local geometric information of the underlying surface. It is decomposed into PCs ordered by decreasing eigenvalues $\lambda_2 \geq \lambda_1 \geq \lambda_0 \geq 0$ with the corresponding eigenvectors $\mathbf{v}_2$, $\mathbf{v}_1$ and $\mathbf{v}_0$. Thus $\mathbf{v}_0$ approximates the surface normal **n** for $\mathbf{p}_i$ and $\boldsymbol{\lambda}_0$ describes the variation along the surface normal. Most techniques [1, 8, 9, 10, 11] use PCA to get the saliency features. Unfortunately PCA estimates for saliency features are sensitive to outliers and inaccuracies, because the mean, variance and the C matrix used in PCA all have a zero breakdown point.

To get robust estimates, Robust PCA (RPCA) computes the eigenvalues and eigenvectors of a robust estimator of the covariance matrix. Many robust centre and covariance estimators have been introduced in the literature. We use the robust PCA proposed by Hubert and Rousseeuw [6] that combines the idea of Projection Pursuit (PP) with the FMCD. The PP is used to pre-process the data so that the transformed data are lying in a subspace whose dimension is less than the total number of data points, and then the FMCD estimator is used to get the robust centre and covariance matrix. In RPCA, at first the data is condensed to the PCs defining possible directions. Then, every direction is scored by its resultant value of outlyingness:

$$w_i = \max_{v} \frac{\left|\mathbf{p}_i\mathbf{v}^T - \mathbf{c}_{MCD}(\mathbf{p}_i\mathbf{v}^T)\right|}{\boldsymbol{\Sigma}_{MCD}(\mathbf{p}_i\mathbf{v}^T)}, \qquad (2)$$

where the maximum is over all directions, **v** is a univariate direction and $\mathbf{p}_i\mathbf{v}^T$ denotes a projection of the i^{th} observation $\mathbf{p}_i$ on the direction $\mathbf{v}$. For every direction a robust centre $\mathbf{c}_{MCD}$ and covariance matrix $\boldsymbol{\Sigma}_{MCD}$ of the projected data $\mathbf{p}_i\mathbf{v}^T$ are computed. Second, a fraction h ($>n/2$) of observations with the smallest values of w_i are used to construct a robust $\boldsymbol{\Sigma}$. Finally, RPCA projects the data onto the r- subspace by the r leading eigenvectors (PCs) of $\boldsymbol{\Sigma}$ and computes their centre and scale by the re-weighted FMCD. The eigenvectors of $\boldsymbol{\Sigma}$ then determine the RPCs.

3. Segmentation

The algorithm proposed in this section consists of three steps: classification, region growing and merging. It needs an estimation of local planar surface parameters **n** and λ_0. We use the K-D tree for finding the k nearest neighbors of an interest point $\mathbf{p}_i$, and construct the **C** for the neighborhood. Local surface parameters are estimated by PCA and RPCA.

3.1. Classification

Classification means the separation of a point cloud into border-line points, edge/corner points and surfels. We find the edge points first and then the boundary points since the boundary points will have the same homogeneity as the specific feature surface and the points on the edge will have a neighborhood from different adjacent feature surfaces and generally will have larger values for λ_0. For planar surfaces, we find that λ_0 gives sufficiently consistent results (Fig. 2(a)). We follow the general rule: (mean (.) + a × standard deviation (.)) (a =1 to 3) for getting larger λ_0 values. We consider the i^{th} point that has

$$\lambda_0 > \text{mean}(\lambda_0) + 1 \times \text{standard deviation}(\lambda_0) \qquad (3)$$

to be an edge point. For boundary point detection, we use the Belton and Lichti [1] measure defined as:

$$c_i^{\,2} = \frac{(s_i)^2}{\lambda_1} + \frac{(t_i)^2}{\lambda_2}, \qquad (4)$$

where $s_i = \mathbf{v}_1.(\mathbf{p}_i - \overline{\mathbf{p}})$ and, $t_i = \mathbf{v}_2.(\mathbf{p}_i - \overline{\mathbf{p}})$. We consider the point that has value larger than the 90+ percentile of the c^2 as the boundary point. It is known that the values of the above two measures are data and neighborhood size dependent so it is not recommended to use specific threshold. We can determine them by their histograms and/or index plots. If a point suddenly comes from both edge and boundary then it is classified as an edge point since an edge point is rarely a boundary point. The rest of the points are surfels.

3.2. Region growing

In region growing, points in the same surface region should have similar normals and low bias angle θ [8, 11, 13, 14]. Inaccurate normals for range points near region boundaries reduce the accuracy of segmentation [4]. We use RPCA to get accurate **n**, λ_0 and θ. The θ between a point and its neighbour is:

$$\theta = \arccos|\,\hat{\mathbf{n}}_1^T \hat{\mathbf{n}}_2\,|, \qquad (5)$$

where $\hat{\mathbf{n}}_1$ and $\hat{\mathbf{n}}_2$ are the two unit normals for the i^{th} point and one of its neighbours. We use the surfels set S and boundary points set B i.e. S ∪ B with the lowest λ_0 value as the seed point (S_p) of the current region R_c. The points whose bias angles are less than an angle threshold θ_{th} are added to R_c and will be used as the next seed points for R_c. We fix an appropriate θ_{th} to avoid under segmentation and biasing to over segmentation. If necessary, the problem of over segmentation can be overcome by merging. After getting a complete region, we select a S_p for the next region from the remaining points in S ∪ B that has the minimum λ_0. If a region has more than or equal to a minimum number m of points it will be considered for the next step otherwise it will be considered as an unexplained region. The same process of region growing will be continued until S ∪ B is empty. The region growing is shown in Algorithm 3.1.

Algorithm 3.1. Region growing

i. Find initial seed point from the S ∪ B, which has minimum λ_0, and put it to R_c and current S_p list S_c , and remove it from S ∪ B.

ii. Find S_k nearest neighbors for each seed point in S_c.
  (a) Calculate θ between the S_p and its neighbours.
  (b) Find the points that exist in S ∪ B, which have $\theta \le \theta_{th}$.
  (c) Put them into R_c and S_c , and remove from S ∪ B.

iii. If size $R_c \ge m$, insert R_c into the region list R.

iv. Repeat the process (i to iii) until S ∪ B is empty.

v. Sort the regions in R.

3.3. Merging

This step merges the neighbouring co-planar regions that belong to a same feature surface. Merging a specific region with a larger and most appropriate neighboring one, should change the Mean Squared Error (MSE) less than for merging with any other region. The MSE for a region can be defined as [10]:

$$MSE = \frac{1}{l}\sum_{i=1}^{n}(\hat{\mathbf{n}}.\mathbf{p}_i + d)^2, \qquad (6)$$

where l is the size, $\hat{\mathbf{n}}$ is the unit normal and d is the bias (distance, origin to the plane) for the region.

Algorithm 3.2. Under-grown region merging

i. Find neighbouring regions R_{ij} for each region $R_i \in R$.

ii. Calculate the MSE for R_i and $R_i \cup R_{ij}$.

iii. Calculate the $DMSE = |\,MSE(R_i) - MSE(R_i \cup R_{ij})\,|, \forall R_{ij}$

iv. Merge R_{ij} with R_i for which $DMSE$ is the least and $DMSE \le DMSE_{th}$, and remove R_{ij} from R.

v. Sort the merged regions in R as the final segments.

To avoid faulty merging, a threshold is fixed so that the least Difference in MSE (DMSE) does not exceed the threshold ($DMSE_{th}$). The merging is summarized in Algorithm 3.2.

4. Experiments

The method has been evaluated on several simulated and laser scanner point cloud datasets with two discussed here. Based on other experiments, we set k=30, S_k=15, θ_{th} =5°, m=10 and $DMSE_{th}$=1.0e^{-04}.

Data set 1: To quantify and compare the accuracy between PCA and RPCA based local planar surface fitting used later for segmentation, we simulate 1000 datasets (for statistically significant results). Every dataset is of 50 points with 1 to 20 % outliers from 3D Gaussian distributions. Regular points have means (2, 8, 6) and variances (15.0, 15.0, 0.01) and outliers have means (15, 15, 10) and variances (10.0, 2.0, 0.1). We calculate average θ (Fig. 1(a)) for the 1000 datasets. Fig. 1(b) shows the accuracy performance for PCA and RPCA. Since RPCA is an iterative process it takes more time than PCA but this is justified in terms of accuracy. More information on computational cost and performance of RPCA can be found in [6, 14].

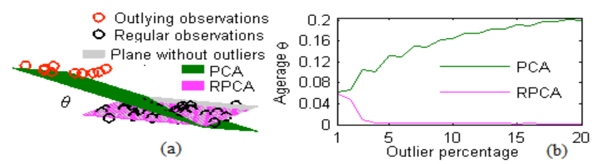

Figure 1. (a) θ between the planes with and without outliers (b) Average θ versus outlier percentage.

Data set 2: This is a point cloud consisting of 2,021 points acquired using a moving vehicle-based mobile mapping system. It has four planar surfaces of road pavement, kerb, footpath and fence. In Fig.2(a), box plots for λ_0 show that the values from RPCA are significantly more consistent than from PCA. We use the proposed algorithm to segment/extract the four planes.

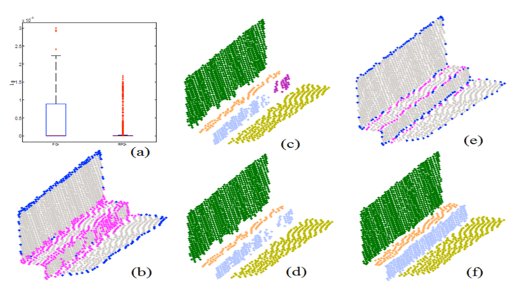

Figure 2. (a) Box plots of λ_0, PCA results: (b) classification (c) region growing (d) merging; and RPCA results: (e) classification (f) region growing.

The colours (magenta for edge/corner points, blue for boundary points and gray for surfels) shows that PCA results in some surfels being misclassified as edge points (Fig.2(b)). The total number of regions is five (Fig.2(c)) and the final segmentation (after merging) (Fig.2(d)) extracts faulty and incomplete planes. For RPCA, Fig.2(e) shows much better classification. Region growing generates four regions that match the four planes (Fig.2(f)) and so no merging is necessary.

Data set 3: This mobile mapping point cloud consists of 28,289 points with three road side buildings, again captured from a mobile mapping system.

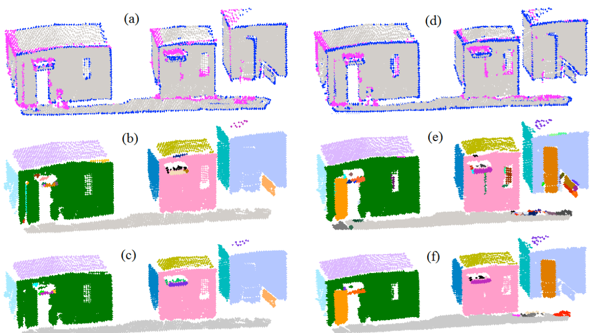

Figure 3. PCA results: (a) classification (b) region growing (c) merging; RPCA results: (d) classification (e) region growing and (f) merging.

Classification of edges and boundaries with RPCA (Fig.3(d)) is finer and more accurate than for PCA (Fig.3(a)). For region growing, PCA misses two bushes beneath the buildings, and does not find the two doors that RPCA finds. RPCA merges the under-grown regions better than PCA. A small region next to the door of the right most building is merged accurately by RPCA (Fig.3(f)) but not by PCA.

5. Conclusions

A statistically robust segmentation algorithm is proposed for multiple planar surface extraction from 3D point cloud data. Results show that robust PCA based segmentation outperforms classical PCA at every step. The robust method efficiently classifies edges, boundaries and surfels and is able to identify region borders accurately and better than PCA. Since the saliency features are estimated in a robust way, the possibility of over or under segmentation is reduced. Less sensitivity to outliers reduces the effects of neighborhood size and thresholds. As for other statistical robust methods, it has the limitation that it breaks down for more than 50% outliers, although in many applications this does not occur. The robust algorithm has potential for complex non-planar surface extraction and is the subject of further research.

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