Pattern Detection in Airborne LiDAR Data Using Laplacian of Gaussian Filter

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Abstract   Methods for feature detection in laser scanning data have been studied for decades ever since the emergence of the technology. However, it is still one of the unsolved problems in LiDAR data processing due to difficulty of texture and structure information extraction in unevenly sampled points. The paper analyzes the characteristics of Laplacian of Gaussian (LoG) Filter and its potential use for structure detection in LiDAR data. A feature detection method based on LoG filtering is presented and experimented on the unstructured points. The method filters the elevation value (namely, z coordinate value) of each point by convolution using LoG kernel within its local area and derives patterns suggesting the existence of certain types of ground objects/features. The experiments are carried on a point cloud dataset acquired from a neighborhood area. The results demonstrate patterns detected at different scales and the relationship between standard deviation that defines LoG kernel and neighborhood size, which specifies the local area that is analyzed.

Keywords  laser scanning; point cloud; feature detection; Laplacian of Gaussian filter

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Introduction

In recent years, Light Detection And Ranging (LiDAR) has emerged as an effective technology, which provides valuable data in various forms and scales for mapping and monitoring land cover features. Its use has increased dramatically due to availability of high-density LiDAR data as well as high spatial/spectral resolution digital images. Nowadays, LiDAR data are often derived from one or multireturns of laser pulses and the digital images usually contain multispectral bands. Pattern detection (segmentation or classification) in LiDAR data has been studied for decades. Though scanning data may be acquired from different platforms (spaceborne, airborne, terrestrial, and mobile), the processing methods usually share common principles. One kind of detection algorithm mainly exploits geometrical derivatives (curvature, normal, etc.) to group points.¹² Another kind of algorithm³ utilizes a parameterized detection method, such as the Generalized Hough Transform⁴ to detect regular shapes including planes, circles, cylinders, and spheres.

Some types of ground objects, such as tree leaves and...
shrubs, cannot be parameterized by regular geometrical shapes partly due to their penetration of laser beams. Researchers\cite{5-8} in the robotics and computer science field have applied machine-learning-based methods to laser scanning data recognition for robotic navigation. These procedures often explore statistics of spatial distribution of returned laser points and classify returned laser data using learned classifiers (e.g., Gaussian Mixture Models and Markov Random Fields). Although different frameworks are developed, local region analysis methods and $k$ nearest neighbors (KNN) search algorithms are often exploited in these procedures.

Methods fusing datasets from different sensors have drawn lots of interests in recent years. Due to its complementary properties to LiDAR data, high spatial/spectral digital images have been combined for improving land cover mapping. Although aerial photography has been used as a mapping tool for a century,\cite{9} the fusion of aerial photography and LiDAR data has only been possible in the past few years due to advances in sensor design and data acquisition/processing techniques. There have been some attempts to fuse LiDAR and high-resolution imagery for land cover mapping. Haala and Brenner\cite{10} applied the Iterative Self-Organizing Data Analysis Technique (ISODATA) algorithm to combined LiDAR-derived DSM and three-color-band aerial images. The normalized Digital Surface Model (nDSM) was used to classify objects that had different distribution patterns in elevation direction. The low-resolution LiDAR data was greatly facilitated to separate trees from buildings by the near-infrared band from the aerial imagery. Sohn and Dowman\cite{11} presented method utilized a divide-merge scheme to obtain the recognized building outline in a combination of multispectral images and airborne laser scanning data. With the availability of full-waveform LiDAR data and hyperspectral images, the problems of data fusion and pattern classification become more complicated. Opportunities with high classification accuracy should be achieved because of its spectral and spatial features. However, there are still challenges in data processing, waveform modeling, and measurements interpretation of full-waveform LiDAR.\cite{12} A few methods have been put forward to tackle these problems, but more efforts should be taken to investigate problems that resulted from theory and application.\cite{13-16}

Marr\cite{17} raised the computational framework for computer vision and suggested Laplacian of Gaussian (LoG) filter for visual information processing. Due to its similarity to biological vision, LoG filter has been well studied for feature extraction (e.g., edge detection) in images. Witkin\cite{18} presented an approach called scale-space filtering to detect image locations invariant to scale change. Lowe\cite{19} introduced Scale Invariant Feature Transform (SIFT) approach for feature point location, which has been widely used for image matching and image-based modeling. Marr and Hildreth\cite{20} had mentioned that the LoG filter could be used for detecting changes in intensity corresponding to properties of physical world, like changes in reflectance, surface orientation, or distance from the viewer. Based on this observation, it should be possible to detect changes and patterns of altimetry values in LiDAR data using LoG filter. The motivation of this research is to study and apply LoG filter for pattern detection in LiDAR data. In the following sections, principles of LoG filter will first be introduced. Then, the convolution scheme will be described. Analysis of experiments and conclusions will be delivered separately in Sections 2 and 3.

1 Convolution with log filter

An appropriate filter for intensity changes at a given scale was found to be the second derivative of a Gaussian.\cite{20} It has been proved that, under some reasonable assumptions, LoG filter is found to be the appropriate one that is independent of orientation.

1.1 Laplacian of Gaussian filter

The 2-D Gaussian smoothing filter is a convolution operator that is often used to remove details and noises in images. It has been shown that under some conditions, the only possible scale-space kernel is the Gaussian function,\cite{21} which is useful for feature localization. Furthermore, Gaussian filter provides “weighted” smoothing and preserves edges better than average filter of similar size. The 2-D Gaussian distribution has the form

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$ (1)
where \( \sigma \) is the standard deviation. The distribution of 2-D Gaussian function with mean \((20, 20)\) and \(\sigma=5.0\) is illustrated in Fig.1.

![Fig. 1  2-D Gaussian function with \( \sigma=5.0 \)](image)

As a smoothing filter, Gaussian filter reduces the range of scales over which intensity changes can take place. Intensity change detection is under the assumption that wherever a change occurs, there will be a corresponding peak in the first directional derivative or, equivalently, a zero-crossing in the second directional derivative of intensity.\(^{[20]}\) To detect the direction of intensity changes, the second-order differential operator Laplacian \( \nabla^2 \) (Eq. (2)) is often used.

\[
L(x,y) = \nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2}
\]  

(2)

Therefore, the detection of intensity changes can be reduced to detect zero-crossings in \( \nabla^2 G \)-filtered image. Fig.2 shows that in areas where the intensity does not change, the LoG response should be zero. When intensity increases in the proximity, the LoG response will be positive and negative, vice versa.

![Fig. 2  Response of 1-D LoG filter (b) to a step edge (a)](image)

Since convolution operation is associative, it is efficient to calculate the filter kernel once and convolve the image with the hybrid filter by convolution of the Gaussian smoothing filter with the Laplacian filter. The 2-D LoG function centered at \((0, 0)\) and with standard deviation \( \sigma \) has the form of Eq.(3). Fig.3 illustrates the distribution of LoG function with mean \((20, 20)\) and \(\sigma=5.0\).

\[
LoG(x,y) = \frac{1}{\pi\sigma^2} \left[ 1 + \frac{x^2 + y^2}{2\sigma^2} \right] e^{-\frac{x^2+y^2}{2\sigma^2}}
\]  

(3)

**Fig. 3  2-D LoG function with \( \sigma=5.0 \)**

### 1.2 Convolution scheme

Wack and Wimmer\(^{[22]}\) used LoG kernel to filter ground objects in raster image derived from LiDAR data so as to model terrain. However, transformation of point cloud data from vector format to raster format unavoidably loses accuracy and introduces uncertainties, which will influence both the detection of above-ground objects and the extraction of ground points. Therefore, we choose to filter the raw point cloud data instead of filtering the raster image. Eq.(3) could be written compactly as

\[
LoG(r) = \frac{1}{\pi\sigma^2} \left[ 1 + \frac{r^2}{2\sigma^2} \right] e^{-\frac{r^2}{2\sigma^2}}
\]  

(4)

where \( r = \sqrt{(x_0 - x_{\text{KNN}})^2 + (y_0 - y_{\text{KNN}})^2} \) is the distance between a point and each of its \( k \) nearest neighbors (KNN) within a given distance \( \delta \), which specifies the local area of the neighborhood. The filter filters \( z \) value of each laser point by convolution of \( z \) values of its KNN in the local area defined by \( \delta \).

There are many available implementations using kd-tree\(^{[23]}\) for KNN search, and we choose the freely available “kd-tree for matlab.”\(^{[24]}\)

### 2 Results and analysis

The presented method was applied to a point cloud dataset acquired from a neighborhood area including
a church that is surrounded by several houses and trees. The dataset contains 146,972 points. The research area is displayed in Fig.4, and Fig.5 shows the corresponding elevation map. Figs.6(a-c) illustrate convolution result with LoG filter with increasing $\delta$. Fig.6(a) suggests that $\sigma=1.0$ with $\delta=1.0$ m is too sharp for edge detection because no filtered $z$ value is beyond 0. The more patterns emerge with increased $\delta$ in Fig.6(b). The Z-value of filtered points ranges from below $-1500$ to beyond $500$. The yellow points indicate the areas of ground objects, where intensity changes little. Blue and red points reflect dramatic intensity change. These as a whole suggest the existence of boundaries between regions of uniform but different intensities. The convolution results with $\sigma=1.0$ slightly change with increasing $\delta$ value larger than 4.0 m. This may indicate the degree of details, which can be detected under the scale limited by $\sigma=1.0$. Though the difference in both filtered value is almost in an order of magnitude when compared with Fig.6(a), Fig.7(a) demonstrates that in the same locale area, detected features generally slightly changes with continuously increasing scales. Trees detected in all these experiments share almost the same patterns. The top areas of trees are often with the smallest filtered values, and this is because the $z$ values of their neighboring points are often smaller than theirs. According to the observation from that in Fig.2, the filtered values to some extent reflect the difference of height between trees, and the shapes of tree canopy begin to emerge (Fig.8). Figs.6(a)-6(c) also show that boundaries of ground object could be
extracted when there’re both positive and negative values in the LoG-filtered point cloud. We threshold the filtered value of Fig.6(b) at 500 to produce a sketch map (Fig.9) where the extracted boundaries represent the locations of zero-crossing points. Then Generalized Hough Transform (GHT) is used to detect circles (Fig.10) that resemble tree canopies and the located trees are shown in Fig.11. Six of the seven trees appear in the test site are correctly located, however the tower of the church is recognized as trees due to similarity in shape.

3 Conclusion

In this paper, we presented some experimental results of a method based on LoG filter to detect patterns in airborne LiDAR data. The filtered results reflect existence of certain types of ground objects and the detected patterns could be further studied and exploited to extract individual trees and buildings. Our method proceeds as weighted smoothing filter on each laser scanning point. Sketch map is extracted by thresholding the filtered values and the Generalized Hough Transform is then carried out to extract circles which indicates canopy of individual trees. Moreover, sketch map may also be used to register LiDAR data with images as well as provide measurement information (such as area) of buildings. Although the method is easy to implement, the \( k \) nearest neighbors search consumes much computation. We are considering random algorithms for the improvement of performance while keeping spatial distribution of points in local areas. Besides, the presented method depends on choice of \( \sigma \) and \( \delta \). The parameter \( \sigma \) defines operation scale of LoG filter and \( \delta \) specifies the convolution area. Though it is more complicated to select the appropriate parameters in raw LiDAR points processing than that in image analysis, the selection of \( \sigma \) should be related to the scale of features to be detected. Parameter \( \delta \) should be determined by the density of the point clouds. And once positive and negative values show in the filtered points, the boundaries of ground object could be extracted. More attention will be paid in our future work to features detected at different scales and possible methods for feature detection with automatic scale selection.
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