Tang, Shijun. *Investigation on segmentation, recognition and 3D reconstruction of objects based on LiDAR Data or MRI*. Doctor of Philosophy (Computer Science), May 2015, 92 pp., 1 table, 27 illustrations, 77 numbered references.

Segmentation, recognition and 3D reconstruction of objects have been cutting-edge research topics, which have many applications ranging from environmental and medical to geographical applications as well as intelligent transportation.

In this dissertation, I focus on the study of segmentation, recognition and 3D reconstruction of objects using LiDAR data or MRI. Three main works are that (I). Feature extraction algorithm based on sparse LiDAR data. A novel method has been proposed for feature extraction from sparse LiDAR data. The algorithm and the related principles have been described. Also, I have tested and discussed the choices and roles of parameters. By using correlation of neighboring points directly, statistic distribution of normal vectors at each point has been effectively used to determine the category of the selected point. (II). Segmentation and 3D reconstruction of objects based on LiDAR or MRI. The proposed method includes that the 3D LiDAR data are layered, that different categories are segmented, and that 3D canopy surfaces of individual tree crowns and clusters of trees are reconstructed from LiDAR point data based on a region active contour model. The proposed method allows for delineations of 3D forest canopy naturally from the contours of raw LiDAR point clouds. The proposed model is suitable not only for a series of ideal cone shapes, but also for other kinds of 3D shapes as well as other kinds dataset such as MRI. (III). Novel algorithms for recognition of objects based on LiDAR or MRI. Aimed to the sparse LiDAR data, the feature extraction algorithm has been proposed and applied to classify the building and trees. More importantly, the novel algorithms based on level set methods have been provided and employed to recognize not only the buildings and trees, the
different trees (e.g. Oak trees and Douglas firs), but also the subthalamus nuclei (STNs). By using the novel algorithms based on level set method, a 3D model of the subthalamus nuclei (STNs) in the brain has been successfully reconstructed based on the statistical data of previous investigations of an anatomy atlas as reference. The 3D rendering of the subthalamic nuclei and the skull directly from MR imaging is also utilized to determine the 3D coordinates of the STNs in the brain.

In summary, the novel methods and algorithms of segmentation, recognition and 3D reconstruction of objects have been proposed. The related experiments have been done to test and confirm the validation of the proposed methods. The experimental results also demonstrate the accuracy, efficiency and effectiveness of the proposed methods. A framework for segmentation, recognition and 3D reconstruction of objects has been established, which has been applied to many research areas.
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CHAPTER 1
INTRODUCTION

In the dissertation, I investigate and elaborate the topics of segmentation, recognition and 3D reconstruction of objects based on light detection and ranging (LiDAR) data as well as MRI. There are many links among these topics. For instance, recognition may be studied based on results and investigation of segmentation and 3D reconstruction.

As a common and important topic, feature extraction from LiDAR data has wide applications in urban areas, such as land use planning, population estimation, emergency management, environment monitoring, and public security [1-5]. Many approaches to feature extraction from LiDAR data have been proposed, such as those based on triangulated irregular networks (TIN) [6-9], curvature-based segmentation techniques [10], and the progressive morphological filtering [11,12]. These methods have shown different degrees of success for LiDAR points with high density, such as classification of ground and non-ground and generation of three dimensional building models. There have been little research on classifying trees and buildings using sparse density LiDAR points (less than 0.5 point/m²) in areas having complex spatial distribution of object points and height-discontinuities at the feature boundaries.

In order to improve classification accuracy of sparse LiDAR points, I proposed a new method of feature extraction for LiDAR point classification. The innovation of my approach is two-fold: (1) only a small number of features are needed due to an assumption that at different heights, there are different object sets, and (2) a new model was employed to describe the distinctive texture of objects.

Image or LiDAR data segmentation separates the objects from background. The typical and distinct approaches to image segmentation include an extension of the edge-detection view
of images [14-18], layers approaches [19], and the normalized cut method [20]. These methods have their own advantages for different applications.

The active contour model along with level set technology has been widely applied to many research fields including computer vision and medical image processing. Chan and Vese [21] introduced a variational model based on any level set function, for which the zero level set segments the image domain into several intensity homogenous regions by minimizing a function.

For a 3D reconstruction, horizontal slices of objects must first be obtained. A slice is related with detection and location of objects in 2D images. As an effective model, the level set technology provided by Chan and Vese [21] can detect the locations of boundaries very well, and is insensitive to placement of the initial curve in the image, which is used to detach the individual tree or clusters of trees from their background and to obtain the contours of the individual trees or clusters of trees.

Forest attributes (such as tree height, canopy closure, and diameter at breast height) can be effectively estimated. The attributes are often employed to evaluate growth, competition, and photosynthesis [22], carbon sequestration, standing timber volume, and biomass of trees (forest) [23-25].

Canopy height models (CHMs) are often used to represent horizontal and vertical distribution of tree canopies. Once a digital elevation model (DEM) and a digital surface model (DSM) are interpolated from LiDAR point clouds, a CHM can be obtained by subtracting the DEM from the DSM. However, CHMs are limited [26] in their capacity to accurately retrieve individual tree and crown attributes [27-28]. The limitations are often due to applying inappropriate crown shapes, overlap with adjacent trees, or canopy gaps [29-30]. Also, the
contained surface irregularities [31], tree top dislocation in the CHMs [32], and underestimation of tree height are commonly reported [33-34].

Parametric height models (PHM) describes the forest canopy as a series of cones fitted to the LiDAR point clouds. From them, tree crown delineations can be extracted through simple geometric operations [26]. Although, by fitting cones to the LiDAR point cloud, the negative height bias can be corrected; nevertheless, positive height bias still exists in the results. This technique may be improved by retrieving inter-crown gap distributions and by modeling radiation regime within trees crowns.

In order to overcome the weaknesses and limitations of the above models (CHM and PHM), in this dissertation, I proposed a new 3D surface reconstruction method for tree canopies based on a region-based active contour model.

The proposed model truly describes the forest canopy, which is not only suitable for a series of ideal cones, but also for other kinds of real shapes. In the proposed method, smoothing techniques are not specifically needed to correct surface irregularities. More significantly, movement and missing tree top locations do not affect individual tree detection, or tree crown delineation.

Numerous shape models from computer vision and pattern recognition have been proposed and applied to geography, forestry, and ecology, but few studies have focused on automated characterizations of 3D canopy shapes using LiDAR data [35-36]. Also, there are various limitations when the previous models are applied to obtain the tree height, crown width, basal area, crown base height, and crown volume using LiDAR data [37-43].

Three-dimensional (3D) shape signatures based on the distance distribution of random point pairs were introduced [44]. Comparison of 3D canopy shapes can be effectively reduced to
the comparison of frequency distributions of distances between random points [44]. This 3D shape signatures [45] based method has its advantages; for example, the statistically-based 3D shape signatures are relatively insensitive to noise [44]. However, the 3D shape signatures cannot be employed to solve all problems. There still are some drawbacks for feature extraction procedures and automatic recognition of different trees from LiDAR dataset. So, more powerful and advanced models are needed for canopy shape analysis in real world environments.

The proposed model will also estimate and calculate the important forest activities, biomass, wildlife habitat, and wildfire risk assessment by tree canopy characterization obtained from LiDAR datasets, which not only monitor and manage forest resources effectively, but also make economic benefits and scientific values. Via the proposed model, several contours corresponding to different heights are utilized to quantitatively describe attributes and categories of trees. Many parameters, such as the horizontal position and the height and crown of the tree, can be calculated with high precision.

The dissertation is composed of six chapters. The main work in each chapter (2-5) is described as following:

In Chapter 2, I proposed a novel method for feature extraction from sparse LiDAR data and described the algorithm and the principle on which it is based. I have also tested and discussed the choices and roles of parameters. By using correlation of neighboring points directly, the statistic distribution of normal vectors at each point has been effectively used to determine the category of the selected point. The results demonstrate that the proposed method can determine the category of each LiDAR point more accurately, especially more suitable for sparse 3D LiDAR data. Moreover, the proposed method is not sensitive to the edges of buildings.
since the separated height layers and the number of neighbors determined by the selected range \( r \) have reduced the scope of misclassification.

In Chapter 3, I have classified the same 3D LiDAR data point clouds using two different feature extraction methods based on normal variations. One is the proposed method, the other one is from paper [13]. The experimental results indicate the proposed method is better and more accurate for classification (trees and buildings) of 3D LiDAR data, and is more suitable for sparse 3D LiDAR data.

In Chapter 4, I proposed a new method for 3D canopy surface reconstruction of individual tree crowns and clusters of trees from LiDAR point data based on a region active contour model. The proposed method allows for delineations of 3D forest canopy naturally from the contours of raw LiDAR point clouds. The proposed model is suitable not only for a series of ideal cone shapes, but also for other kinds of 3D shapes. In my method, smoothing techniques are not specifically needed to correct surface irregularities. Several contours corresponding to different heights are very important to quantitatively describe attributes and categories of trees. Also, many parameters, such as horizontal position, cross sectional areas and tree crowns can be calculated precisely. More significantly, inaccurate or missing treetop locations does not affect individual tree detection, or tree crown delineation. The proposed method can facilitate more accurate estimation of canopy volume which is related to some important biophysical parameters such as biomass and leaf area index.

Many methods have been provided to build 3D reconstruction of the brain and the subthalamic nuclei using MRI and CT [46, 47]; for example, marching-cubes algorithm (MC), and 3D reconstruction based on the region-based level set method [47, 48]. As a classic visualization technique, marching-cubes algorithm (MC) has been applied to 3D reconstruction.
of medical image and data, which constructs a geometrical representation of the iso-surface defined by a density threshold. The main disadvantage of MC is the computationally expensive preprocessing and the lack of basic volume operations such as cutting. The number of generated triangles can be extremely high for high resolution data set [46, 47]. For the segmentation based 3D reconstruction method, the outer boundaries of the brain and the subthalamic nuclei can be separated from 2D magnetic resonance images (MRIs) using the region-based level set method [47, 48]. Then, 3D visual surface of the brain and the subthalamic nuclei are obtained via the superposition of a set of outer boundary slices of the brain and the subthalamic nuclei. The transparent 3D reconstruction [47, 48] is useful for localization between the skull surface and organs, and can provide the direct visualization of the studied objects.

Subthalamic nucleus (STN) is a very small organ in the brain. Through using deep brain stimulation (DBS) to STNs, some disorder diseases (e.g., Parkinson disease) can be treated and improved. Thus, it is very important to analyze position, size and distance of the subthalamic nucleus (STN) in the brain using magnetic resonance imaging and to locate electrodes in the subthalamic nucleus for operation. For the specific area where physicians may concentrate to study, or the region which contains the organs to be analyzed and treated, the 3D spatial reconstruction is very helpful in medical field because it visibly provides the 3D structural information and relationship among three orthogonal sides about the studied objects in the brain.

In Chapter 5, a novel 3D visualization model of the reconstructed subthalamic nuclei in the brain is built for recognition and position analysis of the subthalamic nuclei in the brain. The proposed method is composed of three sections: 3D reconstruction of the subthalamic nuclei, 3D visual surface of the brain, and complete model of the reconstructed subthalamic nuclei in the brain. The method utilizes a region based level set method to segment 2D subthalamic nuclei
from MRI images and to obtain outer contours of the brain from MRIs. Via the localization, registration and conditional interpolation of two orthogonal subthalamic nucleus contours, 3D rendering of the subthalamic nuclei can be obtained. The 3D visual surface of the brain can be displayed from stacks of outer boundaries of the brain corresponding to different layers. Finally, 3D visualization model of the subthalamic nuclei in the brain can be constructed after adjusting size of the subthalamic nuclei and locating the subthalamic nuclei within the brain. With its direct and effective visualization, the 3D visualization model of the subthalamic nuclei in the brain has important applications for the clinical diagnosis and treatment of Parkinson’s disease.

In Chapter 6, the main contributions and conclusions of this dissertation are summarized.
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CHAPTER 2
A NEW METHOD FOR EXTRACTING TREES AND BUILDINGS FROM SPARSE LIDAR

2.1. Introduction

Feature extraction from LiDAR data has wide applications in urban areas, such as land use planning, population estimation, emergency management, environment monitoring, and public security [1-5]. Many approaches to feature extraction from LiDAR data have been proposed, such as methods based on triangulated irregular networks (TIN) [6-9], curvature-based segmentation techniques [10], progressive morphological filters [11,12], etc. While these methods show different degrees of success for LiDAR points with dense density, the algorithms seem to have limitations in classifying low density LiDAR points in areas with complex terrain and height-discontinuities at the feature boundaries.

The researchers [13] employed three features (height, height variation and normal variation) to derive ground features from LiDAR data and organize the features into three classes (buildings, trees, and roads/grasses). They defined the normal variation as the average dot product of each normal with other normals within a 10×10 pixel ($25m^2$) window. One limitation of the method [9] is that the result of an average dot product is a scalar value, which just gives the average angle that the normal at a given point of the surface deviates from the average normal around the point. In other words, an average dot product does not reflect the distribution of normals around the point. While convenient to compute, the neighborhood over which the average dot product is computed is very likely to contain a clutter of objects. Thus, the average dot product method may not be an accurate signature of the object at the given point.

---------------------------------
In order to improve classification accuracy of sparse LiDAR points, I proposed a novel method for LiDAR point classification. I also demonstrated the performance of the method for classification of buildings and trees using a real LiDAR dataset. The dataset was collected in New Orleans, Louisiana, USA using a 1064 nm laser at 15000 to 30000 pulse/s. The point density of the LiDAR dataset is 0.18 points/m². The algorithms were implemented in Matlab.

2.2. Method

The elegance of my approach is two-fold: (1). Only a small number of features are needed due to an assumption that at different heights, there are different object sets and (2). A new model was employed to describe the distinctive texture of objects.

2.2.1. Characteristics of Trees and Buildings in Urban Areas

An urban area may have high-rise buildings, buildings with a large area mass, and other less distinctive buildings and trees, which have not only different distributions of objects at the different layers, but also big differences of height between high-rise buildings and other objects (buildings/trees). The distribution of trees and buildings will vary with height. Generally, with increasing height, there are less trees and buildings (Figure 2.1). This is also visible in the Delaunay triangulation network created from LiDAR data of an urban area in New Orleans, Louisiana, USA (Figure 2.2).

Due to large height differences and sparse LiDAR data, the triangles around the boundary of buildings span large spaces and have completely different slopes from neighboring ones (Figure 2.2). As a result, there exists potential computational errors of normals near the edges/boundaries of trees and buildings, which may lead to misclassifications.
Figure 2.1. Diagram of urban area with a large difference of height. Dashes represent the separated layers at urban area.

Figure 2.2. Planar Delaunay triangulated network based on LiDAR data from an urban area.

In this chapter, I proposed the following model with two features. Actually, the separated height may vary with the distribution type of different objects at the different layers. The adequate number of neighbors around the selected point by way of setting up the range $r$
effectively decreases the influence of edge/boundary and overcomes the disadvantage of TIN-based model.

In this chapter, for classification purpose, each elevation point is described via two features, \( <h_b, \nu_N> \), where \( h_b \) is a height and \( \nu_N \) is a variance of normal vectors. The variance of normal vectors at the point has three components corresponding to the directions in three dimensional space.

### 2.2.2. Feature I: the Height Layers in the Urban Area

For LiDAR point \( p \), define \( h_p = e_p - e_T(p) \), where \( e_p \) is the surface elevation of \( p \) and \( e_T(p) \) is the elevation of the terrain underneath the point \( p \). A height layer, \( H \) consists of all points \( P = \{p_1, p_2, ..., p_M\} \) such that \( \forall p_j \in P, b_L \leq h_{p_j} < b_U \) where \( b_L \) and \( b_U \) are arbitrarily chosen height layer boundaries.

Now, chosen \( k \) boundaries, \( b_1, b_2, ..., b_{k-1} \), such that \( 0 < b_1 < b_2 < ... < b_{k-1} \), This partitions the space of elevation points into \( k \) blocks, \( P \in H_j \) where

\[
\begin{align*}
  j = 1 & \implies h_{p_1} < b_1 \\
  j = 2 & \implies b_1 \leq h_{p_2} < b_2 \\
  & \ldots \\
  j = k & \implies b_{k-1} \leq h_{p_k}
\end{align*}
\]

The height layer block \( h_{p_j} \) is a feature of each elevation point. The use of height layer as a feature is based on two assumptions:
a2.1. Height itself is a distinguishing element of objects and is useful in classification.  
a2.2. Classification rules for some classes (e.g., vegetation) differ by height layer.  

Since the distribution of objects is different at the different layers, I cut the height of LiDAR data at the different height levels (see the dashes in Figure 2.1). The threshold values for variance of normal vectors should also change according to real LiDAR data. If using same thresholds at different height, the accuracy of classification will be affected.

2.2.3. Feature II: Variation of Normal Vectors  

Since each normal is a vector at the selected point (strictly, a normal vector is perpendicular to a plane defined by three points), the variance of normal vectors is reflected through computation as three components of variance of normal vectors. Then, the criterion of labeling buildings or trees can be established using three components of variance (standard deviation) of normal vectors. Building roofs usually consist of limited facets, and the normal vectors of the points on the same facet should have the same or similar direction (small deviation).

Denote \( r \) as the radius which can be adjusted according to different density values of LiDAR point data. If given an \( r \), \( n \) (the number of neighbors at the selected point) is determined. The vector \( A \) (or \( B \)) is from point \( p \) to point \( a \) (or \( b \)). \( N \) is the vector normal to the plane formed by vectors \( A \) and \( B \). The vectors \( A \), \( B \), and \( N \) can be expressed as:

\[
A = (x_a - x_p)i + (y_a - y_p)j + (z_a - z_p)k \tag{2-1}
\]

\[
B = (x_b - x_p)i + (y_b - y_p)j + (z_b - z_p)k \tag{2-2}
\]

\[
N = A \times B = N_x i + N_y j + N_z k \tag{2-3}
\]
As shown in Figure 2.3, the variance/standard deviation of normal vectors at point \( p \) will be calculated after calculating \( m = \binom{n}{2} \) vectors \( N \). Three components of variance of normal vectors are \[ \text{var}_x = \frac{\sum_{i=1}^{m} (N_x - N_{x_i})^2}{m}, \quad \text{var}_y = \frac{\sum_{i=1}^{m} (N_y - N_{y_i})^2}{m}, \quad \text{var}_z = \frac{\sum_{i=1}^{m} (N_z - N_{z_i})^2}{m}, \]
respectively. Three components of the standard deviation of normal vectors are \[ \text{std}_x = \sqrt{\frac{\sum_{i=1}^{m} (N_x - N_{x_i})^2}{m}}, \quad \text{std}_y = \sqrt{\frac{\sum_{i=1}^{m} (N_y - N_{y_i})^2}{m}}, \quad \text{std}_z = \sqrt{\frac{\sum_{i=1}^{m} (N_z - N_{z_i})^2}{m}}, \]
respectively.

2.2.4. Algorithm for the Calculation of Variation of Normal Vectors

According to the above equations and descriptions, the algorithm may be expressed as follows:

**Algorithm**

At each height level \( H_j \in \{ b_1, b_2, \ldots, b_{k-1} \} \)

Initialization:

Set the neighborhood radius \( r \) that determines the range of neighbors of the selected point
FOR Each Point  $p$

Determine the numbers of neighbors of the selected point ($n$) within a given radius $r$

Calculate the vectors of the neighbors of the selected point $\mathbf{A}_{pi}$ and $\mathbf{B}_{pj}$

Calculate and normalize the normal vectors $\mathbf{N}_{pk} = \mathbf{A}_{pi} \times \mathbf{B}_{pj}$ of the selected point $p$ (where $i \neq j$)

Calculate the distribution (Standard Deviation $\text{std}$ or Variance $\text{var}$) of $m=\binom{n}{2}$ normal vectors at the selected point $p$

Apply the criterion of $\text{std}/\text{var}$ to determine if the point belongs to buildings or trees

ENDFOR

2.3. Experimental Section

2.3.1. Parameter Test

During the calculation, parameter $r$ is important because it determines the number ($n$) of neighbors at the selected point, reflects the correlation with neighbors and relates with the variation of normal vectors. Also, parameter $r$ affects the computation time and the accuracy of the results.

I have tested the parameter $r$ values from 3m to 6m. The results are shown in Figure 2.4-2.5. The average number of neighbors is few ($n \approx 4$) when $r$ is equal to 3m and there is little difference in results between $\text{std}<0.85$ and $\text{std}<0.98$ (see Figure 2.4 (a) and (b)). When $r$ is equal to 6m, the average number of neighbors is about 14. The results are different between $\text{std}<0.85$ and $\text{std}<0.98$ (see Figure 2.5 (a) and (b)).

I suggest the parameter $r$ be adequately selected such that the average number of neighbor is 8~30. If the average number of neighbors is large, it affects the speed of calculation.
Figure 2.4. Feature extraction (blue for buildings and green for trees, at $h > 9.14$ m)
(a) at $r=3m$, $\text{std} < 0.85$, $n \approx 4$; (b) at $r=3m$, $\text{std} < 0.98$, $n \approx 4$.

Figure 2.5. Feature extraction (blue for buildings and green for trees, at $h > 9.14$ m)
(a) at $r=6m$, $\text{std} < 0.85$, $n \approx 14$; (b) at $r=6m$, $\text{std} < 0.98$, $n \approx 14$. 
2.3.2 Preprocessing

Preprocessing of LiDAR data is necessary before separated into height layers. A digital elevation model (DEM) was created using elevation of bare earth points, and a digital surface model (DSM) was created using LiDAR points of the actual surface, including trees and buildings. A normalized digital surface model (nDSM) represents the height of ground features, and is obtained by subtracting DEM from DSM, i.e., nDSM=DSM-DEM.

To deal with “height-discontinuities” in LiDAR point elevation that are common in urban environments where buildings height change abruptly, I have employed the methods of height intervals (separated levels) and set different standard deviation/variance threshold of normal vectors (std/var) reflecting the distribution of trees and buildings at different height intervals. The threshold for standard deviation/variance of normal vectors (std/var) may be set and adjusted separately for each component. Alternatively, the norm (only considering one value) may be used. I have used one threshold value for all three components. After considering the height distributions of buildings and trees, I separated the normalized height at the 5 height interval in this chapter, \( h(\text{height}) \leq 2.13 \text{m} \), \( 2.13 \text{m} < h \leq 3.05 \text{m} \), \( 3.05 \text{m} < h \leq 6.10 \text{m} \), \( 6.10 \text{m} < h \leq 9.14 \text{m} \) and \( h > 9.14 \text{m} \). At each height interval, I extracted features first and then determined their category according to the distribution of normal vectors. The results are shown as Figures 2.6-2.7.

Cross validation is used for classification accuracy assessment. The whole study area was divided into many parts for a more detailed comparison. In the following equations, \( a \) is for the number of building points classified as buildings, \( b \) for the number of building points classified as trees, \( c \) for the number of tree points classified as buildings, and \( d \) for the number of tree
points classified as trees. Compared with aerial photographs, the accuracy of the classification results was obtained using equations (2-4)~(2-6), and listed in Table 2.1.

\[
\text{Building\_accuracy} = \frac{a}{a+b} \\
\text{Tree\_accuracy} = \frac{d}{c+d}
\]  

Figure 2.6. Classification results (blue represents buildings and green represents trees). (a) at \(2.13m < h \leq 3.05m\) and \(\text{std} < 0.78\); (b) at \(3.05m < h \leq 6.10m\) and \(\text{std} < 0.98\); (c) at \(6.10m < h \leq 9.14m\) and \(\text{std} < 0.98\); (d) at \(h > 9.14m\) and \(\text{std} < 0.98\).
\[
\text{Cross\_accuracy} = \frac{a + d}{a + b + c + d} \tag{2-6}
\]

\[\text{Table 2.1. Accuracy of classification based on feature extraction}\]

<table>
<thead>
<tr>
<th>Region</th>
<th>Building accuracy</th>
<th>Tree accuracy</th>
<th>Cross accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region 1</td>
<td>93%</td>
<td>91%</td>
<td>93%</td>
</tr>
<tr>
<td>Region 2</td>
<td>89%</td>
<td>96%</td>
<td>89%</td>
</tr>
<tr>
<td>Region 3</td>
<td>95%</td>
<td>87%</td>
<td>94%</td>
</tr>
<tr>
<td>Region 4</td>
<td>90%</td>
<td>93%</td>
<td>91%</td>
</tr>
<tr>
<td>Average</td>
<td>92%</td>
<td>92%</td>
<td>92%</td>
</tr>
</tbody>
</table>

It can be seen that the cross accuracy is 91.73%. The average accuracy for detecting buildings and trees is 91.68% and 91.63%, respectively. In this study, my purpose is to use the...
extracted feature to classify buildings and trees from sparse LiDAR data. I omitted classification accuracy of objects at heights less than two meters. At such heights, the possibilities include vehicles, impervious surfaces, vegetation of different types, and numerous other cultural and natural phenomena.

From Table 2.1, region 2 and region 3 have lower accuracy than the other two regions. This can be attributed to the fact that some man-made features on the roofs (such as water boxes, pipelines, and channels) were misclassified as trees. In fact, I find that misclassification often occurs in the following situations: (1) existence of some irregular man-made features on rooftops, and (2) big trees with flat tops.

2.4. Conclusions

I proposed a novel method for feature extraction from sparse LiDAR data and described the algorithm and the principles on which it is based. I have also tested and discussed the choices and roles of parameters.

One advantage of my method is that it is not sensitive to edges of buildings. The reason is that the separated height layers and the number of neighbors determined by the selected range \( r \) have reduced the scope of misclassification. By using the correlation of neighboring points directly, the statistic distribution of normal vectors at each point has been effectively used to determine the category of the selected point. The results demonstrate that my method can determine the category of each LiDAR point more accurately, especially more suitably for sparse 3D LiDAR data.
Chapter 2 References


CHAPTER 3

COMPARISON OF TWO CLASSIFICATION METHODS

FOR FEATURE EXTRACTION FROM LIDAR DATA

3.1. Introduction

Many approaches to feature extraction from LiDAR data have been proposed, such as TIN (triangulated irregular network)-based models [1], which has conveniently been employed to manipulate 3D spatially distributed LiDAR points based on the Delaunay triangulation network. Lodha et al. [2] used three features - height, height variation, and normal variation to derive ground features from LiDAR data and organize the features into three classes (buildings, trees, and roads/grass). They [2] defined the normal variation as the average dot product of each normal with another normal within a $10 \times 10$ pixel $(25m^2)$ window.

The above methods still have several limitations because of the complex terrain and the differences in spatial distribution of ground object points. The TIN-based model and average dot product method are not suitable for sparse LiDAR data, and for areas with boundary/edge having a vertical height-jump. A novel method [3] I proposed takes into account these characters. In order to test the accuracy of my method, I used the same LiDAR data and two different methods to conduct a comparative study.

My approach evolves from an observation by Brattberg [4] that states methods which work well for one data set and geographical region which do not translate well when either changes. For LiDAR data collection, a significant characteristic is the collection density. I showed that a method for high density data [2] performs poorly when low density data is used. Additionally, I proposed a related method that is more appropriate for low density data.
In fact, it’s very difficult to compare different methods in this case. This is because there is not a set of reproducible programs which can be used as criteria. Some papers only give the algorithm. Some papers vaguely describe the methods. Even if I reconstructed the codes from published algorithms, I may not know the details of the parameters and how to vary them with different LiDAR data sets. Moreover, different LiDAR data has very different properties. The collection density is directly related to collection costs. LiDAR missions flown at higher altitudes have gathered data at low costs but also reduced density. Most missions are flown in order to collect data for floodplain mapping, which does not require very dense data -- typically between 0.1 points/m$^2$ and 0.2 points/m$^2$. This chapter compares two different methods of feature extraction to classify the same sparse LiDAR data (very low density data -- 0.18 points/m$^2$).

3.2. Method

First, I described the two different methods for feature extraction from the same LiDAR data. One is the method I proposed in [3] and the other is one from the paper by Lodha, et al. [2]. Although both [2] and [3] employed the height and normal vector variation as features to classify LiDAR data, their methods and definitions are totally different.

3.2.1. My Method: Variation of Normal Vector

Let us denote $r$ as the range I selected and $r$ may be adjusted according to the different density of LiDAR data. Once $r$ is selected, $n$ (the number of neighbors at each point) will be determined. The vector $A$ (or $B$) is from point $p$ to point $a$ (or $b$). $N$ is a normal vector at the point $p$, which is perpendicular to a plane defined by three points. These vectors may be expressed as follows:
\[ A = (x_a - x_p)i + (y_a - y_p)j + (z_a - z_p)k \] (3-1)

\[ B = (x_b - x_p)i + (y_b - y_p)j + (z_b - z_p)k \] (3-2)

\[ N = A \times B \] (3-3)

The variation of normal vectors at the point \( p \) will be calculated after getting \( m = \binom{n}{2} \) vectors \( N \). Three components of the variance of normal vectors are

\[ \text{var}_x = \sum_{i=1}^{m} \frac{(N_x - \overline{N}_x)^2}{m}, \]

\[ \text{var}_y = \sum_{i=1}^{m} \frac{(N_y - \overline{N}_y)^2}{m}, \]

\[ \text{var}_z = \sum_{i=1}^{m} \frac{(N_z - \overline{N}_z)^2}{m}, \]

respectively. Three components of the standard deviation of normal vectors are

\[ \text{std}_x = \sqrt{\sum_{i=1}^{m} \frac{(N_x - \overline{N}_x)^2}{m}}, \text{ std}_y = \sqrt{\sum_{i=1}^{m} \frac{(N_y - \overline{N}_y)^2}{m}}, \text{ and std}_z = \sqrt{\sum_{i=1}^{m} \frac{(N_z - \overline{N}_z)^2}{m}}, \]

respectively. The buildings and trees will be classified via applying the components’ threshold values of variance (standard deviation) of normal vectors.

3.2.2. Average Dot Product Method: Normal Variation

Lodha \textit{et al.} [2] identified five features to be used for data classification purposes: normalized height, height variation, normal variation, LiDAR return intensity, and image intensity. They also used three features: height, height variation and normal variation to derive ground features from LiDAR data and organize the features into three classes (buildings, trees, and roads/grass).

The normal variation (NV) in paper [2] is defined as: (i). the normal has been computed at each grid point using finite differences at first; (ii). the normal variation is the average dot
product of each normal with other normals within a 10×10 pixel (25 m²) window. This value
gives a measure of planarity within the window.

According to the description in the paper [2], the computational process is the following:

First, using data interpolation, the grid data (x, y, z(x,y)) may be obtained from sparse
LiDAR data.

Second, the normal is computed at each grid point using finite differences: calculating the
vectors at point p on x direction \( \mathbf{r}_x = \mathbf{i} - (\delta z_x) \mathbf{k} \) and y direction \( \mathbf{r}_y = \mathbf{j} - (\delta z_y) \mathbf{k} \). When computing the
normal at point p, two ways can be considered. One way (case I) is to compute \( \mathbf{r}_x \) and \( \mathbf{r}_y \) just one
time and to then obtain \( \mathbf{N}_p = -\delta z_x \mathbf{i} - \delta z_y \mathbf{j} + \mathbf{k} \) via cross product of \( \mathbf{r}_x \) and \( \mathbf{r}_y \). The other way (case II)
is to give a range \( R \). For each point (x, y), if the distance \( D \) between point p and point (x, y) is
less than \( R \) (i.e. \( D = |X_p - X_{x,y}| < R \)), the calculation of a scaling factor \( S \) is:

\[
S = 1.0 - \frac{|X_p - X_{x,y}|}{R} \quad (3-4)
\]

In other words, the contribution of points decreases linearly with distance, reaching zero at
distance \( R \).

I added the scaled contributions of \( \mathbf{r}_x \) and \( \mathbf{r}_y \) and divided each by the sum of the scaling
factor \( S \) to estimate \( \mathbf{r}_x \) and \( \mathbf{r}_y \) at point p. Next, I calculated normal vectors \( \mathbf{N}_p = \mathbf{r}_x \times \mathbf{r}_y = -\delta z_x \mathbf{i} - \delta z_y \mathbf{j} + \mathbf{k} \) at point p within the range \( R \) using cross product: I only considered case II since case II
includes case I.

Third, the calculation of an average dot product is as follows:
The definition [2] of normal variation is the average dot product of each normal with
other normals within a 10×10 pixel (25m²) window. So,
\[ \{ \overrightarrow{N_p} \bullet (\overrightarrow{N_1} + \overrightarrow{N_2} + \ldots + \overrightarrow{N_{100}}) \}/(n) = \overrightarrow{N_p} \bullet \overrightarrow{N}/100 \]

where \( \overrightarrow{N} = (\overrightarrow{N_1} + \overrightarrow{N_2} + \ldots + \overrightarrow{N_{100}}) \) and \( \overrightarrow{N_p}, \overrightarrow{N_1}, \overrightarrow{N_2} \ldots \overrightarrow{N_{100}} \) are normalized vectors

Note: \( \{ \overrightarrow{N_p} \bullet (\overrightarrow{N_1} + \overrightarrow{N_2} + \ldots + \overrightarrow{N_{100}}) \}/100 = \{ \overrightarrow{N_p} \bullet \overrightarrow{N_1} \} + \overrightarrow{N_p} \bullet \overrightarrow{N_2} + \ldots + \overrightarrow{N} \bullet \overrightarrow{N_{100}} \}/100\)

\[ = \{ \cos \theta_1 + \cos \theta_2 + \ldots + \cos \theta_{100} \}/100 = \overrightarrow{N_p} \bullet \overrightarrow{N}/100 = \cos \theta. \]

Finally, the criterion (threshold) of \( \cos \theta \) can be applied to each point to determine if the point belongs to the building class or tree class.

3.3. Experimental Results and Analyses

In this chapter, I used LiDAR dataset covering the region of New Orleans, Louisiana, which was collected using a 1064 nm laser at 15,000 to 30,000 pulses per second. The density of the LiDAR dataset I used is 0.18 point/m\(^2\). First, I preprocessed the raw LiDAR data to get normalized height. Due to the characters of the urban region, I employed the methods of height interval (separated levels) to reduce the errors of computing normal vectors.

To compare the two methods fairly, I just took the data when height \( h > 9.14 \) m in this chapter. Figure 3.1 shows raw LiDAR data point cloud in 3D after getting normalized height.

In order to use the average dot product method to compute the normal variation [2], I interpolated the sparse raw 3D LiDAR data into a grid matrix. Figure 3.2 shows the 3D LiDAR data after interpolation.

After overlapping the raw 3D LiDAR data on the interpolated new points, I obtained Figure 3.3. The surface and basic shapes of LiDAR data after interpolation are consistent with the raw 3D LiDAR data but its density is denser than that of raw 3D LiDAR data.
Now I employed the average dot product method [2] to calculate the normal variation, then classified the same 3D LiDAR data (height>9.14m). The Figure 3.4 (a)-(c) was obtained for the classification of buildings and trees. The blue color stands for buildings. The green color represents trees or objects with uneven top.

Figure 3.5 gives the classification results using my method. Here I employed the normal vector variation that I proposed to classify objects (buildings and trees). I took the same threshold value for three components of standard deviation of normal vectors in this chapter. The blue color represents buildings. The green represents trees.

In this chapter, the visual analyses of Figures 3.4, 3.5 and 3.6 indicate that my method is better and more accurate for classifying trees and buildings.

Figure 3.6 is an aerial photograph corresponding to the LiDAR data I used. According to the Figure 3.6, the above results from two different methods can be compared each other.
In Figure 3.4, many areas that have no buildings are placed in the “building” category. Obviously, the misclassifications occurred mostly around the boundary, and still exist at the vicinity of the edge of buildings even with changing threshold values of average dot product ($\cos \theta$).
(a) \( \cos \theta > 0.9935 \)

(b) \( \cos \theta > 0.9977 \)

(c) \( \cos \theta > 0.9997 \)

Figure 3.4. Classification of buildings and trees using average dot product method (case II, blue stands for buildings, green for trees)
Figure 3.5. Classification results using my method at $h > 9.14m$ and std $< 0.98$ (taking same threshold value for three components), blue represents buildings and green represents trees.

Figure 3.6. An aerial photograph corresponding to the LiDAR data

In paper [2], the normal vector is computed at each grid point using finite difference, and the sparse LiDAR data needs to be interpolated. However, interpolation not only increases computational time and complexity, but also brings misclassifications. The defined normal variation (average dot product) [2] does not reflect the distribution of normal vectors and may be
correlated and affected by a few larger normal vectors among the 100 neighbors in an urban area with big height differences. Since the average dot product is a scalar that represents the average angle between normals at each point and neighbors’ normals around the point, it can easily contain a clutter of objects and cause misclassifications. Thus, my method is better and more suitable for the sparse LiDAR data in urban region.

3.4. Conclusions

In this chapter, I have classified the same 3D LiDAR data point clouds using two different feature extraction methods based on normal variations. One is my method, the other one is from paper [2]. The experimental results indicate my method is better and more accurate for classification (trees and buildings) of 3D LiDAR data, and is more suitable for sparse 3D LiDAR data. Since my method only involves the data within a small range I specified, it reduce the influence from the faraway data points. By using correlation of neighboring points and statistical information of normal vector variation directly, my method can be used to determine the categories of each point with more accuracy and efficiency.
CHAPTER 3 REFERENCES


4.1. Introduction

Forests are closely related with the development of life and human civilization. Through the use of light detection and ranging (LiDAR), forest attributes (such as tree height, canopy closure, and diameter at breast height) can be effectively estimated. These attributes are often employed to evaluate forest growth, competition, and photosynthesis [1], carbon sequestration, standing timber volume, and biomass of trees [2-4].

Canopy height models (CHMs) are often used to represent horizontal and vertical distribution of tree canopies. Once a digital elevation model (DEM) and a digital surface model (DSM) are interpolated from LiDAR point clouds, a CHM can be obtained by subtracting the DEM from the DSM [5]. However, CHMs are limited in their capacity to accurately retrieve individual tree and crown attributes [6-8]. The CHMs’ limitations are often due to applying inappropriate crown shapes, overlap with adjacent trees, or canopy gaps [9, 10]. Also, the contained surface irregularities [5], tree top dislocation in the CHMs [11], underestimation of tree height are commonly reported [12, 13].

Parametric height models (PHM) describe the forest canopy as a series of cones fitted to the LiDAR point clouds. From them, tree crowns can be extracted through straightforward geometric operations [8]. However, for parametric height models, negative height bias or positive...
height bias still exists in the results. When fitting cones to the LiDAR point clouds, there exists matching errors depending on the properties and distribution of LiDAR point clouds.

Forest growth, competition, and biomass are directly correlated with tree height, canopy area, and volume [1, 2, 8, 14]. Extraction, identification and characterization (the related parameters) of trees have been cutting-edge topics. Besides canopy height models (CHMs), other methods based on active contour theory can detect a single tree from local maxima, in which the detection and measurement method of individual trees starts with the creation of a raster area, then uses a parabolic surface to fit crown surface[15-17], and [7]. In addition, many additional techniques were applied with CHM, such as interpolation [18] and smoothness of the CHM using a Gaussian filter. Previous models also have various limitations. For example, there is a limited applicability for analysis of individual trees, especially for dense deciduous forests because it is difficult to separate tree crowns from each other. Moreover, there exists the shortcomings such as complex algorithm and special requirements (e.g. salient features) for segmentation and tree species classification when the previous models are applied to obtain the tree height, crown width, basal area, crown base height, and crown volume using LiDAR data [19-22].

Although many models from computer vision and pattern recognition have been proposed and applied to geography, forestry, and ecology[23, 24]and [8], few studies have focused on automated characterizations of 3D canopy shapes using LiDAR data [25, 26]. 3D canopy shapes can be effectively described through the use of frequency distributions of distances between random points [26]. Three-dimensional (3D) shape signatures were introduced via the distance distribution of random point pairs [27]. The 3D shape signatures based method has many advantages; for example, statistically based 3D shape signatures are relatively
insensitive to noise [26]. Nevertheless, 3D shape signatures cannot be employed to automatically recognize different trees based on LiDAR point clouds. Moreover, the 3D shape signatures have restrictions because of the irregular boundaries and large area cover of trees.

In order to overcome the weaknesses and limitations of the above models, in this chapter, I proposed a novel 3D surface reconstruction method for tree canopy using a region-based level set method. Using the proposed method, several contours corresponding to different heights are employed to further calculate tree parameters (e.g., position, equivalent radius, crown area and volume of trees) and to identify tree species based on the same 3D surface reconstruction of trees from LiDAR point clouds so that attributes and categories of trees can be described quantitatively.

4.2. Methodology

4.2.1. Study Area

The study area is located in the Soquel Demonstration State Forest in California, USA. Soquel Demonstration State Forest contains redwood, mixed hardwoods, sag ponds and riparian ecosystems. The ecosystems do not vary much with the seasons, ranging from 90°F (Max) to 32°F (Min), and experiences relatively cool, often foggy summers, mild falls, and chilly, rainy winters.

The LiDAR data was collected on March 29, 2007 by the GeoEarthScope Northern California LiDAR project [28], and downloaded from the OpenTopography Facility at the San Diego Supercomputer Center. The LiDAR point density is on average 9.6 points / m². Major tree types in the study area include Douglas fir, redwood, and oak.
4.2.2. Data Processing

Preprocessing of LiDAR data is necessary before separating data points into height layers. A digital elevation model (DEM) was created from ground points using inverse distance weighted (IDW) interpolation. The height from the ground for each LiDAR point was then obtained by subtracting the DEM-derived ground elevation beneath the point from the elevation of the point.

4.2.3. Segmentation Based on Region-based Level Set Method

The active contour model along with level set theory has been widely applied to many research fields including computer vision and medical image processing. The authors [29] introduced a variational model based on the level set function \( \phi(t, x, y) \), for which the zero level set segments the image domain into several intensity homogenous regions by minimizing the following function. The level set function \( \phi(t, x, y) \) presents the zero-level curve at time \( t \).

\[
F(c_1, c_2, \phi) = \mu \int_{\Omega} \delta(\phi(x, y)) | \nabla \phi(x, y) | dxdy + \nu \int_{\Omega} H(\phi(x, y)) dxdy + \lambda_1 \int_{\Omega} | u_0(x, y) - c_1 |^2 H(\phi(x, y)) dxdy + \lambda_2 \int_{\Omega} | u_0(x, y) - c_2 |^2 (1 - H(\phi(x, y))) dxdy
\]  

(4-1)

where \( u: \Omega \rightarrow R \) is an image defined on \( \Omega \), \( c_1 \) and \( c_2 \) are constants, \( \lambda_1 \) and \( \lambda_2 \) are parameters, and \( H(\cdot) \) is the Heaviside function and \( \delta(\cdot) \) is Kronecker delta function. Of the four terms in equation (4-1), the first is the length of the contour; the second is the area
within the contour; the third and fourth terms are proportional to the energy within and outside the contour, respectively.

This minimization problem is solved by taking the Euler-Lagrange equations and updating the level set function \( \phi \) by gradient descent.

\[
\frac{\partial \phi}{\partial t} = \delta(\phi) [\mu \cdot \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) - \lambda_1 (u_0 - c_1)^2 \\
+ \lambda_2 (u_0 - c_2)^2 ]
\] (4-2)

For a 3D reconstruction, each slice of an object must first be obtained. The slice is related with detection and location of the object in each 2D image. As an effective model, the level set technology provided by [29] can detect the location of boundaries very well, and is insensitive to placement of the initial curve in the image. I use this model to separate the individual trees or clusters of trees from their background and to obtain the contours of the individual trees or clusters of trees.

4.2.4. 3D Reconstruction of Individual Trees or Clusters of Trees

At height intervals, I utilize the above region-based level set method to complete the segmentation. Thus, at the given heights, the contours of individual trees or clusters of trees are obtained.

After obtaining a series of tree slices (boundaries) from different heights, a 3D canopy of trees is reconstructed by stacking all the slices together according to their height orders.
Using interpolation or MESH function in Matlab (Version 7.8.0.347 R2009a The Mathworks Inc.), 3D reconstruction with finer and smoother canopy surface is obtained for individual trees or clusters of trees.

4.2.5. Calculation of Cross Sectional Area and Equivalent Radius of Trees

The contours of trees or clusters of trees are obtained by means of a region-based level set method applied at a specified sequence of heights. The enclosed area $A$ of each contour is the cross sectional area of a plane through trees at each given height. The area can be computed by a method similar to the trapezoidal rule commonly used in calculus. The area of any irregular shape can be calculated to the desired precision by defining a divided width approaching the infinitesimal.

To smooth irregular boundaries and to conveniently render the shape of trees for visualization, it is useful to have an equivalent radius for each area.

The equivalent radius of an irregular shape can be defined as:

$$r_e = \sqrt{\frac{A}{\pi}} \tag{4-3}$$

where $A = \pi r_e^2$ and $A$ is obtained via the above described method similar to the trapezoidal rule commonly used in calculus.

4.2.6. Crown Volume of Trees

Let $A_i$ denote the area enclosed by the contours at the $i^{\text{th}}$ height interval. After the cross sectional areas of the trees at each height layer are calculated, trees’ volume can be obtained as:
\[ V = \sum_{i=1}^{M} A_i \cdot \delta \]  

(4-4)

where \( M \) is the number of height layers, and \( \delta \) is the height interval between the layers. The more precise the tree’s volume, the smaller the height interval \( \delta \).

4.2.7. Tree Species Identification

By comparing with geometric models including cones, hemispheres, and half-ellipsoids, 3D surface reconstruction of trees from LiDAR point clouds can be used to automatically recognize some tree species such as Douglas fir and oak.

The approach employs the relationship between the equivalent radius of cross sectional area and height because their proportional relations tend to differ for different tree species. The formula for describing a cone may be expressed as:

\[ r_2 = \left( \frac{h_2 + h_3}{h_1 + h_2 + h_3} \right) r_1 \]  

(4-5)

For half-ellipsoids,

\[ r_2 > \left( \frac{h_2 + h_3}{h_1 + h_2 + h_3} \right) r_1 \]  

(4-6)

where \( r_1 \) and \( r_2 \) are the equivalent radii of two different areas; \( h_3 \), \( h_2 \) and \( h_1 \) are the distances from the top to center corresponding to cones, hemispheres, and half-ellipsoids, respectively. For a hemisphere, the height is

\[ h_{hs} \ll h_{he} \text{ or } h_c \]  

(4-7)
That is, \( r_{hs} = h_{hs} \) the radius of sphere is its height when their normalized radii (\( r_i \)) are the same. Where \( h_{hs} \) is height of the hemisphere, \( h_{he} \) the height of the half-ellipsoid, and \( h_c \) height of the cone. Thus, the tree species may be classified by observing which condition (Equ. 4-5~Equ.4-7) the values of a tree satisfies: a cone, half ellipsoid or hemisphere.

4.2.8. Estimation of Missing Tree Components

Frequently, treetops are missing from LiDAR point clouds due to the limited sampling density. If the treetop is missing from the data, the tree height \( h_3 \) can be derived as:

\[
h_3 = \frac{r_x}{(r_2 - r_3)} h_2
\]

Other missing information, such as the volume, can be found after obtaining height \( h_3 \). \( h_2 \) is height interval between two neighboring intersection areas; \( r_2 \) and \( r_3 \) are the equivalent radii of two neighboring cross sectional areas and can be obtained from equation (4-3). Therefore, using the proposed model, the omitted components may be derived from the known ones.

4.3. Experimental Examples, Results and Analysis

Figure 4.1 shows 3D raw LiDAR point clouds with height from ground.
Figure 4.1. Perspective view of raw 3D LiDAR data.

Figure 4.2. (a) 2D image of trees at heights \( h \geq 25 \text{m} \) is obtained from raw 3D LiDAR data; (b) Boundaries of trees in the 2D image are segmented based on region-based level set method; (c) The contours of individual trees or clusters of trees are obtained by using region-based level set method.
Figure 4.2(a) shows a 2D image of trees from LiDAR data at heights \( h \geq 25 \text{ m} \). By employing the region based level set method to separate individual trees or clusters of trees from their background, the contours of individual trees or clusters of trees are obtained and shown in figure 4.2(b) and 4.2(c).

A 3D canopy surface is reconstructed by putting together a series of tree slices (boundaries) corresponding to different heights following their height orders. After using interpolation or the MESH function in Matlab (Version 7.8.0.347 R2009a The Mathworks Inc.), a finer and smoother canopy surface is achieved.

Figure 4.3(a) shows the stack of slices for all trees in the study area including individual trees and clusters of trees. Figure 4.3(b) depicts the 3D canopy surface reconstructed with smoother surfaces from different heights for trees which contain individual trees and clusters of trees.

Figure 4.3(c) is the 2D section obtained by overlapping the slices for individual trees and clusters of trees at different heights. That is, the figure is the 2D image viewed from the top of the 3D reconstruction. Much important information may be obtained from Figure 4.3(c). For example, it clearly displays changes in contours (attenuating with increasing height). Several observations are: Case I: Many apexes corresponding to higher or top positions are enclosed in contours. That implies that the contours will shrink as tree height increases, and the contours corresponding to the greater heights are located inside the contours corresponding to lower heights. In other words, a large contour contains many trees or belongs to a cluster of trees. The
trees that touch crowns can be detected from case I. It was found that the irregular contours (marked Case I-a) come from the interlocking of trees. With the increment of height, several separated small circles appear, suggesting the irregular contours are composed of several individual trees. In other words, my method can detect individual trees in a large contour. Case II: One apex corresponding to a higher or top position is included in an initial contour corresponding to a lower layer, implying individual trees. Case III: No apex corresponding to
Figure 4.4. (a). Area of single contour (blue line) is obtained using integral; green circle is based on equivalent crown radius derived from the area of the contour; (b). The separated contours at the height ($h = 25$ m) for the calculation of their areas; the pink number is the index of the separated areas.

higher positions exists in the contours. Case III occurred frequently. In most circumstances, the information from LiDAR data reflecting the tops of trees was missing, for which results manifest as Case III. Unlike the previous models (CHM and PHM), surface irregularities and missing apexes in my model have no impact on the calculation of tree height and crown volume. That is, my method is not affected by missing treetop information.

Figure 4.4(a) shows an example of the calculation of the area enclosed by a contour by using the trapezoidal rule method in calculus. In Figure 4.4(a), one contour is cut into 500 rectangular slices. The area of the contour is 743.21 m$^2$ using proposed method. The equivalent radius ($r_e = 15.38$ m) is derived from Equation (4-3). The green circle represents the area approximated by the equivalent radius. Figure 4.4(b) shows the cross sectional area calculation of each contour at the same height level ($h = 25$ m) for the studied region. The total cross sectional area is 3220.80 m$^2$, represented as by the 24 closed contours. The pink number in Figure 4.4(b) is the index of the separated areas.
Figure 4.5(a) is the diagram for calculation of tree missing components. According to the proposed model, the omitted tree components can be calculated when encountering case III of Figure 4.3(c). Figure 4.5(b) shows the obtained area (72.10 m$^2$) and equivalent radius (4.79 m) of a tree at height 25 m by using Equation (4-3). Figure 4.5(c) shows the obtained area (9.28 m$^2$) and equivalent radius (1.72 m) of tree at height 33 m by using Equation (4-3), in which the radius of the green circle is the equivalent radius using Equation (4-3). From Figure 4.5(b), 4.3(c) and Equation (4-8), the missing height and volume of tree can be obtained as 4.48 m and 13.84 m$^3$, respectively.

Figure 4.6(a) is the stack of tree segmentation slices at the different heights. Figure 4.6(b) shows 3D canopy reconstruction from the separate slices, which represents the outer shape of the tree with half-ellipsoid type. Figure 4.6(c) exhibits an oak tree radius varying with height. Figure 4.6(d) shows the 3D canopy reconstruction of the tree which indeed has the appearance of a cone. In Figure 4.6(c), the configuration satisfies the condition (Equation 4-6). Thus, the type of trees may be recognized via the calculations in Equation (4-5)–(4-7). More simply, the type of trees may be quickly identified from visualization of slice stack after obtaining the separate contours. For cone types such as Douglas fir or redwood, contours will proportionally shrink as the height increases. However, for half-ellipsoid type, the contours will show a rapid decrease in the area only near the top.
Figure 4.5.  (a). Calculation of missing components of tree; Dotted lines represent the omitted components; (b). The cross sectional area (72.10 m²) and equivalent crown radius (4.79 m) of tree at height = 25 m; (c). The cross sectional area (9.28 m²) and equivalent crown radius (1.72 m) of tree at height = 33 m.
Figure 4.6.  (a). Stack of separated slices corresponding to different height levels at the location A in Figure 4.7; (b). 3D canopy reconstruction of an oak tree with half-ellipsoid type; (c). The tree crown radius varying with its height demonstrates 3D canopy reconstruction of an oak tree with half-ellipsoid type which comes from the calculation of tree crown radii and their heights corresponding to the crown radii in the Figure 4.6(b); (d). 3D canopy reconstruction of a redwood tree with cone shape.
Figure 4.7. Canopy height model showing individual trees and tree clusters, and comparison between a canopy height model and a high-resolution aerial photograph. (a) Visualization of trees in the 3D LiDAR data. The green frame represents the study area with size about 120 m × 90 m. The center coordinates are latitude 37° 05’ 21.93” and longitude 121° 53’ 21.26”. (b) Natural color aerial photograph (2007) corresponding to the LiDAR data. Letters (A, B) and numbers (1, 2, 3, 4, 5) represent the corresponding tree pairs between the canopy height model and the high-resolution aerial photograph. Letters (A, B) indicate oak trees; numbers (1, 2, 3, 4, 5) indicate redwoods or Douglas firs.

Letters (A, B) indicate oak trees; numbers (1, 2, 3, 4, 5) indicate redwoods or Douglas firs.

In a field survey, I identified two oaks (Figure 4.7, marked A and B) and five redwoods (Figure 4.7, marked 1, 2, 3, 4, and 5). By comparing with Figure 4.7, the results from Figure 4.6(b) and (d) are further confirmed from the CHM, high-resolution aerial photographs, and field measurements in which tree heights were measured using a laser ranger and tree crown, widths were measured using a tape. All of these demonstrate the effectiveness of the method in recognizing different types of trees by their 3D surface reconstruction. The LiDAR point density
in this article is on average 9.6 points/m². The LiDAR point density is a critical parameter. If the point density is too low, the results will be affected.

4.4. Conclusions

In this chapter, based on a region-based level set method, I proposed a new approach for 3D canopy surface reconstruction of individual tree crowns and clusters of trees from LiDAR point clouds. In the proposed method, several contours corresponding to different heights are shown to be quantitatively effective in describing attributes and categories of trees. The proposed method allows for delineations of 3D forest canopy from the contours of raw LiDAR point clouds, and is suitable not only for a series of ideal cone shapes, but also for other kinds of 3D shapes. More importantly, the proposed method can detect individual trees in a large contour (i.e. a tree cluster). In contrast to previous methods using CHM, the proposed approach does not require fitting to the elevation data using a parabolic surface, and the choices of a scale for different parts of the image is not necessary.

Also, I proposed a new method for the recognition of tree types and the calculation of tree parameters, including cross sectional area, horizontal position, equivalent radius, crown volume, and estimation of omitted components. Significantly, inaccurate or missing treetop locations do not affect individual tree detection, or tree crown delineation. The proposed method can facilitate more accurate estimation of canopy volume which is related to some important biophysical parameters such as biomass and leaf area index[30-32]. These parameters, derived from 3D raw LiDAR data, enable us to obtain the properties of a forest, not only from direct visualization, but also from quantitative description.

In this chapter, I have mainly provided a practical approach for 3D surface reconstruction
of trees using LiDAR point clouds, and confirmed its correctness from experimental examples based on real exploration and 3D LiDAR point clouds. Experimental results demonstrate the value of the proposed method, which can be potentially applied to the study of biophysical properties of trees, such as estimation of biomass and leaf area index.
CHAPTER 4 REFERENCES


CHAPTER 5

3D VISUALIZATION OF THE SUBTHALAMIC NUCLEI IN THE BRAIN BASED ON LEVELSET METHOD USING MRI

5.1. Introduction

The subthalamic nucleus (STN) is a pea-sized organ within the human brain and plays an important role in deep brain stimulation (DBS). Electrical stimulation of the subthalamic nucleus (STN) can be employed to treat Parkinson’s disease (PD) and to improve the life function and quality of patients. In order to implement the electrode stimulation in DBS, it is important and necessary to accurately locate the STNs [1, 2, 3].

Many methods have been developed to seek and locate the STNs. There are two basic approaches for primary targeting of the STNs. The classical method, called ‘indirect targeting’, is based on determining geometric coordinates of the STN. Stereotactic atlases such as the Schaltenbrand and Bailey atlas [1, 4, 5] are helpful for indirect targeting. The second method for primary targeting is called ‘direct targeting’. This approach directly visualizes the STNs and allows targeting STNs without the use of atlases and predetermined landmark based coordinates, which is taken from spontaneous contrasts between white (WM) and gray (GM) matter with appropriate sequences delineating STN contours from MR Images [6].

The general approach is to combine an anatomic image with a stereotactic frame, atlas coordinates, and intraoperative neurophysiology [7]. Direct or indirect primary targeting can be used in different ways, alone or mixed, depending on the surgical environment (technology, habits), institutional and/or national rules on quality assurance, and professional guidelines [6]. Although direct or indirect primary targeting has been utilized for clinical treatment, there exists problems for targeting STNs because of the several factors: (i). the locations of the STNs differ
with patients. The shape and size of STN vary during course of the disease[8]; (ii).the size of an
STN is relatively small ( 20 – 30 mm³ ) so that conventional methods (i.e. the automatic
superposition of multiple successive contours) are not suitable for its 3D reconstruction [2, 3]. In
fact, except for hand drawings[8], no 3D reconstructions of an STN based on MRI have been
reported. (iii). the STN is not visualized in CT imaging and is difficult to distinguish among
the gray background of an MRI [2, 3]. (iv). Even if an STN can be identified directly on MRI at
1.5 or 3 T[9], it is difficult to secure the several successive MR images with STNs for 3D
reconstruction due to the thinness of an STN.

Motivated by these limitations, I have provided a unique and novel approach to 3D
reconstruction of the STNs from two orthogonal images of each STN using magnetic resonance
images (MRIs) and level set methods. I have utilized the 3D rendering of the STNs and the skull
directly from MR imaging in this chapter, determined the 3D coordinates of the STNs in the
brain by taking the statistical data of previous investigations of an anatomy atlas as a reference,
and constructed a 3D model of the subthalamus nuclei in the brain with direct vision.

5.2. Methodology

5.2.1. Region-based Level Set Method

The active contour model along with level set technology has been widely applied to
many research fields, such as computer vision, remote sensing [10] and biomedical image
processing[2,3].

Chan and Vese [11] introduced a variational model based on the level set
function \( \phi(t, x, y) \), for which the zero level set segments the image domain into several intensity
homogenous regions by minimizing the functional:
\[
F(c_1, c_2, \phi) = \mu \int_{\Omega} \delta(\phi(x, y)) \left| \nabla \phi(x, y) \right| dxdy \\
+ v \int_{\Omega} H(\phi(x, y)) dxdy \\
+ \lambda_1 \int_{\Omega} \left| u_0(x, y) - c_1 \right|^2 H(\phi(x, y)) dxdy \\
+ \lambda_2 \int_{\Omega} \left| u_0(x, y) - c_2 \right|^2 (1 - H(\phi(x, y))) dxdy
\]

Where \( u : \Omega \rightarrow \mathbb{R} \) is an image defined on \( \Omega \); \( c_1 \) and \( c_2 \) are constants; \( \mu, v, \lambda_1 \) and \( \lambda_2 \) are fixed parameters; \( H(\cdot) \) is the Heaviside function; and \( \delta(\cdot) \) is the Kronecker delta function. This minimization problem is solved by taking the Euler-Lagrange equations and updating the level set function \( \phi \) by the gradient descent.

\[
\frac{\partial \phi}{\partial t} = \delta(\phi)[\mu \cdot div(\nabla \phi) - \lambda_1(u_0 - c_1)^2 \\
+ \lambda_2(u_0 - c_2)^2]
\]  

For a 3D reconstruction, each slice of the object is first obtained. The slice is related with detection and location of the object in a 2D image. As an effective model, the level set technology provided by Chan and Vese [11] can detect the location of boundaries very well, even though the initial curve is placed anywhere in the image. I used this method to separate the subthalamic nuclei and boundaries of the brain from their background, and to obtain the contours of the subthalamic nuclei and skull.

5.2.2. 3D Reconstruction of the Subthalamic Nuclei

Through application of the above level set method, the contours corresponding to two subthalamic nuclei are obtained. Because of thinness of the subthalamic nuclei, it is very difficult to obtain multiple layers of neighboring 2D MRI with STNs. A novel approach is
proposed for the 3D reconstruction of the subthalamic nuclei using MR image containing two orthogonal sides of the STN. The proposed method has wide application and important guidance to medical diagnosis and treatment.

The 3D reconstruction of the subthalamic nuclei is summarized in the five steps [3]: [a]. Searching for two endpoints. [b]. Matching two vertical slices. [c]. Interpolating the planes. [d]. Switching the role of contours. [e]. Combining data sets.

5.2.3. 3D Surface Reconstruction of the Brain

After using the region-based level set method to complete the segmentation on the brain from its background in MRI, some tissues inside the boundary at each slice still remain. I have proposed a method of extracting the outer contours to improve the conventional region-based level set method [2]. Via finding and keeping the contour with maximum area, the enclosed clutters have been removed. After obtaining a series of outer boundaries of the brain from different layers, a 3D transparent skull is reconstructed by putting all outer contours together following their layer orders [2].

5.2.4. Review of Size and Location of the Subthalamic Nuclei

In paper [1], the AC-PC orientation and subsequently the axis is defined as: (a) laterality along the x-axis on both sides of the vertical AC-PC plane; (b) anterior-posterior direction along the y-axis, the AC-PC line (anterior, positive; posterior, negative); the reference point is often the PC or the mid-commissural point (MCP); (c) superior-inferior direction, or depth, along the z-axis above (positive) or below (negative) the horizontal AC-PC plane. Stereotactic AC-PC-based diagrams show the position of the STN within the stereotactic space.
STN can be identified directly on MRI at 1.5 or 3 T, as reported by different teams [11-15]. The right and left STN were identified and contoured for all 22 subjects [1]. Mean ± SD lengths of stereotactic landmarks measured on MRI were: AC-PC = 24.7 ± 1.57 mm according to Talairach et al. [1], and 24.89 ± 1.54 mm according to Benabid et al [4]. The thalamus height (TH), TH = 16.8 ± 0.88 mm. Following their average values, I approximately obtained AC-PC = 24 mm, width = 3 mm and TH/8= 2 mm, and the overall shape of the STN as shown in Figure 5.1 (c).

![Diagram of STN size](image)

**Figure 5.1.** The diagram of STN size. (a) is a combination from Fig.5.3(a) and 5.4(a) in paper[1]. (b) is a combination from Fig.5.3(b) and 5.4(b) in paper[1]. (c) is obtained from the description of the above Fig.(a) and (b), which provides the 3D size of the STN from previous statistical data.

5.2.5. Summary on Algorithm of 3D Visualization Model of the Subthalamic Nuclei

Figure 5.2 shows the algorithm of building the 3D model of the STNs in the brain. First, the boundaries of the STNs and the brain can be extracted from individual MRIs using the region-based level set method. Then, the skull is reconstructed via putting all segmented brain contours together in their primary order. The proposed method for 3D reconstruction of the
STNs is very special and exclusive because only two orthogonal contours are used due to the characteristics of small and thin STNs. Third, the size adjustment and location of the STNs can be determined using statistical data from previous studies [1-3]. Finally, the 3D visualization model of the subthalamic nuclei in the brain is built via combining the 3D reconstruction of the STNs and the brain with the following investigated coordinates.

![Diagram of algorithm for 3D model of STNs in the brain](image)

*Figure 5.2.* The diagram of algorithm for 3D model of the STNs in the brain.

5.3. Experimental Results

According to the mentioned method in the section (5.2.2.), 3D subthalamic nuclei are reconstructed from two orthogonal contours of STN from MRIs. Figure 5.3 is the diagram of 3D
reconstruction of the subthalamic nuclei. The size and location of the STN will be further adjusted following the obtained data of previous research.

5.3.1. Size of the STN

The STN is so thin (~3mm) that many neighboring MRI slices within 3mm depth cannot be obtained. Thus, it has been a cutting-edge issue to obtain 3D STN from MRI directly. 3D STN has more advantages than 2D STN in the applications since it can offer spatial information and significant guidance in the process of treating on Parkinson’s disease. In this chapter, I have not only provided a method for 3D reconstruction of the STNs, but also obtained the entire 3D model of the STNs in the brain.

Based on the discussion of the STN size in the methodology section (5.2.4.), the maximum length, maximum width and maximum height of 3D STN can be taken as 9 mm × 2 mm ×3 mm.

5.3.2. Location of the STN

I have combined two Figures (i.e. Fig. (6.5) and (6.6)) from paper [1]. Assuming that the positions of two STNs are symmetric and that PC in the Figures is taken as the primary point, the location of the right STN will be \(X_0= 11.5\) mm, \(Y_0= 0\) mm, \(Z_0= -2\) mm, and the maximum length of the STN will be approximately 9 mm.
Figure 5.3. 3D reconstruction of the STNs is obtained from two orthogonal contours extracted from two MRIs with vertical cross sectional area of the STN using level set method [3].

Following the marked coordinates on the three orthogonal MRI slices [16], 3D coordinates of the STNs in the brain can be determined. That is, the x-axis goes through the lateral sides of two STNs; the y-axis travels along AC-PC line; the z-axis goes vertically across the x-axis and y-axis. Once the axial section similar to Fig. 5.5.(A) is found and taken as the reference, the position of the STN coordinates in the brain are obtained and shown as the green lines in Fig.(5.6) and (5.7).
Figure 5.4. The figure combines the Figure (5.5) with Figure (5.6) in paper [1]. The first green line (left) in the figure reflects the starting position of the STN. The red line represents the center of the STN on the sagittal section.

Figure 5.5. 3D coordinates for 3D spatial visualization of the subthalamic nuclei in the brain. The three orthogonal images from MRIs are taken from paper [13]. 3D coordinates were defined on the three orthogonal images from MRIs and marked with white crosses in the paper [13].
5.3.3. 3D Model of the Subthalamic Nuclei in the Brain

After the preliminary work (including the reconstruction and size adjustment of the STNs as well as the location determination of the STNs in the brain) is done, the final step is to move the adjusted STNs to the proper position in the brain. The obtained 3D visualization model of the subthalamic nuclei in the brain has been constructed and shown in Fig. (5.6) and (5.7).
Fig. 5.6. 3D visualization model of the subthalamic nuclei in the brain with surface smoothing. (a), (b) and (c) display the different visual effectiveness from different angles. (a) and (b) exhibit the 3D relationship between STNs and skulls from different sides. (c) shows the 2D relationship between STNs and boundaries of the brain.

The 3D model of the subthalamic nuclei in the brain provides a simple and direct relationship between the STNs and the skull. The advantage of the model is that all sources can be obtained directly from MRI. Although the model is based on statistical data from previous research, the model can be corrected conveniently according to the clinical MRIs of patients. Some functions of the model can be further improved, developed and matured. The difference of size and location of the subthalamic nuclei can be quickly adjusted according to individual case and sources (e.g. individual MRI).
Fig. 5.7. 3D visualization model of the subthalamic nuclei in the brain with its contours stacking. (a) shows the 3D relationship between STNs and the skull. (b) shows the 2D relationship between STNs and boundaries of the brain.
5.4. Conclusions

In this chapter, a 3D visualization model of the subthalamic nuclei in the brain has been constructed using MRI and a region-based level set method. The method overcomes the limitations of 3D reconstruction of the STNs due to its small size, and provides the complete picture as well as spatial information of the STNs within the skull.

The model is based on the clinic data as well as MRIs, and can be adapted to individual patients. The model offers the direct visualization of spatial relationship between the subthalamic nuclei and the surface of the brain, and effectively guides the professional training and understanding pathway of diagnosis and treatment. The proposed models can also render assistance in the course of diagnosis or treatment, enhances the accuracy of operation and brings many benefits to patients and medical staff.
CHAPTER 5 REFERENCE


CHAPTER 6

CONCLUSIONS

In the dissertation, the segmentation, recognition and 3D reconstruction of objects are investigated, which include, three-dimensional surface reconstruction of tree canopy from LiDAR point clouds using a region-based level set method, a new method for extracting trees and buildings from sparse LiDAR data in urban areas, comparison of two classification methods for feature extraction from LiDAR data in urban areas, 3D reconstruction of subthalamic nuclei from MRI and 3D surface reconstruction of a brain based on level set method. In the dissertation, I proposed and established the framework for segmentation, recognition and 3D reconstruction of objects, and successfully applied the proposed methods to many research areas from 3D LiDAR data analysis, remote sensing, medical and geographical applications.

The main contributions in this dissertation are described as follows:

[1]. I proposed a novel method for feature extraction from sparse LiDAR data. Based on the proposed method for feature extraction from sparse LiDAR data, I further provided and narrated the new algorithm and the principle. Moreover, we have also tested and discussed the choices and roles of parameters in the experiments. My method directly uses the sparse LiDAR point clouds and avoids misclassification caused by interpolation.

[2]. I defined a different version of the normal variation which effectively uses the statistical distribution of the normal vectors at each point to determine the category of the selected point.

The proposed method is not sensitive to edges of buildings due to the partitioning of height layers and the optimal selection of the parameter $r$ and $\sigma$ thresholds. The reason is that
the separated height layers and the number of neighbors determined by the selected range \( r \) have reduced the scope of misclassification.

The results demonstrate that my method determines the category of each LiDAR point with relatively high accuracy, and is especially suitable for sparse LiDAR data.

The parameters (e.g., threshold value \( \sigma \) ) can be obtained based on testing and analyzing the distribution of buildings and trees in the study area.

The advantages of the proposed method include that the experimental results are independent of the influences from the faraway data points, that correlation of neighboring points and statistical information of normal vector variation have been directly employed so that the categories of each point can be determined with more accuracy and efficiency.

[3]. I have classified the same 3D LiDAR data point clouds using two different feature extraction methods based on normal variations. Via comparison, it is found that the proposed method is better and more accurate for classification (trees and buildings) of 3D LiDAR data, and is more suitable for sparse 3D LiDAR data.

[4]. In this dissertation, based on a region active contour model, I proposed a new method for 3D canopy surface reconstruction of individual tree crowns and clusters of trees from 3D LiDAR point data. In the proposed method, several contours corresponding to different heights are shown to be quantitatively effective in describing attributes and categories of trees. The proposed method allows for delineations of 3D forest canopy naturally from the contours of raw LiDAR point clouds.

The proposed model is suitable not only for a series of ideal cone shapes, but also for other kinds of 3D shapes. In my method, smoothing techniques are not specifically needed to correct surface irregularities.
More importantly, the proposed method can detect individual trees in a large contour (i.e., a tree cluster). In contrast to previous methods using CHM, the proposed approach does not require fitting to the elevation data using a parabolic surface, and the choice of a scale for different parts of the image is not necessary.

[5]. Also, many parameters, such as horizontal position, cross sectional area, tree crown radius and volume can be calculated precisely. More significantly, inaccurate or missing treetop locations do not affect individual tree detection, or tree crown delineation.

The proposed method can facilitate more accurate estimation of canopy volume which is related to some important biophysical parameters such as biomass and leaf area index. These parameters, derived from 3D raw LiDAR data, enable us to obtain the properties of a forest, not only from direct visualization, but also from quantitative description.

By way of the comparison and confirmation with the real field, the results also demonstrate the correctness, effectiveness and accuracy of the proposed method.

[6]. In additional, a new and effective approach for 3D spatial visualization of the subthalamic nuclei in the brain is presented. The orthogonal STN slices from MRIs have been merged to form a 3D visual rendering of the subthalamic nuclei in the brain after completing segmentation and registration.

[7]. A 3D visualization model of the subthalamic nuclei in the brain has been constructed using MRI and a region-based level set method. The method overcomes the limitations of 3D reconstruction of the STNs due to its small size, and provides the complete picture as well as spatial information of the STNs within the skull.

The proposed model is based on the clinic data as well as MRIs, and can be adapted to individual patients, which offers the direct visualization of spatial relationship between the
subthalamic nuclei and the surface of the brain, and effectively guides the professional training and understanding pathway of diagnosis and treatment. The proposed models can also render assistance in the course of diagnosis or treatment, enhances the accuracy of operation and brings many benefits to patients and medical staff.
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