# TOPOLOGY BASED CLASSIFICATION OF MOBILE LASER DATA WITH CONDITIONAL RANDOM FIELDS FIELDS

[YIZHEN LAO]
[February, 2016]

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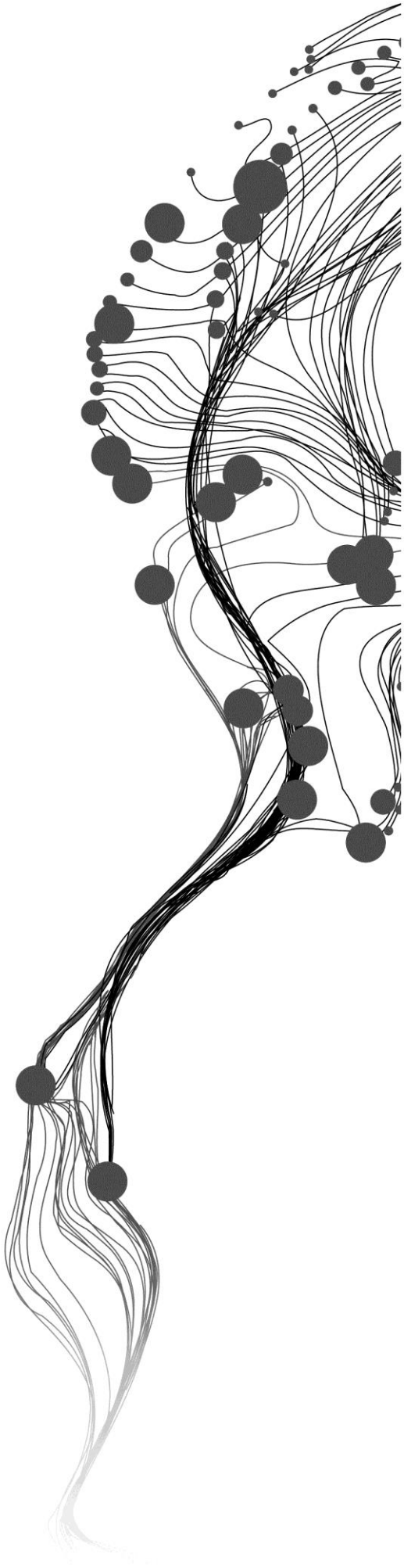

# TOPOLOGY BASED CLASSIFICATION OF MOBILE LASER DATA WITH CONDITIONAL RANDOM FIELDS

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Enschede, The Netherlands, [February, 2016]

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
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# ABSTRACT

Nowadays, with the development of laser scanning technologies and improved needs for automatic object recognition technologies in many practical applications such as 3d urban street mapping, modelling and road furniture management, more and more works have been done for exploring classification of mobile laser scanning data based on different algorithms, for instance, model matching and supervised learning.

The main objective of this work is to design a robust framework for classification of Mobil Laser Scanning (MLS) data which can achieve a higher classification quality both in completeness and accuracy than previous methods by using topological information. The whole framework is focus on segment-based level. There are four main steps to achieve this main objective: segmentation, generation of graphic structure, feature calculation, classifier training and inference in the end. In the first step, surface growing algorithms has been used to filter meaningful objects out. In the flowing phase, a minimum distance between segments approach has been used to create graphic network structure. In feature calculation work, 18 node features and 3 edge features have been calculated, where 3 node features and 2 edge features of them are based on topological information. In the next step, conditional random fields (CRF) classifier will be trained by using training data set and do inference based on a testing data set in the end. In order to evaluate performance of CRF model and explore contribution of topological information to CRF classifier, four contrast experiments have been designed: CRF with fully topological information, CRF without any topological information, Super Vector machine (SVM) with topological information and SVM without topological information.

The results show that proposed approach in this work performs well both in recall rate and precision for the classification task in urban street environment. 12 classes objects have been classified in total. Besides, the results also show that CRF with an overall accuracy at 91.5% have advantages against previous approaches such as SVM with overall accuracy at 68.2%. And the results also show that topological information indeed plays an important role in improving CRF model's performance while it does not in SVM model.

**Keywords**
Mobile Laser Scanning (MLS), Classification, Segment-based, Conditional Random fields (CRF), Topological information, Super Vector Machine (SVM)

# ACKNOWLEDGEMENTS

This thesis would not be possible without the contribution and help from several people. Therefore, I want to take this chance to express my gratitude here.

First and foremost, I would like to express my heartfelt gratitude and regards to my supervisor, Michael, for his intellectual guidance, strong support and warm encouragement during whole my MSc research period. Besides, I also want to say thank you to Sander, my second supervisor, discussion with you always push me think deeper into research questions.

I am also deeply grateful for all staffs of GFM program, for your rigorous scientific attitude and enthusiastic lectures. I learned a lot from you all and your lectures during these unforgettable 18 months in ITC.

On the personal side, I'd like to thank all my friends at ITC for good company and interesting discussions over years including Bage, Baozi, Jianwei, Yifei, Kebing, Pengpeng. Thanks to you guys shared many great times with me and helped during hard pates.

I'm incredibly grateful to my girl Yumeng for love and encouragement, for the company and endless happiness you give to me. Love to you.

Finally, I want give many thanks to my family – my father Ningjun, my mother Liling – for all love, support and trust you given. I am proud of you as my family.

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# 1. INTRODUCTION

## 1.1. Motivation

Nowadays, with the development of laser scanning technologies which can extract largely and accurate spatial information of objects, more and more industry applications are based on 3D modelling of real world. For instance, 3d city modelling can assist with urban planning, disaster management, pollution analysis and cultural heritage etc.

Classification of laser points is one of important step and task for many specific applications which based on point cloud data set. For example, doing 3d street mapping task should also infer the class of object in point cloud in order to obtain semantic information (2008). Besides, pre-knowledge about labels of points cloud can make us to choose different appropriate 3D modelling method, which will lead to a high quality modelling result. What is more, for change detection task in urban street, pre-classification of object also be used (2013).

Currently, the main classification of urban street object are based on manual recording, analysis of 2d map which are all time-consuming and the result quality is strongly depend on human eye work. But laser scanning technologies give us a chance to detect and recognize objects along the road automatically and rapidly.

## 1.2. Problem statement

However, the procedure of classification of LIDAR data (point cloud) is a big challenging task. Although points from objects can be easily selected and classify into different object types by hand. But for big point cloud dataset, it is difficult to classify all the objects manually. Therefore, automatically classification is a valuable technology but difficult to develop. On the one hand, three dimensions information leads to a much more complex modelling environment than traditional 2D images, on the other hand, we need to process mass irregularly distributed points data instead of regular data structure. Both importance and difficulties of this task make it become a hot topic in remote sensing, photogrammetry and computer vision etc. fields.

Considering about data sources, there are three applications of laser scanning technologies, Terrestrial Laser Scanning (TLS), Mobile Laser Scanning (MLS) and Airborne Laser Scanning (ALS). TLS has advantages in measuring range, data accuracy and resolution. However, the sensors need to be fixed in a location, makes it the main limitation of TLS for we need to set more than one sensors in order to measure a large or complex scene. On the other hand, ALS has advantages in quickly data extraction from large area. But, high expensive fee of survey and low resolution can be drawbacks of ALS. On the contrast, MLS system makes it possible to extract accurate 3d information quickly without multiple registrations operations. Thus, recently MLS become a hot topic in related fields.

Although there are several existing approaches of classify ALS data. But for MLS, with higher point density, more types of objects needed to be recognized from MLS data set. Besides, new classification algorithms should be designed for MLS data in urban street area environment.

As far as I know, there are few of researches focus on classification of MLS data in urban street area. Most of previous works are just detect certain objects such as road inventory (Pu et al., 2011), manhole (Yu et al., 2014) and façade of buildings (Rutzinger et al., 2011) based on geometric characteristics and topological relationships of segments. However, there is still big room to improve classification quality, and more types of street furniture should be capable to be recognized.

More specifically, in this research, how to better use segment-based contextual information especially topology information to do classification has not been fully studied. For example, if there are two intersected and perpendicular rectangles, they could be part of wall intersect with road, besides, also can be car roof intersect with the door. But if we know one of these two rectangles is part of wall in advanced, another intersected rectangle is highly possible to be part of road instead of door of car.

## 1.3. Research objective and question

### 1.3.1 Research objectives

The main objective of this research is to design a robust framework for classification of Mobil Laser Scanning data which can achieve a higher classification quality both in completeness (recall rate) and precision than previous methods. In order to achieve this main object, some sub-objects should be addressed which listed bellowed:

1. Analysing the advantages and drawback of previous algorithms for MLS data classification.

2. Developing a prototype of automatic MLS data classification system for certain targets objects in urban streets environment based on the framework I propose which have the potential to be extended to classify other types of objects.

3. Analysing the classification results, and comparing them with existed methods.

### 1.3.2 Research questions

The following research questions should be answered in order to achieve above objectives:

1. If there are some pre-processing such as point reduction in order to speed up processing efficient and improve quality of classification?

2. What are the differences between point-based and segment-based classification? Which one should be performed? Or using both in the same framework?

3. Based on CRF theory, how to generate graphic structure simulate spatial relationship of objects in reality?

4. Which segmentation method should be implemented in order to use the geometric and topology information of different object class?

5. Which features (unary and pair-wise potentials) such as geometric and topological properties can be used to describe different types of objects?

7. What is appropriate size of training data in order to get a good CRF classifier?

8. How to asset the experiments result? How to compare my method against previous researches' outcomes?

## 1.4 Innovation aimed at.

The innovation of this research is to design a new framework to classify street objects automatically by fully using topological information. It proposes a general classification method which can be used to classify multiple complex objects.

## 1.5 Thesis structure

This thesis is divided into six chapters. The first one is to give a general concept about this research such as motivation, research objects and questions. Chapter 2 reviews some previous work in classification of laser scanning data. In Chapter 3, the details of the whole framework are presented. Chapter 4 shows the implement of the method and results. Chapter 5 gives evaluation and discussion of the results. In the last chapter, the final conclusion and recommendations are given.

# 2 LITERATURE REVIEW

In this chapter, previous about classification of object in point clouds are reviewed. Particularly, I focus more on methods which using machine learning technologies. Section 2.1 gives the principle of mobile laser scanning. Section 2.3 focus on existed methods about classifying laser points. Four different general types of classifiers have been summarized and compared, and some specific researches also are described in this section. In the following section, the algorithms which adopted and developed in this research will be introduced and reviewed. In the end, a short summary about reviewed researches are given.

## 2.1 Principle of laser scanning technologies

There are many literatures before reviewed laser scanning technologies (Marshall & Stutz, 2011; GV Vosselman & Maas, 2010). There are two basic methods to extract spatial and attribute information in active laser scanning technologies: speed/coherence of light and triangulation (GV Vosselman & Maas, 2010).

Speed/coherence of light can use time-of-flight (TOF) or phase measurement techniques. Equation 2-1 and figure 2-1 shows the basic theory that the range form sensor to target can be calculated by time delay between emitted and received laser pulse (GV Vosselman & Maas, 2010):

$$d = \frac{\Delta t}{2} C \quad (2\text{-}1)$$

Where C indicates speed of light and $\Delta$t is time delay between emitted and received laser pulse. While phase measurement uses phase difference between two waveforms to calculate time delay and range based on equation 2-1.

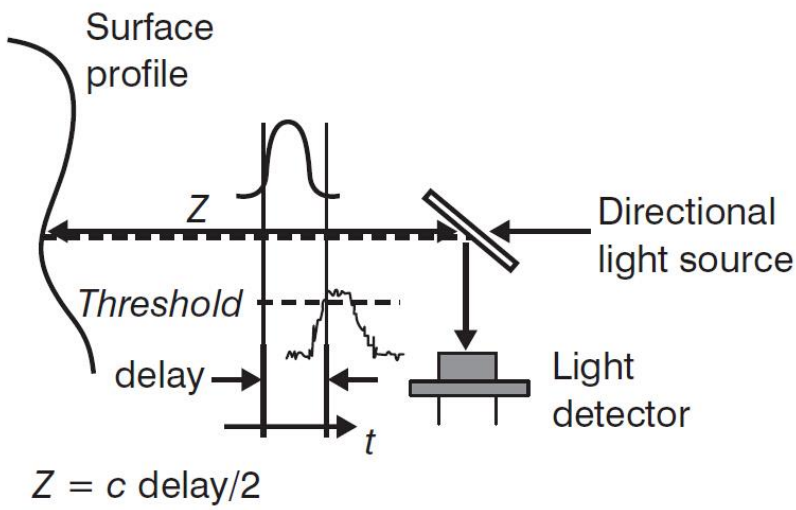



Figure 2-1 TOF for range measurement (GV Vosselman & Maas, 2010)

Triangulation measurement is based on triangles theory, using both projection and collection angles relative to baseline in order to calculate coordinate of a point on surface. However, the laser scanning system based on this kind of measurement technologies are usually used for surveying distance smaller than 5m (GV Vosselman & Maas, 2010).

## 2.2 Mobile laser scanning

Mobile laser scanning (MLS) also known as mobile light detection and range (LIDAR) is a rapid and flexible method for extracting high-resolution and three-dimensional data, besides, a lidar-based mapping

system which produce 3D point cloud from surrounding scene by using profiling scanners (Kukko et al. 2012). Ellum and El-Sheimy (2002) gave a detailed description of MLS system. MLS system can be installed in different platforms such as car, boat and train, which shows its high flexible and adaption (Puente & González-Jorge, 2013). Figure 2-2 give a example of a active MLS system called Stereopolis II developed by French National Mapping Agency (IGN) which is used in this research (Paparoditis & Papelard, 2012).

Figure 2-2 Stereopolis II MLS system (Paparoditis & Papelard, 2012)

## 2.3 Classification of point clouds

### 2.3.1 Types of classifier for classification task of point clouds

There are four main types of previous methods to classifying laser scanning data (Shapovalov et al., 2010): Filtering, unsupervised learning, supervised learning without using Markov Random Fields (MRF) and supervised learning with MRF. Each method has its own advantages and disadvantages.

For the methods based on filtering, the filters were used to extracting interested objects such as roads (Clode et al., 2004) and bare-earth (Sithole et al., 2004), which can be seen as a binary classifier. But these approaches just consider about attribute information of each point, and ignore the relationships between neighbourhood points that can offer context knowledge.

The second method use semantic segmentation based classification such as K-means clustering (Chehata et al., 2008). These approaches can help to exclude the noise and do not need labelling training dataset but small objects will probably be ignored as a side effect.

The third way using some specific supervised learning methods such as Random Forest (Chehata et al., 2009) or Support Vector Machine (SVM) (Lodha et al., 2006). But there is a drawback, when perform these methods in complex scenes such as urban area, it may lead to inhomogeneous result (Niemeyer et al., 2011).

In order to improve the performance of classification of point cloud dataset, more and more researchers are concentrating on probabilistic graphic model methods, for example, MRF (Anguelov et al., 2005). Similar to MRF, Lu et al. (2009) use Conditional Random Fields (CRF) to perform a classification for ground detection.

When these four different approaches are compared, Niemeyer et al. (2011) indicates that CRF conduct to a better result than MRF and SVM especially for the objects which are easily mistaken identify, such as roof and ground. That is mainly because CRF from a more general model.

### 2.3.2 Three levels of classification methods

There are three different basic types of classification of point cloud data, point-based, regular-unit-based classification and segment-based.

Point-based classification means that classify target is each single Lidar point, which will assigned to an object label in the classification process(Niemeyer et al., 2012). The advantage of point-based classification is that its result do not depends on quality of segmentation against segment-based classification, however on the other hand, quite computational-consuming.

Regular-unit-based classification is kind of method belong to the level between point-based and segment-based. The classify target is regular unit which could be 2D or 3d with pre-define size instead of each points or unregularly segments. Smeeckaert et al. (2013) let 3D lidar attributes interpolated in a 2D regular grid for large scale processing firstly, then classify each 2D grid by using super vector machine. In 3D regular unit application, super-voxels (Lim et al., 2009) have been used.

The first step of segment-based classification is to do the segmentation of point clouds. Then calculate attributes for each segments (Elberink et al., 2011). Finally, using these attributes to classify all segments based on different classifiers.

Recently, a novel approach which combines point-based and segment-based classification together which forms a two-stages classification had been proposed (Niemeyer et al., 2015). It performs a point-based classification at first to get rough classification result, then based on this result to do the segmentation. Finally, they improve final classification result by doing a segment-classification again.

Point-based classification can better use context information to avoid misclassification of small objects, for example, building edges can be easily labelled as vegetation (Vosselman et al., 2004). While segment-based classification can use both information about averaging values of points within segments and specific to the segments which will help to improve classification quality (Vosselman, 2013).

All levels of classification types can offer spatial and attribute information from each entities. But point-based can not offer topological and geometric information, while regular-unit-based classification method can supply limited topological information. However, segments in segment-based classification can fully with spatial, geometric and topological information.

### 2.3.3 Classification of mobile laser scanning data set

Compared to airborne laser scanning and terrestrial laser scanning data set, mobile laser scanning faces more complex environment and more high point density.

Pu (Pu et al., 2011; Pu et al., 2009) using knowledge-based searching tree which belong to template based matching approach to detect objects along street. It has high accuracy in classifying traffic sign and road surface, while low quality for detecting complex objects such as vegetation. Besides, its quality is strongly depends on the value of some model parameters (thresholds) which defined manually.

Markov chain Monte Carlo (MCMC) has been used in street furniture detection task. Li (2015) uses this approach to train models of street objects such as car, lamppost and traffic light and fitting to target object. Yu et al. (2014) use similar method to detect manhole and sewer well. Although both of these researches achieve high accuracy, however, these approaches are hard to extend to used in some other testing data set, environment or classify some other objects. Because, the shape of object can varies strongly in urban environment which means even a specific target object can have many potential models.

A method of classifying points clouds based on line-filter in three layers corresponding to height had been used by Fan et al. (2014). Some sample objects have been detected with accuracy at around 80%. The

drawbacks of this approach are that it just applied for certain and difficult to extend for strongly depends on prior knowledge.
Some statistic learning methods also be used in classification of MLS data task such as support vector machine (SVM) (Li, 2014). A typical segment-based classification procedure has been used: ground filtering, segmentation, feature extraction and classification.

## 2.4 Condition random fields

Conditional random fields (CRF) firstly proposed to be used in labelling sequential data in natural language processing fields (Lafferty et al., 2001). It belongs to graphic model, more specifically, undirected graphic model.
We assume that in a graph G(n,e) where n and e represent for nodes and edges respectively. And we give labels $y_i$ to each node $n_i \in \mathrm{n}$. Besides, X indicates observed data sequence. Then we can mode the posterior distribution $\mathrm{p(y|X)}$ deirectly (Kumar & Hebert, 2006):

$$\mathrm{p(x|y)} = \frac{1}{Z(x)}\left(\prod_{i\in n} \emptyset_i(x, y_i) \cdot \prod_{i,j\in e} \varphi_{ij}(x, y_i, y_j)\right) \quad (2\text{-}2)$$

where $\emptyset_i(x, y_i)$ called unary potential while $\varphi_{ij}(x, y_i, y_j)$ named pairwise potential. Moreover, e indicates set of edges. Z(x) performs as normalization constant. Based on Eq.2-2 we can infer the most possible of labels of a sequence by knowing graphic structure and observation sequence.
In remote sensing and computer vision fields, CRF has been widely used in varied classification tasks both in 2D image or 3D point clouds environment.
The work of Zhong et al. (2007, 2010) shows that CRF has the ability in classifying hyperspectral remote sensing images in urban area. Besides, CRF also had been used in doing classification by fusion different data source, for example, satellite images and synthetic aperture radar (SAR) images (Kenduiywo, 2012, 2014).
In point clouds classification tasks, CRF also been used in some application. A multiple-scale CRF been proposed by Lim (2009; 2007) to classify TLS data within regular-unit-based level. In point-based level, Niemeyer et al (2012; 2014; 2013; 2011) gave sort of examples about using CRF to do classification task. Luo (2014; 2013) focus on segment-based level to perform a CRF to recognize railway objects.
From previous works, we can find out that there are three important steps in point clouds classification task:

1. Choose suitable classification level, e.g. point-based or segment-based.
2. How to generate graphic network. If there are lack of edges, many isolated sub-graphic can occur or loss some depended information. On the other hand, too many nodes connected may lead to a smoothness effect (Niemeyer te al. 2015).
3. Design enough node features and edges feature for CRF model.

## 2.5 Summary

From the literature reviewing, we can find out that mainly existing methods for classification of MLS data can be divided into model-driven and data-driven. For the first types, it strongly depends on the object features description which made it lack of potential to extent to classify new or complex object types. But as to data-driven methods, it can forms a more general classifier and have potential to detect and recognize object with complex structure. However, previous data-driven works are mostly doing the classification based on properties of objects such as geometric or reflectance information. For some pairwise information such as topological information which can help to improve quality of classification have not been fully explored. Therefore, conditional random fields, that can combine both unary potential

and pairwise potential together, is considered can be feasible and promising in realizing the research objects.

# 3 METHODOLODY

## 3.1 Introduction to methodology

Although from the literature review, we all know that CRF can base on three different levels: point-based, regular-unit-based and segment-based. However, only segment-based classification can utilized with topological information which act as both node and edge features.

Topological relationships between segments will be used as emission features. There are three basic topological relationships between segments: intersect and angle (perpendicular, parallel and skew). Because initial labelling of segments after point-based classification and segmentation are used as transition features, therefore, topological relationships between segments and attribution (type) information of segments can be integrated. So, it is more likely that a segment belongs to balcony which perpendicular and intersects to a segment of wall instead of car roof.

Although there are many previous works about classification or detection of objects in MLS point clouds data set, but as far as I know, there is not any project use CRF with topological information to do this task. For this reason, I choose segment-based classification as the level where a segment-based CRF will perform.

There will be four main steps of my classification framework: segmentation, create graphic, features value calculation, training and final inference. The rest section of these chapter will give details about the classification method I proposed.

## 3.2 Framework

The framework of this research is given in Figure 3-1.

In the first step, most previous research (Li, 2014; Li, 2015; Fang, 2014) will try to remove noise points and ground as pre-processing. The reasons why I abandon these two pre-processing will be explained in Section 3.3.

The following phase of this research is segmentation which can be act as a footstone for the whole classification task. For segment-based classification, it is extremely important to have integrated classification result, because normal vector of segment will be used largely. If two segment with large angle are treated as a single segment, then the average of this mix-segment will not make any sense to represent the spatial direction. Therefore, we need to carefully do the segmentation in order to get a clearly and meaningful segments.

A next step is generation of graphic structure. The problems are that, on the one hand, we can not connect too many edges along street which will lead to smoothness effect which will affect on final classification quality and also computation-consuming. On the other hand, if there are not enough edges connect segments, context information will not be fully used and contribute to final classification result.

The fourth and fifth steps are features design and calculation. There are three main source of features:

1. Attribute of laser scanning saw data such as height, echo and reflectance.
2. Geometric information of segment such as projection area.
3. Topological information of segment such as perpendicular and paralleled relationships.

Both node and edge features will be calculated for all nodes and edges.

The next phase is training CRF classifier, there are two objects here:

1. Avoid over-fitting, which can easily influence on final classification accuracy.
2. Choosing suitable training algorithms.

After training, inference should be performance and quality assessment should also be done.

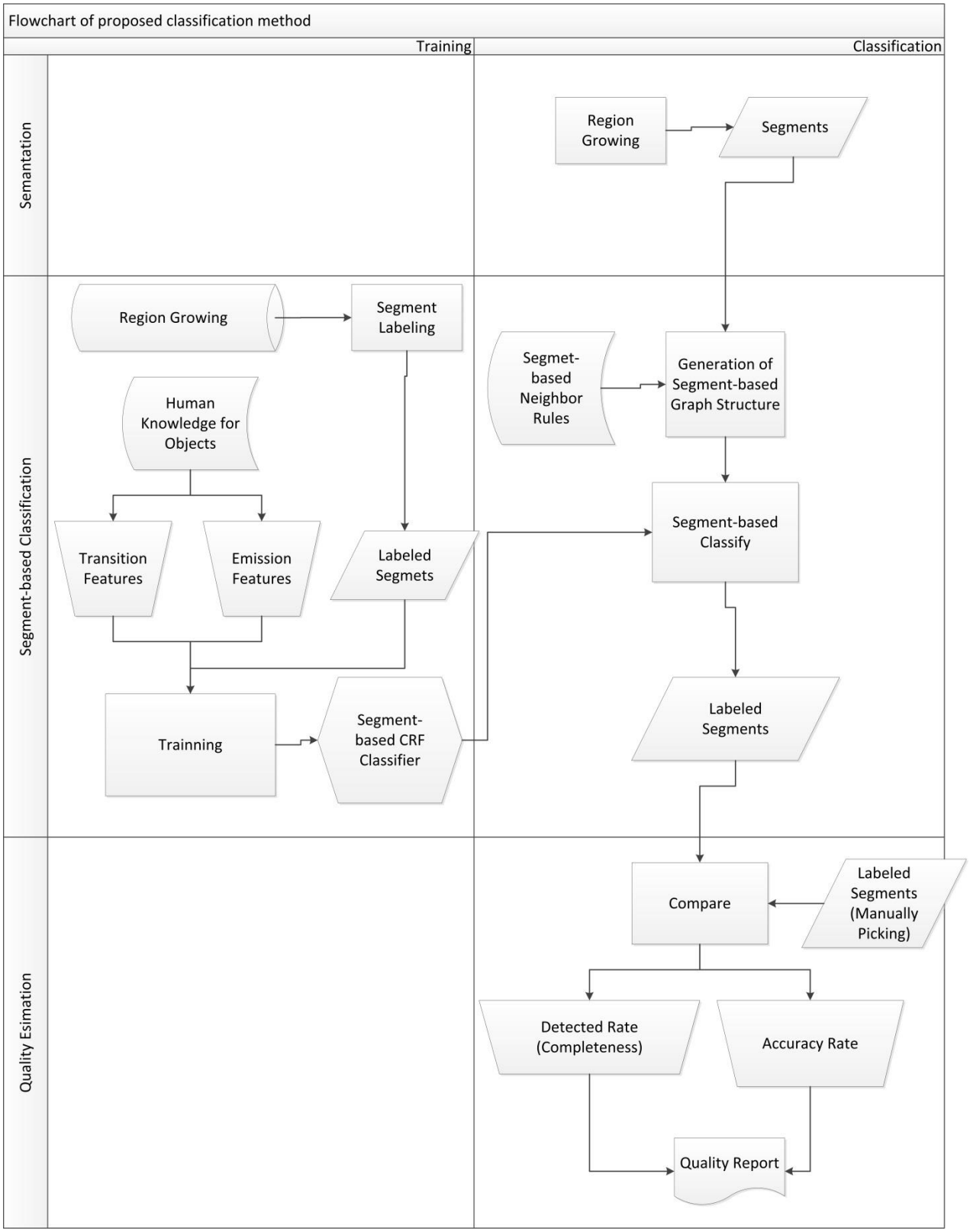



Figure 3-1 Framework of methodology

## 3.3 Data preparation

#### 3.3.1 Allocation of training and testing data set

In training procedure, within segment-based level, it is obvious that the more objects of each class, the better of training. But for limitation of size of training data set, In this research, two objects at least for each class are needed.

For testing data set, it does no matter what is the size. However, we need to try keep the inference data set has the similar environment as training data set. If objects in a inference data set which varies strongly from original training data set, a new training possibility needed.

#### 3.3.2 Ground point

In order to get ideal segmentation result, ground should be removed first include road and side walk, especially for region growing algorithm.

However, different from exist works for classification task in ALS, TLS and MLS data sets, I will add ground segment back to training and testing data set. The reason here is the usage of topological information of segments. Keeping road and side walk in the data set (graphic network) will have a great contribution to classification result. For example, if there is a big segment perpendicular to sidewalks, it should likely to be building façade instead of tree or street lamp. In other word, keep road and sidewalk can make the whole graphic network more integrated and help for inference.

Therefore, for both training and testing data sets, I remove ground points first to perform a segmentation algorithm separately, then combine segments together again as input for the next phase.

### 3.4 Segmentation

There are four types of segmentation algorithms: region growing, Hough transformation, RANSAC and clustering. For Hough transformation, it can detect regular objects such as rectangle and cylinder, while objects in urban street environment usually with complex structure are hard to recognize under this method. As to RANSAC, it is hard to detect a integrated segment with curving surface. Besides, clustering algorithm can be easily mis-segment two segment together for the distance between them are less than threshold. Theoretically, region growing is the most suitable method to do the segmentation process in urban street environment. However, there are two types of region growing algorithms.

#### 3.4.1 Smoothness constraint (Rabbani, 2006)

1. Calculate curvature value of each point.
2. Sorts all points based on their curvature value.
3. Picks up the point with minimum curvature and add it to seeds set.
4. For every seed points, find its neighbourhood under following rules:
   - If the angle between the seed points' normal vector and one of its neighbour point's normal vectors is less than a threshold value, then this neighbour point is added to current region.
   - If a neighbour point's curvature value is less than a threshold value, then add this point into seeds set.
   - After testing all neighbour points' normal vector angle value and curvature of a seed point, we need to remove this seed point form seeds set.
5. Iterates all seeds set until there is none point within inside.

#### 3.4.2 Surface growing & Hough transform ( Vosselman, 2004)

1. Determines seed points by using 3D Hough transform. If the neighbourhood of a point is a planar, then labels this point as a seed point.
2. Grows every seed points to find its neighbour points. Checks if these neighbours points can fit the planar, if so, add all these points to this planar.
3. Using competing surfaces to solve the situation that if a point will be accepted to more than one planar.

4. Iterates all points in the dataset.

#### 3.4.3 Compare of two surface growing method

From the experiment results, I think smoothness constraint is can decompose street furniture better especially for those with complex structure. The reasons are follows:

1. Smoothness constraint method is based on normal variation to do the growing procedure. For street furniture, there are usually big normal variations between different components. Therefore, it can more easily decompose one object into different meaningful parts (components).
2. Hough transform and surface growing method assumes that components are all planar. But in reality, many object components are small irregular geometries such as curved planar and curved poles. Therefore, it is difficult for it to decompose street target objects into meaningful components.

#### 3.4.4 Segmentation objectives

Even the classification will be performance at segment-based level, however, there are two different specific types of sub-level in segment-based level. One is object-level which will have big segment represent whole meaningful entity such as a car. The other one planar-level, which segment whole object as many sample geometries such as planar and pole.

In this work, the classification will focus on object level such as car, instead of roof or side-planar of car. The reasons here are:

1. In most class case, the structure of one class object can varies quite often, for instance, street light can be standing on the ground or hanging by walls of building. Therefore, if we classify objects at sub-object level, many models need to be designed for target objects. It will decrease universality and improve operation complexity of the whole framework.
2. Although it is not a good idea to estimate normal vector of object such as car because it can contain two main normal vector directions. However, the normal vectors of car within one data set will keep stable and solid. The same thing also happens for most classes. For example, road, building and pedestrian all have different but stable normal vector direction. Therefore, even we estimate normal vector by combining more than one planar together, the classifier still can distinguish different class by using normal vector direction which is quite stable.

### 3.5 Generation of graphic network

Generation of graphic network structure is a fundament of training or inference of CRF.

#### 3.5.1 Comparison of graphic network generation methods

At segment-based level, for creating this network, it is most important to set up an appropriate connect criterion. Consider about previous research, there were three main method to connect segments:

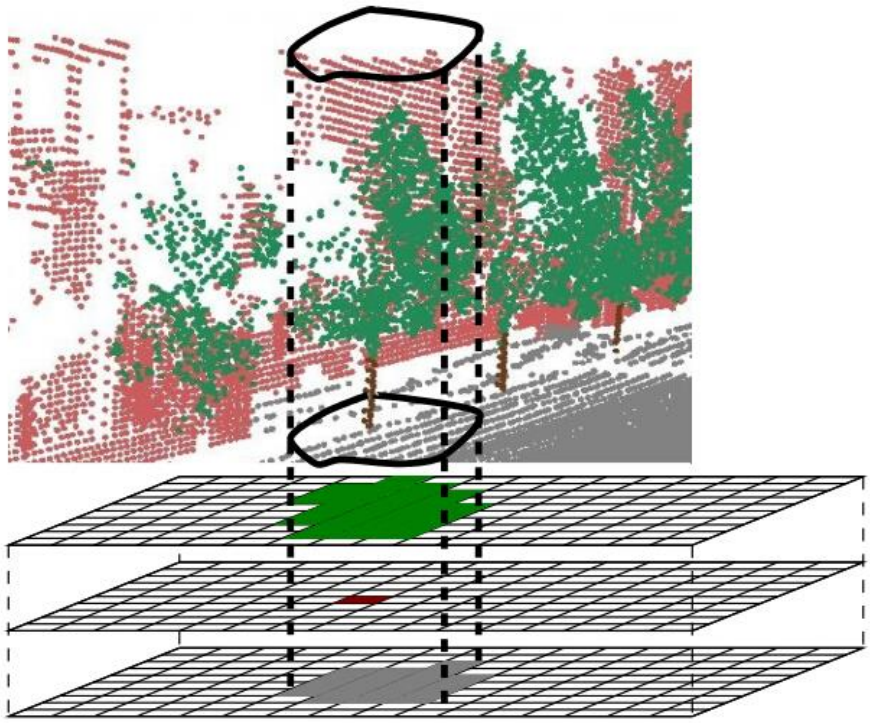


Figure 3-2 Projection of segments (Najafi, 2014)

1. Najafi (2014) project all segment to ground plane first, then connect segments together on this plane if distance between them less than a threshold. Fig 3-2 shows the theory behind this method. However, these method can achieve a good result in distinguish objects along horizontal direction, but in vertical direction, it is impossible to decide if two segments should or should not be connected.
2. Connect segments together, if the distance between geometric centre is smaller than a pre-define threshold. But sometime, even two big segments are intersect, they still can not be connected for their geometric centres are far away from each other.
3. Minimum distance between segments based on all possible pair of points is the best approach. But it is quite computation and time consuming for calculating all distances between points within point clouds.

### 3.5.2 Generation method in this work

However, considering about this research is not to develop a real-time classification system, therefore, using minimum distance as the approach to generalize network structure. Fig 3-3 shows a example of a connected segment-based network structure. a minimum distance threshold to decide if two segments should or should not be connected. Therefore, by given a pre-define distance threshold, if the minimum distance between a pair of segment is lower than it, then they will be connected such as L1K1 and SG1. In this case, a segment can have more than one relation with its neighbourhoods. The advantage of this method is that it can keep spatial dependences into graphic network. Sometimes, one outlier segment will not have any connection to others. On contrast, some segments located in complex environment will have many connections (relations) to surrounding objects, for example, segment PMNQ and UTSRQ have more connections than segment BELD and FGHI.

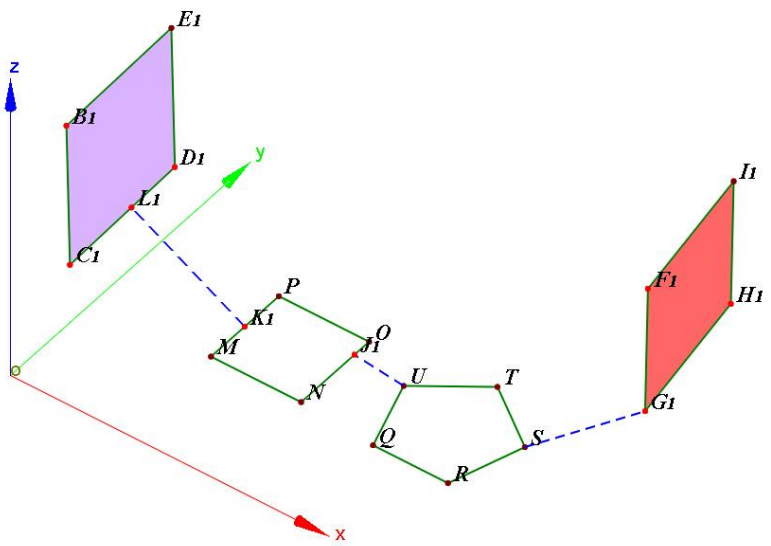



Figure 3-3 A example of connected segment network

Although so, there is still a proposed method in this work which can speed up calculation procedure of nearest distance between segments. Firstly, judge if minimum box of two segments intersected. If so, we can calculate distance between all possible point pairs and record the minimum distance which will compared to distance threshold.

## 3.6 Features list

### 3.6.1 Introduction to feature list

There are four main types of features used to describe the properties of object: location, geometric information, laser point properties, and topological information. Table 3-1 shows specific categories of features.

Table 3-1Categories of features

| Location | Geometric information | Laser point properties | Topological information |
|---|---|---|---|
| Average Height | Projection area xy | Point density | Number of perpendicular segment |
| X shift | Projection area yz | Average echo | Number of parallel segment |
| Height difference | Projection area xz | Average reflectance | Normal vector |
| | Projection area xy/yz | Average range | Include angle |
| | Projection area yz/xz | Average theta | If intersected |
| | Projection area xy/yz | | |
| | Average curvature | | |

### 3.6.2 Node features

1. **Average height of segment**
   Calculate average height value of points within a segment.
2. **X shift from middle line of the street**
   Firstly, I need to determine middle line along the street, there can be three ways:
   i. Using trajectory data of car where MLS system installs, besides, the width of the car can also be used to estimate middle line more accuracy.
   ii. Rotating the whole point cloud data set, in order to make middle line will coincide with

axis Y. Then there is no need to know equation of the middle line.

iii. Estimate the middle line by picking a series of points located in middle Street, and then calculate equation of the middle line.

In this research, I choose third approach which is easier to be estimated.

After getting the middle, we need to calculate all distances of points within a segment to middle line according to equation. 3-1:

$$\mathrm{d} = \frac{|\mathrm{A}x_0+\mathrm{B}y_0+\mathrm{C}z_0+\mathrm{D}|}{\sqrt{A^2+B^2+C^2}} \qquad (3\text{-}1)$$

Where $(x_0, y_0, z_0)$ is the point outside the line $\mathrm{A}x_0 + \mathrm{B}y_0 + \mathrm{C}z_0 + \mathrm{D} = 0$. And d is the distance from this point to the line. After we getting all distances, find the minimum value, which treated as X shift value.

Fig 3-4 shows a example of X shift value. The red line if the middle line along the street. The distance of yellow line which one is perpendicular to the middle line is X shift value.

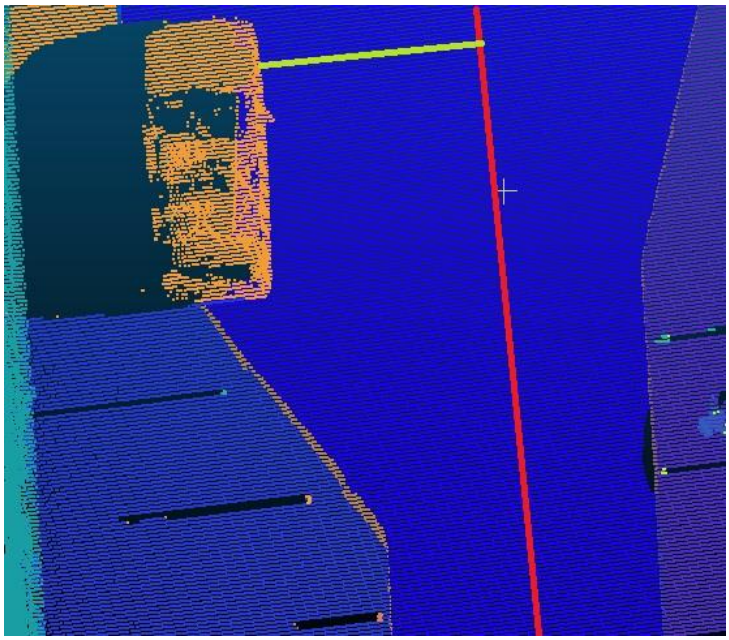


Figure 3-4 example of X shift

### 3. Projection area

Although the size of segment can be used to distinguish objects in different class, but there are indeed two drawbacks by using this feature. Firstly, sometimes two segments with same size can not ensure that they belong to same class such as trash can and scooter. On the other hand, calculation segment size especial for those with complex structure is a quite complicated processing. However, project segment into tree axis directions, can estimate projection area approximate. Fig 3-5 shows how get projection area.

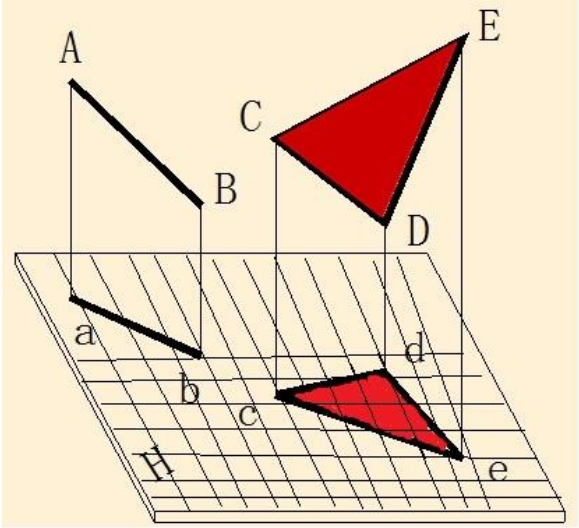



Figure 3-5 example of projection area

In order to estimate projection area, we can establish a regular grid on projection plane. If there is at least one point project in a cellular, then this cell can be set as active. Finally, counting how many cells have been active, combine with constant cell size, the projection area will gotten.

For three projection area in directions: PAxy, Paxz and PAyz will calculated for each segment. What is more, in order to measure relationship between three projection areas, ration between them will also calculate. In this way, six node features come from projection will added into CRF classifier, as table 3-2 shows:

Table 3-2 Node features comes from projection area

| | |
|---|---|
| 1. | Projection area xy (PAxy) |
| 2. | Projection area yz (PAxz) |
| 3. | Projection area xz (PAxz) |
| 4. | PAxy/PAyz |
| 5. | PAyz/PAxz |
| 6. | PAxy/PAxz |

**4. Point density**

Even the most accuracy approach to estimate point density of a segment is using total number of points divided by area of segment. As we mentioned in the above section, it is hard to estimate exacted area of a segment especially when this segment with complex geometric shape. However, there is an alternative method to obtain estimated point density by using multi-point buffer analysis.

Firstly, we pick up one-tenth of points randomly as candidate points, and build sphere buffer space for each point with a pre-define radius. Here choose one-tenth of points randomly within a segment can ensure the point distribute averagely and avoid process all points which will be too computing consuming. Fig 3-6 shows that there are nine points located in buffer sphere of point O. Then the point density can be calculated by using total point number inside divided by radius.

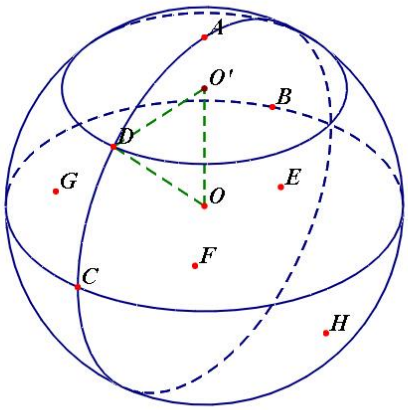



Figure 3-6 Point buffer analysis

### 5. Normal vector

The normal vector of a segment can be calculated by using average normal vectors of points within this segment. For estimating normal vector of each points, there are many methods exist. In this research, I simply use a method, which treats the problem of determining the normal vector of a point approximated to the problem of estimating the normal of a planar tangent to the surface. To estimate surface normal can be reduced to an principal component analysis of a covariance matrix from neighbours (Point Cloud Library, n.d.).

$$\mathrm{C} = \frac{1}{k}\sum_{i=1}^{k} \cdot (P_i - \bar{P}) \cdot (P_i - \bar{P})^T,\ C \cdot \vec{V_j} = \lambda_j \cdot \vec{V_j},\ j\epsilon\{0,1,2\} \qquad (3\text{-}2)$$

where k is neighbourhood points of $P_i$, $\bar{P}$ is 3D centroid of nearest points. $\lambda_j$ is j-th eigenvalue.

### 6. Number of perpendicular

Based on normal vectors and graphic network structure we can calculate topological relations between a pair of segments. By using equ.3-3, the angle between segments can be obtained:

$$\mathrm{Cos}\theta = \frac{\vec{a}\cdot\vec{b}}{|\vec{a}|\cdot|\vec{b}|} \qquad (3\text{-}3)$$

Where $\vec{a}$ and $\vec{b}$ are two normal vectors, $\theta$ is the angle between them.

In topological relationships, perpendicular, parallel and intersect are three important ones. But it is really rare that the angle between two segments is exactly equal to 90 degree. Therefore, an angel range should be predefined as the condition if they can be regard as perpendicular. In this work, angle between [75,105] degree can be seem perpendicular.

The total number of segments perpendicular to a segment then can be used as value of a node features: number of perpendicular.

### 7. Number of parallel

As the same method of calculating number of perpendicular, the angle range of parallel is set as [-15,15] degree.

### 8. Number of intersected

Because we can not estimate equation of segments, therefore we can not use normal algebra approach to calculate if two segments intersected.

An alternative method is using three projection area we obtain before to analysis if they intersected. In three projection plane, if all these two segments have intersect (in regular grid, they have common

cell), we can say that these two segments are intersected. Fig 3-7 shows how we decide if two segments intersected in projection plane:

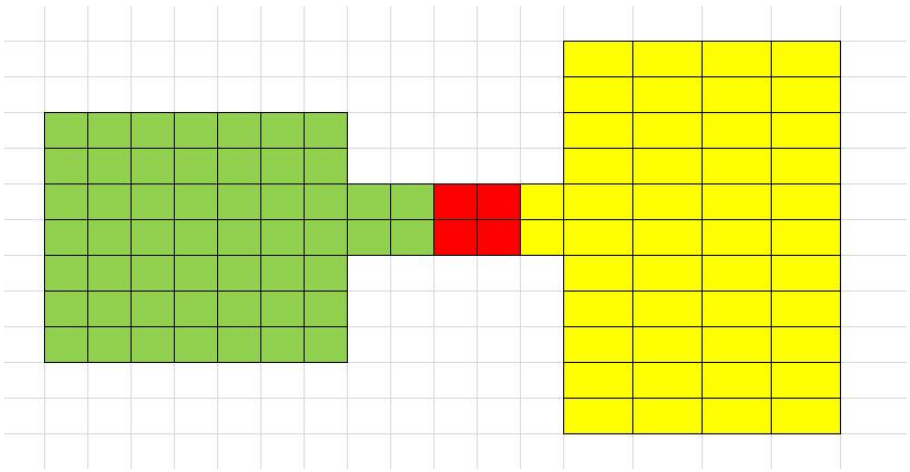


Figure 3-7 Example of two segments intersected in projection plane

**9. Average curvature**

The curvature is estimated by relationship between eigenvalues of the covariance matrix (Point Cloud Library, n.d.) based on equation 3-2 and equation 3-4:

$$\sigma = \frac{\lambda_0}{\lambda_0+\lambda_1+\lambda_2} \qquad (3\text{-}4)$$

In order to get average curvature, all curvature values of points within this segment should be calculated.

**10. Average echo**

**11. Average reflectance**

Reflectance strength of laser beam after reflected by object surface.

**12. Average range**

The distance between laser sensor and reflectance point.

**13. Average theta**

### 3.6.3 Edge feature

1. **Height difference**
   The segments on one edge have their own height (average height), using height difference as one edge feature.
2. **Include angle**
   Based on normal vector calculated before, include angle between segments can be constructed.
3. **Intersected**
   Same as the method we decide if two segments intersected in node features part, we can also build a new edge feature called intersected. If a specific pair of segments intersected, then the value of this feature will be give 1, otherwise, 0.

## 3.7 CRF training

There is an important concept in training CRF, maximum entropy – an approach to estimate probability distribution. Entropy of a probability distribution is a measure of uncertainty and is maximized when the distribution in question is as uniform as possible (Shannon, 1948).

One applied method to achieve maximum entropy is by maximum likelihood parameter estimation. By given equation. 2-2, we can assume that:

$$\prod_{i\in n} \emptyset_i(x, y_i) \cdot \prod_{i,j\in e} \varphi_{ij}(x, y_i, y_j) = \exp\left(\sum_{j\in edge} \lambda_i t_i(y_{i-1}, y_i, x, i) + \sum_k \mu_k . s_k(y_i, x, i)\right) \quad (3\text{-}5)$$

Here, we specify unary and pairwise potential to edge feature function $t_i(y_{i-1}, y_i, x, i)$ and node feature functions$s_k(y_i, x, i)$. Where $\lambda_i$ and $\mu_k$ indicate edge feature and node feature parameters. However, we can still further assume that:

$$F_j(i,j) = \sum_{i=1}^{n} f_j(y_{i-1}, y_i, x, i) \qquad (3\text{-}6)$$

Where each $f_j(y_{i-1}, y_i, x, i)$ can be either one $t_i(y_{i-1}, y_i, x, i)$ or one $s_k(y_i, x, i)$. In this way, we unify both edge and node features together into one equation as:

$$\mathrm{P}(\mathrm{y}|\mathrm{x},\lambda) = \frac{1}{Z(x)}\exp(\sum_j \lambda_j F_j(y,x)) \qquad (3\text{-}7)$$

Now, both node and edge parameters can be unify as $\lambda_j$. Now, the log-likelihood is given by:

$$\mathrm{L}(\lambda) = \sum_k [log \frac{1}{Z(x^{(k)})} + \sum_j \lambda_j F_j(y,x)] \qquad (3\text{-}8)$$

This function can be proved is a concave, which means that it have global maximum (optimized result). Of course, using first derivative of Eq.3- as:

$$\frac{\partial L(\lambda)}{\partial \lambda_j} = E_{\check{p}(y,x)} F_j(y,x) - \sum_k E_p(y|x^{(k)}, \lambda) F_j(y, x^{(k)}) \qquad (3\text{-}9)$$

Where $\check{p}(y,x)$ is the empirical distribution of training data and $E_p$ denotes expectation with respect to distribution p. Let this equation equal to zero, we can get global maximum solution of $\lambda_j$, however, for computer, it is a difficult task. Fortunately, some alternative algorithms can be used to solve likelihood maximum estimation problem such as dynamic programming (Wallach, 2004) and Stochastic Gradient descent (SGD) (Bottou, 2005). According to Bottou (2005), for complex graphic network, SGD has better performance than dynamic programing which often be used in solving linear-chain structure MRF and CRF optimization problem. Therefore, in this work, we choose SGD as the approach to train CRF classifier.

### 3.8 Classification

Classification task, known as inference in machine learning fields, is by given unlabelled entity with features' value to do labelling based on trained classifier. In CRF, the inference is computing the partition function and marginal probabilities, in other word, giving a most likely labelling sequence.

Nevertheless, inference in CRF can be treated as a #p-hard problem which similar to NP-hard problem. In the work of Piatkowski (2011), it shows that Loopy Belief Propagation (LBP) algorithms conduct to a reasonable running time for inference task in CRF based on Graphics Processing Units (GPU) computing. Besides, considering about the complexity of our graphic network structure which with multiple tree and loop, LBP should be better adapted to this environment than traditional belief propagation algorithms. Hence, LBP is chosen for CRF inference in this research.

We firstly performs segmentation to testing data set with same parameters setting as training procedure one. Then calculating for features the according to training features candidate list and generating the graphic structure. Input features table and structure into classifier. After inference, optimized labelling sequence will be obtained.

### 3.9 Quality assessment

After we getting classification result for the testing data set, we can compare it against to reference data set. At this stage, confusion matrix will be used to analysis performance of CRF classifier. At the same time, result from SVM classifier will also be compared, in order to illustrate the advantages of CRF.

# 4 IMPLEMENT AND RESULT

## 4.1 Study area and data set

### 4.1.1 Study area

The database contains 3D MLS data from a dense urban environment in Rue Cassette, 6th Parisian district, France, composed of 300 million points. Fig.4-1 shows the reality environment. The acquisition was made in January 2013 (Vallet et al, 2015). It has been acquired by Stereopolis II, a MLS system developed at the French National Mapping Agency (IGN).


Figure 4-1 Reality environment of study area ("16 Rue Cassette-Google Maps," n.d.)

### 4.1.2 Training data set

Fig.4-2 shows raw training data set before doing segmentation. Table.4-1 and Table.4-2 show general description and entities list.

Figure 4-2 training data set

Table 4-1 General description of training data set

| | |
|---|---|
| Size | 120m |
| Number of points | 6479592 |

Table 4-2 Entities in training data set

| | |
|---|---|
| other ground | 2 |
| road | 2 |
| sidewalk | 35 |
| curb | 33 |
| building | 29 |
| Post | 46 |
| floor lamp | 2 |
| trash can | 2 |
| pedestrian | 3 |
| other pedestrian | 6 |
| still pedestrian | 4 |
| holding pedestrian | 2 |
| scooter | 14 |
| car | 15 |
| tree | 2 |

### 4.1.3 Testing data set

Fig.4-3 shows raw testing data set before segmentation. Table.4-3 and Table.4-4 show general description and entities list.

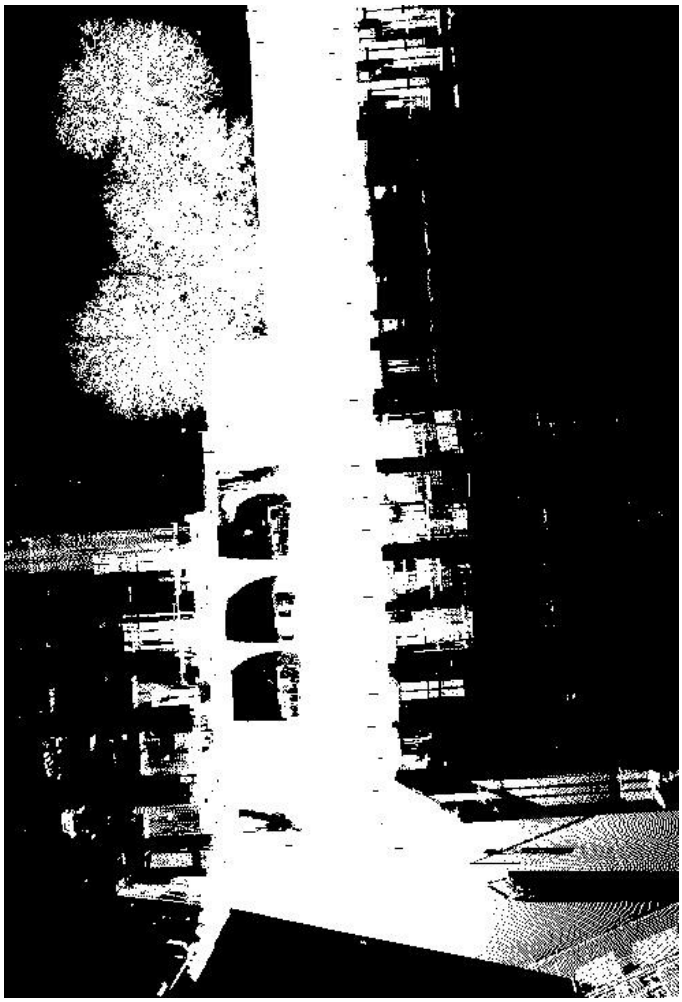


Figure 4-3 Raw testing data set

Table 4-3 General description of testing data set

| | |
|---|---|
| Size | 80m |
| Number of points | 4680016 |

Table 4-4 Entities in testing data set

| | |
|---|---|
| other ground | 3 |
| road | 1 |
| sidewalk | 5 |
| curb | 6 |
| building | 11 |
| Post | 53 |
| floor lamp | 2 |
| trash can | 2 |

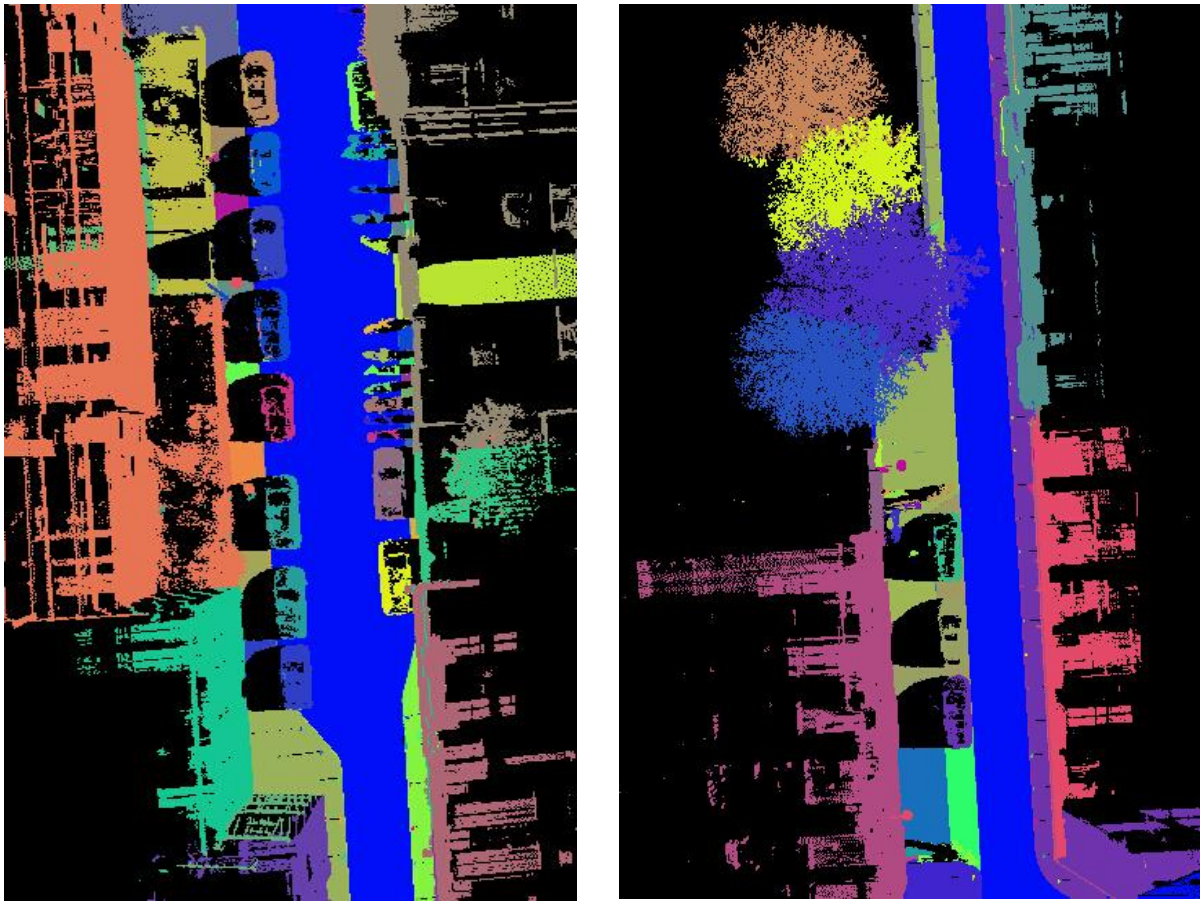
| | |
|---|---|
| pedestrian | 2 |
| other pedestrian | 3 |
| still pedestrian | 4 |
| holding pedestrian | 2 |
| scooter | 3 |
| car | 6 |
| tree | 4 |

## 4.2 Implement

For segmentation, region growing in point cloud library (PCL) (Point Cloud Library, 2015), which also known as surface growing algorithms had been used as segmentation approach to do this task.
As to generation of graphic network structure, the optimal algorithm mentioned before in section 3.5 has been implemented in C++ environment.
All Features calculation are implemented in C++ environment.
About training and testing procedure, a 3rd party library called UGM (Schmidt, 2010)has been used to realize CRF modelling, training, and inference in Matlab environment.
Finally, some statistic functions in Matlab have been used for quality assessment.

## 4.3 Segmentation result

Based on segmentation method in Chapter 3, raw data of training and testing point cloud successfully transform to segment level shown in Fig 4-4 (a) and (b).



(a) (b)

Figure 4-4 Segmentation result for training (a) and testing (b) data sets

## 4.4 Classification result

### 4.4.1 Experiments design

In order to compare the proposed method in this thesis to previous methods, besides, prove the contribution of topological information to CRF model. I design four contrast experiments to achieve this purpose. The first one is CRF classifier with all features both for node and edge mentioned in section 3.6, which is also the proposed method in this work. The second one is CRF classifier without topological features both in node and edge features. Experiment 3rd and 4th follow the pattern of experiment 1st and 2nd for topological, but implemented by using SVM classifier. Table. 4-5 shows the list of topological features.

Table 4-5 List of topological information

| | |
|---|---|
| Node feature | 1. Number of perpendicular<br>2. Number of parallel<br>3. Number of intersected |
| Edge feature | 1. Include angle<br>2. Intersected |

### 4.4.2 Evaluation method

One of quantitative evaluation method for classification is using confusion matrix also known as contingency table. This approach is especially useful for supervised learning in machine learning field. In our case, CRF model, this can also use confusion matrix to do the evaluation.

There are four basic terminologies for a confusion matrix (Olson, 2008):

1. TP (True Positive): The number of objects classified as expected class.
2. TN (True Negative): The number of objects classified as other classes.
3. FP (False Positive): The number of other objects classified as expected class.
4. FN (False Negative): The number of expected object classified as other class.

Recall rate and precision which also known as completeness and correctness are two indicators used to descript quality of classification. Recall rate is the fraction of relevant instances that are retrieved, while precision is the fraction of retrieved instances that are relevant. Overall accuracy gives us an overall quality about classification result.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4\text{-}1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4\text{-}2)$$

$$\text{Accuracy} = \frac{TP}{TP+FP+FN} \quad (4\text{-}3)$$

### 4.4.3 General comparison of four experiments

Overall accuracy is used to assess quality of classification based on whole testing data set. It will influenced not only by accuracy of each class but also number of classes. The overall accuracy of four experiments is shown in Table.4-6.

Table 4-6 Overall accuracy of four experiments

| | |
|---|---|
| CRF with topological information | 91.5% |
| CRF without topological information | 34.5% |
| SVM with topological information | 68.2% |
| SVM without topological information | 68.2% |

### 4.4.4 CRF with topological information

Doing experiment with testing data set based on CRF model with fully features. It achieve overall accuracy at 91.5%. The classification result is shown in Fig.4-5, Fig.4-6, Fig.4-7,Fig.4-8,Fig.4-9 and Fig.4-10.

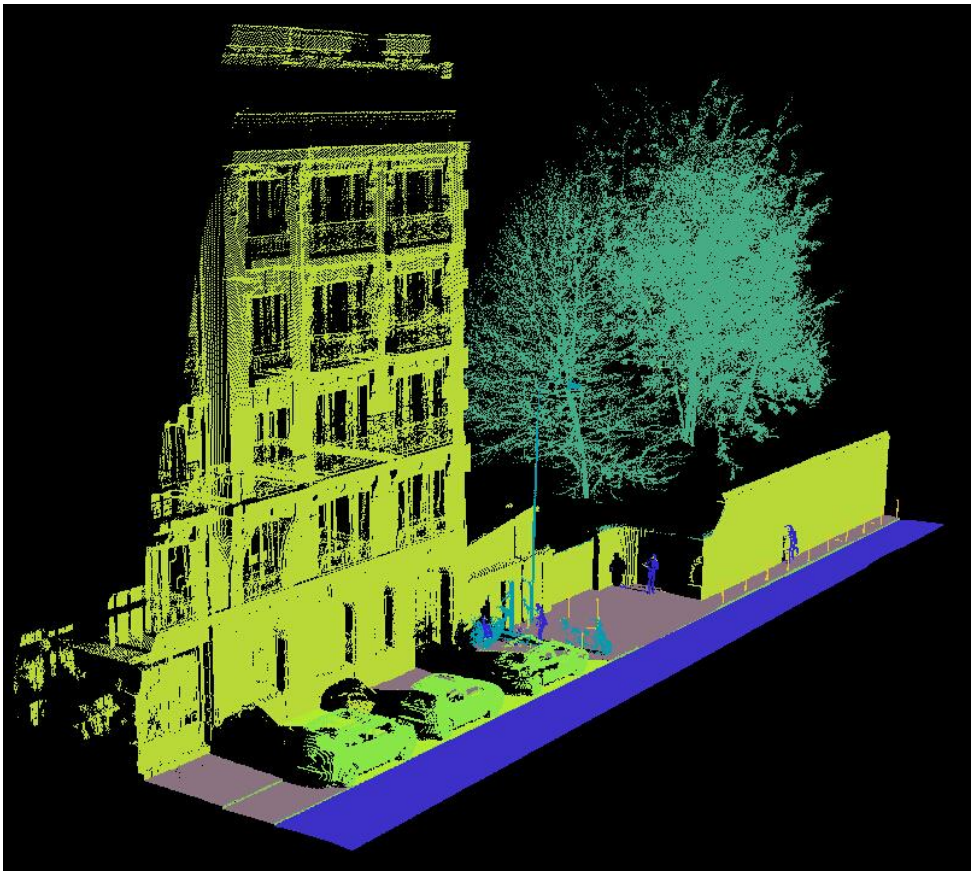


Figure 4-5 Classification result for whole scene

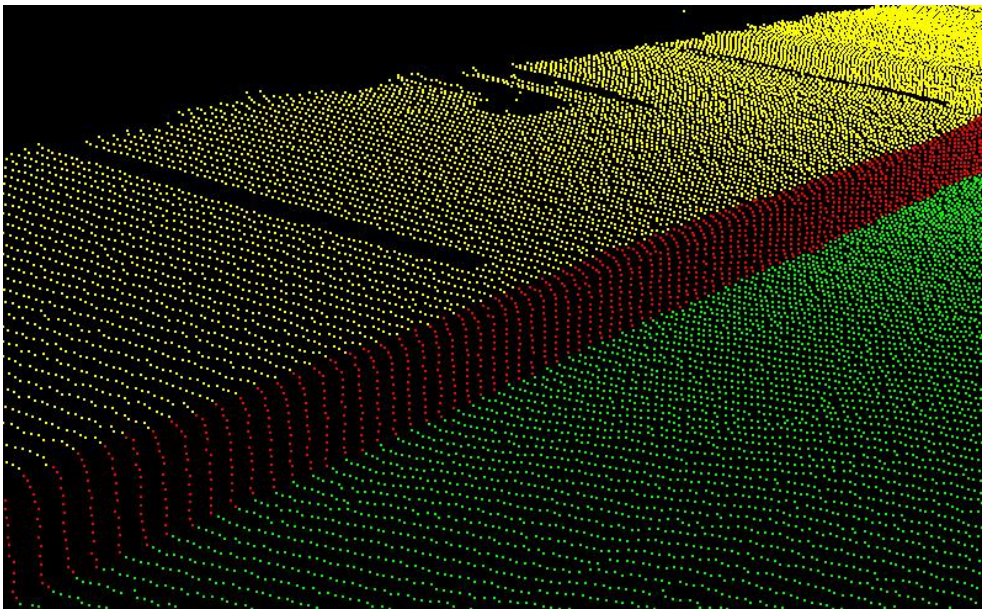


Figure 4-6 Classification result of curb (red), sidewalk (yellow) and main road (green)

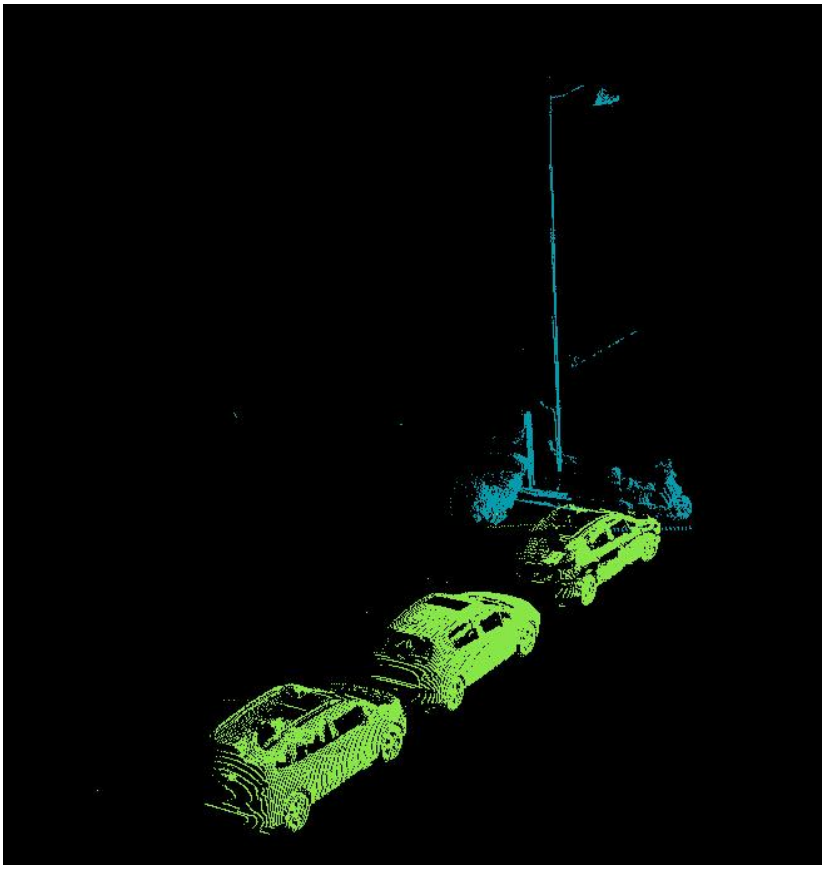


Figure 4-7 Classification result of car (green), scooter (blue) and street light (misclassify to scooter as blue)

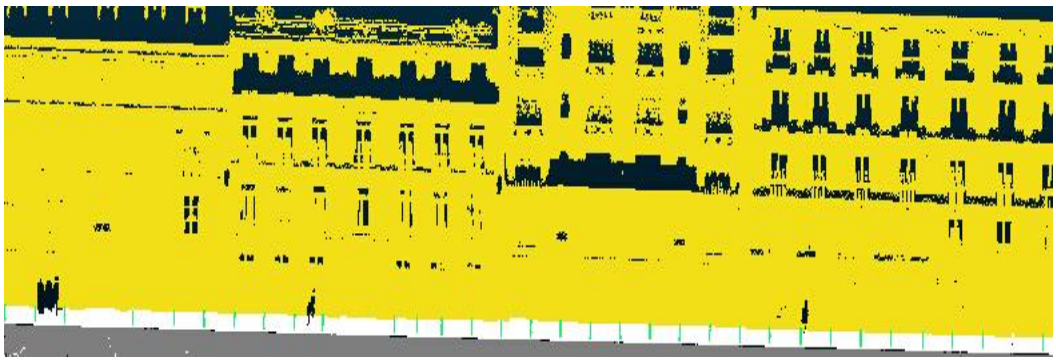


Figure 4-8 Classification result of building and post

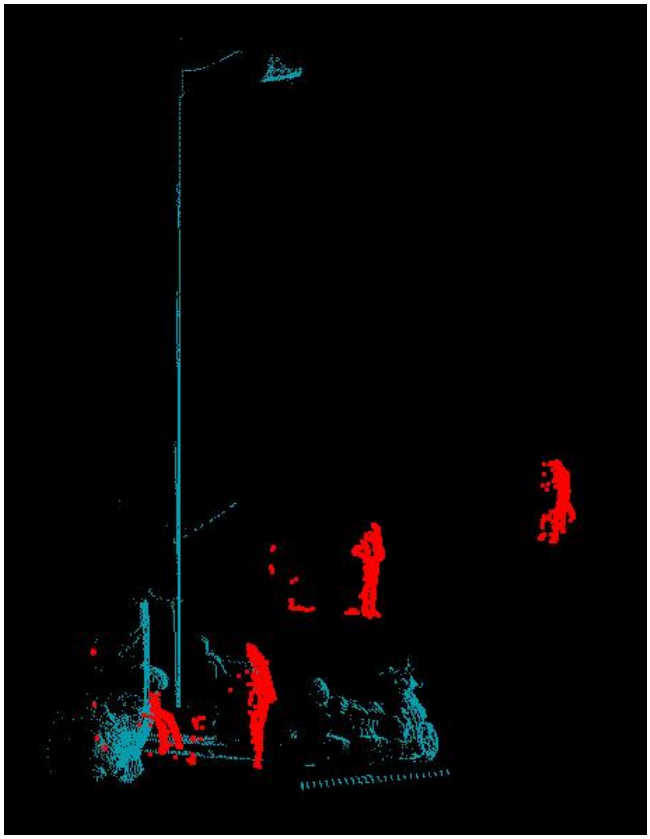


Figure 4-9 Classification result of pedestrian (red), scooter and street light (blue)

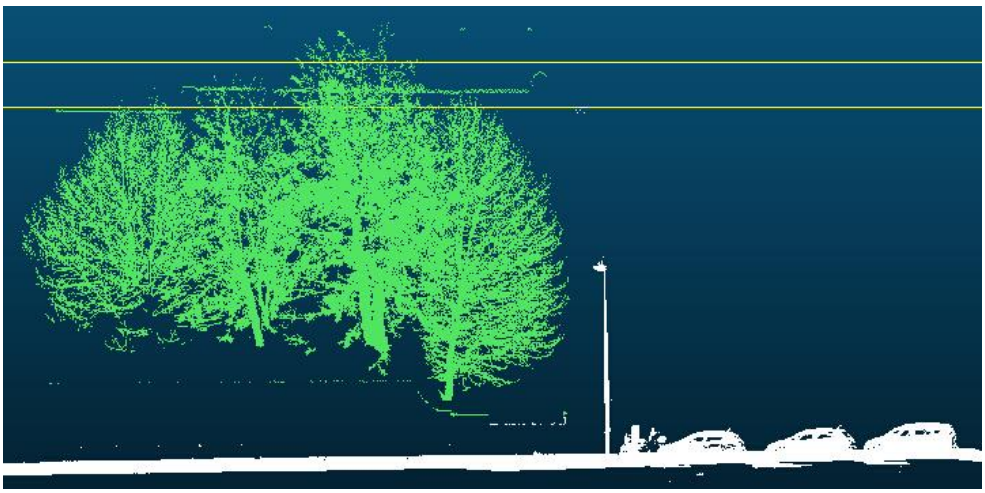


Figure 4-10 Classification result of tree

The recall rate and precision of 12 different classes had been calculated, and summarized in Table 4-7.

Table 4-7 Evaluation result of 12 classes by using CRF with topological information

| Label | Name | Recall rate | Precision | Accuracy |
|---|---|---|---|---|
| 1 | Other ground | 66.7% | 66.7% | 50% |
| 2 | Road | 100% | 100% | 100% |
| 3 | Sidewalk | 80% | 80% | 66.7% |
| 4 | Curb | 83.3% | 100% | 83.3% |
| 5 | Building | 90.9% | 100% | 90.9% |

| | | | | |
|---|---|---|---|---|
| 6 | Post | 100% | 100% | 100% |
| 7 | Street light | 0% | 0% | 0% |
| 8 | Trash can | 0% | 0% | 0% |
| 9 | Pedestrian | 90.9% | 100% | 83.3% |
| 10 | Scooter | 100% | 33.3% | 33.3% |
| 11 | Car | 100% | 100% | 100% |
| 12 | Tree | 100% | 100% | 100% |

#### 4.4.5 CRF without topological information

Doing experiment with testing data set based on CRF model without topological features. It achieves overall accuracy at 34.5%.

The recall rate and precision of 12 different classes had been calculated, and summarized in Table 4-8.

Table 4-8 Evaluation result of 12 classes by using CRF without topological information

| Label | Name | Recall rate | Precision | Accuracy |
|---|---|---|---|---|
| 1 | Other ground | 66.7% | 66.7% | 50% |
| 2 | Road | 100% | 100% | 100% |
| 3 | Sidewalk | 80% | 80% | 66.7% |
| 4 | Curb | 50% | 100% | 50% |
| 5 | Building | 100% | 47.8% | 47.8% |
| 6 | Post | 0% | 0% | 0% |
| 7 | Street light | 0% | 0% | 0% |
| 8 | Trash can | 0% | 0% | 0% |
| 9 | Pedestrian | 100% | 100% | 16.1% |
| 10 | Scooter | 0% | 0% | 0% |
| 11 | Car | 0% | 0% | 0% |
| 12 | Tree | 100% | 100% | 100% |

#### 4.4.6 SVM with topological information

Doing experiment with testing data set based on SVM model without topological features. It achieves overall accuracy at 68.2%.

The recall rate and precision of 12 different classes had been calculated, and summarized in Table 4-9.

Table 4-9 Evaluation result of 12 classes by using SVM with topological information

| Label | Name | Recall rate | Precision | Accuracy |
|---|---|---|---|---|
| 1 | Other ground | 0% | 0% | 0% |
| 2 | Road | 0% | 0% | 0% |
| 3 | Sidewalk | 0% | 0% | 0% |
| 4 | Curb | 66.7% | 100% | 66.7% |
| 5 | Building | 100% | 28.2% | 28.2% |
| 6 | Post | 100% | 100% | 100% |
| 7 | Street light | 50% | 100% | 50% |
| 8 | Trash can | 100% | 50% | 50% |
| 9 | Pedestrian | 9% | 9% | 14.28% |
| 10 | Scooter | 0% | 0% | 0% |

| | | | | |
|---|---|---|---|---|
| 11 | Car | 0% | 0% | 0% |
| 12 | Tree | 0% | 0% | 0% |

#### 4.4.7 SVM without topological information

Doing experiment with testing data set based on SVM model with topological features. It achieves overall accuracy at 68.2% which the same as SVM with topological information.

The recall rate and precision of 12 different classes had been calculated, and summarized in Table 4-10.

Table 4-10 Evaluation result of 12 classes by using SVM without topological information

| Label | Name | Recall rate | Precision | Accuracy |
|---|---|---|---|---|
| 1 | Other ground | 0% | 0% | 0% |
| 2 | Road | 0% | 0% | 0% |
| 3 | Sidewalk | 0% | 0% | 0% |
| 4 | Curb | 66.7% | 100% | 66.7% |
| 5 | Building | 100% | 28.2% | 28.2% |
| 6 | Post | 100% | 100% | 100% |
| 7 | Street light | 50% | 100% | 50% |
| 8 | Trash can | 100% | 50% | 50% |
| 9 | Pedestrian | 9% | 9% | 14.28% |
| 10 | Scooter | 0% | 0% | 0% |
| 11 | Car | 0% | 0% | 0% |
| 12 | Tree | 0% | 0% | 0% |

#### 4.4.8 Weights vector of CRF and SVM

Weights vector after training can indicate how helpful of each feature to classifier. For CRF, there are 18 node features and 3 edges features. Thus, there will be 21 dimensions for weights vector of CRF. As to SVM, because none edge features can be fuse with it, only 18 dimensions in weights vector for SVM. The order of weights in vector list for both CRF and SVM are shown in Table. 4-11.

Table 4-11 Orders of weights for features in classifier

| Features | CRF | SVM |
|---|---|---|
| Average Height | 7 | 9 |
| X shift | 16 | 12 |
| Projection area xy | 2 | 1 |
| Projection area yz | 13 | 2 |
| Projection area xz | 1 | 4 |
| Projection area xy/yz | 12 | 3 |
| Projection area yz/xz | 22 | 6 |
| Projection area xy/yz | 17 | 5 |
| Point density | 15 | 10 |
| Normal vector x | 9 | 15 |
| Normal vector y | 19 | 16 |
| Normal vector z | 20 | 13 |

| | | |
|---|---|---|
| Number of perpendicular | 4 | 7 |
| Number of parallel | 3 | 14 |
| Average curvature | 18 | 17 |
| Average echo | 11 | 19 |
| Average reflectance | 14 | 8 |
| Average range | 21 | 11 |
| Average theta | 10 | 18 |
| Height differences | 5 | Can not fused with edge features |
| Include angle | 8 | Can not fused with edge features |
| If intersected | 6 | Can not fused with edge features |

For example, projection area in xz area contributes most to distinguish objects in CRF while projection area in xy plays this role in SVM. Besides, by comparing both weights vectors for CRF and SVM, we can find out that all topological features have high ranking in CRF. However, in SVM, these topological features rank quite behind.

## 4.5 Running time

The running time and iteration number is shown in Table 4-12 for both CRF and SVM.

Table 4-12 Running time for classifiers

| | CRF | SVM |
|---|---|---|
| Training time | 406.8S | 0.187S |
| Training iterations | 314 | 210 |
| Inference time | 2S | 0.01S |

From table above we can find out that CRF pay much more time than SVM for training task. That is because during every iteration, CRF will consider about whole graphic network at the same time.

# 5 DISCUSSION

The result and evaluation of classification of street environment object based on proposed method has listed in Chapter 4. In this chapter, at each stage of proposed classification framework, the performance will be discussed. A short summary will be given in the final section.

## 5.1 Discussion of segmentation

In segmentation procedure, the ground laser point including road, sidewalk and other ground has been successfully removed at the first step.
In surface growing step, the result in Fig.5-1 shows that segmentation can clearly segment objects out such as scooter and car.

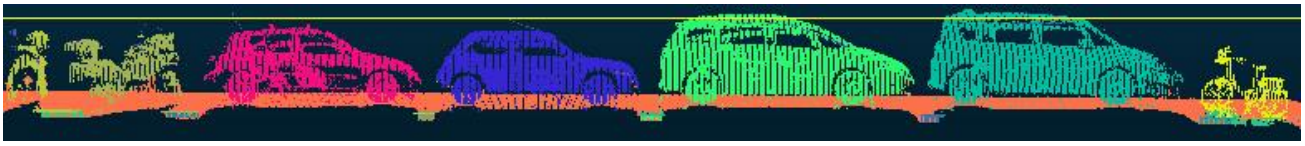


Figure 5-1 Segmentation result for car and scooter

However, there are still some drawbacks of this proposed segmentation approach. Since much topological information will be used as features for classification, therefore, clearly isolated sample objects should be picked out after segmentation such as planar, circle and pole. But in practical, many types of objects are composed of complex structure. For example, street light is can simply treated as composed of a pole and lampshade. It is more ideal that we can filter lamp standard and lamp shade as two segment as Fig. 5-2.

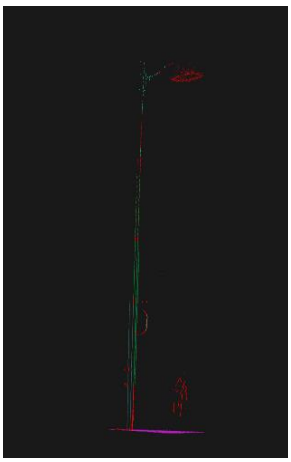


Figure 5-2 Segmentation of street light I

This kind of operation called decomposition of street furniture. However, there are two difficulties for this approach even it make more sense to use this method with topological information. The first one is that if we design sub-component pattern for object, then we still need to design many subclass for classifier such as lamp standard or roof of car, which will lead to improve complexity of whole classification framework. However, even we decide to design enough subclass for classifier model, but we still need to consider about the changeful of objects epically in urban street environment. For example, some street lights are standing on the ground while some others are connect to the wall of building. Therefore, segmentation lead to integrated object result can be more suitable for variety environment and form a more general classification framework.

## 5.2 Discussion of graphic network creation

In experiments, I use 0.6m as connection threshold. There are 808 edges for 143 objects in testing data set. It is obvious that appropriate number of edges connected for training and testing data set is important. If the threshold set too big, there will be too many segment being connected, and it will decrease the reasonability of spatial dependency, also computation-cost. In contrast, if the connection threshold set too small, it is possible many objects which indeed have spatial dependency with each other can not be connected. Thus, It will strongly effect on CRF classification result.

On the other hand, we should notice that classification environment will change based on different data set. About the criteria of creating a good graphic network in different data sets, it is quite based on experiences. Indeed, the quality of created network is decided by both minimum distance threshold and dataset. If the objects within a dataset are dense and crowded, then the threshold should be set bigger in order to keep enough connections (relations) between nodes (segments). On contrast, if objects are sparse, this threshold should stay small. Therefore, it is impossible that we can find an optimal threshold setting for all datasets, users should update it by checking their dataset first.

## 5.3 Discussion of feature calculation

Feature calculation is main task of whole classification. 19 node features and 3 edge features have been calculated in total. Now, we go to analysis the contributions of features to classification:

Average height: The average heights of most target classes are stable such as car, pedestrian building. However, some classes such as street lamp, which will varies strongly depend on type of lamp.

Projection area: For different classes, the projection area and ratios between them are following some patterns. For instance, projection areas of car in three directions are approximate, while building only has big area value in one direction (projection area yz).

X shift: In common urban area scene, different class objects are also following some stable patterns. From middle line to two sides along x axis, the orders of objects layout are: road, car (near the boundary between road and sidewalk), side walk, pedestrian or trash can or scooter or street lamp, tree, building. X shift will help to distinguish object based on this pattern.

Average normal vector: Although that normal direction of each class is stable, but there are still some classes will have similar normal vector direction, for example, road and sidewalk.

Topological features: If graphic network has been appropriate created, the topological will be great help for the classification. Spatial relation with sematic of topological information can be assist for classification task.

## 5.4 Discussion of classification result of CRF model

### 5.4.1 Comparison of classification results

The classification results of four contrast experiments have been listed in last chapter and summarize as chart in Fig. 5 – 3, Fig.5-4 and Fig. 5-5 of recall rate, precision and accuracy.

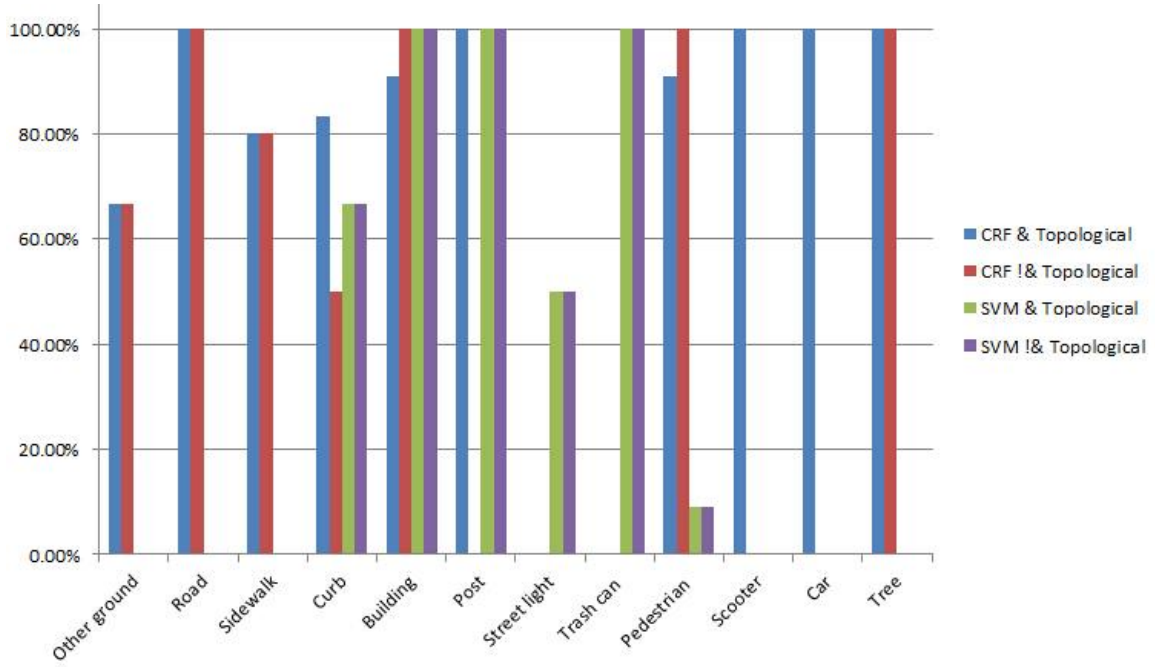



Figure 5-3 Recall rate of four classifiers

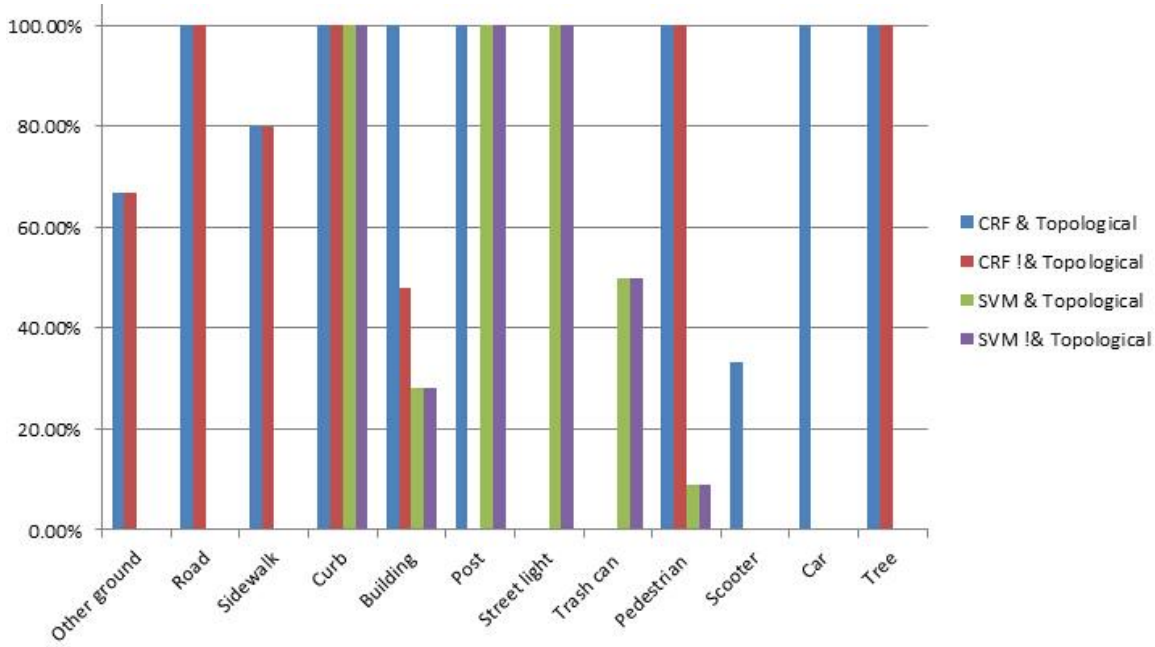



Figure 5-4 Precision of four classifiers

Both two CRF classifiers have high recall rate for road, sidewalk and curb which are regular ground class, while two classifiers only perform good in classify curb. All classifier do good in detect building, however, CRF classifiers perform far behind SVM classifier in detecting street light and trash can. Finally, CRF with topological information has advantage in detecting scooter, car and tree with perfect performance.

As to precision, situations are similar to recall rate for classifying ground object. But for building classification, only CRF model with topological information achieve high precision. All classifiers do well in classifying post except CRF model without topological. Street light and trash still be a difficulty for CRF model while SVM model do well. However, CRF model with topological still have advantages in classifying scooter, car and tree in precision against rest classifiers.

Things are similar in accuracy, CRF keeps advantages in classifying ground, building, post, pedestrian, car and tree, while SVM do good in recognize street light and trash can. In overall, CRF have higher accuracy against SVM.

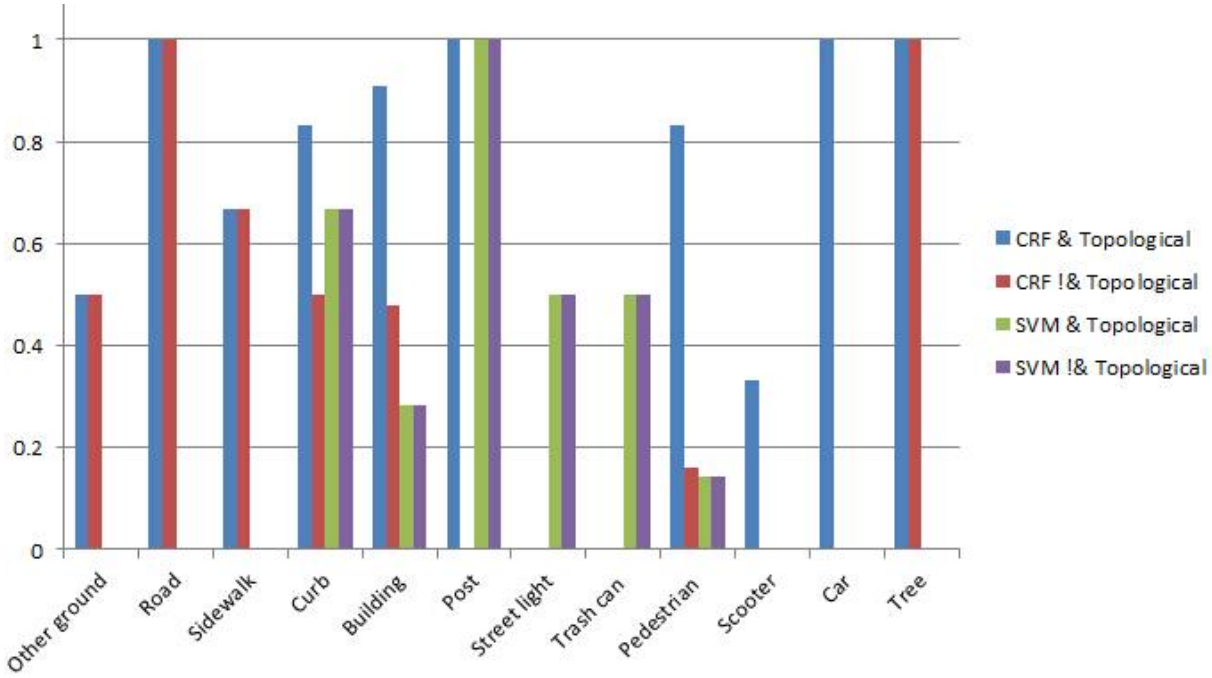



Figure 5-5 Accuracy of four classifiers

### 5.4.2 Advantages and disadvantages of classifiers

Compare CRF model against to SVM model, in general, CRF has advantages in classifying most type of classes such as road, side walk, building, pedestrian scooter, can and tree. Most of them are object with clearly geometric and topological features. For some tiny and changeful object such as trash can and street light where SVM model has advantage in classification.

Weights vector of CRF can also give us some insights about the reasons of CRF fails in classifying street and trash can. Street lights in both training data sets are changeful in structure, for instance, standing on ground or hinging to wall. In such case, different street lights can give large different feature values especially for topological and geometric features. Moreover, topological features have high weights in CRF model, thus, it will have a strongly bad effect on classification result for changeability of topological features of street light.

As to trash can, it usually located with same x shift value and height as scooter. Besides, they all have similar projection area for all directions, which act as important features in classification according to weights vector in Table. 4-11. That is one of the important reason that CRF classifier can easily misclassify trash can as scooter.

### 5.4.3 Roles of topological information in CRF

From result comparison in section 5.4.1, we can find out that topological information give an obvious improvement for CRF model in recall rate, precision and accuracy for most classes, while it do not have significantly help for SVM model, actually, they get the same classification result even we remove all topological features away.

There are two reasons why topological information do not helpful for SVM while it plays an important role for CRF classification:

1. Firstly, not all topological features can be used in SVM. For instance, some edge features such as

include angle can not be fused with SVM. From Table. 4-11, we know that two topology edge features (include angle and if intersected) have high weights, moreover, higher than topology node features (number of perpendicular and parallel). According to this, we can infer that the topology edge features are the main factor to improve classification quality which we can add to CRF instead of SVM. Although all topology node features can be fuse with both CRF and SVM, but lack of help of topology edge features, SVM could not be pushed to improve.

2. Even SVM can fuse with topological node information, after training, the weights for these topology node features stay low. With the same node features, CRF give much higher weights for them, that main because for during training, CRF will calculate weight values based on not only features sequence but also labels and features of neighbors. Graphic network simulate spatial distribution and dependencies and make topology information more meaningful when consider about neighbor nodes.

In this case, we can prove that topological information can be helpful for segment-based classification, but not for all classifier, but only for CRF model which based on graphic network structure where spatial relation can be easily fused.

## 5.5 Summary

In this chapter, the results has been discussed and organized for each step of classification framework. The results shows that proposed approach can basically realized objectives of this work and have some advantages compared to previous works of classification point cloud in urban street environment.

# 6 CONCLUSIONS AND RECOMMENDATIONS

## 6.1 Conclusions

The main object of this research is to design a robust framework for classification of Mobil Laser Scanning data which can achieve a higher classification quality both in completeness and accuracy than previous methods. There are four main steps to achieve this main objective: segmentation, generation of graphic structure, feature calculation, classifier training and inference in the end. In the first step, surface growing algorithms has been used to filter meaningful object out. In the flowing phase, a minimum distance between segments approach has been used to create graphic network structure. In feature calculation work, 18 node features and 3 edge features has been calculated, where 3 node features and 2 edge features are topological information. In the next step, CRF classifier will be training by using training data set and doing inference based on a testing data set in the end. In order to analysis performance of CRF model and explore contribution of topological information to CRF classifier, four contrast experiments have been designed: CRF with fully topological information, CRF without any topological information, SVM with topological information and SVM without topological information.

The results show that proposed approach in this work performs well both in recall rate and precision for the classification task in urban street environment. 12 classes objects have been classified in total. Besides, the results also show that CRF model have advantages against previous approaches such as SVM, and topological information indeed play an important role in improving CRF model's performance. Some conclusions are summarized based on evolution of results in Chapter 4 and discussion in Chapter 5:

1. Surface growing algorithm by using smoothness constrains is an efficient and effected approach to segment raw point cloud data set to meaningful entity which form a solid step stone for next phases of segment-based classification.

2. Using nearest distance between segments as criteria of connecting segments is more reliable than previous works such as using distance between geometric center of segments or distance between projected segments. The threshold can vary corresponding to point cloud data set.

3. 21 features have been calculated for each segment, and will be automatically given weights in training procedure. There are 5 features indicate topological information of segments.

4. Stochastic gradient descent (SGD) has been used to train CRF classifier which proved with high efficient. Loopy Belief Propagation (LBP) has been used for inference task which is more suitable for urban street environment that will lead to complex graphic network structure with multiple loops and tree structure.

5. Geometric information especially for projection area have highest weights for both CRF and SVM which means they are most helpful for classification.

6. Beside projection areas, topological also have second higher ranking in weights vector for CRF while they stay low in SVM. From this, we know that topology information can better help CRF to distinguish object while they do not be recognized as helpful features for classification by SVM classifier.

7. The result of contrast experiments shows that CRF classifier performance well than SVM classifier for segment-based classification task in urban street environment in general.

8. CRF classifier has high classification accuracy for objects with clearly geometric and topological feature such as building, car and road. However, for some objects with changeful geometric,

topological and location features can be easily be misclassified by CRF model.

9. Topological information can strongly improve classification performance of CRF classifier while it does not show significantly help for SVM classifier. It proves that topological information plays an important role in segment-based classification by using CRF.

## 6.2 Answer to research questions

1. If there are some pre-processing such as point reduction in order to speed up processing efficient and improve quality of classification?

   Removing noise point as pre-processing step can be helpful for segmentation which can avoid meaningful small segments occur after segmentation. Before doing real segmentation, ground points should be removed include main road and sidewalk.

2. What are the differences between point-based and segment-based classification?

   Point-based classification can not offer topological and geometric information, while regular-unit-based classification method can supply limited topological information. However, segments in segment-based classification can fully with spatial, geometric and topological information.

3. Based on CRF theory, how to generate graphic structure simulate spatial relationship of objects in reality?

   Using nearest distance between segments as criteria of connecting segments is more reliable than previous works such as using distance between geometric center of segments or distance between projected segments.

4. Which segmentation method should be implemented in order to use the geometric and topology information of different object class?

   Surface growing algorithm is more suitable for segment object with complex structure than other segmentation algorithms such as RANSAC and clustering. Comparing two different surface growing algorithms, smoothness constrains performance better.

5. Which features (unary and pair-wise potentials) such as geometric and topological properties can be used to describe different types of objects?
   21 features have been proposed to be used for CRF classifier. There are three main types of feature: geometric feature, topological feature and attribute feature of segment.

6. How to asset the experiments result? How to compare my method against previous researches' outcome?

   Confusion matrix has been used to evaluate classification result which usually used for evaluating supervised classification task. Comparing result of CRF and SVM based on same feature list and training & testing data set.

## 6.3 Recommendation

Although results show that this proposed approach basically achieve research objective, however, due to some drawbacks and limitations of this work, several aspects can be explored and modified in order to improve classification quality.

1. Segmentation

The parameters of surface growing algorithm are based on properties of data set such as point density and structure complexity of object. Therefore, a standard should be summarized in future about how to choose ideal parameter setting for segmentation task.

2. Graphic network structure creation
   The nearest distance threshold between segments is manually set. However, more research about how to better set this parameter should be given corresponding to different point cloud data set.

3. Feature calculation
   More features should be proposed and added into classifier, and given weight automatically by classifier. Since we have already prove that topological can strongly improve classification result with CRF for segment-based classification, more topological information features should be designed.

4. CRF training
   Some techniques for training in machine learning fields can be used to improve training effect such as regulation which can avoid over-fitting for classifier.

5. Inference
   In this work, only one type of classifier (SVM) has been implemented to use as a compared method, it is more convincing that if more classifiers can be compared with CRF model.

6. Classification level
   Combine of both point-based and segment-based CRF together to forms a two-stage classification framework for urban street furniture can be explored.

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# APPENDIX

Appendix 1 Confusion matrix for CRF with topological information

| | other ground | road | sidewalk | curb | building | Post Higher than 1 m | floor lamp | trash can | pedestrian | scooter | car | tree | Overall accuracy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| other ground | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 66.67% |
| road | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100.00% |
| sidewalk | 1 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 80.00% |
| curb | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 83.33% |
| building | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 90.91% |
| Post Higher than 1 m | 0 | 0 | 0 | 0 | 0 | 53 | 0 | 0 | 0 | 0 | 0 | 0 | 100.00% |
| floor lamp | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0.00% |
| trash can | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0.00% |
| pedestrian | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 1 | 0 | 0 | 90.91% |
| scooter | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 100.00% |
| car | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 0 | 100.00% |
| tree | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 100.00% |
| Precision | 66.67% | 100.00% | 80.00% | 100.00% | 100.00% | 100.00% | 0.00% | 0.00% | 90.91% | 33.33% | 100.00% | 100.00% | 91.59% |
| Accuracy | 50.00% | 100.00% | 66.67% | 83.33% | 90.91% | 100.00% | 0.00% | 0.00% | 83.33% | 33.33% | 100.00% | 100.00% | 0.00% |

Appendix 2 Confusion matrix for CRF without topological information

| | other ground | road | sidewalk | curb | building | Post Higher than 1 m | floor lamp | trash can | pedestrian | scooter | car | tree | Overall accuracy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| other ground | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 66.67% |
| road | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100.00% |
| sidewalk | 1 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 80.00% |
| curb | 0 | 0 | 0 | 3 | 2 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 50.00% |
| building | 0 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100.00% |
| Post Higher than 1 m | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 53 | 0 | 0 | 0 | 0.00% |
| floor lamp | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.00% |
| trash can | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.00% |
| pedestrian | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 100.00% |
| scooter | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.00% |
| car | 0 | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| tree | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 100.00% |
| Precision | 66.67% | 100.00% | 80.00% | 100.00% | 47.83% | 0.00% | 0.00% | 0.00% | 16.18% | 0.00% | 0.00% | 100.00% | 33.64% |
| Accuracy | 50.00% | 100.00% | 66.67% | 50.00% | 47.83% | 0.00% | 0.00% | 0.00% | 16.18% | 0.00% | 0.00% | 100.00% | 0.00% |

Appendix 3 Confusion matrix for SVM with topological information

| | other ground | road | sidewalk | curb | building | Post Higher than 1 m | floor lamp | trash can | pedestrian | scooter | car | tree | Overall accuracy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| other ground | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| road | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| sidewalk | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| curb | 0 | 0 | 0 | 4 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 66.67% |
| building | 0 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100.00% |
| Post Higher than 1 m | 0 | 0 | 0 | 0 | 0 | 53 | 0 | 0 | 0 | 0 | 0 | 0 | 100.00% |
| floor lamp | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 50.00% |
| trash can | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 100.00% |
| pedestrian | 0 | 0 | 0 | 0 | 7 | 0 | 0 | 2 | 2 | 0 | 0 | 0 | 18.18% |
| scooter | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0.00% |
| car | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.00% |
| tree | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.00% |
| Precision | 0.00% | 0.00% | 0.00% | 100.00% | 28.21% | 100.00% | 100.00% | 50.00% | 40.00% | 0.00% | 0.00% | 0.00% | 68.22% |
| Accuracy | 0.00% | 0.00% | 0.00% | 66.67% | 28.21% | 100.00% | 50.00% | 50.00% | 14.29% | 0.00% | 0.00% | 0.00% | 0.00% |

Appendix 4 Confusion matrix for SVM without topological information

| | other ground | road | sidewalk | curb | building | Post Higher than 1 m | floor lamp | trash can | pedestrian | scooter | car | tree | Overall accuracy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| other ground | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| road | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| sidewalk | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| curb | 0 | 0 | 0 | 4 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 66.67% |
| building | 0 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100.00% |
| Post Higher than 1 m | 0 | 0 | 0 | 0 | 0 | 53 | 0 | 0 | 0 | 0 | 0 | 0 | 100.00% |
| floor lamp | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 50.00% |
| trash can | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 100.00% |
| pedestrian | 0 | 0 | 0 | 0 | 7 | 0 | 0 | 2 | 2 | 0 | 0 | 0 | 18.18% |
| scooter | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0.00% |
| car | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.00% |
| tree | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.00% |
| Precision | 0.00% | 0.00% | 0.00% | 100.00% | 28.21% | 100.00% | 100.00% | 50.00% | 40.00% | 0.00% | 0.00% | 0.00% | 68.22% |
| Accuracy | 0.00% | 0.00% | 0.00% | 66.67% | 28.21% | 100.00% | 50.00% | 50.00% | 14.29% | 0.00% | 0.00% | 0.00% | 0.00% |