

# EXTRACTION OF VERTICAL POSTS IN 3D LASER POINT CLOUDS ACQUIRED IN DENSE URBAN AREAS BY A MOBILE MAPPING SYSTEM

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## ABSTRACT:

This paper focuses on extracting vertical objects from 3D terrestrial point clouds, acquired in dense urban scenes. We are especially interested in urban vertical posts whose inventory is useful for many applications such as urban mapping, virtual tourism or localization. The proposed methodology is based on two steps. The first is a focalization step providing hypothetical candidates consisting of vertical features. The second step validates or rejects these candidates. In the case of validation, the features are classified according to the posts pattern library. The extraction of vertical objects is processed by projecting the point cloud in a horizontal plan. The accumulation density, the minimal and maximal heights are used to filter out ground points, tree leaves and to solve acquisition problems such as a region multiscans. After filtering step, the accumulation image is updated. Connex regions correspond to the vertical objects. These candidates are then validated regarding the posts pattern library. An analysis of the 3D vertical point distribution is processed. To do that, each region is characterized by its eigenvalues and eigenvectors based on a Principal Component Analysis in 3D space. The classification is processed by a decision tree algorithm. Results are presented on large and various datasets acquired under real conditions in a dense urban area. A global accuracy of 84 % is reached.

## 1 INTRODUCTION

For the last years, many research projects are interested in urban feature extraction in order to obtain a more realistic urban representation. Dense high resolution data are acquired at the street level using ground-based vehicles that are equipped with georeferencing devices (GPS, INS, odometer), laser scanners and optical cameras. Laser scanners provide accurate 3D point clouds characterized by  $x, y, z$  coordinates and intensity value per point depending on the target properties. In this work, we are interested in extracting urban vertical posts (cf. Figure 1). These posts are numerous and often implemented at the limits of pavements and streets. In urban designing, their inventory is crucial. The introduction of these objects in existing 3D city models provides more realistic scenes that are particularly interesting in virtual tourism and urban planning. Moreover, these objects are useful as landmarks in localization process and also as visual warnings for Advanced Driver Assistance Systems (ADAS).

The posts extraction may be complex in dense urban scenes due to real acquisition conditions (perturbating objects such as pedestrians, cars, bicycles, trees,). In a city, the posts sizes and shapes are governed by strict geometric specifications. In our study, we focus on 3 classes of posts that are described by a pattern library. The terrestrial point cloud is obtained by a RIEGEL LMS-Q120i laser which gives out 10000 points per second with an angular resolution of 0.01 degree and a wavelength of 904 nm. It is directed with a 90 degree angle from the direction of vehicle. The scanner has a scanning range of 80 degrees. The vehicle has a constant speed of 50 km/h which makes the point cloud resolution homogeneous.

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ization step providing hypothetical candidates consisting of vertical features. The second step validates or rejects these candidates. In the case of validation, the features are classified according to the posts pattern library. The paper is organized as following: a general state of the art is presented in section 2. The methodology is detailed in section 3. The focalization step is first presented and then the vertical object classification using a decision tree and a principal components analysis. Results will be presented in section 4 and conclusions drawn.

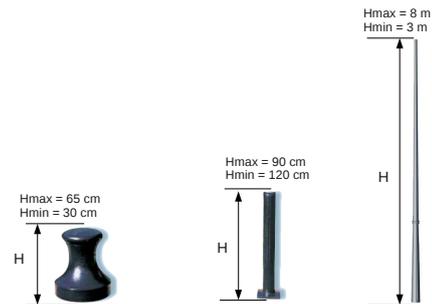


Figure 1: Posts pattern library

## 2 STATE OF THE ART

In the literature, techniques used for the segmentation of laser point clouds in urban environment can be grouped into three approaches. A first approach analyzes 3D point profiles in a perpendicular direction from the vehicle one. It is based on the analysis of points distribution in  $x, y, z$  space. (Abuhadrous et al., 2004) analyzes the distribution of point distances to the scanner. Histograms show modes that correspond to different objects in the scene, localized at different depths. Taking into account the

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mode width, *i.e.* the object thickness, two classes can be distinguished: trees and vertical objects. Nevertheless this method presents two drawbacks (1) it does not allow to discern posts from facades, (2) it is sensor-dependent. In (Manandhar and Shibasaki, 2001, Manandhar and Shibasaki, 2002), the authors analyze vertical point profiles by means of altitude histograms to extract the ground. The 3D points are clustered. The clusters are then classified using their spatial dispersion. For instance, a cluster with a high dispersion in  $x$ ,  $y$  and  $z$ -coordinates is likely to be a tree. Similarly, building facades lead to a higher dispersion along the  $Z$  axis. However, the dispersion criteria is not sufficient as tree trunks for instance will lead to similar values as facades and confusions could happen.

The second approach consists in projecting 3D points onto a discrete horizontal plan and using the accumulation image. In (Hernandez and Marcotegui, 2009), two kinds of images are obtained from this projection. The accumulation image returns the number of 3D points which are projected on the same cell. The second image is a range image which provides the maximal height in each cell. For facade detection, the authors assume that, on the same street, the facades are aligned. A Hough transform is used to detect their direction. Besides, they suppose that the ground is flat. It is extracted by region growing from the range image. Once the ground and the facades are filtered out, urban objects are extracted with a morphological Top-Hat filter and classified by Support Vector Machines which is a supervised algorithm. This method works well under the assumption that objects are isolated, which is not always verified in dense urban scenes. In (Zhao and Shibasaki, 2002), authors use both the analysis of vertical profiles and the projection of points in a discrete horizontal plan. The analysis of profiles allows to extract facades and ground. Remaining objects are classified in a second step. This classification takes into account the object height and the corresponding accumulation value. Object heights are computed from maximal and minimal altitudes in each cell.

A third approach is based on an analysis of the 3D local neighborhood of each 3D point. A Principal Components Analysis (PCA) is used ((Gross et al., 2006, Lalonde et al., 2006)). Local features are computed and are used for the classification process. This method requires a consistent computing time since features are computed for each 3D point. Moreover it is not an object-based method.

### 3 METHODOLOGY

The proposed methodology is based on two steps. First, the focalization step provides hypothetical candidates consisting of vertical features. These candidates may contain various objects such as posts, cars, trees or pedestrians. The second step validates or rejects these candidates. In the case of validation, the features are classified according to the posts pattern library using a decision tree. The global strategy is depicted in Figure 4.

#### 3.1 FOCALIZATION ON VERTICAL OBJECTS CANDIDATES

Dense urban scenes are very complex. The extraction of vertical objects from 3D point clouds is complicated since the data are "noisy". In fact, the objects of interest may be overlapping (for instance posts under trees). In addition, many 3D points belong to hang-up objects such as balconies or tree leaves. In this study, in order to simplify our problem, we assume that building facades are localized (Hernandez and Marcotegui, 2009, Hammoudi et al., 2009) and that corresponding points are filtered out from the 3D point cloud. We focus on the foreground of the scene.

The proposed method is based on the second family of approaches where 3D points are projected into a discrete 2D horizontal plane. One parameter is needed which is the discretization step. The discretization step is a critical parameter. A small value leads to a sparse accumulation. Small posts may be underdetected. A high value leads to high accumulation and many overlapping objects. This parameter is discussed in section 4. Three images are used: the minimal height, the maximal height images and the accumulation image. We assume that posts are characterized by continuous vertical features whose minimal height is on the ground plane. Our first objective is to filter out undesired 3D points to point out hypothetical candidates. The minimal height image values correspond to 3D points minimal height per cell. The minimal height points per cell are likely to belong to the ground. Consequently, the ground is locally approximated by a 3D plane, estimated using a robust RANSAC algorithm with norm  $L_1$  (Fischler and Bolles, 1981), based on minimal height points. This allows to filter out minimal height points that do not belong to the ground.

The accumulation image (*cf.* Figure 2(b)) corresponds to the number of projected points per pixel. The signature of an object depends on its height and should be independent to its distance from the scanner (depth). Consequently, each 3D point is weighted by its depth so that similar objects will give the same accumulation value regardless of their spatial position in the scene. Given an object pattern (height, width), the corresponding accumulation signature is known. Therefore, a threshold can be set automatically and applied to the accumulation image. In urban scene, in most of cases, a high accumulation value is likely to correspond to a vertical object. However, due to real acquisition conditions, high accumulation may occur in case of multiple scans, in bends for instance. This problem is solved using the ground approximation to filter out undesired points. Besides, the difference between the maximal and minimal height images (*cf.* Figure 2(a)) leads to the height of each cell which is a parameter of the pattern library. It is used in the classification step (Section 3.2).

After the filtering step, the accumulation image is updated. Connex regions point out the hypothetical candidates for vertical objects.

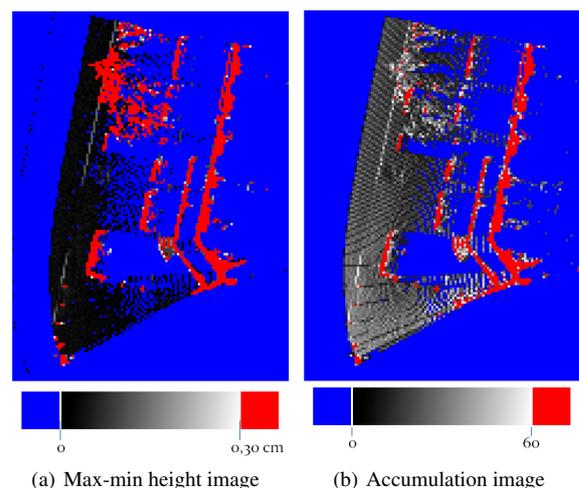


Figure 2: Images obtained by 3D point projection in a horizontal plane

Each connex region may correspond to at least one vertical object. An analysis of points vertical distribution allows to filter out hanging objects but also to separate overlapping objects. Considering the discretization step in 2D, the points vertical distribution is analyzed in a  $3 \times 3$  neighborhood size. We assumed

that posts are characterized by continuous vertical features so that corresponding 3D points should be uniformly distributed in Z-coordinate. In case of overlapping objects, a discontinuity will be detected. On a 3D point profile, we note  $z_n, z_{n+1}$  and  $z_{n+2}$  the altitudes of three consecutive points. A discontinuity  $d$  is detected as follows:

$$d = z_{n+1} - \frac{z_{n+2} + z_n}{2} > T_h \quad (1)$$

In case of regular vertical point distribution, the altitude of point  $z_{n+1}$  could be approximated by the the average altitude of previous and following points ( $z_n$  and  $z_{n+2}$ ). The threshold  $T_h$  depends on the laser resolution. In this study,  $T_h$  was set to 10 cm. If  $d > T_h$ , a discontinuity is detected, all points whose  $z > z_n$  are filtered out.

At this stage, hypothetical vertical objects candidates are detected (cf. Figure 3.1). Our method has the following advantages: (1) An object signature is constant independently from its spatial position (2) it takes into account acquisition problems such as multiple scans and (3) it deals with overlapping objects.

In the following section, the validation and classification processes are presented.

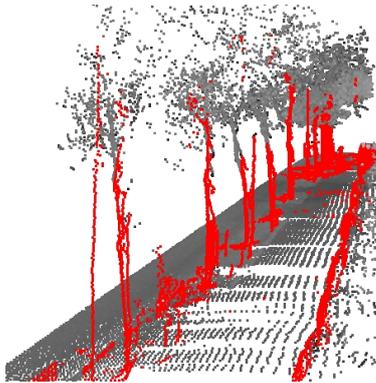


Figure 3: Example of detected objects

### 3.2 CLASSIFICATION OF VERTICAL OBJECTS

The previous focalization step provides a set of connected pixels (regions) in horizontal accumulation space. These regions are hypothetical vertical objects. They may contain cars, pedestrians and other vertical objects. In the validation step we aim at keeping only posts. As mentioned before the geometric characteristics (height and width) of these posts are given by a pattern library (cf. Figure 1).

### 3.3 Classification by decision tree

The proposed method consists in using a decision tree. This decision tree uses the pattern library (cf. Figure 1) to label objects in three principal classes of posts of different sizes. Table 1 gives the size range of these three classes (min and max of height).

The Principal Components Analysis (PCA) is used to determine the 3D point distribution in each label. The eigenvectors and eigenvalues provide useful information about the distribution of points. They are particularly discriminating in the case of vertical posts because:

- The first eigenvector is parallel to the ground  $z$  axis and the first eigenvalue approximates the height of object.

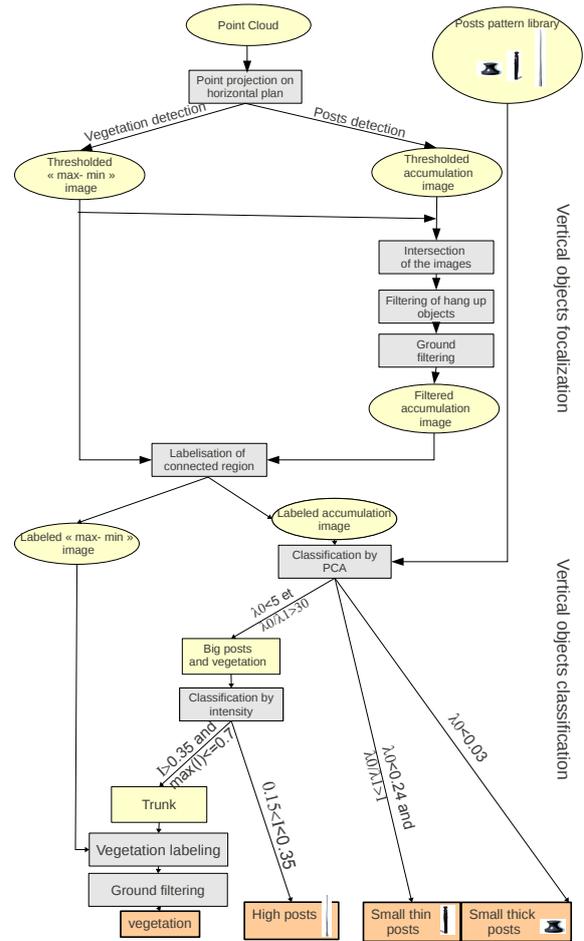


Figure 4: Global scheme

- Since the post height is larger than its width the first eigenvalue is very larger than the second and third eigenvalues.

Given the height and width of posts (pattern library), it is possible to compute the first and second theoretical eigenvalues (cf. Table 1). The first eigenvalue and the height of a post are related according to the following equation:

$$\lambda_0 = \frac{h^2}{4 \chi_{3;0.95}^2} \quad (2)$$

$\lambda_0$  : theoretical value for first eigenvalue

$h$  : height of post

$\chi_{3;0.95}^2$  : chi square distribution with freedom degree of 3 and significance of 95%

The validation step is based on a comparison of the theoretical values (eigenvalues and eigenvectors) with the computed values for each label (connected region). The used theoretical values are shown in Table 1 ( $\lambda_0$  and  $\frac{\lambda_0}{\lambda_1}$ ). However due to similar heights trees trunks are confounded with lamp posts. In order to differentiate lamp posts with tree trunks the intensity of laser points is used.

**3.3.1 Analysis of points intensity** The laser has lengthwave of 904nm. As shown in Figure 5, the intensity of reflected point

	small thick post	small thin post	lamppost	tree
height max	65 cm	120 cm	8 m	?
thickness max	30 cm	7 cm	?	?
$\lambda_0$ max	0.03	0.15	5	5
$\frac{\lambda_0}{\lambda_1}$ min	1	10	100	30
average intensity	0.2	0.2	0.2	0.4

Table 1: Geometric characteristics of posts and theoretical eigenvalues.

on vegetation is higher than on metal posts. We can see that laser intensity does not change with angle of incidence. That is due to the calibration of scanner laser by the manufacturer. In order to finalize classification and disambiguate trees from lamp posts, average intensity of each object is used.

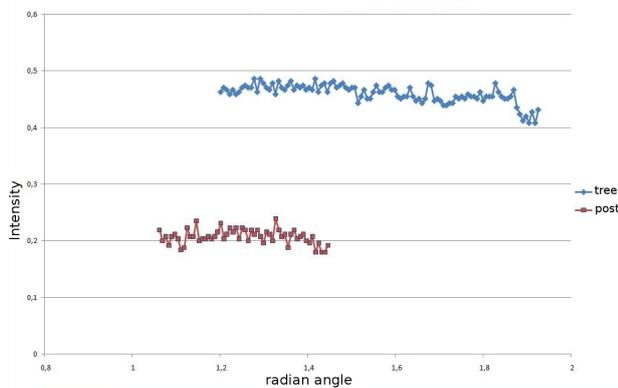


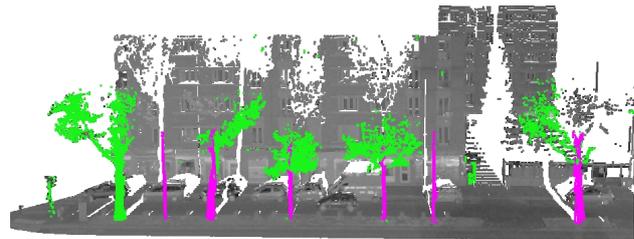
Figure 5: Value of intensity by angle of incidence

**3.3.2 Classification of vegetation point** At this step only trunk of trees are extracted. The entire tree including leaves and branches provides very useful information for many applications such as in faade texturing and GPS signal mask analysis. The entire tree can be easily extracted by a region growing algorithm taking into account tree trunk as initial seed and height of nearby points as growing criterion. Figure 6 shows an example of obtained result for tree segmentation.

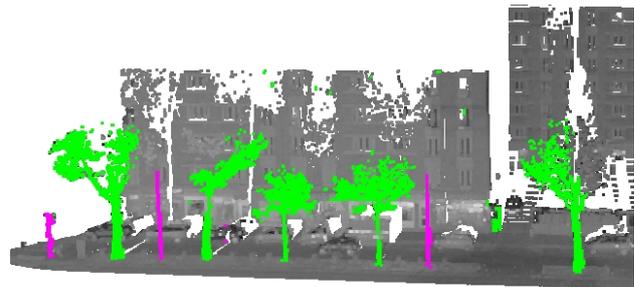
## 4 RESULTS

In order to evaluate the performance of our algorithm, it is applied to a set of 30000 points acquired in the city of Paris under real conditions (traffic, moving objects, . . .). Within these reference points, there are a total of 300 objects of four classes (cf. Table 1). These objects are segmented manually. We compare the results obtained by the presented algorithm with the reference data in term of completeness.

Except discretization step in focalization stage, most of the parameters of the algorithm depend on geometric characteristics of posts. These parameters are deduced from the pattern library (cf. Table 1). The discretization step is tuned on a set of reference points excluded from those used for the final evaluation. The best discretization step is obtained by ROC curves analysis in order to find a trade-off between the false positives (*FP*) and the true positives (*TP*). As shown in Figure 7 the obtained optimal value



(a) Result without using intensity



(b) Result using intensity

Figure 6: Discrimination of lamppost and tree using laser intensity and global tree detection.

(20 cm) corresponds to 0.3% of *FP* and 90% of *TP*.

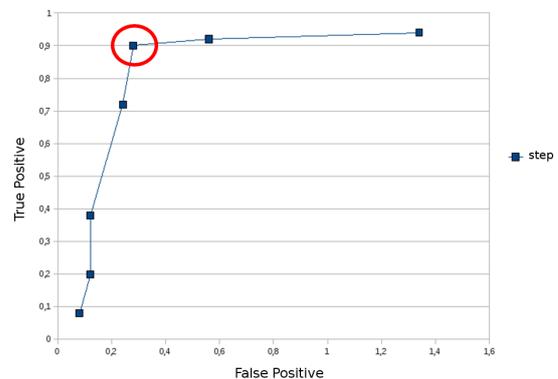


Figure 7: ROC curves analysis for optimal discretization step

Figure 8 shows an example of obtained result. The algorithm reaches a *TP* rate of 90% at a *FP* rate of 7%. The algorithm fails on the posts that are very close to other objects such as cars. This is due to the focalization step. Most of the *FP*s correspond to isolated objects having the similar geometric characteristics to posts. This problem is due to the validation step that wrongly accepts other objects as posts or tree trunks.

Our decision tree classification algorithm is compared to a SVM algorithm. A set of learning objects are injected in the SVM process. The algorithm is then applied to the same reference data (with 30000 points). The obtained results are globally similar to our decision tree algorithm. The main advantage of decision tree in the case of available pattern library is that learning step can be avoided.

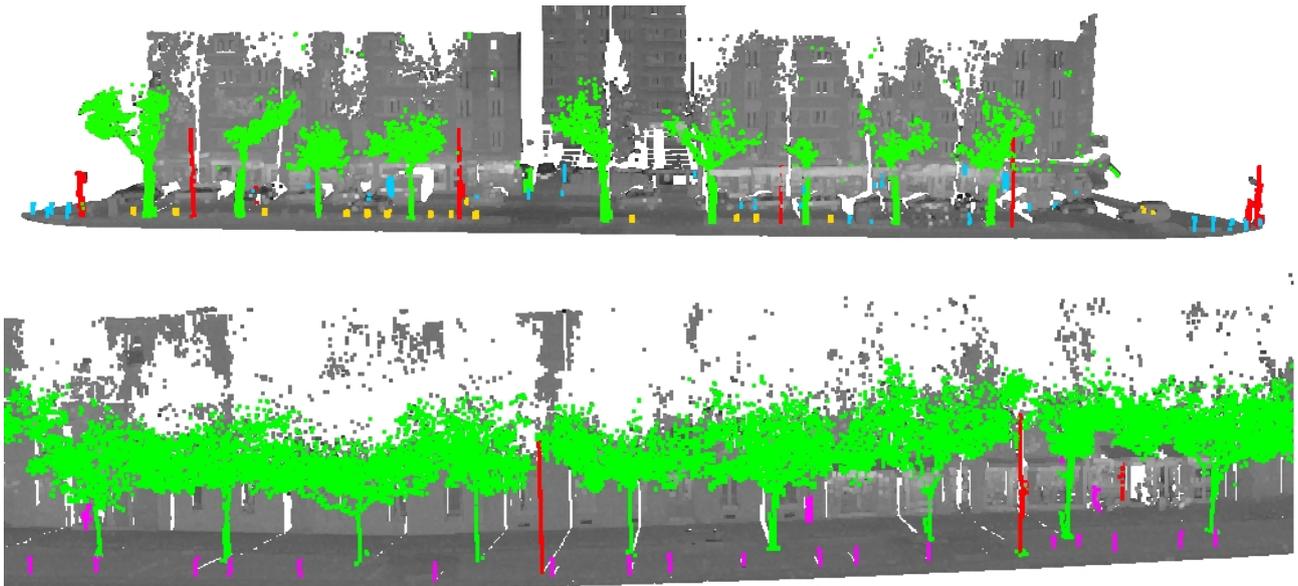


Figure 8: Examples of classified point clouds

## 5 CONCLUSION

We presented a method to detect automatically vertical posts in laser point clouds of urban environment. This method allows not only to detect and to distinguish posts and trees but also to differentiate each kind of posts. Objects we want to detect have a standard form therefore a pattern library is used. A group of decision rules based on the local distribution of 3D points and their intensity allows classifying these objects.

In classification step, an object approach is used by applying a principal components analysis to each label. Thus the robustness is increased and the computing time is reduced with comparison to per-point classification methods. The focalization step uses horizontal projection of points, however it deals correctly with overlapping objects (posts under trees for instance). The method is used on various scenes. 90% of objects are correctly detected and classified and only 7.5% of detected objects are false positives.

A perspective of this work is to integrate georeferenced image data in order to deal with more complex cases such as pedestrians that are confused with posts. It would also be interesting to test our method on laser data provided by Velodyne<sup>1</sup> scanner. Indeed this scanner provides 3D points with higher frequency but lower accuracy.

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