Tentative Tests on Two Rapid Multispectral Classifiers for Classifying Point Clouds

Mingxue Zheng

Delft University of Technology
Faculty of Architecture Delft, the Netherlands;
State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing
Wuhan University, Wuhan, China,
m.zheng-1@tudelft.nl

Mathias Lemmens

Delft University of Technology
Faculty of Architecture Delft, the Netherlands,
M.J.P.M.Lemmens@tudelft.nl

Peter van Oosterom

Delft University of Technology
Faculty of Architecture Delft, the Netherlands,
P.J.M.vanOosterom@tudelft.nl

Abstract

This paper focusses on the feasibility of classifiers, developed for classifying multispectral images, for assigning classes to point clouds of urban scenes. The motivation of our research is that dense point clouds require fast classification methods to extract meaningful information within a reasonable amount of time and multispectral classifiers do have this property. We employ two encoding methods acting on one feature: the altitude above street level. We emphasize computation time and therefore we use just one feature in this preliminary test. The classification accuracy is below 50% but the computational performances encourage further investigation using more features.

Keywords: Classification, point clouds, feature encoding.

1 Introduction

Dense point clouds may contain billions of points and hence fast classification methods are required to extract meaningful information within a reasonable amount of time. Point cloud classification can be decomposed into (1) feature extraction, (2) point representation, and (3) class assignment. Feature extraction aims at finding suitable features for each point derived from the original data. Here we use the altitude above street level. In this study point representation aims at transforming the features derived in step one into a vector expression, one vector per point. This paper focuses on the latter step, i.e. step two. Much research on improving image classification performance has been conducted in the field of multispectral image classification. The promising results encourage us to apply the classification methods of multispectral images on point clouds. In particular, we consider histogram encoding (VQ) (Sivic et al., 2003) and Kernel codebook encoding (KC) (Philbin et al., 2008) because they have proven to be not computationally demanding. Both methods are briefly considered in the next section

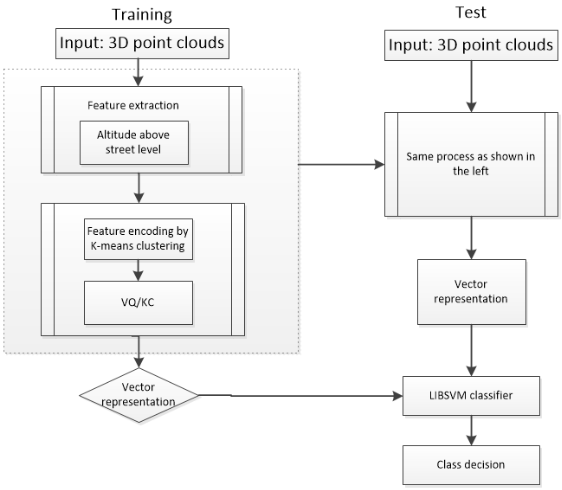
2 Basics

Before treating both methods, we briefly consider K-means.
Given a set $x_1, \ldots, x_n \in R^D$, K-means seeks k vectors $\mu_1, \ldots, \mu_k \in R^D$ and a data-to-means assignments $q_1, \ldots, q_n \in \{1, \ldots, k\}$ such that the cumulative approximation error $\sum_{i=1}^{n} \parallel x_i - u_{q_i} \parallel^2$ is minimized, through alternating between seeking the best means given the assignments ($\mu_k = \mathrm{avg}\{x_i : q_i = k\}$), and seeking the best assignments given the means

$$q_{ki} = argmin_k \parallel x_i - u_k \parallel^2 \qquad (1)$$

The classification flowchart is shown in Figure 1.

Figure 1: Overview of point cloud classification model



2.1 Histogram encoding

Histogram encoding works by dividing a large set of points (vectors) into sub-groups having approximately the same number of points closed to them. The construction of the encoding starts by learning k-means average vectors $\mu_1, \dots, \mu_k$. Given a set $x_1, \dots, x_n$, let q_i be the assignments of each point sample x_i as given by (1). The histogram encoding is the non-negative vector $f_{hist} \in R^K$ such that $[f_{hist}]_k = |\{i: q_i = k\}|$.

2.2 Kernel codebook encoding

Kernel codebook encoding is a variant in which descriptors are assigned to $[f_{kcb}(x_i)]_k = K(x_i, \mu_k)/\sum_{j=1}^{n} K(x_j, \mu_k)$. Especially $K(x, \mu) = \exp(-\frac{\gamma}{2} \parallel x - \mu \parallel^2)$ is a common kernel function, γ is a smoothing parameter. A set of n descriptors is extracted from an image as $f_{kcb} = \frac{1}{n}\sum_{i=1}^{n} f_{kcb}(x_i)$.

3 Experiments

3.1 Data

We use a benchmark dataset created by Serna et al. (2011), which consists of two PLY files with 10 million points each. To each point (X, Y, Z) coordinates, reflectance value, label and class have been assigned. There are 26 classes. We use one PLY file, i.e. 10 million points, and choose five classes: pedestrians, motorcycles, traffic signs, trash cans and fast pedestrians. The selection is based on the similar amount of points (around 10,000) reflected on each object surface. Figure 2 shows an orthophoto of the test site. In our tentative test we assume that street level is everywhere the same, i.e. the points at street level do have the same height. So, we use the original height values (Z) as feature.

Figure 2: Rue Madame, Paris (France). Orthophoto from IGN-Google Maps.

3.2 Results

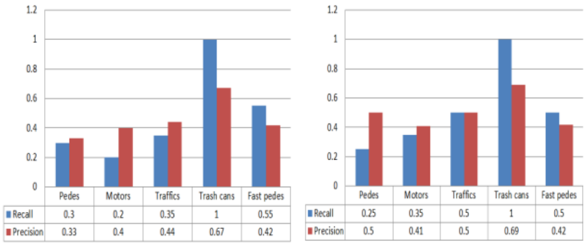
To conduct our experiments we use the public Library for SVMs (LIBSVM) package (Chang et al., 2011). After applying both the VQ and KC classifiers the overall accuracy, kappa coefficient, and computation times are computed (Table 1).

Table 1: Performance

Method	VQ	KC
Overall accuracy	52%	42%
Kappa coefficient	43%	35%
Computation time (sec.)	2.9	1.9

The accuracies of both classes are lower than 60%, but VQ has a better accuracy than KC. In addition, the more accurate a method is (i.e. VQ) the more computation time is required. This demonstrates that accuracy comes at the cost of increasing computational efforts. The Recall and Precision of two methods are shown in Figure 3. The class Trash cans acquires the best Recall and Precision values with VQ and KC. The average values of Recall and Precision are nearly 50% with VQ and nearly 40% with KC.

Figure 3: the Recall and Precision of KC (left) and VQ (right)



4 Conclusions

We tested two classifiers, developed for use on multispectral images, on their feasibility for classifying massive amounts of points rapidly. Using one feature (height above street level) VQ and KC demonstrated to be fast classifiers but the classification accuracy is low. Nevertheless the results of our tentative tests are promising, especially with respect to computation time. So, we continue to carry out refinements by using more features, including reflectance values. In addition, we will store data in a Database Management System (DBMS) to manage the massive amount of points efficiently and to incorporate classification functionality into the DBMS to reduce further computation time.

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