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# Parzen windows and nonparametric density estimation applied in high resolution imagery classification

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**Abstract:** This scientific research considers the problem of estimating class probabilities for an unknown pattern, which is represented by a feature vector, using a nonparametric method, such as Parzen Windows. This paper's contribution is the application of the nonparametric density estimation approach in the intra-urban land cover classification.

**Keywords:** Pattern Recognition, Bayes Decision Theory, Nonparametric Density Estimation, Parzen Windows, High Resolution Images.

## 1. Introduction and Review

The latest advances in the spatial resolution of orbital sensor systems have effectively increased our ability to discriminate earth surface targets. One of the application fields mostly favored by this new sensor data is the remote sensing of urban areas. Although urban remote sensing already disposed of information sources with high spatial resolution (aerial photos), this application field could not rely so far on a data type that offered high spatial resolution and at the same time high radiometric and temporal resolutions.

Within these few years fine spatial resolution satellite sensor imagery become widely available. Such as the QuickBird satellite, several new satellite sensors are being developed producing imagery with spatial resolutions as fine as 1.0 m in panchromatic mode (Pan) and 4.0 m in multispectral mode (MS). Many details such as buldings, roads, trees, grass and other unit of urban scenes can be clearly identified from this high resolution satellite images (Herold et al., 2002; Jensen and Cowen, 1999).

Merging these characteristics enables the detection of intra-urban targets, and therefore, proves to be suitable for mapping urban and intra-urban land cover with the aid of automatic classifiers. At purpose, the application of automatic classification routines to high spatial resolution images has been facing many challenges, for such images present remarkable noise as well as high intra and inter-classes spectral variability (Blaschke and Strobl, 2001). However, it may be possible to employ or to adapt existing per-pixel classification algorithms to produce maps of land cover for urban areas from fine spatial resolution images (Bauer and Steinnocher, 2001). An alternative to this failing is the nonparametric estimation of the probability density functions (*pdf*) used in Bayes decision theory based classifiers. This scientific research is committed to explore the nonparametric density estimation approach in the intra-urban land cover classification using high spatial resolution images.

## 2. Nonparametric Density Estimation Using Parzen Windows

Pattern recognition aims to classify data (*patterns*) based on either *a priori* knowledge and on statistical information extracted from the patterns. The patterns to be classified are usually groups of measurements or observations, defining points in a proper multidimensional space (Theodoridis and Koutroumbas, 2003).

There are two divisions of classification: *supervised classification* (or discrimination) and *unsupervised classification* (or clustering). Supervised learning is a pattern recognition technique for creating a function from training data. In this case, a set of training data are available and the classifier is designed by exploiting *a priori* known information (Webb, 2002).

An approach to discrimination based on Bayes decision theory (**Figure 01**) is presented here. The first assumes the *a priori probabilities* are known. This is a reasonable assumption, because even if they are not known, they can easily be estimated from the available training feature vectors. The other statistical quantities assumed to be known are the class-conditional *probability density functions* (*pdf*).

$$posterior = \frac{likelihood \times prior}{evidence} \qquad P(\omega_i \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid \omega_i) P(\omega_i)}{p(\mathbf{x})} = \frac{P(\mathbf{x}, \omega_i)}{p(\mathbf{x})}$$

**Figure 01** – Bayes decision theory.

So, it assumes the probability density functions are known. However, this is not the most common case. In many problems, the underlying *pdf* has to be estimated from the available data. There are various ways to approach the problem and this paper focus in a specific nonparametric technique, Parzen windows, which assumes the density is characterized by a set of parameters and there is no formal structure for the density prescribed.

Parzen windows approach could be applied, for example, to classify classes of roofs which behave differently to the variations of incidence angle and to the orientation of its faces. In high resolution images, classes of roofs could present a bimodal distribution matched by Parzen windows classification.

The basic ideas behind many of the methods of estimating an unknown probability density function are simple. In the multidimensional case, instead of bins of size $h$, the *l*-dimensional space is divided into hypercubes with length of side $h$ and volume $h^l$. This function is equal to $1$ for all points inside the unit side hypercube centered at the origin and $0$ outside it.

The summation equals $k_N$, that is, the number of points falling inside this hypercube. Then the *pdf* estimate results from dividing $k_N$ by $N$ and the respective hypercube volume $h^l$. However, this is a continuous function that can be generalize by using smooth functions (**Equation 01**) in its place (Theodoridis and Koutroumbas, 2003).

The optimal choice of $h$ depends on several factors, it depends on the data: the number of data points and their distribution (Webb, 2002). About the variance of the estimate, the following remarks are valid:

- For fixed $N$, the smaller the $h$ the higher the variance, and this is indicated by the noisy appearance of the resulting *pdf* estimate;
- For a fixed $h$, the variance decreases as the number of sample points $N$ tends to infinity.

$$\hat{p}(x/w_i) = \frac{1}{h^l}\frac{1}{N}\sum_{i=1}^{N}\left( (2\pi)^{-\frac{l}{2}} \exp\left( -\frac{\left(\frac{x_i - x}{h}\right)^t \left(\frac{x_i - x}{h}\right)}{2} \right) \right) \quad \textbf{(Equation 01)}$$

## 3. Results and Discussion

Parzen windows classification algorithm was implemented in IDL (Interactive Date Linguage) and it is available in the SCID system. SCID is an image processing package developed in IDL language by DPI/INPE team. For the intra-urban study area, the city São José dos Campos, São Paulo, Brazil was picked out. The data set selected to process these experiments contains only single-family residential units covered by ceramic roofs.

The QuickBird image used for this study was processed from an Ortho-ready Standard scene composed by one panchromatic band with 0.60 m spatial resolution and another multispectral with 2.40 m resolution at blue, green, red and infrared bands. The images dated from May 17th 2004, have an off-nadir incidence angle of 7.0º and a radiometric resolution of 16 bits, although the pixels are spread along only 11 bits. The data was pansharpened using nominally 1m panchromatic and 4m multispectral data, and is was resampled resulting in a file that was an 8 bits gray scale.

The selection and characterization of classes of interest was done based on visual interpretation of the fused image (**Figure 02**), aiming to identify the main materials used for paving streets, for the cover of constructions as well as vegetation types.

Thus, to process some experiments, a truth image was generated considering classes Vegetation (Green), Paving (Thistle), Ceramic (Orange) and Shade (Black), showed in **Figure 3**. The training data was getting considering these classes, being the size ( $N$ ) of each class equal to 2965 pixels, 2819 pixels, 3239 pixels and 1894 pixels, respectively. The algorithm was processed to different values of $h$ .

Fused Image (RGB)

Dims: 400 x 400 x 3

Size: 489,960 bytes.

File Type: TIFF

Sensor Type: QuickBird

Projection: UTM, Zone 23S

Datum: WGS-84

Pixel: 0.6 Meters

**Figure 02** – QuickBird image subset.

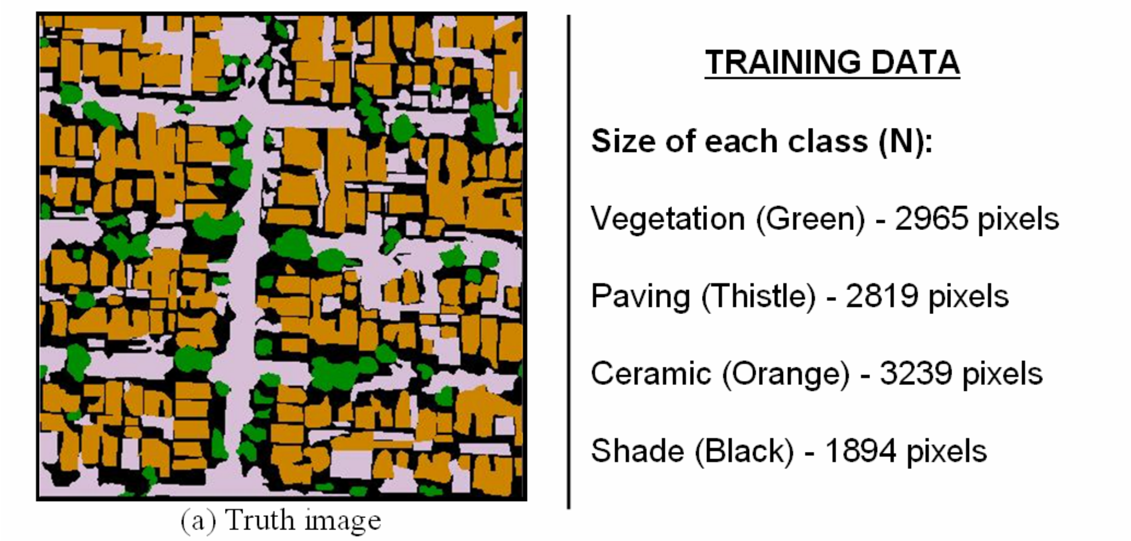
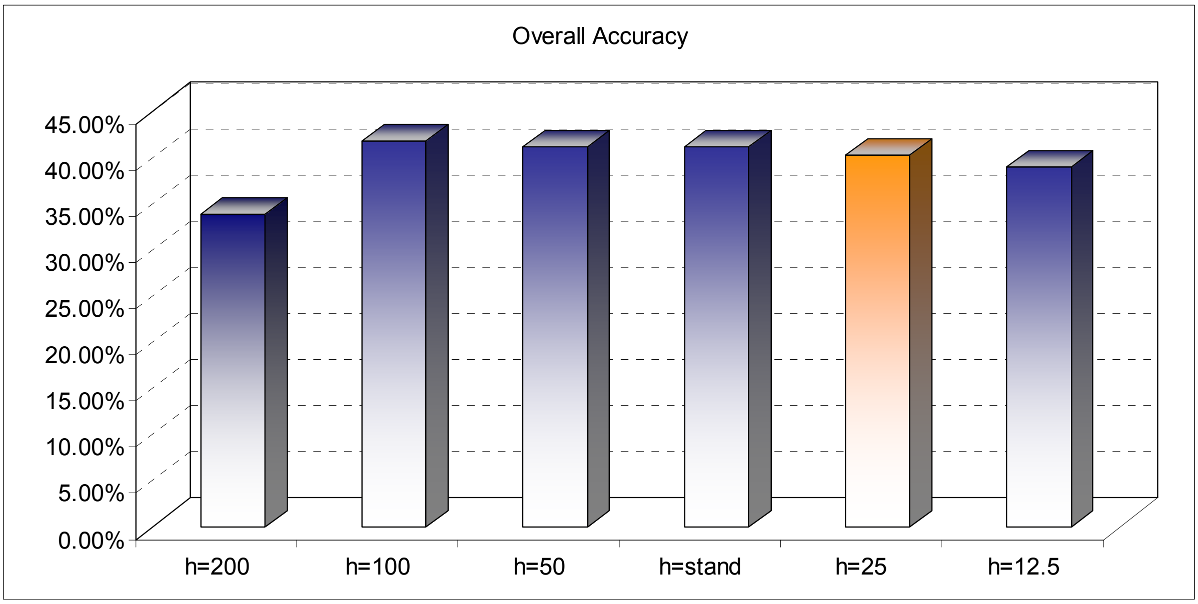



**Figure 03** – Truth image and training data.

**Graphic 01** shows the overall accuracy got to the pos-classification to different values of $h$. It is possible to see that the nonparametric method got the best result to $h = 100$ (**overall accuracy = 41.8035%**).




**Graphic 01** – Overall accuracy to different values of $h$.

## 4. Conclusion

Nowadays the analysis of information about urban areas from remotely sensed images is essentially carried out by aerial photo interpretation with the aid of ground surveys. Improving this spatial resolution now taking place has awakened the interest of people working in urban areas.

In this paper, the experimental results displayed the potential of the nonparametric density estimation approach for land use mapping in a small study area using QuickBird images. From the analysis of these results is possible to confirm that the approach presents a relative potential to classify urban land cover using high resolution satellite images.

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