

URBAN TEXTURES:

A MULTISCALE ANALYSIS OF SOCIO-SPATIAL PATTERNS

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Abstract: This paper proposes a multiscale method based on the concept of lacunarity to recognize and classify textures of remote sensing images from urban areas with different inhabitability conditions. Experiments were done with several fragments of Recife (northeast of Brazil) intra-urban tissue. The results suggest that it is possible to describe and distinguish spatial patterns through its textures, and that there is a strong correlation between its morphological and social patterns.

Keywords: urban textures, satellite images, lacunarity, sociospatial patterns

1.INTRODUCTION

The nature of the urbanization process has been bolstered by increasing social inequalities which are reflect on the spatial organization of cities. The bigger the city, the more visible its sociospatial heterogeneity. This is particular evident in metropolises of underdeveloping countries, but may also depends on the scales through which they are analyzed.

Since the beginning of the 1980s, many Brazilian cities have adopted a new concept of urban planning based on the preservation of the morphological structure of some consolidated areas and, at the same time, their improvement or upgrading, in terms of basic infrastructure, facilities and services. The recognition of the cities diversity and the treatment of their informal areas as integrated parts of a whole are relatively new and have opened up a new perspective to interpret urban tissues as social expressions of a more complex dynamic (Barros Filho and Sobreira, 2005).

Despite those efforts, different areas within the cities are still being treated as similar. As a result, general urbanistic parameters that are applied indiscriminately in them have been inefficient instruments to manage and control their dynamics, and the public resources available for the implementation of urban improvements in these settlements, are often not channelled towards the neediest areas. Without keeping up with the informal growth, urban improvements have been happening slowly, discontinuously and are restricted to small areas, contributing to perpetuate their different spatial patterns (Barros Filho, 2000).

In this context, the understanding of different morphological patterns seems to be a way to improve the management and planning of such settlements. However, one of the greatest problems in analyzing urban tissues is due to the fact that conventional sources of information about them are inadequate and heterogeneous. In general, the necessary data are outdated, unreliable, or, in some cases, simply unavailable. In this way, satellite images seem to be an important alternative data source, providing widespread availability, frequency for update and low costs, given powerful information for a better understanding and management of different spatial patterns. Digital images acquired by satellite sensors are frequently processed using supervised, multispectral classification algorithms in order to derive thematic maps. However, the use of high spatial resolution images increases the within-class spectral variability that confused per-pixel classifiers (Marceau and Hay, 1999).

The use of texture information in addition to spectral features may result in more accurate image classification. Texture analysis involves the categorization of image pixels on the basis of their spatial relationship with pixels surrounding them. It measures the variability from one pixel to another in the amount of brightness in panchromatic images. Very little variability would indicate a homogeneous or uniform surface, while a great deal of variability would suggest a heterogeneous surface.

Multi-scale based measures can be described as different texture recognition approaches that provide a flexible yet theoretically consistent mean of characterizing the morphology of urban spatial patterns across different scales. With the recognition that cities are complex systems consisting of heterogeneous spatial components, non-linear interactions, self-organization and scale-dependence, multiscale analysis represents an increasingly important issue in the understanding of urban spatial patterns. Actually, there is not an unique or optimal scale for analysis. Changing the scale changes the spatial patterns, which has implication for the understanding the dynamics of any complex urban system. Thus, urban analysis performed at a single scale is incomplete and insufficient for understanding spatial patterns.

In this context, this article purposes a methodology to extract and assess spatial information from image data of urban areas with different inhabitability conditions using a multi-scale based algorithm that are replicable and which can produce a statistically quantifiable result. In the next section, we introduced the concept of lacunarity. In the third section, we describe the image samples selected and the method adopted. In the fourth section, we present some results and a brief discussion. Finally, in the fifth and last section, we make some conclusions and comments on the challenges and future works to be done for next steps of this research.

2. LACUNARITY

The concept of lacunarity was established and developed from the scientific need to analyze multi-scaling texture patterns in nature (mainly in medical and biological research), as a possibility to associate spatial patterns to several related diagnosis. Focusing on the urban perspective, if one observes intra-urban and consolidated areas like squatter settlements, despite their apparent disorder, the conclusion will be

that they share the same spatial features, regarding fragmentation and scaling of morphological structure, wherever in the world (Sobreira, 2002). But, if fragmentation patterns reveal what is the common feature in slums, on the other hand, a more detailed view of slums urban textures will reveal the socio-economic and cultural diversity that is so typical of these settlements.

The term 'lacunarity' was first introduced by Mandelbrot (1982) to describe the characteristics of fractals of same dimension with different texture patterns. Lacunarity is related to the distribution of empty spaces (lacunas) of an image. Applications to lacunarity were firstly registered in research related to image processing in Ecology, Medicine, Biology and other related fields (Plotnick et al 1996). Our conjecture, in this paper, is that we can use lacunarity as an indicator of urban texture.

Regarding texture analysis of urban spaces registered by satellite images, lacunarity is a powerful analytical tool as it is a multiscale measure, that is to say, it permits an analysis of density, packing or dispersion through scales. Lacunarity measures are not based on a unique scale, but through multiscale graphs that reveal the texture variation at several scaling levels. At the end, it is a measure of spatial heterogeneity, directly related to scale, density, emptiness and variance. It can also indicate the level of permeability in a geometrical structure.

In this research, we used the gliding-box algorithm proposed by Allain and Cloitre (1991). According to this algorithm, a box of size r slides over the whole image, registering the box mass S , that is, the number of pixels inside the box at each stop of the sliding process. Then, the size of the box is enlarged by sequentially adding cells, and the gliding box procedure is repeated for each new box size, until eventually the box size equals the image extent (figure 1).

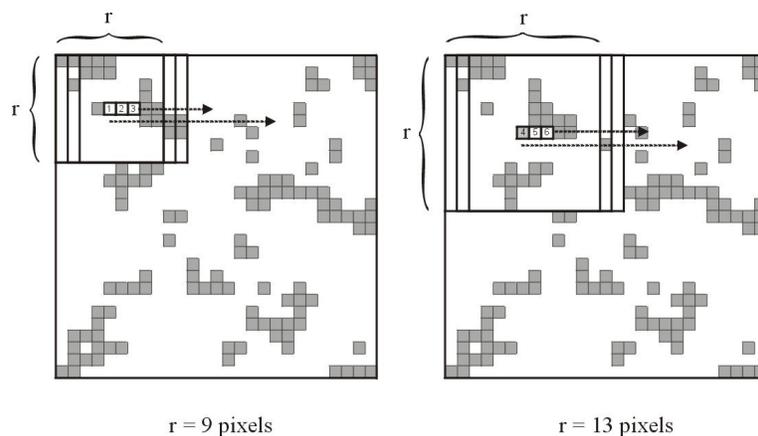


Figure 1: example of the convolution process of the gliding-box algorithm

A frequency distribution is then created of box masses $n(S,r)$. This frequency distribution is converted to a probability distribution $Q(S,r)$ by dividing each frequency value by the total number of gliding boxes of a given size $N(r)$. Finally, the moments $Z(1)$ and $Z(2)$ are calculated from these values:

$$Z(1) = \sum S Q(S,r) \quad (1)$$

$$Z(2) = \sum S^2 Q(S,r) \quad (2)$$

The lacunarity $L(r)$ of a given box size r can be calculated as:

$$L(r) = Z(2) / [Z(1)]^2 \quad (3)$$

In general, a low lacunarity indicates homogeneity, while high lacunarity indicates heterogeneity. The higher the lacunarity, the bigger will be the variation of pixels distribution in an image. In other words, high lacunarity means that pixels with similar gray levels are grouped in a wide variety of sizes of islands, surrounded by a widely variant emptiness, indicating heterogeneity of spatial pattern or texture. Lacunarity can be viewed through graphs which show the lacunarity variation through scale (according to distinct box sizes).

3 EXPERIMENTS

In this analysis we selected a QUICKBIRD sensor image data of 0.70 m spatial resolution from the city of Recife (Brazil), captured in October 2001. Initially, 30 samples of this image with 250 x 250 meters were selected, half of these samples (15) are from rich areas with high inhabitability condition (A1 - A15 of figure 2), while the other 15 samples are from poor areas with low inhabitability conditions (B1 - B15 of figure 3). Then, these image samples were enhanced through a histogram equalization and converted to binary images.

The image samples selection requires the construction of a methodology to define the inhabitability values for Recife. In this context, an Inhabitability Index (IH) was created from Census 2000 data. The IH values range between 0 and 1. The closer to 1 an urban area is, the higher its inhabitability conditions. Then, the IH values were georeferenced to each census sector's centroid of the city. After that, these centroid's points were interpolated by Ordinary Kriging, generating a matricial surface which was used as a reference to the image samples selection. Finally, the mean IH values of the urban areas covered by the selected image samples were calculated. It is not the aim of this paper to describe details about this methodology, more information can be found in Barros Filho (2007; 2006, 2000).



Figure 2: binary images with 250 x 250 m from urban areas with high inhabitability conditions



Figure 3: binary images with 250 x 250 m from urban areas with low inhabitability conditions

The texture analysis of the selected image samples was based on an unsupervised approach. This approach assumes that it is not necessary to classify land use types from the image, such as built and non-built areas, because the image's spatial elements are simply considered as inherent parts of a specific global texture pattern generated by the combination of such features. It does not focus on the specific elements of the image. The combination of shadows, trees, voids, cars, river, buildings, plots or the absence of all these elements in the binarised image will generate a specific kind of texture.

A supervised approach, on contrary, is based on the assumption that the binary images should be able to resemble particular features or classes on the original image. So, this approach requires a higher level of human interaction and a great deal of training and practice on visual interpretation of satellite images. It is time-consuming, very subjective (Donnay et al, 2001), and not necessarily replicable from place to place and time to time (Weeks, 2003). Moreover, intensive field survey may be necessary and could be problematic in some urban areas, especially those where accessibility is difficult or inhibited for security reasons (Baudot, 2001).

The main issue was to keep the same method to all samples to permit a comparative analysis, limiting the changing variables. The gliding-box algorithm was setup to calculate the lacunarity values of 10 box sizes for each binary image sample. The smallest box size was 1 x 1 pixel and the subsequently boxes increase 15 pixel on each dimension. In this way, the biggest box size corresponds to 45 percent of the linear dimension M of the image sample (356 pixels).

From each image was calculated the mean lacunarity value (L_m) of the 10 box sizes. This measurement offers a single lacunarity value which permits a direct comparison between the texture patterns of all image samples:

$$L_m = \frac{\sum_{r=1}^n L(r)^a}{n} \quad (4)$$

Where $L(r)$ is the lacunarity value in box size r , and n is the total number of box sizes.

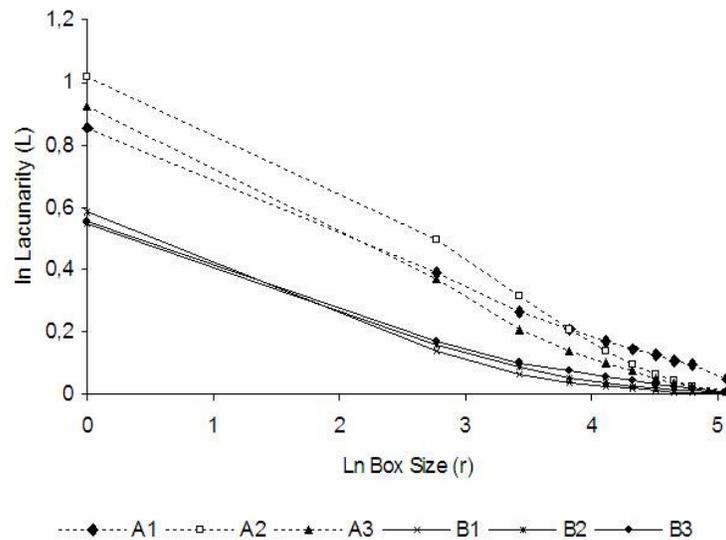
RESULTS AND DISCUSSION

Table 1 shows the inhabitability and mean lacunarity values of image sample A's and B's. We can observe that the lacunarity values permits to distinguish the texture patterns of both group of images. Urban areas with better inhabitability have, in average, higher values of lacunarity, what is probably a consequence of the outstanding emptiness of spaces, associated to large and regular avenues, and overall low density. On the other hand, when analyzing areas with worse conditions (slums), the result is low lacunarity, indicating low permeability, resulting from typical feature of such urban structures: highly dense occupation and tortuous alleys.

Table 1: IH and Lm values of the selected images

Image	IH	Lm	Image	IH	Lm
A1	0.7931	1.3092	B1	0.5785	1.1121
A2	0.8087	1.3403	B2	0.5739	1.1152
A3	0.7953	1.2807	B3	0.5753	1.1292
A4	0.7979	1.2878	B4	0.5792	1.1164
A5	0.8069	1.3451	B5	0.5524	1.1345
A6	0.8136	1.3429	B6	0.5543	1.0958
A7	0.8088	1.3117	B7	0.5565	1.0981
A8	0.7910	1.2701	B8	0.5635	1.1112
A9	0.8115	1.2820	B9	0.5543	1.1310
A10	0.8090	1.3194	B10	0.5670	1.1263
A11	0.8207	1.3159	B11	0.5639	1.1296
A12	0.8185	1.4380	B12	0.5726	1.1092
A13	0.8128	1.3165	B13	0.5717	1.1334
A14	0.8130	1.3214	B14	0.5730	1.1163
A15	0.7977	1.2780	B15	0.5776	1.1199

The differences of the lacunarity values between image samples A's and B's can also be shown by logarithm graph 1 which describes the lacunarity curves behaviour of image samples A1, A2, A3, B1, B2 and B3, along scales.



Graph 1: lacunarity curves of 6 selected image samples

This graph shows that the lacunarity curves of images B's have lacunarity values lower than images A's in all box sizes, and that the curves of images B's are more convex downward than those of images A's, revealing that urban areas with low

inhabitability condition have a more uniform gap distribution than areas with high inhabitability conditions. These difference, however, tends to decrease as the box sizes increase.

Even if the binary images may not resemble built and non-built areas, and may yield different lacunarity curves, it is possible to speculate that, in all box sizes, non-built areas correspond to the black pixels on the image samples which are smaller and more uniform distributed in urban areas with worse inhabitability conditions (such as slums). This could be explained due to the higher density and more irregular occupation in informal areas which create a great number of small gaps, while in formal areas, the occupation is more dispersed and follows the parameters established by the present urban legislation of the city.

These results are coherent with other experiments done with IKONOS sensor image samples from formal (orthogonal geometry) and informal urban areas (slums) of Campinas (Brazil) (figure 4). The results (graph 2) show that the former have higher lacunarity values than the later (Barros Filho and Sobreira, 2005).

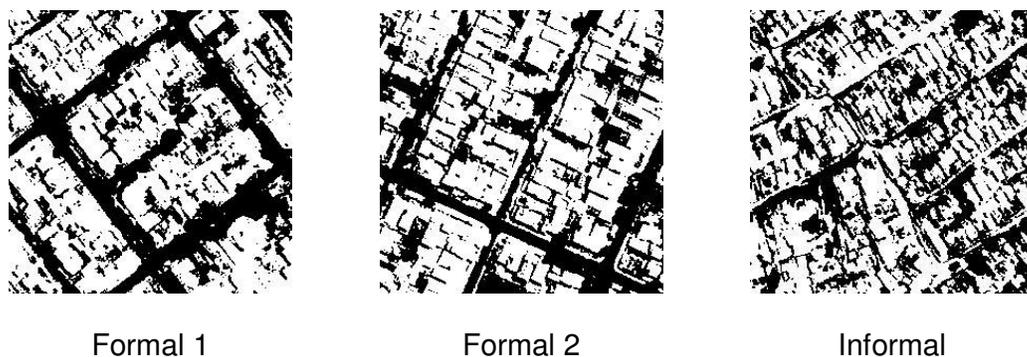
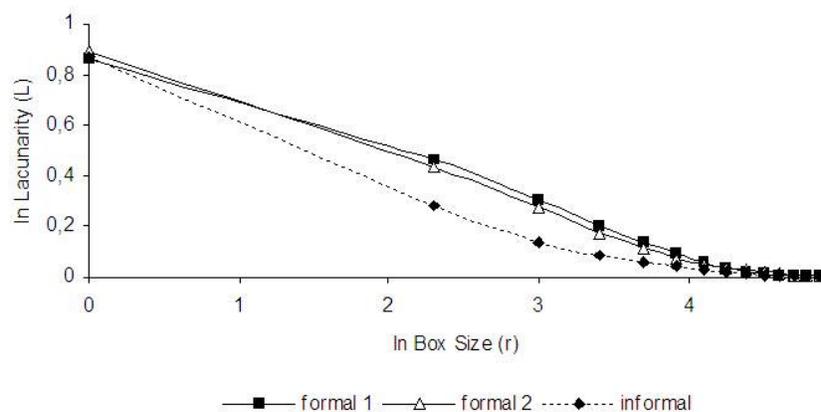


Figure 4: binary image samples from formal and informal urban areas in Campinas (Brazil) (Barros Filho and Sobreira, 2005)



Graph 2: lacunarity curves of the image samples of figure 4

CONCLUSION, CHALLENGES AND FUTURE RESEARCH

Our experiments suggest that exist a strong correlation between morphological and inhabitability urban conditions. It is not only possible to distinguish urban areas with very different inhabitability condition, but also areas traditionally seen as similar in urban legislations, like informal settlements and slums. Thus, texture analysis based on the concept of lacunarity has proved to be an important tool in the recognition and classification of intra-urban patterns.

Despite these findings, texture analysis of remote sensing data yet involves great challenges. The correlation between lacunarity and inhabitability is only significant when the analysed images do not have large gaps. For example, some image samples from areas in the outskirts of the cities, in general with very low inhabitability conditions, or from areas with large and homogeneous land covers (such as forests, water bodies and large non-occupied plots) tend to show high lacunarity values, and the difference between areas with high and low inhabitability conditions becomes less significant. Our analysis was restricted to urban areas with the best and the worse inhabitability conditions of the city. Between these two extreme conditions, exist areas whose lacunarity values were not analyzed.

Besides that, in this analysis, it was only used image samples with a single size (250 x 250 m) and spatial resolution (0.70 m). These scales may not necessarily represent the operational scale of a spatial phenomenon or process. In this context, the gray-level of a pixel could represent an integrated sign of several image objetos or could be smaller than a single image object. The image size could not covered an entire texture pattern or could contain more than a single texture pattern. Thus, it is necessary to analyze samples with different sizes (extents) and resolutions (grains).

Experiments done with a binary CCD/CBERS-2 sensor image data of 20 m spatial resolution of the same city (Recife, Brazil), captured on August 19 2005, shown an opposite relation between lacunarity and inhabitability: in general, image samples from urban areas with better inhabitability conditions have lower lacunarity values than poor areas. This could be explained because small gaps, very common in slums, cannot be detected in low spatial resolution images (Barros Filho, 2007).

Moreover, binary image samples do not represent the real textures of the original images. Lacunarity results strongly depend on the image threshold (Barros Filho and Alves Junior, 2005). Some valuable information about the spatial arrangement of the image tones may be lost when a gray-level image with 8 bits, for example, is converted to a binary one with only 1 bit. New lacunarity methods has been proposed to work with gray-level images (Dong, 2000; Myint and Lam, 2005; Myint et al, 2006), and could offer more accurated results.

Actually, the recognition and classification of texture patterns depend on several decisions made during the analysis. Thus, it is important to do several comparisons between image samples with different scales (extents, grains and gliding-boxes), using different methods and parameters, and combining their results for a better understand how texture patterns reacts to these variations.

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