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ENHANCING URBAN ANALYSIS THROUGH LACUNARITY MULTISCALE MEASUREMENT

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Enhancing urban analysis through lacunarity multiscale measurement

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Abstract

Urban spatial configurations in most part of the developing countries show particular urban forms associated with the more informal urban development of these areas. Latin American cities are prime examples of this sort, but investigation of these urban forms using up to date computational and analytical techniques are still scarce. The purpose of this paper is to examine and extend the methodology of multiscale analysis for urban spatial patterns evaluation. We explain and explore the use of Lacunarity based measurements to follow a line of research that might make more use of new satellite imagery information in urban planning contexts. A set of binary classifications is performed at different thresholds on selected neighbourhoods of a small Brazilian town. The classifications are appraised and lacunarity measurements are compared in face of the different geographic referenced information for the same neighbourhood areas. It was found that even with the simple image classification procedure, an important amount of spatial configuration characteristics could be extracted with the analytical procedure that, in turn, may be used in planning and other urban studies purposes.

1. Introduction

Evolution of cities in low-income countries has consistently led to different urban forms. Latin American cities are particularly characterized by rapid and heterogeneous urbanization processes and highly irregular urban forms. This has led to fragmented spatial configurations resulted from a combination of neighbourhoods with different social and spatial patterns (Barros and Alves Junior, 2003).

The use of novel tools for the analysis of spatial configurations may offer new insights to problems of planning and the understanding of the connection between these spatial forms and the processes from which they derive. A new wave of urban models and methods for understanding urban environments has come to the fore in recent years. Multi-scale analytical measures such as lacunarity are important part of these tools.

Lacunarity was first introduced by Mandelbrot (1983) to describe complementary characteristics of fractals. The term was drawn from the word ‘lacuna’, which means gaps or holes and was originally used to differentiate fractals with the same *fractal dimensions* but with different texture appearances (Voss, 1986; Lin & Yang 1986). In its original sense, Lacunarity can be seen as a counterpart measurement of fractal dimension. In a broader sense, Lacunarity is related to the distribution of empty spaces or gaps in a spatial structure. Despite its original use for the description of fractal structures, lacunarity has been evaluated and extended to describe spatial patterns that are not necessarily fractals (Plotnick et al, 1996). In this regard, Lacunarity can be understood more generally as a multi-scale measure that describes the texture of a spatial pattern.

There have been many applications of lacunarity in landscape ecology, remote sensing (Krug and Henebry, 1995; Henebry and Kux, 1995, McIntyre and Wiens 2000) and other areas such as biology and medicine (Losa et al, 1998). There are also other multiscale measures such as wavelet and spectral analysis that may fulfil the same segment of applications that lacunarity is placed (see Saunders et al. 2005 for a recent comparison). In urban and regional studies, fractal dimensions have been used to describe land use types and other variables, whose irregularities are repeated across many urban scales (Batty and Longley, 1994; Frankhauser, 1997; De Keersmaecker et al, 2003). In ‘*Fractal Cities’*, Batty and Longley (1994) dealt with properties of two basic urban evolving shapes seen as fractals, the boundaries of urban development and the growth of cities in terms of size, shape and density.

More recently, lacunarity has been used in urban analysis to distinguish different spatial patterns in different areas, from more socially centred characteristics as in racial and socio-economic segregation (Wu and Sui, 2002) to more physically oriented processes as in urban growth monitoring and analysis (Sui and Zeng, 2000). Lacunarity based measures has also been used to improve accuracy of urban image classification (Myint and Lam, 2005; Du and Yeo, 2002).

Barros Filho & Sobreira (2005a;2005b) used lacunarity measures to differentiate density, urbanisation and land parcelling within urban areas. Using an unsupervised binary classification over high resolution satellite images of some irregular Brazilian neighbourhoods (‘favelas’), they showed that these areas had similar fractal dimensions, but different lacunarities. Following this direction, the purpose of this paper is to test and use lacunarity based measures for the analysis of urban form in low-income countries context where informality (Rolnik, 1997; ECLAC, 2000), inequality (Ferranti et al, 2003) and even illegality (Fernandes and Varley, 1998) are on the foundations of urban development. Specifically, we will explore lacunarity-based measurements using a simple binary classification method, but in possession of a dataset that includes ground controlled referenced images that were manually interpreted and can be used to explore and compare the lacunarity measures extracted from the classified images alone.

2. Study area

Our study area was the small Brazilian town of Piraí, located on the west part of Rio de Janeiro State, along the motorway that connects Rio de Janeiro and Sao Paulo. Figure 1 shows a partial view from the town. Figure 2a and 2b shows the location of Piraí and its neighbouring cities in the Brazilian Southeast region.

Figure 1 – Partial view of Piraí, Brazil

Most of the Piraí municipality's area of 504 km^2 is scarcely populated. There is a larger urban concentration on the core of the municipality, where the town of Piraí is actually found[1]. The municipality's population is around 23,000 inhabitants, from which 81.7 % live in urban areas (IBGE, 2002). Despite its small population size, Piraí presents some economic and urban morphological characteristics similar to other larger areas of Brazil and Latin America.

Urban morphology of the town follows the irregular pattern present in most parts of Latin American and low-income countries' cities. According to a 1998 detailed land use classification performed for Piraí municipality, 65% (6.31 km^2) of the total 9.67 km^2 of urban built up area were classified as '*areas of unorganized expansion*'. This is defined as "*urban land with ratio of land occupation between 10 and 50 % and where no urban design can be observed*" (Piraí, 2002). Like other Latin American cities, Piraí's urban spatial configuration may be explained by the bulk of irregular and unplanned urban development that continuously takes place on these cities. This is closely related to the more general aspect of economic inequality that creates many divided and fragmented cities.

In the middle of the 90's, Piraí was hit hard by the Brazilian economic restructuring policies. The government accomplished the privatization of the state owned electrical supply company – Light Co. The company was by far the major employer in the town and following the privatization, 1,200 employees were made redundant. For such a small town this would be a heavy hit, even if it was not considered the incipient system of unemployment protection in countries such as Brazil.

[1] Brazilian political administrative system is a three level system in which municipalities (municipios) are at the bottom level. There are no formal differentiation between cities and towns. Each municipality is a town and subdvisions within muncipalities can only be approximately translated to towns or villages that in Portuguese are called 'distritos' and 'vilas. In our study area case, Piraí is the name of the municipality (political entity) and also of the main 'distrito' (not political entity).

In order to tackle some of these problems, Piraí’s administration started the development of a digital city programme. The town’s programme called ‘Piraí Digital’ has received many awards and Piraí has recently been regarded as part of an increasing number of cities across the world that are promoting successful programmes of digital inclusion and e-governance. In June 2004, the free wireless network of ‘Piraí Digital’ was highlighted by the American magazine Newsweek (Newsweek, 2004).

Figure 2. Study Area – Piraí, Brazil

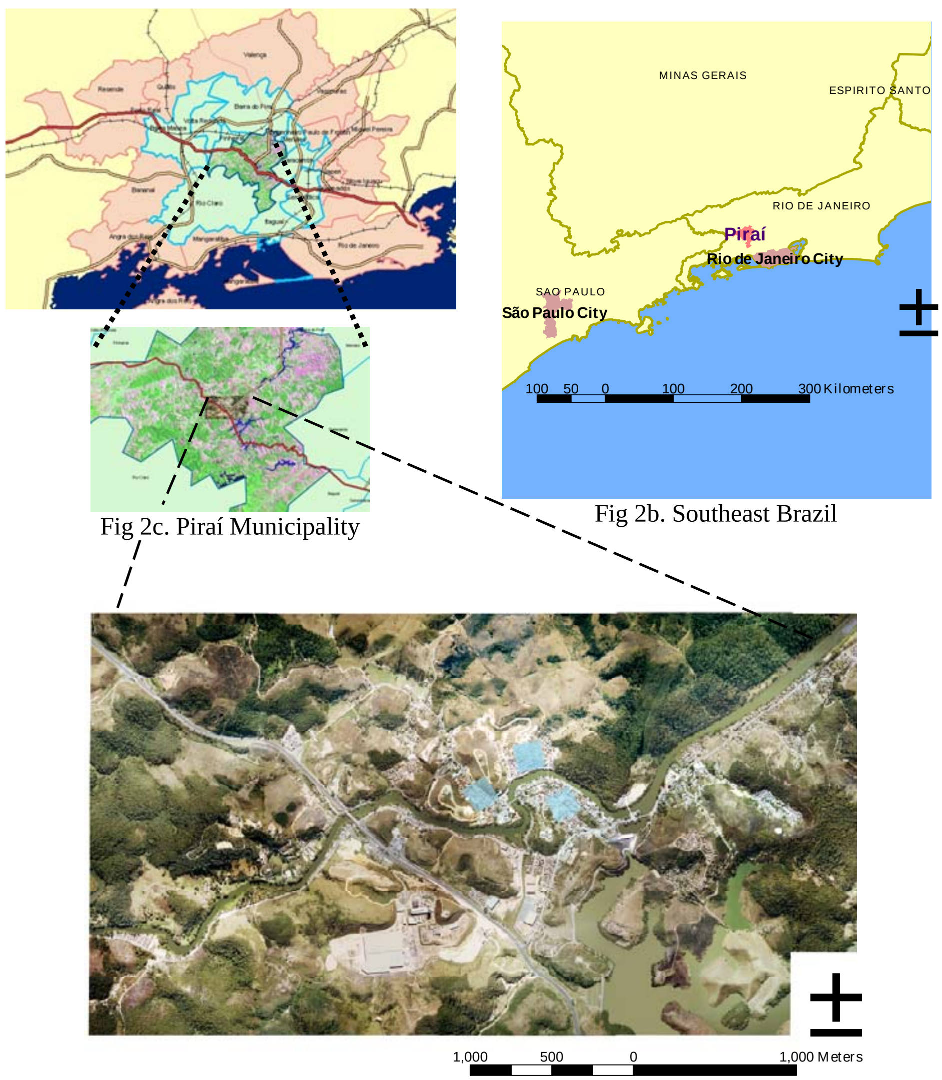


Fig 2c. Piraí Municipality

Fig 2b. Southeast Brazil

Figure 2d. Aerial Photo of the main part part of Pirai Town

As part of these e-government and digitally oriented initiatives, Piraí’s administration is involved on the development and maintenance of an update GIS database from which we were able to use georeferenced data. This data consisted of high resolution orthorectified aerial photo (Figure 1d) and other digital information about the major part of the town's housing stocks and neighbourhoods that we selected for the lacunarity analysis.

3. Methods

3.1. Selection of image samples

The dataset available from the study area includes an aerial photo image corresponding to approximately 14 Km^2 at a resolution of 0.25 m. The original images were collected and orthorectified in 2001. The composition completely covers the main area of the town. We also used a set of digital vector maps corresponding to the interpretation of this image and with information about urban development and the identification of the town's housing stock within this core area. This interpretation work was also carried out in 2001.

When selecting the areas for the study we avoided neighbourhood areas with spatial configurations totally stretched along the river that cross the town. The selected areas were different but near each other. These were the neighbourhoods of Centro, Hospital and Asilo.

Centro is an urban area situated at the town centre. Its spatial structure is composed by basic elements that characterized the Portuguese model of colonization such as the main church, the central square and a network of irregular roads. The image sample from Centro contains 28 buildings (table 1).

Hospital is an area composed by buildings that are more dispersed than in Centro and aligned on linear roads. The image sample of Hospital has 25 buildings, almost the same number of Centro. The average building size values are larger than the other areas, and as diverse as Centro (table 1).

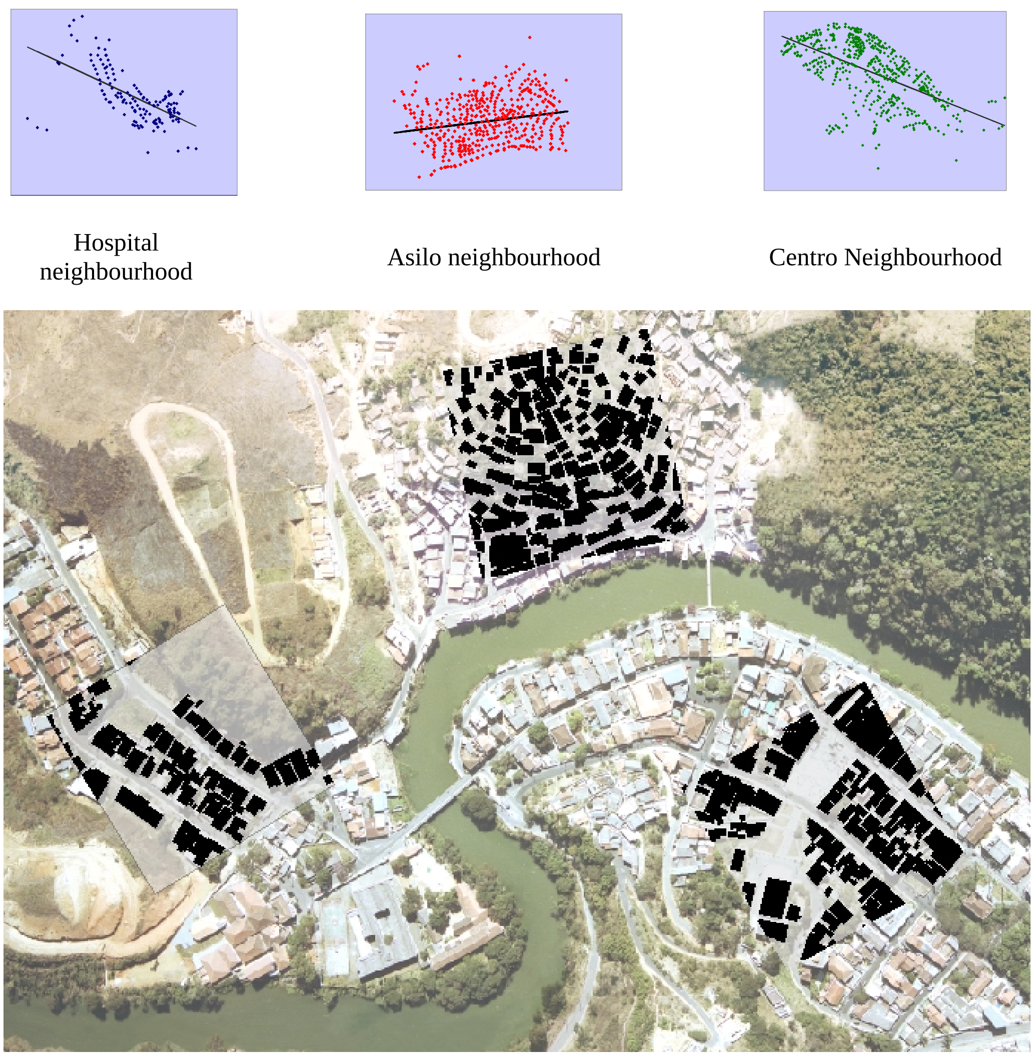
Table 1: Number and size of buildings on the selected image samples

Areas	Built Areas	Size Mean	Size Std Dev	Size CV
Asilo	59	10,3590	2,3164	0,2236
Centro	28	12,5140	4,7045	0,3759
Hospital	25	13,9640	4,6372	0,3321
All	112	11,7024	3,8877	0,3322

Asilo represents a typical squatter settlement. This urban area was intensively occupied over a hill site, defining a radial network of roads that adjusts to its topography. Its non-built spaces are smaller and more distributed in the image. The image sample of Asilo contains 59 buildings, more than the double of the other areas. The average building size is smaller and more similar than the other areas (table 1).

To select the image samples, we took the coordinate of the buildings from the GIS Database and computed the centre of the neighbourhood as the average coordinate of all buildings in a selected neighbourhood area. From this point, we proceeded to select image samples considering the predominant geometric direction of each area analyzed. The operation involved the turning of each square sample according to the global physical orientation of the neighbourhoods. We first took the centroid's coordinate values for each identified building of each neighbourhood from the GIS database. Then we computed a simple regression line on the clouds of centroid points to extract the angular-coefficient corresponding to the angle we used to turn our squared samples. Figure 3 is a detailed view of the relative location of the three neighbourhoods that were used in our analysis. The top part of figure 3 shows the clouds of centroids of each neighbourhood. The bottom part of fig 3 shows the vector maps overlayed on top the analyzed image with boundaries of selected areas.

Figure 3. Neighbourhood's physical orientation



As reference images for each of these neighbourhoods, we converted the equivalent vector maps of the selected samples to images, classified into built (black) and non-built (white) areas. Pixels in black colour represent buildings and pixels in white represent empty spaces (see figure 3). In what follows these reference images are called by the name of the neighbourhood followed by the letter V (AsiloV, Centro V and Hospital V).

3.2. Binary Classification

The RGB image samples obtained from the different neighbourhoods of Piraí, as described in the previous section, were converted into binary images using a threshold algorithm implemented in PASSAGE, an image analysis software developed by Michael Rosemberg from the Department of Biology at Arizona State University, USA. A simple binary classification in PASSAGE involves two conversion steps (Rosemberg, 2001). In the first step, RGB values of each pixel of the original image are converted into an average grey value scaled to a range between 0 and 100. In the second step, this average grey value is converted into a binary, 1 or 0 according to a chosen threshold value.

We are aware that the use of this simple conversion procedure that reduces three layers of 1 byte into 1 bit information for each correspondent pixel location may result in considerable differences between the representation of built and non-built areas for each binary image result. In order to have multiple texture signatures from the RGB sample images, we used three different thresholds: 25, 50 and 75, based on the quartile distribution of the image samples' grey values.

Accordingly, from each image sample of the aerial photos we produced three binary images with the same threshold values. This was followed by an inversion of the pixel values and for all used images, the higher the number that follows the letter P, the lower the fraction of **black pixels** representing **buildings**. Figure 4 below shows the RGB sample images, the reference and the converted images. In total nine images were obtained from this threshold and pixel value inversion procedure. Hereafter, we use the term threshold to refer to whole procedure of apply a threshold and invert the pixel values.

3.3. Image comparison

Although the main focus of this experiment was not to compare the performance of the binary conversion per se, have an assessment of this type of classification was an important step before the computation of lacunarity for the different images generated.

A visual inspection of the binary converted images from the aerial photo allows us to see different levels of classification. The images labelled P25 have much less 'gaps' and many more pixels converted as built, whereas images converted using the threshold 50, Hospital P50 and Asilo P50 are apparently more similar to their references Asilo V and Hospital V. Asilo P75 is even more similar from a visual inspection. The images from Centro cannot be said to have capture built and not built sites in any closer way to the images from Hospital or Asilo, although it is possible to notice some texture information and a general pattern closer to the reference images, mainly in case of Centro P75.

Apart from the visual assessment we built an error matrix to compute some common quantitative indices of accuracy and image comparison. An error matrix or confusion table is a square array of values set out in rows and columns which express the number of pixels assigned to a particular category relative to the actual category, as verified by ground truth information or a reference data set. The columns usually represent the reference data, while the rows indicate the classification results. Our error matrix was built using the values from the vector maps as reference data set.

From the error matrix we obtained the observed proportion of agreement, Po (also called fraction correction) (Story and Congalton, 1986) and other two indices, Kappa coefficient (Congalton et al., 1983) and Tau coefficient (Ma and Redmond, 1995).

Figure 4. Aerial Photo samples, reference images and binary converted at different threshold

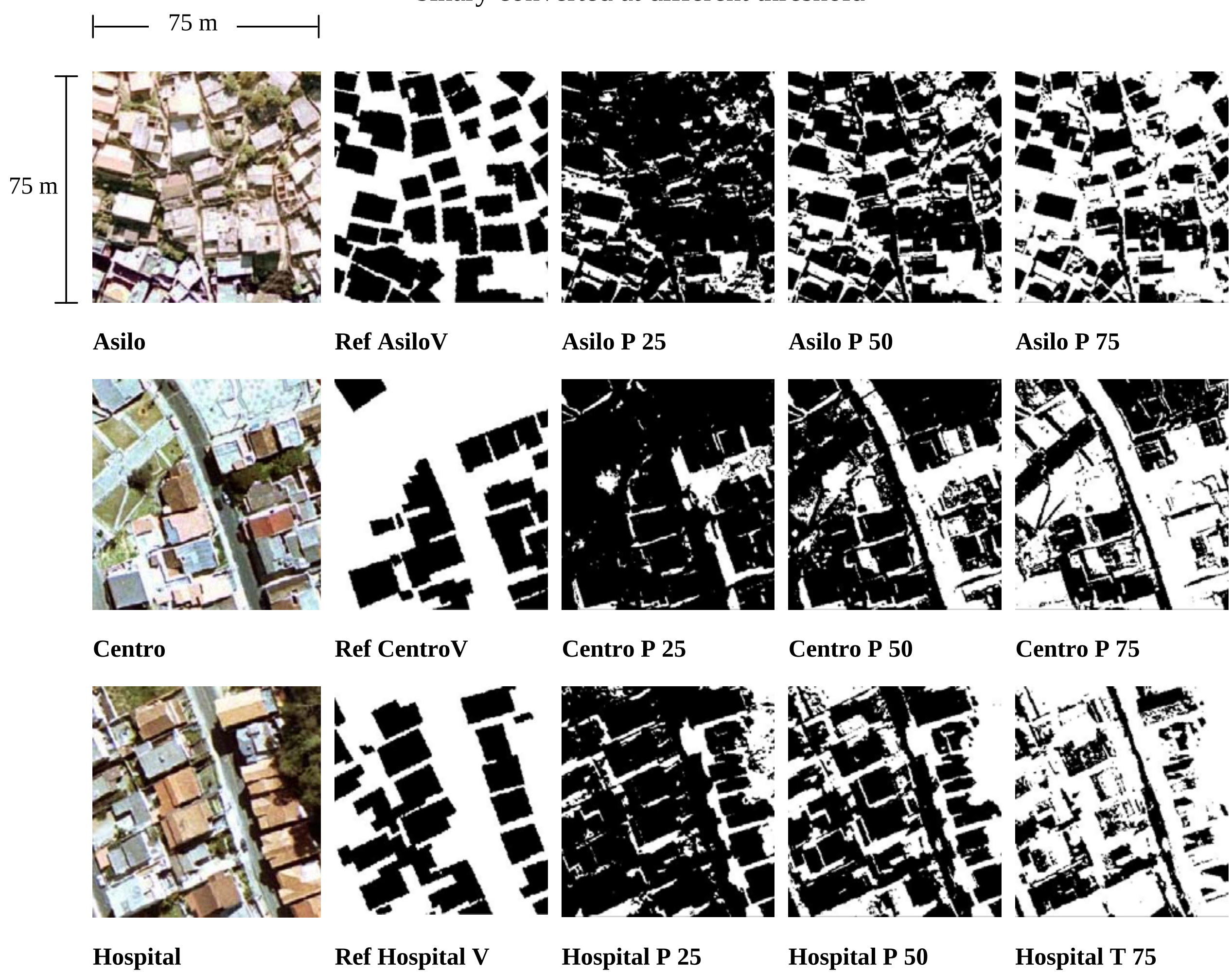


Table 4 above shows these quantitative indices for all 9 binary converted images. Some of the images scored relatively high in terms of the reported indices for such a simple method, namely Asilo P75, Asilo P50 and Hospital P50. In a less extent, Hospital P75 also can be seen as relatively closer to the reference images although the Tau index is low.[2]

Looking at table 4 and based only on these 'crisp' assessment agreement indices for the thresholds P25 and P50 for the area Centro, one could almost say that these images were completely different from the their reference ones. However, even if these images did not present particularly good results in any of the chosen thresholds, we will check the texture extracted using lacunarity measures in order to see how much the images depart from the correspondent reference images.

Table 4 – Quantitative indices of classification accuracy

Study Area	Asilo			Centro			Hospital		
Threshold	**25**	**50**	**75**	**25**	**50**	**75**	**25**	**50**	**75**
Proportion of Agreement	0.63	0.70	0.72	0.44	0.50	0.51	0.60	0.69	0.65
Kappa Coefficient	0.34	0.55	0.63	0.20	0.34	0.43	0.43	0.60	0.60
Tau Coefficient	0.27	0.40	0.43	-0.11	-0.01	0.03	0.20	0.38	0.29

3.4. Lacunarity Analysis Method

There are several methods for computing the lacunarity of a texture pattern (Mandelbrot, 1983; Gefen et al, 1984; Lin & Yang, 1986; Dong, 2000). In this paper we used the gliding-box algorithm proposed by Allain and Cloitre (1991) and popularized by Plotnick et al. (1993). According to this algorithm, a box of size **r** slides over a space of total size **M**, registering the box mass **S** that is obtained by count 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. A frequency distribution of the box masses ***n(S,r)*** is then computed. 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)***. Then, the first and second moments of this distribution are determined:

$$Z(1) = \Sigma\, S\, Q(S,r) \qquad (1)$$

$$Z(2) = \Sigma\, S^2\, Q(S,r) \qquad (2)$$

Lacunarity **(Λ)** is in turn calculated from these moments by:

$$\Lambda(r) = Z(2) / [Z(1)]^2 \qquad (3)$$

The first and second moments can also be described by the mean **E(S)** and the variance **Var(S)** of the box masses as:

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[2] Tau index uses a priori probability. Based on the number of classes M = 2 (built and non-built) this assumed 0.5 (1/M).

$$Z(1) = E(S) \quad (5)$$

$$Z(2) = Var(S) + E^2(S) \quad (6)$$

As a result, the lacunarity index (Λ) of given box size **r** can be calculated:

$$\Lambda(r) = 1 + (Var(S)/E^2(S)) \quad (7)$$

Lacunarity measurements are sensitive to the *geometric distributions* of objects over space, to the *fraction of occupation* of a given space and to the *scale* it is measured. Plotnick et al (1993, 1996) and Dale (2000) discussed the interpretation of Lacunarity. In general when voids or gaps of a spatial structure are almost homogeneously and evenly distributed, its lacunarity will be low. In contrast, for an equal fraction of occupation, a spatial structure whose gaps vary in size and are heterogeneously distributed will have higher lacunarity values for a given scale. Gaps that are more homogeneously distributed in a particular fine scale can be more heterogeneously distributed when examined at a coarse scale and vice-versa. As a multiscale measure, lacunarity permits an analysis of density, packing, dispersion and permeability of a geometrical structure through several scales.

Lacunarity is usually plotted in a double log form. Regularly, a concave upward lacunarity curves represent spatial patterns which gaps are randomly distributed and have lower lacunarity values. Conversely, concave downward curves represent texture patterns composed by clumped data and have higher lacunarity. Initially straight curves represent regularly dispersed patterns. Curves very similar to a straight line across all box sizes may represent fractal patterns, because they have the same appearance at all scales.

In order to compute lacunarity we set a parameter for the maximum size of the sliding box (**r**). This parameter is expressed as a percentage of **M** and lacunarity here was calculated setting this parameter to 45%. This means that for all images lacunarity was calculated for 135 different boxes sizes starting at **r = 1** and subsequently increasing **r** at pace of 1 pixel until the final box of 135 x 135 that represented a square of side equals to 33.75 meters, considering the image resolution of 0.25 meters.

Using PASSAGE, lacunarity was computed for thirteen images. Nine images were the converted from the aerial photos as in section 3.1 above. Other three were our reference set of images, corresponding to those converted from the vector maps (Asilo V, Centro V and Hospital V). Finally, a binary randomly generated image at one scale with a probability fraction p equals to 0.5 was used to assess the divergence between the lacunarity curves of random pattern and the other images.

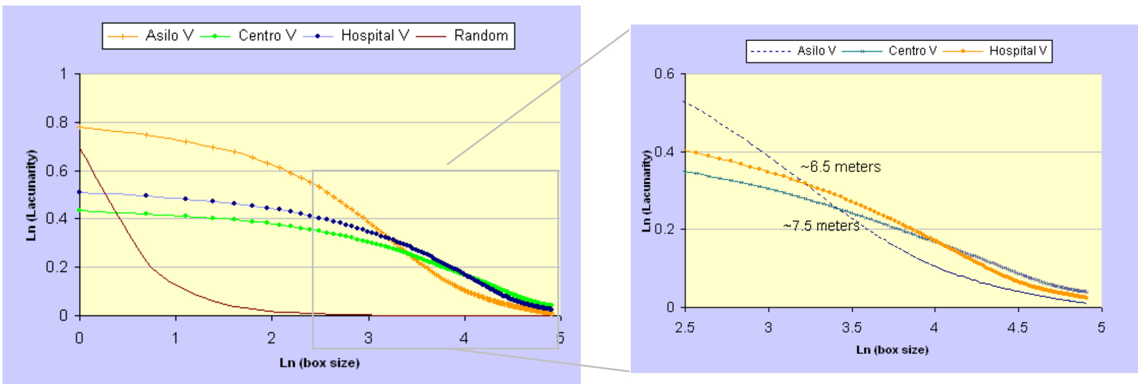
4. Results and Discussion

In this section, graphs present lacunarity values (Λ) plotted against the box sizes (**r**) in a natural log-natural log graph form. For the sake of simplicity we call lacunarity for the ln(Λ) value and box size for the ln(**r**) value.

4.1. Lacunarity and the reference images

Looking at the lacunarity results of the reference images (images from the vector maps, figure 4 above, 2nd column), graph 1a shows the curves for the three images Asilo V, Centro V and Hospital V. As one would expect from a set of urban features, all areas have particular spatial patterns. The curves differ from one produced from a random spatial pattern that is a concave upwards curve as shown in graph 1a.

Graph1. Lacunarity Analysis of the Reference Images



AsiloV is denser than the other two areas. In graph 1a this can be seen by the lacunarity values at the box size value equals to 0 where Asilo V scores higher than the other areas and the random. In fact lacunarity at the smallest possible box size of r = 1 (ln =0) is only function of the fraction of occupation; here, the **density (d)** of the class ***built*** in each area. This property is intrinsic to the sliding box method (Plotnick, 1996). Considering the density d, at r=1, $\Lambda(1) = 1/\mathbf{d}$ since $Q(1,1) = \mathbf{d}$ and $Z(2) / [Z(1)]^2 = \mathbf{d}/\mathbf{d}^2$ (*see equations 1, 2, and 3 above*). On the opposite side of the graph, the observed convergence to 0 at largest possible scale happens when r = M, then ln(lacunarity) is 0 given that Var (S) will be equal to 0 (*ibid*).

More important is that the curves from AsiloV starts from a higher lacunarity and then change the order of their lacunarity values with respect to the other two areas as they go along the X axis of the box size. These changes occur at a specific interval of the box sizes, around the value of box size just below 3.5. Graph 1b is a 'zoom' of the rectangular area highlighted in graph 1a that focus only at this larger scale. The values in meters in figure 1b are the correspondent ground values at the scale which these changes start to occur, 6.5 m for Hospital V and to 7.5 m for Centro V (remembering that the resolution of the images is 0.25m). Asilo, which is the more irregular and dense area of our sample, has a higher lacunarity only up to this scale.

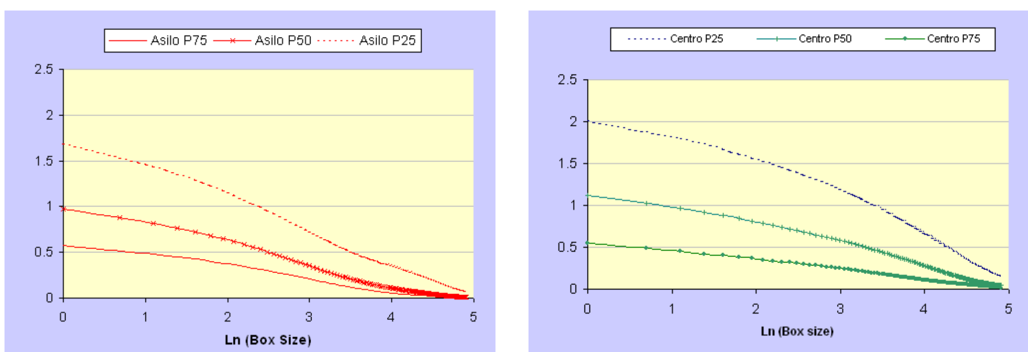
These differences in lacunarity are related to the sizes of the building's footprint represented by the images. In this regard, these box sizes correspond to the scales more appropriated to urban analysis of the selected area. Lacunarity measurement captures the differences between the different areas. At a particular scale there is another hierarchical relation among the curves and that is the way changes in the average and sizes of the different selected areas are captured. This hierarchy corresponds with the sizes of the properties which in turn may be more generically revealing in terms of the identification of different types of neighbourhoods.

4.2. Lacunarity and the converted images

Now turning to the binary classification of the sample images, it is clear from the foregoing section 3.1 that different thresholds affected the simulations. Graph 2a and 2b show lacunarity for the binary images of Asilo and Centro. We can see that at small scale, lacunarity values are shifted upwards as the threshold values decreases.

In effect, the different threshold parameters changed the global density of the images, hence the lacunarity values. However, different threshold values to the same area do not necessarily change the overall texture pattern as captured by the lacunarity in multiple scales. In other words, changes in the threshold do not change the hierarchy of lacunarity values of the different images at the same scales. This can be seen in all analyzed areas. Graphs 2a and 2b show this property for the areas Asilo and Centro. The area Hospital is not shown but behaved in the same way. As the graphs reveal, all curves converge to a value of lacunarity near to 0, but the curves do not cross each other. Lacunarity values are consistently higher for lower threshold values in all scales and vice-versa.

Graph 2. Lacunarity of values for different threshold in the same area



More generally, when a different threshold is applied, the density obviously changes according to the level of the applied threshold. Lacunarity captures density, therefore, for the same area, a different threshold gives a different density and lacunarity value at the very small scale, but variations in other scales can be captured.

In our experiment, as we set threshold boundaries to the 1st and third quartile of the grey level distributions for each aerial photo image, the limit where all images would completely fade or darken was not reached and the lacunarity curves have similar shapes.

4.3. Lacunarity results of the images compared

Looking back at the image comparison between the reference and the converted images in section 3.3, we recall that the classification for Asilo 75, Asilo 50 and Hospital 75 scored relatively high for such a simple method. On the other hand, all Centro images resulted in considering lower similarities, both on the qualitative and quantitative assessment. The following set of graphs 3 to 5 place together the lacunarity results from the reference images (Vs) and the images (Ps). To aid the comparison, the reference images and the images from figure 4 are placed on the side of the graphs.

Graph 3 shows the images Asilo P50 and Asilo P75 together with the reference image Asilo V. From the image comparison section above, Asilo P75 scored slightly higher than Asilo P50 in terms of similarity with AsiloV (see table 4). However, it is clear from graph 3 that the image Asilo P50 has a more similar lacunarity curve with the one from AsiloV than it is the case with Asilo P75. Asilo P50 and P75 are both images with relatively high similarities with the reference. Furthermore, they are statistically indifferent according to a significance test based on the Tau index value significance test (Ma and Redmond, 1995).

Graph 3. Lacunarity for converted and reference images – area Asilo

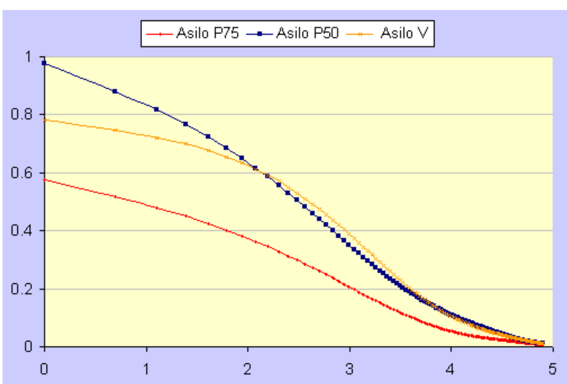
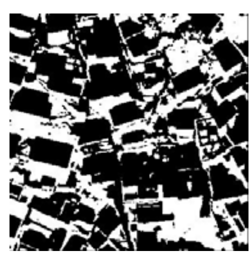
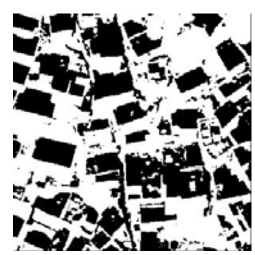


Figure 5. Reference image and binary converted

Ref Asilo V



Asilo P 50

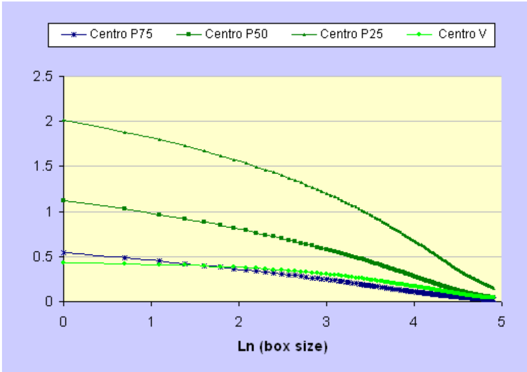


Asilo P 75

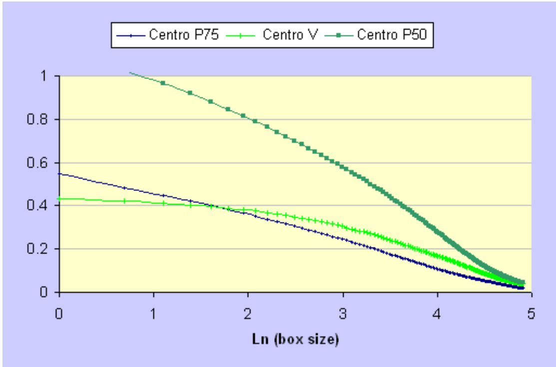
Beyond the result for the image assessment in itself, lacunarity curve may also inform the scale from when the similarities results became and continue consistently closer. This suggests that lacunarity measures may be useful as tools for image assessment as well as for the enhancement of classification methods. It is important to remember that the comparison indices for both of the areas here were based on a per-pixel crisp calculation and the threshold may retain part of the texture as it can be perceived even by the human eye, but it is certainly not a good classifier of built areas in a such a complex space as urban areas, as we can also easily perceive.

Graph 4. Lacunarity for binary converted and reference images –Centro

Graph 4a



Graph 4b



For all Centro images, quantitative and qualitative comparison assessment showed that the representation of ***built*** on the binary images were quite dissimilar from the reference image CentroV. Graph 4a and 4b show the lacunarity values for Centro. As it can be seen in graph 4b, the lacunarity curve of the least dissimilar image (Centro P75) is right below the reference image CentroV and has closer values with its respect. However, the curve shape of lacunarity across the different scales is different from the curve of the reference image and though they cross, they do not really overlap.

Graph 5. Lacunarity for converted and reference images – area Asilo

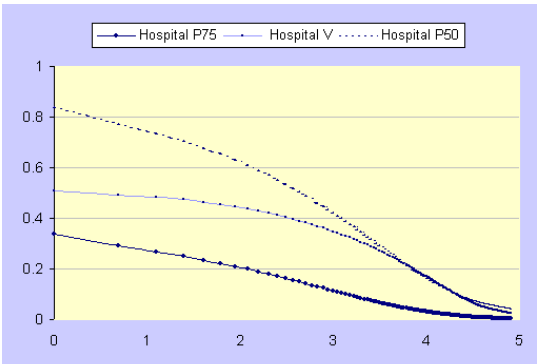
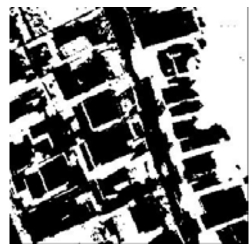


Figure 6. Reference image and binary converted – Area Hospital

Ref Hospital V



Hospital P 50

Hospital P 75

In the case of the area Hospital (graph 5), the highest scored converted binary image (Hospital P50) was also the one with the closest lacunarity behaviour as compared with the reference image. However, the shapes of the curves are not so precisely similar and it is only at larger box sizes that this relationship is clear (graph 5). After the scale of around 7.5 meters on the ground (ln [box size] equals to 3.46) the lacunarity values between the reference image from the vector maps and binary converted were consistently closer.

On note of the used accuracy measurement, our capacity to recognize simple texture patterns certainly work better than the pixel based indices of accuracy, at least for a few classes. It is known that the richness of texture is not captured by a pixel based accuracy index alone. The issue is relevant for remote sensing and also for calibration of land use simulation. Development on this direction is exemplified by the Map Comparison Kit developed by Riks (Hagen, 2003) that takes a multiple indices approach and may incorporate lacunarity or other multiscale analysis with other approaches.

5. Concluding remarks and future research

This study explored the use of lacunarity multi-scale measures for urban analysis in the context of more irregular urban forms as they are commonly found in cities of low-income countries and particularly in Latin America. We showed how lacunarity measures applied to urban context might reveal details of scale and density. The type of texture analysis here can be directly valuable for urban planning as for example through the identification of common patterns of different neighbourhoods at specific urban scales.

This experiment reinforces current calls asking for a place for spatial metrics in the urban dynamics research agenda (see e.g., Herold et al 2005). Multi-scale measures such as lacunarity are part of these metrics and need to be more present in analytical urban studies. This is even further the case where contrasting urban forms are more often found. Cities are complex by nature (Portugali, 2000) and it is certain that spatial metrics may not reveal the myriad of actions that happens in the everyday life of cities. Yet, the vision of cities from a fractal geometry and multi-scale point of view has not been fully explored under the context of renewed processes of urban involution (Armstrong and McGee, 1980; Davis, 2004) in low-income countries.

Latin America region is already highly urbanized. Many of the region's urban problems are somewhat different from those found in western industrialized countries, requiring innovative and more locally adapted solutions. Another aspect is that geographic data collection has historically been presented as an important problem and geographic databases are generally more scarcely found in low-income countries. However, data availability may change swiftly as testified the popularization of remote sensing in Brazil through the free available images from the joint China-Brazil Earth Resources Satellite (CBERS) Program (Camara 2002 and 2003).

It is important to note that our study has some limitations that we intend to address in future work. The samples from the chosen neighbourhoods, although typical of the selected areas, were relatively small in comparison with the whole town. Another more fundamental aspect is that lacunarity is one of multiple multi-scale measurements and it would be desirable in future to address texture analysis with other techniques such as for instance wavelet. This was pointed out by Dale (2000) who recommended data to be analysed by more than one multiscale method and the results compared for greater insight into the characteristics of the areas. We also believe that it is necessary to develop a computer programme to customize multi-scale analysis for performing tasks specifically related to urban complexity and we are engaged in this task.

Finally, the texture patterns of an urban area are not only given by the amount of gaps in roads or by the distance between buildings, but they may well be explained by the dissimilar and unequal social structure of cities. The spatial configuration of different neighbourhoods would correspond to this social differentiation at a certain extent, and a natural extension of this work is to link multi-scale pattern of social-economic variables together with these physical patterns as explored here. Also, the use of auxiliary socio-economic information linked with remote sensing for the characterization of urban density and space filling (Longley and Mesev, 2002) could well be extended using a multiscale approach.

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