EXPLORING THE DISCRIMINATING POWER OF TEXTURE IN URBAN IMAGE ANALYSIS

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ABSTRACT

This paper presents some preliminary results from a series of investigations into the use of texture analysis in urban image understanding. High spatial resolution satellite imagery of urban areas contains much information that is not adequately exploited using per-pixel classification techniques. The principal hypothesis addressed is that detailed spatial features may be recognised by the analysis of urban morphological texture. Results from two analyses are reported. First, co-occurrence matrix measures of homogeneity are used on a Spot Panchromatic scene of Harare, Zimbabwe, to predict housing densities stored in a co-registered database. Second a Fourier domain statistic is developed to measure residential block density and is tested on a Spot panchromatic scene of Cardiff, Wales. The statistic is used to predict urban population counts stored in a co-registerd population surface. The results demonstrate that useful morphological information can be extracted from Spot panchromatic images using such methods.

Key Words: Texture, Urban Pattern, Spot.

INTRODUCTION

In the human visual interpretation of an urban image three factors are important: tone, texture and context. Tone is the colour or shade of any particular element of the image; texture is the pattern of colour or shade variation and this can be observed at a variety of different scales; and context is the relationship between texture elements. Context is illustrated by the identification of a central business district which is generally achieved by observing the orientation of texture in the rest of the urban area. Similarly, urban fringe is identified by observing the sharp boundary between areas of greater and lesser homogeneity. We could also say that the urban fringe is demarcated by the boundary of areas of contrasting tone. In this case we are making a textural observation at a small scale.

If the above is a reasonable proposition, it can be suggested with some degree of confidence that texture and context should be powerful concepts when applied to the automated, or semi-automated interpretation of digital urban images. Infact, the analogy may even suggest that texture and context should be more powerful interpretation concepts than tone.

The importance of texture has long been recognised in many applied fields of digital image analysis and its quantification comes under the more general heading of pattern recognition. Much of this work had its origins in the vision branch of artificial intelligence. Thus the analysis of shape and movement in robotic vision makes considerable use of the measurement of surface texture of objects. In medical images, texture analysis can help identify structure in soft tissue. In earth observation studies texture measurements have been used to identify structures in the lithosphere (for example Saraph and Inamdar 1982), hydrosphere (for example Eppler and Farmer 1991), biosphere (for example Mauer 1974) and the atmosphere (for example Welch et al 1990) . Considerable work has been done on urban images by digital photogrammetrists and defense agency scientists applying pattern recognition techniques to the task of identifying individual building structures (Huertas and Nevatia 1988), ie. at a large urban scale. Much less work has been done on quantifying the intuitively meaningful variations in urban texture at a small urban scale. There has been some attempts to measure urban texture as part of otherwise conventional urban satellite scene classification exercises. Jensen and Toll (1982), for example, incorporate a texture term in the supervised classification of urban fringe ground-cover in an urban change detection analysis. There has been less effort directed towards a systematic search for meaningful texture measurements. A good example of such work, which explores the discriminating power of various texture measures at different level of spatial resolution is Marceau et al (1990).

THE TEXTURE-CLASSIFICATION PARADOX

While texture analysis has found an established place in many image processing application areas its benefits are generally regarded as unproven in the field of satellite image interpretation (Mather 1987). There is a paradox here however, since the same commentators typically recognise that intuitively, texture should be more important than has frequently been demonstrated so far, given its role in the human interpretation calculus. Indeed, some studies have achieved significant improvements in classification accuracy using texture features (see, for example, Shih and Showengerdt 1983). This suggests that it might not be the idea **per se** of using texture in satellite image interpretation that is inappropriate but the texture measures that have been tried. Since there are an infinite number of ground cover textures that can be characterised in many different ways at any chosen scale, it is easy to see that the nature of the texture measure selected to identify a particular phenomenon is crucial. The fundamental difficulty is that the problem of finding the 'best' texture measure is an unstructured one.

There are two important dimensions to this problem: choice of statistic and choice of scale. A statistic will characterise a texture in one out of many possible dimensions. If the objective of the analysis is to use texture information to classify an image into meaningful categories, then the most appropriate statistic is one that achieves the best discrimination between different categories. The notion of a best statistic is therefore meaningful only in relationship to a particular category scheme and different schemes are likely to have different best discriminators. It might be supposed that for any given type of classification exercise, (urban landuse, upland vegetation etc) certain texture methods will be better than others. For some problems, and urban classification is one of them, it is likely that general statements about best discriminators will only hold for limited geographical areas. The texture of ground cover in a commercial area or a newly developed urban fringe area in South-East Asia, for example, is likely to be significantly different to equivalent areas in Europe and best discriminators need to be explored for both locations.

Just as important as the choice of statistic is the choice of spatial scale at which the statistic is measured (Marceau et al 1990). At one extreme we can imagine an image window just one pixel square in which no texture measurement (and therefore no discrimination between areas) is possible. As the size of the window is increased different levels of regularity will be captured within it, starting with repetitive patterns associated with building arrangement and progressing to patterns related to building lots, local roads, city blocks, arterial roads and so on. The general proposition implied here is that the scale at which texture is measured must reflect the scale at which significant texture appears. Significant texture can be defined as texture which is likely to contribute to the discrimination between meaningful categories in an image.

In a 10m resolution Spot image of a city scene it might be hypothesised that significant texture begins to appear with window sizes that exceed the dimensions of the smallest type of housing lot. Extending this it may be hypothesised that discrimination between different types of residential areas may be achieved with window sizes ranging from the smallest to the largest types of housing lots. The lowest level of urban texture that may be examined, therefore is at the housing lot scale. This will be an appropriate scale of texture analysis if the objective is to classify an image into areas of homogeneous housing types, ie. into residential neighbourhood categories. If the interest is in broader categories of urban landcover type (residential, commercial, industrial; residential areas by age or style; categories of urban fringe etc), then it may be hypothesised that significant texture will begin to appear when window size exceeds the typical spacing of local distributor roads (or the width of city blocks). Above this there are any number of scales at which texture may be meaningfully measured. At the smallest scale, windows that embrace whole urban areas may support statistical comparisons of different towns using texture measures that are sensitive to a town's compactness, linearity, radiality, nodality and so on. Batty's measures of the fractal dimension of city boundaries is of this nature, albeit the measures are of lines not surfaces (Batty 1991). At this scale, however, we have ceased to be interested in urban texture as an aid to urban image interpretation; using it rather as means of quantifying urban shape and informing speculation about the relationship between shape and process.

The remainder of this paper reports on two exploratory studies which systematically investigate the possibilities of texture-based urban image interpretation.

IMAGE-DOMAIN MEASURES OF URBAN MORPHOLOGICAL HOMOGENEITY

Four types of texture measure are applied to a Spot panchromatic scene of the city of Harare and summary statistics correlated with ground-truth information held in a GIS layer registered to the satellite image. The GIS data record the density of housing for residential suburbs and the assumption is that there is a significant relationship between measured housing density and image texture. If this hypothesis is supported for any particular texture measure then it may be assumed that the measure can be used as a tool in the interpretation of urban images. The study limits itself to establishing the discriminatory power of the texture measures; it does not test the performance of the measures in classification.

The interpretive power of texture is examined within the framework of the hypothesised {tone,texture,context} calculus. This is done using a linear model in which housing density is expressed as a function of the three types of explanatory variable [1].

$$D_i=a+b_1B1_i...+b_6B6_i+b_7T1_i ...+b_{10}T3_i+b_{11}C1_i \quad [1]$$

Where: D_i=housing density for sub-image i; $B1_i$ to $B7_i$=mean grey-level values on TM bands 1,2,3,4,5 and 7 for sub-image i; $T1_i$ to $T3_i$=texture measures for sub-image i; and C_i=a context measure for sub-image i.

The model assumes that residential density can be predicted on the basis of tone and texture information derived from satellite imagery together with subsidiary context information. If this is the case, then the continuously-measured predicted density variable may be used to create a density surface at any level of aggregation. Fine aggregation categories will produce a finely differentiated residential land-cover classification.

Data and Methodology Four databases are used in the study: Spot panchromatic and Landsat TM digital satellite images of Harare, Zimbabwe; digitised administrative boundaries of Harare; and housing density statistics for the administrative suburbs.

A sample of 47 suburbs was selected, stratified to achieve an approximate balance between high, medium and low density housing suburbs in the analysis. 47 sub-images of 30x30 pixels were extracted, one from within each sampled polygon. The size of the sub-image corresponds approximately to the dimensions of the largest housing lots in the city. The sub-images were located so as to capture the characteristic texture of the residential areas within the Suburbs, ie. avoiding obvious areas of open space. For each sub-image, measures were derived for tone, texture and context.

(i) Tone Six tone variables were defined by recording the mean grey-scale values on each of the Landsat TM bands:

$$Bn=\left(\sum_{i=1}^{900} r_i\right) / 900 \qquad (n=1 \text{ to } 5,7) \quad [2]$$

(ii) Texture Three types of texture measures are used: urban pixel density, Haralick's homogeneity statistic (f1) and entropy (E). The first is derived from the grey-scale frequency distribution and the other three from the grey-scale joint probability distribution (co-occurrence or P matrix) defined as:

$$P(i,j,d,t) \quad [3]$$

where P=probability of grey-scales i and j occurring at distance d and angle t.

Urban pixel density A grey-level frequency statistic that has been used in several urban applications is urban pixel density. Although this is measured in the grey-level frequency domain, it should be thought of as recording the general urban/nonurban texture in the image plain (a specific measure of variation). Measured as the proportion of all pixels classified as urban land-cover:

$$\frac{N^u}{N^T} \quad [4]$$

it may be thought of a simple measure of homogeneity of urban land-cover. It is cruder than the homogeneity measures derived from the P matrix, however, since it does not capture the pattern of aggregation of urban pixels. It cannot differentiate, for example, between an image with a few large clusters of urban pixels and an image with the same proportion of urban pixels but where those pixels are scattered more evenly.

Homogeneity (f1) The f1 measure of image homogeneity is derived from a P matrix by measuring the sum of squares of the matrix entries. The statistic takes on higher values for textures in which there are a few dominant grey-scale transitions and the P matrix therefore has a small number of large P values. It is expressed by the following:

$$f1=\sum_{i=m}^{n}\sum_{i=m}^{n}\left(\frac{P(i,j,d,t)}{R}\right)^2 \quad [5]$$

Where:
R=is a normalising factor which equals the number of pixel pairs used in the calculation of f1; Min=minimum grey-scale; and Max=maximum grey-scale.

Entropy Entropy is a commonly employed measure of variance in data. Applied to a P matrix using [7], it gives higher values when matrix entries are equal and lower values when they are unequal. This is therefore another method of measuring the homogeneity/ heterogeneity of an image.

$$E=-\sum P(i,j,d,t)\ \log(P(i,j,d,t)) \quad [6]$$

The P matrix methods of recording texture were applied in three different ways. First, the statistics are derived for an entire matrix of 256 grey-levels:

$$P(i,j,d,t) \quad [i=1..256,\ j=1..256] \quad [7]$$

thus measuring texture over all grey-scales within a window. Second, they were derived for a partition of the full P matrix defined as:

$$P(i,j,d,t) \quad [U<i<256,\ U<j<256] \quad [8]$$

where U is a threshold value above which grey-scales are assumed to represent ground-cover of a broadly urban nature. This effectively measures the texture of the urban part of each window. Third, they are derived for a re-classified binary image defined as:

$$P(i',j',d,t) \quad [i'=1..2,j'=1..2] \quad [9]$$

where:
i'=1 if i<U and i'=2 if i>=U;
and j'=1 if j<U and j'=2 if j>=U.

Co-occurrence statistics were computed for the urban part of [10] only, thus measuring the texture of the monotonic urban surface. The expressions for f1 and Entropy under these circumstances simplify to:

$$f1=\left(\frac{P(2,2,d,t)}{P(2,1,d,t)+P(2,2,d,t)}\right)^2 \qquad [10]$$

$$Entropy= -P(2,2,d,t)\log(P(2,2,d,t)) \qquad [11]$$

(iii) Context A single context measure is used: distance from city centre. For each of the 47 sub-images the Euclidean distance between the sub-image's centroid and a point taken to be the centroid of the Central Business District is measured. This expresses the theoretical notion that density of development falls off towards a city's periphery.

Results We present for illustrative purposes the results from an analysis using a P matrix defined as in [9] and f1 and E measures defined as in [10] and [11]. Expression [1] was calibrated over all 47 windows. For each, housing density and distance were retrieved from the GIS attribute table; percent urban was measured from the panchromatic layer; f1 and E were measured from the P matrix of a classified binary panchromatic layer as defined in [9]; and B1 to B7 were derived from the 6 respective TM layers.

The results, summarised in Table 1, are interesting for a number of reasons. First, all three texture measures have a significant amount of predictive power, each individually explaining approximately 70% of the variance in housing density between suburbs. Second, when the full model as expressed in [1] was run, the significant explanatory terms are %urban (panchromatic) and TM band 4, ie. a mixture of 'tone and 'texture' but not context. An even better fit is achieved, however, using f1 (panchromatic) and TM bands 5 and 7. This model (Table 1a) explains approximately 80% of the variance in housing density between suburbs. It should be recalled that f1 is a normalised measure so that its size is independent of the absolute number of 'urban' pixels in a sub-image. This strongly supports the contention that texture is important in urban image interpretation. This is all the more significant when it is considered how the housing density data were created. The density values were computed at the suburb level with open space included in the denominator term and are therefore gross density values. Texture was measured, however, for sample areas displaying characteristic residential pattern, excluding significant areas of open space. There is **apriori** reason to believe therefore that texture should display a stronger relationship with net-housing density than with the gross housing density figures used.

That the context variable did not enter the model is not surprising since the highest density suburbs in Harare are not concentrated around the city centre, but rather towards the periphery in one sector of the city. It could be expected to attain greater importance in a city displaying more conventional monocentric landuse patterns.

TABLE 1 PREDICTING HOUSING DENSITY WITH MEASURES OF IMAGE-PLANE HOMOGENEITY

(a) Density=f(f1)

Variable	T	Sig T
f1	10.487	.0000

Multiple R=0.8424 R^2=0.7097
Adjusted R^2=0.7032

(b) Density=f(E)

Variable	T	Sig T
E	-10.214	.0000

Multiple R=0.8359 R^2=0.6986
Adjusted R^2=0.6919

(c) Density=f(%urban)

Variable	T	Sig T
%urban	10.908	.0000

Multiple R=0.8518 R^2=0.7256
Adjusted R^2=0.7195

(d) Full Model: Density=f(%urban, f1, E, B1..B6, Distance)

Variable	T	Sig T
%urban	10.378	.0000
B4	-2.352	.0232

Multiple R=0.8697 R^2=0.7562
Adjusted R^2=0.7451

(e) Density=f(f1,B1..B6,distance)

Variable	T	Sig T
f1	4.968	.0000
B5	-4.499	.0001
B7	3.251	.0022

Multiple R=0.8974 R^2=0.8054
Adjusted R^2=0.7918

FOURIER-DOMAIN MEASURES OF URBAN MORPHOLOGICAL STRUCTURE

One way of measuring regularity in image texture is to define relevant summaries of the image's Fourier transform. A Fourier power spectrum records complex information concerning the wavelength, amplitude, phase and orientation of recurring image patterns. The significant features of an urban image are essentially linearments which recur with varying degrees of regularity. Since the linearments are, in general, ultimately determined by street or block pattern, the regularity will be greater within a neighbourhood of homogeneous morphology than between neighbourhoods. It may therefore be supposed that a Fourier power spectrum of an urban image will contain information about street patterns and may be used to discriminate between diverse urban morphologies.

We test this supposition using a simple, but potentially powerful statistic defined by the following generalised algorithm:

(a) transform image to optical power spectrum;
(b) find spectrum's maximum peak(s);
(c) find Fourier-space coordinate of maximum peak furthest from origin and measure frequency by hypotenuse;
(d) divide image width by frequency, taking into account angle of wave-forms, to get image-plane distance (u1);
(e) take this distance to be a measure of regularity corresponding to street or block patterns.

Since a two-dimensional Fourier transform is defined as:

$$F(w,v)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)\,e^{-i2\pi(wx+vy)}\,dx\,dy \qquad [12]$$

the block pattern statistic u1 can be expressed as:

$$u1=D/\sqrt{w_{max}^2+v_{max}^2} \qquad [13]$$

where: D=image width in world coordinate distance;
w_{max} and v_{max} = two-dimensional frequencies from F(w,v);

Data and methodology Two data sources are used in this part of the analysis; a Spot panchromatic scene of the city of Cardiff (June 1988) and a rasterised population surface at a spatial resolution of $200m^2$. The population surface is a modelled distribution of census population counts onto a grid. It adopts a method that achieves an allocation of a given population total over space that is spatially more accurate than conventional polygon mapping (it is less likely to 'place' people in parks and industrial areas, for example, than databases based on census tracts). The Spot scene and the surface are registered to the UK National Grid.

Each population cell corresponds to 400 Spot panchromatic grey-scale values. A sample of 25 cells was taken from a transect extending from the city centre to the low-density suburbs giving a vector of 25 population counts p_i. The texture of the corresponding sub-image was measured using u1 (over 400 pixels), forming a vector of 25 u1 values $u1_i$. The power of u1 in discriminating between areas of different residential density is tested by regressing p_i against $u1_i$.

Results The success of u1 in capturing distinctive block regularity can be gauged by comparing it with the actual inter-block distance measured from a large-scale map. In addition, the orientation of streets on the map can be compared with the orientation of u1 in frequency space. This is easily observed from the optical power spectrum but can also be approximated by the slope of the line joining $F(w,v)_{max}$ to the origin, given by:

$$w_{max}/v_{max} \qquad [14]$$

The relationship between Fourier statistics and ground truth information from a map is illustrated in Tabel 2 for three $200m^2$ cells representing distinctive neighbourhoods.

TABLE 2 RELATIONSHIP BETWEEN FT MEASURES AND GROUND-TRUTH DATA FOR THREE SAMPLES REPRESENTING HIGH, MEDIUM AND LOW DENSITY NEIGHBOURHOODS

	High	Med.	Low
u1 (from FT)	70m	46m	24m
Inter block Distance (from map)	65m	45m	25m
Frequency (from FT)	4	6	12
No. of rows of houses (from map)	4	6	10
Orientation (from FT)	E-W	NW-SE	NW-SE
Orientation (from map)	E-W	NW-SE	NW-SE

Table 3 shows the results of regressing population against u1. Approximately 70% of variance in population is explained by u1 alone. This is a promising result when compared to the Harare analysis where the best texture variable in [1] accounted for little more than 50% of variance on its own. This illustrates the potential of texture measures that record the regularity in urban linear features and in particular, of Fourier-domain statistics which give orientation-independent statistics.

TABLE 3 CORRELATION COEFFICIENT FOR A REGRESSION OF POPULATION ON u1

R	0.85912
R^2	0.73808
Adj R^2	0.72669
F	64.812
Signf F	0.000

Conclusions

Our exploration of two approaches to extracting textural information from urban imagery demonstrates both the problem and the potential of such an endeavour. The problem is, by nature, an unstructured one and there are few clues about how best to reduce the solution space. The importance of the arrangement of linear surface features in aiding visual interpretation of analogue maps is one such clue. Another is the intuition that different urban areas will have characteristic ground-cover homogeneity. Even then, there are many different ways of measuring a hypothesised type of regularity. Having discovered a method with discriminating potential, there is the risk of refining it for specific morphologies until it is no longer a general tool.

For these reasons, we are encouraged by the results reported here. The P matrix measures of homogeneity demonstrate that a simple measure of 'clumpiness of development' can modestly but significantly improve upon the discriminating power of grey-level values alone. The Fourier domain u1 measure of 'street/block spacing' appears to be even more powerful. Its attraction lies (a) in its ability to capture the visually most striking textural features of an urban image, namely street or block patterns; (b) in its ease of interpretation (u1 is expressed in world-coordinate distance); and (c) in its robustness. It is robust in that a given morphological pattern will, in principle, produce the same u1 statistic whatever the orientation of the streets and whatever the position (phase) or size of the window. u1 is orientation-independent because it is defined by extending an arc from the origin of the optical power spectrum and searching for the furthest maximum peak in any direction. u1 is independent of the position of the window in relation to the street pattern (ie its value will remain the same as a window is shifted accross an image as long as the frequency of streets remains the same) because the FT power spectrum is phase-shift independent. u1 is independent of window size because it is expressed in world-coordinate distance units by standardising the significant street/block frequency by the world-coordinate dimension of the window.

The findings have significance for a number of lines of inquiry. First, they demonstrate the potential of using texture in image classification; as a supplement to per-pixel approaches, or as part of hybrid classification techniques. Second, they have relevance to the development of tools for the extraction of complex objects in urban GIS (Webster et al 1992). Third, they demonstrate the utility of integrating RS data with other urban data in co-registered GIS layers. Although we use the the high resolution population surface (Bracken and Martin 1991) in the Cardiff analysis as a source of ground-truth data, we have also explored the use of image texture, in refining the model population surface; a problem that suggests some form of iterative movement towards an optimum solution.

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