A COMPARISON OF TEXTURE FEATURE ALGORITHMS FOR URBAN SETTLEMENT CLASSIFICATION

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ABSTRACT

Texture features derived using Haralick's Gray-Level Co-occurrence Matrix (GLCM) are by far the most popular in urban remote sensing research — but are they the best features for every application? In order to select the most appropriate texture algorithm for an automated informal settlement classification system, we performed an experiment to compare the performance of the GLCM with that of other texture features. The performance of a texture feature is measured by computing the classification accuracy achieved on a supervised set of images spread over 8 settlement classes, focusing on informal and low-cost housing. The results show that GLCMs perform very well, but that Local Binary Pattern texture features have a small advantage in this classification problem.

Index Terms— Settlement classification, Texture features

1. INTRODUCTION

Many developing countries struggle with the rapid growth of informal settlements. These settlements are characterised by a complete lack of formal planning and formal construction methods, leading to poor living conditions for their inhabitants. By their very nature these settlements are unpredictable, and effective management of these settlements (*e.g.*, the provisioning of services) depends on their successful identification and classification in a timely manner. Remote sensing, particularly in the form of high-resolution imagery, may offer some hope of developing systems that allow for the effective detection, monitoring and management of rapid urban growth.

Manual photointerpretation of QuickBird imagery quickly leads one to believe that settlement type can be inferred directly from the local spatial characteristics ("texture") of the image with a high degree of accuracy. The question remains whether this can be performed in an automated manner with an acceptable level of accuracy.

The objective of the research presented in this paper is to establish which of the well-known texture feature extraction algorithms are most suitable for automatic classification of settlement type using QuickBird imagery.

Before delving into the experiment, a brief overview of related work in urban texture feature extraction is presented in Section 2. Section 3 provides an overview of the texture features used here, followed by a discussion of the test data in Section 4. A discussion of the results of the experiment are presented in Section 5.

2. RELATED WORK

A recurring problem in high resolution urban remote sensing is the poor separability of certain classes using spectral information alone; one possible solution is to include some geospatial information. An example of this approach is presented by Shackelford and Davis [1], who proposed a fuzzy classifier that used GLCM texture features to separate classes that are spectrally very similar, such as *Trees* and *Grass*. This has led to improved classification in urban environments on the order of 10%.

A different approach to the urban classification problem is to initially disregard the multi-spectral information completely, and to focus purely on spatial features derived from panchromatic images. One such example is presented by Pesaresi [2], who investigated the effect of GLCM parameters on classification accuracy in urban environments. He selected 16 different classes (*e.g.*, *Continuum built-up surface, regular pattern, high density*), and varied the GLCM window size and displacement vector to determine the best parameters for that specific classification problem. Using a window of $205 \times 205\text{m}^2$, Pesaresi obtained an overall accuracy of 98% using a maximum likelihood classifier.

Pesaresi also introduced a set of morphological texture features derived using geodesic opening and closing operators [3]. These morphological profiles were harnessed in a multiscale texture segmentation algorithm, which was demonstrated to be highly effective, particularly in areas where traditional gradient/watershed methods prove ineffective. Later work by Benediktsson *et al.* built on these morphological features, using them to classify urban regions [4]. The focus of their experiment was on reducing the dimensionality of differential morphological profile features; the effectiveness of a particular dimensionality reduction method was evaluated with a supervised classifier trained on 7 target classes.

3. TEXTURE FEATURES

The following texture feature algorithms were investigated:

Moran's I: A 1-dimensional feature, analogous to a simple correlation coefficient [5].

Geary's C index: A simple correlation-based 1-dimensional feature, similar to Moran's I [5].

G index: Another correlation-based 1-dimensional feature, but unlike Moran's I or Geary's C index, this one can distinguish between "hot spots" and "cold spots" [5].

TPSA: The Triangular Prism Surface Area metric is an estimate of the fractal dimension of the surface formed by treating the image intensity as a height value [6].

Lacunarity: A measure of the scale-dependent deviation of a geometrical pattern from homogeneity, that is, a measure of the distribution of gaps [7]. Lacunarity is calculated from a bi-level image computed by optimal thresholding. Experimentation indicated that a 7×7 window yielded the best results.

DWT: Discrete Wavelet Transform [8]. Three features are derived from the Daubechies-4 wavelet coefficients: the *log energy*, the *entropy*, and the *angular second moment*.

Granulometrics: A granulometric pattern spectrum with dimension 20 is computed using repeated morphological opening with a circular structuring element [9]. Note that this method is not as sophisticated as the one used by Pesaresi [3] which used geodesic morphological transforms. The granulometric pattern spectrum can be interpreted intuitively as a histogram of object (building) sizes.

GLCM: Gray-level Co-occurrence Matrix features [10] are derived using the a displacement vector of (1,0). A total of 8 features are derived, corresponding to *contrast*, *dissimilarity*, *homogeneity*, *angular second moment*, *entropy*, *mean*, *variance*, and *correlation*. A window size of 200×200 was found to yield good results.

LBP: The Local Binary Pattern method produces contrast and rotation invariant texture features [11].

The LBP method is not nearly as well known as the GLCM method in remote sensing applications; one of the few examples is by Lucieer *et al.* [12]. A brief description of the method is thus in order.

The first step of the LBP method is the construction of a set of P sampling points along the circumference of a circle of radius r. The intensity of a pixel at each of these sampling points is denoted g_p where $0 \leq p < P$, with the symbol g_c denoting the center pixel. The neighbouring intensities $(g_0, g_1, \ldots, g_{P-1})$ are transformed to obtain the sequence $G_p = (s(g_0 - g_c), s(g_1 - g_c), \ldots, s(g_{P-1} - g_c))$ where $s(x) = 1$ if x is non-negative, and 0 otherwise. The bit sequence G_p can then be mapped directly to an integer value, but Ojala *et al.* derived a compact, rotation invariant encoding [11].

Let $U(G_p)$ represent the number of transitions from 0 to 1 (or 1 to 0) in the sequence of bits G_p. Then the encoding

$$\mathrm{LBP}_{P,R}^{\mathrm{rui2}} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & U(G_p) \leq 2 \\ P + 1 & \text{otherwise} \end{cases}$$

yields a value in the range $[0, P+1]$ which can then be accumulated over a window to provide a histogram that serves as the feature vector.

A multi-resolution representation can be obtained by concatenating the histograms of various LBP encodings. For example, $\mathrm{LBP}_{8,1}^{\mathrm{riu2}} + \mathrm{LBP}_{16,2}^{\mathrm{riu2}}$ represents the combination of LBP features measured over 8 points at a radius of 1 pixel, and over 16 points measured at a radius of 2 pixels. A few of these combinations will be evaluated in experiment.

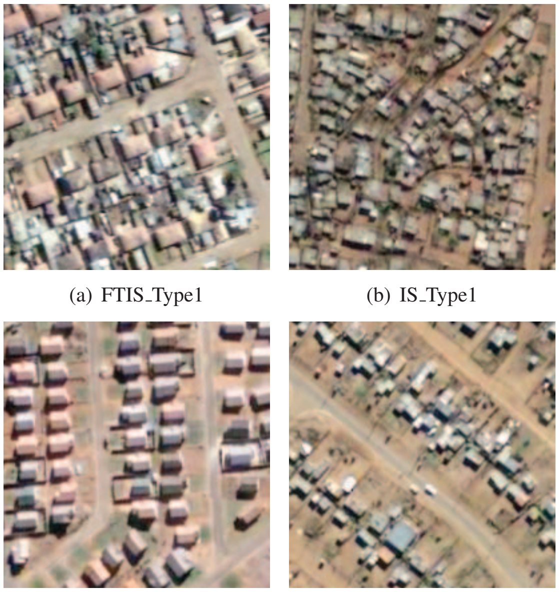
4. DATA & EXPERIMENT

The study area for this experiment is Soweto, located in the Gauteng province of South Africa. The following settlement types (examples of which can be seen in Figure 1) have been identified in the study area:

- Formal Township, identified with the labels FT_Type1 and FT_Type2. This type contains permanent (brick) structures. The buildings are laid out in a planned manner. Type 1 and 2 are differentiated on the homogeneity of the house sizes.

- Informal shacks, labeled as IS_Type1. Non-permanent shack type dwellings (typically made out of tin, cardboard, wood, etc.) established on informal, non-serviced sites. Typically characterised by high building densities.

- Formal Township plus Informal Shack, labeled as FTIS_Type1, FTIS_Type2, and FTIS_Type3. Any type of residential unit, of any density, can be found in this category, but buildings appear in pairs — a larger building will be accompanied by a backyard shack.



(a) FTIS_Type1 (b) IS_Type1

(c) FT_Type1 (d) Informal township

Fig. 1. Examples of some of the settlement classes found in Soweto

The three sub-types are differentiated based on the size of the primary building.

- Formal suburban regions, characterised by permanent residential structures, either single or multi-level, located in or near well-established residential areas.
- Informal townships, characterised by permanent or semi-permanent shack type dwellings laid out in a planned manner, both on serviced and unserviced sites. Building density can vary from low to high.
- Non-urban, a catch-all class to represent all other land cover / land use types. Note that this is a class that can not easily be defined through positive examples only; it is included here just to illustrate the ability of the classifier (using a given set of texture features) to separate samples from this class from the rest. In a real classification system, a hierarchical classification scheme should be used: first apply a one-class classifier to filter out patterns that are not settlements, and then apply the supervised classifier to determine the correct settlement type.

Panchromatic QuickBird imagery at a resolution of 0.6m over Soweto was acquired, from which polygons were extracted according to target class. A set of pure samples of each class was generated by extracting 120m×120m tiles from random locations within these polygons, ensuring that each tile was completely contained in the relevant polygon. This process yielded a set of 3338 tiles over all the classes.

Table 1. Overall classification accuracy obtained with various texture algorithms

Texture algorithm	**# features**	**Classification Accuracy (%)**
Moran's I	1	28.64
Geary's C	1	33.58
G index	1	33.19
TPSA	1	29.69
Lacunarity (7×7)	1	40.29
DWT	3	60.90
Granulometrics	20	91.13
GLCM (200×200)	8	93.59
$\mathrm{LBP}^{riu2}_{8,1}$	10	89.51
$\mathrm{LBP}^{riu2}_{8,1}+\mathrm{LBP}^{riu2}_{8,3}$	20	97.09
$\mathrm{LBP}^{riu2}_{8,1}+\mathrm{LBP}^{riu2}_{16,2}$	28	97.15
$\mathrm{LBP}^{riu2}_{8,1}+\mathrm{LBP}^{riu2}_{8,3}+\mathrm{LBP}^{riu2}_{8,8}$	30	98.11
$\mathrm{LBP}^{riu2}_{8,1}+\mathrm{LBP}^{riu2}_{16,2}+\mathrm{LBP}^{riu2}_{24,3}$	54	98.41

Table 2. Precision and Recall figures for the GLCM method and the $\mathrm{LBP}^{riu2}_{8,1}+\mathrm{LBP}^{riu2}_{8,3}$ method.

GLCM		LBP		
Prec.	Rec.	Prec.	Rec.	Class
0.964	0.976	0.984	1.000	Formal suburban
0.935	0.943	0.955	0.941	FT_Type1
0.916	0.858	0.980	0.980	FT_Type2
1.000	0.968	0.989	0.995	FTIS_Type1
0.896	0.943	0.954	0.973	FTIS_Type2
0.735	0.830	0.994	0.994	FTIS_Type3
0.960	0.950	0.942	0.942	Informal township
0.994	1.000	0.986	0.997	IS_Type1
0.974	0.956	0.996	0.973	Non-urban

The various texture feature extraction algorithms listed in Section 3 were applied to the training tiles to obtain a set of labeled feature vectors for each algorithm. The discrimination ability of each texture feature extraction algorithm was then assessed by training a support vector machine (libSVM [13]) to classify the labeled feature vectors.

5. DISCUSSION OF RESULTS

The values reported in Table 1 are the overall classification accuracy values obtained using 10-fold cross-validation, and should therefore be indicative of performance on unseen data. From the table it is clear that the methods that produce only a 1-dimensional feature vector performed very poorly. It would appear that Moran's I, Geary's C and the G index fail to capture the complex patterns present in urban settlements. Surprisingly, the fractal dimension estimate produced by the TPSA algorithm also performed quite poorly, delivering the second worst result. Only the Lacunarity measure stands apart from the other methods yielding 1-dimensional feature vectors, although its performance is still quite poor. A second performance group contains only the DWT; this method is the next most complex method in terms of the dimensionality of its feature vector, and its performance is significantly better than any of the simpler methods.

The third performance group contains the Granulometric, GLCM and LBP methods; all these methods can be considered to be effective. Although the most complex LBP method (with dimension 54) produced the best overall classification accuracy, it does so at a higher computational cost, and an unnecessarily high-dimensional feature vector. In contrast, the performance of the LBP method with dimension 20 produced an accuracy of 97%, with a significantly shorter feature vector. It would appear that the LBP method is relatively insensitive to the number of sampling points measured at distances greater than 1 pixel for this particular settlement classification problem; the $\text{LBP}_{8,1}^{\text{riu2}}$+$\text{LBP}_{16,2}^{\text{riu2}}$ combination performed only slightly better than the $\text{LBP}_{8,1}^{\text{riu2}}$+$\text{LBP}_{8,3}^{\text{riu2}}$ combination.

A more detailed look at the classification results for the GLCM and $\text{LBP}_{8,1}^{\text{riu2}}$+$\text{LBP}_{8,3}^{\text{riu2}}$ methods is presented in Table 2. For the sake of brevity, only the precision and recall statistics are shown, rather than the full confusion matrix. The GLCM method performed very well on most classes, but appears to have problems in separating the FT_Type2 from the FTIS_Type3 class. In contrast, the LBP method appears to perform more consistently across all the classes, but one should keep in mind that the GLCM method performs very well considering its shorter feature vector.

6. CONCLUSION

Similar to the results obtained by Pesaresi [2], it was found that some of the texture features were able to separate the different urban settlement classes very well. In addition, it appears that the LBP features are more powerful than the commonly used GLCM features for this particular problem, if one can justify the increase in the dimensionality of the feature vector.

Future work will focus on the development of a mapping application, considering both direct mapping via classification followed by Markov-random field regularisation, as well as a segmentation followed by classification approach.

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