Extended Local Binary Pattern Features for Improving Settlement Type Classification of QuickBird Images

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Abstract—Despite the fact that image texture features extracted from high-resolution remotely sensed images over urban areas have demonstrated their ability to distinguish different classes, they are still far from being ideal. Multi-resolution gray-scale and rotation invariant texture classification with Local Binary Patterns (LBPs) have proven to be a very powerful texture feature. In this paper we perform a study aiming to improve the performance of the automated classification of settlement type in high resolution imagery over urban areas. That is, we combined the LBP method based on recognizing certain patterns, termed “uniform patterns” with the rotational invariant variance measure that characterises the contrast of the local image texture, then combined multiple operators for multiresolution analysis. The results showed that the joint distribution of these orthogonal measures improve performance over urban settlement type classification. This shows that variance measure (contrast) is an important property when classifying settlement types in urban areas.

I. INTRODUCTION

Rapid and massive growth of population and migration to urban areas results in a rapid and random spread of formal and informal physical infrastructure. Effective and regular monitoring of this spread of infrastructure is vital in delivering basic engineering services such as water, sewerage and solid waste removal, and providing essential services such as health and education. For a successful monitoring system, an effective detection method of this infrastructure is crucial. Traditional methods such as census, gathering demographic data, and mapping using samples are impractical and unsatisfactory for urban management [1]. However, using remote sensing tools an automated system can be used as a detection tool of physical infrastructure [2]. Using high resolution imagery (e.g., QuickBird, a high-resolution commercial earth observation satellite), texture feature algorithms have been shown to be effective in detecting and describing settlement types in urban areas [3].

In a study to compare texture algorithms in urban settlement classification, the Local Binary Pattern (LBP) texture feature algorithm proved to be most effective in classifying the low-income and informal settlement types [4]. A 2-D surface texture has two properties, spatial structure (pattern) and contrast (“amount of texture”). The LBP is simple to compute and by definition is gray scale invariant, that is, it neglects contrast properties which makes the LBP algorithm an excellent measure for spatial structures. However, due to viewing- and illumination-geometry effects, the LBP algorithm was shown to offer less than ideal generalization performance [3]. For settlement classification one would think neglecting the contrast measure would improve performance, but this does not appear to be the case for generalization performance. Contrast may have a significant effect in the classification of settlements.

Ojala [5] showed that combining spatial structure with the gray level contrast can improve performance in classifying texture features. In an attempt to improve performance for urban settlement classification, we apply this theory and evaluate the significance of contrast in urban settlement classification. The proposed algorithm uses the same rotational gray scale and rotational invariant LBP and combines it with a rotational invariant Variance measure which characterises the contrast.

In this paper (using Van den Bergh’s [3] work on cross-date imagery for comparative results), we show that adding the rotational invariant variance measure to the gray-scale and rotational invariant LBP improves performance. The performance of the extended LBP algorithm then depends on the number of bins (features) used to calculate the Variance measures.

Section 2 briefly discusses prior and related urban settlements classification algorithms, and a brief derivation of the algorithms used. Section 3 discusses the experimental procedure i.e., extraction of the input images, LBP features extraction, extended LBP feature extraction and classification of the settlement types. Results with discussion are discussed in section 4, followed by conclusions in section 5.

II. PRIOR AND RELATED WORK

Image texture analysis methods have been broadly divided into three categories: statistical methods (here a texture image is described by a collection of statistics of the selected feature, e.g., Co-occurrence Matrix), model based methods (a texture
image is modeled as a probability model or as a linear combination of a set of basis functions, e.g., Wavelet transform [6] and Markov model [7]) and structural based methods (a texture image is viewed as consisting of many textural elements called texels, arranged according to some placement rules, e.g., Morphological Profiles [8]) [9].

In urban area images structural based methods have been shown to be successful in setting apart different settlement types [2]. The LBP (structural method) appeared to be most effective when compared to other known texture algorithms (e.g. Gray-level Co-occurrence Matrix (GLCM), Granulometries and Discrete Wavelet Transform (DWT)) [4]. The LBP was used for cross-date Quickbird image (Soweto, located in Gauteng, South Africa as study area) urban settlement type classification and the results were not as impressive due to effects of varying viewing- and illumination geometry of satellite images [3].

The cross-date images study [3] involved the classification of two scenes of the same area acquired under different conditions. The images were acquired at different times of the year, which altered the orientation and length of the shadows. An ideal texture feature is one that is insensitive to such changes whilst being sensitive to settlement type. The addition of a contrast component to the LBP features does not directly effect the desired invariance to shadow orientation and length, but it is expected that the richer features will nevertheless improve settlement classification accuracy. The same data set (Soweto case study) will be used as basis for comparison with the extended LBP algorithm.

The extended LBP is a joint distribution of gray-scale and rotational invariant LBP with the rotational invariant Variance measure. We do not go into detail in the derivation of the algorithms but only report the equations used. The full derivations can be found in [5].

A. Gray-Scale and Rotational Invariant Local Binary Patterns

LBP features are then calculated using the rotational invariant LBP with “uniform patterns” (uniform circular structures, illustrated in figure 2b):

\[
LBP_{P,R}^{\text{riu2}} = \begin{cases} 
\sum_{p=0}^{P-1} s(g_p - g_c) & \text{if } U(LBP_{P,R}) \leq 2 \\
0 & \text{otherwise}
\end{cases}
\]

where

\[
U(LBP_{P,R}) = \frac{1}{P+1} \sum_{p=0}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| + \sum_{p=0}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)|.
\]

U(“pattern”) is a uniformity measure, which corresponds to the number of spatial transitions in the “pattern” and superscript (riu2) is rotation invariant “uniform” binary patterns that have a U value of at most 2.

B. Rotational Invariant Variance Measures

Local gray level variance can be used as a contrast measure and can be derived as follows:

\[
\text{VAR}_{P,R} = \frac{1}{P} \sum_{p=0}^{P-1} (g_p - \mu)^2, \text{ where } \mu = \frac{1}{P} \sum_{p=0}^{P-1} g_p.
\]

\text{VAR}_{P,R} is invariant against shifts in gray scale and rotation along the circular neighbourhood.

To improve performance of the LBP we consider its joint distribution with the local variance denoted as

\[
\frac{LBP_{P,R}^{\text{riu2}}}{\text{VAR}_{P,R}}
\]

III. EXPERIMENT

The data consisted of two QuickBird images over the Soweto area: one acquired on 2005-10-18 (early summer, rain season, called d1), and another on 2006-05-30 (early winter, called d2) [3]. QuickBird is a sun-synchronous polar-orbiting remote sensing satellite with a panchromatic sensor with a 0.6 m ground sampling distance. This high resolution band, together with four multispectral bands at 2.4 m resolution, makes QuickBird ideal for urban monitoring. The study area contains a large variety of formal and informal settlements. Four settlement types are investigated: formal suburbs(FS), formal settlements with backyard shacks (FSB), ordered informal settlements (OIS), and a non-built-up (NBU) class to represent vegetation and bare areas. Figure 1 provides some samples of what these settlement classes look like.

The experimental procedure was as follows:

1) Extract input images

Two QuickBird images (Panchromatic images with a resolution of 0.6 m) over the same area at different times with different viewing- and illumination geometries were acquired. From each image, polygons containing examples of different settlement types were extracted, from which multiple non-overlapping examples of each type were extracted. From each polygon, square tiles (120 m × 120 m) from random locations entirely within the demarcated polygons were extracted. Tiles were
paired, so that the same location is extracted from both dates (images) [3].

2) **Extract LBP features**

We construct regular circular neighbourhoods with $P \ (P > 1)$ image pixels and radius $R \ (R > 0)$, with the coordinates of the gray values $g_P$ being $(-R \sin (2\pi p/P)),(R \cos (2\pi p/P))$ at $g_c(0,0)$. Gray values that do not fall exactly in the centre pixel are estimated by interpolation, see figure 2a. From the circular neighbourhood we measure the LBPs using equation 3. We construct a look-up table that contains all the uniformity measures corresponding to the number of image pixels used, see figure 2b. Using the look-up table LBPs with uniform patterns are extracted. Uniformity measures $U$ with the value of at most 2 are stored as uniform patterns with bin labels ($0 \rightarrow P - 1$) while the non-uniform patterns are stored as bin label ($P + 1$), where bins $0 \rightarrow P - 1$ correspond to a texture feature from equation 5, see figures 2b and 2c.

3) **Extended LBP features extraction**

Using the circular neighbourhoods as mentioned above we calculate the Variance measure using equation 6. Since Variance measures have continuous outputs, quantization is needed. The bin breaks are constructed such that they are evenly spaced according to the variance percentiles, that is, by adding up all the feature distributions for every single model image in a total distribution and using $R^1$ we calculate the bin breaks for different number of bins ($3 \rightarrow 20$ bins in this case). We then constructed a simple 2D joint distribution histogram i.e LBP/VAR for each bin size for different $P$ and $R$ values. Multiresolution features are obtained by simply concatenating LBP features extracted at multiple radii ($R$ parameter in equations 4 and 6).

4) **Training (Subset A) and Testing (Subset B)**

We determine the generalization performance for the different texture features algorithms by evaluating the
A more detailed comparison of the LBP and extended LBP with multiresolution is reported in table II, where we can clearly see the effects of adding the variance measures, bin sizes, and multiple resolutions. In all cases the LBP$^{\text{ran2}}$ / VAR$^{\text{P,R}}$ features outperform the LBP$^{\text{ran2}}$ features. The performance drastically improves with the increase of bin sizes (3–6) but then fluctuates slightly as the number of bins are increased. Table II also shows a slight improvement from LBP$^{\text{ran2}}$ / VAR$^{\text{P,R}}$ (8,1) to LBP$^{\text{ran2}}$ / VAR$^{\text{P,R}}$ (8,1 + 16,2) but for LBP$^{\text{ran2}}$ / VAR$^{\text{P,R}}$ (8,1 + 16,2 + 24,3) we observe slightly higher increase on accuracies. On all the figures in figure 4 we observed a peak around bin 7, and as the number of bins increased the performance was not meaningfully better. We then took bin 7 as the optimum number of bins and
Fig. 4. Boxplots showing the overall performance(%) for $\text{LBP}^{\text{riu2}}_{P,R}$ (LBP) and $\text{LBP}^{\text{riu2}}_{P,R}/\text{VAR}_{P,R}$ (Bins) over same date and cross date imagery with multiresolution data sets (b) and (c).

investigated its accuracies in terms of per-class true positive (TP) rate (see table III). It is clear that the performance of the algorithm is depended on the settlement type, where we see that for formal settlements with backyard shacks (FSB) and non-built up (NBU) classes the TP values are much higher than those of formal settlements (FS) and ordered informal settlements (OIS) classes. The standard deviations for $A_{d1} \equiv B_{d2}$ are high in all cases except for the NBU class where its standard deviation is high at $A_{d1} \equiv A_{d2}$. Table III also reveals that 100% classification accuracy was attained for certain classes, which is too good to be true, and calls for further investigation of the algorithms with a larger data set.
**TABLE II**

A sample of the results in Figure 4 in table format, where the highest performance is highlighted in each data set.

<table>
<thead>
<tr>
<th>Data set</th>
<th>LBP_{P,R}^{\mathbb{R}^2}</th>
<th>LBP_{R_{1,2}}^{\mathbb{R}^2} \over \mathbb{R}^2_{1,2}</th>
<th>\text{Accuracy}(%)</th>
<th>TP(%)</th>
<th>TP(%)</th>
<th>TP(%)</th>
<th>TP(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A_{d1} \iff B_{d1}</td>
<td>92.44 (1.185)</td>
<td>93.91 (1.507)</td>
<td>95.09 (0.708)</td>
<td>95.83 (0.814)</td>
<td>95.36 (1.658)</td>
<td>95.75 (0.932)</td>
<td>95.53 (1.537)</td>
</tr>
<tr>
<td>A_{d1} \iff A_{d2}</td>
<td>78.48 (3.610)</td>
<td>84.80 (5.675)</td>
<td>93.30 (0.864)</td>
<td>92.81 (1.982)</td>
<td>93.89 (1.259)</td>
<td>92.85 (1.891)</td>
<td>93.67 (1.453)</td>
</tr>
<tr>
<td>A_{d1} \iff B_{d2}</td>
<td>71.44 (15.932)</td>
<td>81.09 (3.921)</td>
<td>90.06 (1.745)</td>
<td>85.68 (5.302)</td>
<td>88.89 (1.909)</td>
<td>85.50 (5.274)</td>
<td>87.02 (3.251)</td>
</tr>
<tr>
<td>B_{d1} \iff B_{d2}</td>
<td>78.44 (14.956)</td>
<td>79.81 (1.549)</td>
<td>87.89 (6.545)</td>
<td>88.08 (6.537)</td>
<td>87.70 (7.207)</td>
<td>88.42 (6.309)</td>
<td>88.25 (6.814)</td>
</tr>
<tr>
<td>A_{d2} \iff B_{d1}</td>
<td>75.90 (3.820)</td>
<td>82.45 (5.730)</td>
<td>90.79 (3.757)</td>
<td>91.29 (3.227)</td>
<td>90.11 (4.327)</td>
<td>89.82 (4.720)</td>
<td>90.20 (4.571)</td>
</tr>
<tr>
<td>A_{d2} \iff B_{d2}</td>
<td>91.99 (2.149)</td>
<td>95.22 (3.294)</td>
<td>98.33 (1.656)</td>
<td>98.00 (2.053)</td>
<td>98.01 (2.027)</td>
<td>98.08 (1.946)</td>
<td>97.73 (2.257)</td>
</tr>
</tbody>
</table>

**TABLE III**

Overall classification accuracy for multiresolution LBP_{P,R}^{\mathbb{R}^2}/VAR_{P,R} at lowest bin size that yields optimum performance.

<table>
<thead>
<tr>
<th>PR</th>
<th>Bins</th>
<th>Data set</th>
<th>Overall Accuracy(%)</th>
<th>FS TP(%)</th>
<th>FSB TP(%)</th>
<th>OIS TP(%)</th>
<th>NBU TP(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>7</td>
<td>A_{d1} \iff B_{d1}</td>
<td>95.782 (1.584)</td>
<td>87.170 (12.486)</td>
<td>96.330 (3.662)</td>
<td>96.060 (4.370)</td>
<td>100.00 (0.000)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A_{d1} \iff A_{d2}</td>
<td>94.061 (0.885)</td>
<td>82.255 (20.412)</td>
<td>98.910 (0.485)</td>
<td>86.870 (3.202)</td>
<td>95.895 (4.277)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A_{d1} \iff B_{d2}</td>
<td>89.658 (0.798)</td>
<td>76.580 (24.491)</td>
<td>97.615 (0.767)</td>
<td>65.725 (3.179)</td>
<td>99.900 (0.205)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B_{d1} \iff B_{d2}</td>
<td>87.194 (7.533)</td>
<td>79.032 (20.347)</td>
<td>94.340 (3.273)</td>
<td>62.645 (37.457)</td>
<td>99.950 (0.154)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A_{d2} \iff B_{d1}</td>
<td>91.641 (3.418)</td>
<td>79.412 (19.230)</td>
<td>95.675 (3.214)</td>
<td>82.310 (15.862)</td>
<td>97.905 (2.224)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A_{d2} \iff B_{d2}</td>
<td>98.029 (2.050)</td>
<td>96.817 (5.791)</td>
<td>99.985 (0.067)</td>
<td>90.085 (10.299)</td>
<td>100.00 (0.000)</td>
</tr>
</tbody>
</table>

| 8+16 | 7   | A_{d1} \iff B_{d1} | 96.643 (1.343) | 88.608 (10.171) | 95.365 (3.387) | 99.380 (0.763) | 100.00 (0.000) |
|      | A_{d1} \iff A_{d2} | 95.24 (0.898) | 91.088 (12.430) | 99.175 (0.505) | 85.685 (5.515) | 96.220 (3.924) |
|      | A_{d1} \iff B_{d2} | 93.680 (2.471) | 83.285 (18.089) | 94.890 (1.558) | 87.390 (10.179) | 99.900 (0.205) |
|      | B_{d1} \iff B_{d2} | 92.882 (1.954) | 82.093 (16.429) | 96.550 (0.839) | 84.915 (14.865) | 99.950 (0.154) |
|      | A_{d2} \iff B_{d1} | 94.572 (1.676) | 80.125 (18.795) | 98.275 (1.166) | 91.720 (7.774) | 98.350 (1.913) |
|      | A_{d2} \iff B_{d2} | 99.054 (0.987) | 96.537 (5.980) | 99.850 (0.199) | 97.255 (2.874) | 100.00 (0.000) |

| 8+16+24 | 7 | A_{d1} \iff B_{d1} | 97.765 (0.476) | 90.170 (10.245) | 98.650 (1.402) | 99.080 (1.123) | 100.00 (0.000) |
|         | A_{d1} \iff A_{d2} | 94.312 (1.702) | 83.343 (17.415) | 99.090 (1.800) | 82.685 (14.843) | 97.100 (3.007) |
|         | A_{d1} \iff B_{d2} | 93.842 (2.980) | 76.737 (22.774) | 98.735 (1.323) | 85.930 (14.559) | 99.950 (0.154) |
|         | B_{d1} \iff B_{d2} | 96.107 (0.904) | 85.737 (18.993) | 97.970 (0.683) | 95.630 (3.977) | 99.975 (0.112) |
|         | A_{d2} \iff B_{d1} | 95.398 (0.482) | 83.028 (18.519) | 98.530 (1.249) | 92.940 (2.316) | 99.470 (0.983) |
|         | A_{d2} \iff B_{d2} | 98.995 (1.047) | 95.340 (7.982) | 99.665 (0.367) | 98.440 (1.693) | 100.00 (0.000) |

V. CONCLUSION

This paper presented a settlement classification experiment involving two scenes of the same area, acquired under different conditions, including seasonal changes in vegetation and the length and orientation of shadows cast by the buildings. The results indicate that adding the rotational invariant variance measure to the rotational and gray-scale invariant LBP does improve performance in classifying settlement types in urban areas. We can then conclude that contrast properties are significant in the task of classifying settlement type. Some differences remain between the classification performance in same-date experiments vs cross-date experiments; this is not entirely unexpected, since the addition of the contrast features is unlikely to provide robust invariance to the influence of
shadows. The good news, however, is that the gap between same-date and cross-date classification performance closed somewhat with the addition of contrast features, rather than widen.

Improvements to image features that result in better classifier generalization performance brings us one step closer towards operational implementation of a fully automated settlement type classification system. Once such a system has achieved adequate classification accuracy, the goal of automated change detection in urban areas is within reach.

REFERENCES


