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Original

A comparative study of the use of local directional pattern for texture-based informal settlement classification

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Abstract

In developing and emerging countries progression of informal settlements has been a fast growing phenomenon since the mid-1990s. Half of the world's population is housed in urban settlements. For instance, the growth of informal settlements in South Africa has amplified after the end of apartheid. In order to transform informal settlements to improve the living conditions in these areas, a lot of spatial information is required. There are many traditional methods used to collect these data, such as statistical analysis and fieldwork; but these methods are limited to capture urban processes, particularly informal settlements are very dynamic in nature with respect to time and space. Remote sensing has been proven to provide more efficient techniques to study and monitor spatial patterns of settlements structures with high spatial resolution. Recently, a new feature method, local directional pattern (LDP), based on kirsch masks, has been proposed and widely used in biometrics feature extraction. In this study, we investigate the use of LDP for the classification of informal settlements. Performance of LDP in characterizing informal settlements is then evaluated and compared to the popular gray level co-occurrence matrix (GLCM) using four classifiers (Naive-Bayes, Multilayer perceptron, Support Vector Machines, *k*-nearest Neighbor). The experimental results show that LDP outperforms GLCM in classifying informal settlements.

Keywords: Informal settlements; Texture features; Gray level co-occurrence matrix; Local directional pattern; Classification

1. Introduction

In developing countries, informal settlements have become a phenomenon which grow very fast specially in the 21st Century. Half of the world's population is housed in urban settlements. The reason for this phenomenon is the immigration of people from the rural areas to the cities. Many previous studies aimed at extracting houses outline to quantify shape-based features of informal settlements. Object-based image analysis (OBIA) method estimates the size, spacing and shape of the houses by extracting the houses footprint (Blaschke & Lang, 2006). OBIA partitions remote sensing (RS) imagery into meaningful image-objects and assesses their characteristics through spatial, spectral and temporal scale (Hay & Castilla, 2008). Previous studies on geospatial methods have been used to estimate populations and to distinguish the human settlements. For example, a study by Aminipouri, Sliuzas, and Kuffer (2009) estimates the population by creating an accurate inventory of buildings. The computer vision community is facing a very complex and challenging task extracting the spatial data from informal settlements. Constructions in informal settlements are built using various materials and are very close to each other and have no suitable organization. It makes the classification of informal settlements images an uphill task (McLaren, Coleman, & Mayunga, 2005). A number of researchers have tried to develop tools and techniques to characterize the informal settlements areas from remotely sensed data. Mayunga, Coleman, and Zhang (2007) present a new semi-automatic approach to extract buildings from informal settlements images obtained using Quick Bird. Snackes and radial casting algorithm were used to map the informal settlements images. The main limitation in this study is the difficulty of characterizing small houses. Khumalo, Tapamo, and Van Den Bergh (2011) applied two feature methods, Gabor filters and GLCM to distinguish different textural regions in Soweto area (Johannesburg, South Africa). They found Gabor filters more

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accurate than GLCM in classifying informal settlements. A study carried out by

Ella, Van Den Bergh, Van Wyk, and Van Wyk (2008) compared gray level co-occurrence (GLCM) and local binary pattern (LBP) in their ability to classify urban settlement. It is shown that both methods performed very well with a superior performance for LBP. Van Den Bergh (2011) investigates the powers of two features methods, GLCM and LBP, to classify Soweto (Johannesburg, South Africa) areas. It is established that the performance of the gray level co-occurrence matrix is superior to the local binary pattern on a combined spatial and temporal generalization problem, but the LBP features perform better on spatial-only generalization problems. In Owen and Wong (2013) an analysis is conducted on the shape, texture, terrain geomorphology and road networks to characterize the informal settlements and formal neighborhoods in Latin America. The results achieved were promising when finite data were used to recognize informal settlements. Asmat and Zamzami (2012) introduced an automated house detection technique to extract legal and illegal settlements in Pulau Gaya, Saba. The result shows that the edge to edge features can separate between houses that are less than 2 m away from each other. In Graesser et al. (2012), an investigation of nine statistics methods (GLCM PanTex, Histogram of Oriented Gradients, Lacunarity, Line Support Regions, Linear Feature Distribution, Psuedo NDVI, Red-blue NDVI, Scale Invariant Feature Transform, and TEXTONS) is presented with different direction, structure size and shape and tested in four different cities. The GLCM PanTex, LSR, HoG and TEXTON features were found to be the best in characterizing the informal settlements and formal areas. A new feature method, local directional pattern (LDP), based on the known Kirsch kernels was recently proposed by Jabid, Kabir, and Chae (2010a). LDP has mainly been applied in biometrics: face recognition (Jabid, Kabir, & Chae, 2010b), signature verification (Ferrer, Vargas, Travieso, & Alonso, 2010) and facial expression recognition (Jabid, Kabir, & Chae, 2010c). In Shabat and Tapamo (2014) the powers of GLCM and LDP to characterize texture images are compared; the result shows that LDP outperforms GLCM. In this paper, GLCM and LDP are investigated using different numbers of significant bits; the final goal is to identify the most effective amongst them. The computation of the local directional pattern is based on the number of significant bits, and in this work four alternative values are considered: 2, 3, 4, 5 instead of 3 as in the classic LDP.

2. Materials and methods

In the following sections the different feature methods used the in the paper are presented

2.1. Gray level co-occurrence matrix (GLCM)

In the early 1970s Haralick, Shanmugam, and Dinstein (1973) proposed the extraction of fourteen features, from the GLCM of a gray level, to characterize the image texture. The computation of GLCM depends on two parameters: the orientation θ formed by the line-segment connecting the two considered pixels, and the distance (d)[number of pixels] between them. The direction θ is usually quantized in 4 directions (horizntal – 0°, diagonal - 45°, vertical – 90°, anti-diagonal – 135°).

To compute the gray-level co-occurrence matrix of a window in an image, the following parameters are considered:

- The window size, $N_x \times N_y$, where N_x is the number of rows and N_y the number of columns.
- Distance (d) and directions θ.
- And the range of gray values to consider in calculations $0, \ldots, G-1$.

We adopt the formulation used in Bastos, Liatsis, and Conci, 2008 and Eleyan and Demirel (2011) to present the calculation of GLCM. The GLCM is defined as the probability of occurrence of two gray levels at a given offset (with respect to given distance and orientation). Given the image I, of size $N_x \times N_y$, the value of the co-occurrence for the gray values i and j, at the distance (d) and direction θ, $P_{d,\theta}(i, j)$ can be defined as

$$P_{d,\theta}(i, j) = \sum_{x=0}^{N_x-1} \sum_{y=0}^{N_y-1} \delta_{d,\theta,i,j}(x, y) \tag{1}$$

Where

$$\delta_{d,\theta,i,j}(x, y) = \begin{cases} 1 & \text{if } I(x, y) = i \text{ and } I(x + \pi_x(d, \theta), y + \pi_y(d, \theta)) = j \\ 0 & \text{otherwise} \end{cases}$$

The offset $(\pi_x(d, \theta), \pi_y(d, \theta))$ is used to compute the position of (x, y) with respect to its neighbor at the distance ($\underline{d}$) and direction θ. For the 4 directions (0°, 45°, 90°, and 135°) and the offsets are given in Table 1.

2.1.1. Haralick's features

Given an image I with G gray levels, an angle θ and a distance (d), after the gray level co-occurrence matrix, $(P_{d,\theta}(i, j))_{0 \leq i,j \leq G-1}$, number of features can be extracted, amongst which the most popular are the 14 Haralick features (energy or angular second moment (ENR), contrast (CON), correlation (COV), variance (VAR), inverse different moment (IDM), sum average (SAV), sum variance (SVA), sum entropy (SEN), entropy (ENT), difference variance (DIV), difference entropy (DEN), information measures of correlation (IMC1, IMC2), maximum correlation coefficient (MCC)). The computation of Haralick features is done using a normalized GLCM. The $(i, j)th$ normalized entry,

Table 1
Definition of different offsets.

θ	0°	45°	90°	135°
$\pi_x(d, \theta)$	0	$-d$	$-d$	$-d$
$\pi_y(d, \theta)$	d	d	0	$-d$

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