TEXTURE CHARACTERIZATION IN REMOTE SENSING IMAGERY USING BINARY CODING TECHNIQUES

M. Musci [a] , R. Q. Feitosa [a, *] , M. L. F. Velloso [b], T. Novack [c], G. A. O. P. Costa [a]

[a] Pontifical Catholic University of Rio de Janeiro – PUC-Rio - (musci, raul, gilson)@ele.puc-rio.br
[b] Rio de Janeiro State University – UERJ - mlfv@centroin.com.br
[c]National Institute for Space Research – INPE - tessio@dsr.inpe.br

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ABSTRACT:

In this paper rotation invariant *Local Binary Patterns* (LBP) texture based descriptors are evaluated experimentally in the context of land-use and land-cover object-based classification. The texture descriptors were employed in the classification of an Ikonos-2 and a Quickbird-2 image. The experiments have shown that texture characterization approaches perform well when combined with the grayscale variance. We further investigate a novel descriptor resulting from the concatenation of the grayscale variance histogram and the histogram of codes generated by LBP. These experiments have demonstrated that the proposed descriptor, though more compact, performs as well as a bidimensional histogram representing the joint distribution of both quantities. Finally, the paper compares the discrimination capacity of the LBP based textural descriptors with that of features derived from the Gray Level Co-occurrence Matrices (GLCM). The related experiments revealed a noteworthy superiority of LBP descriptors over the GLCM features in the context of remote sensing image data classification.

1. INTRODUCTION

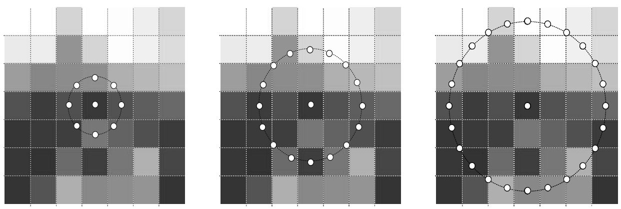
Among the numerous texture descriptors proposed for image classification thus far, the features derived from the Gray Level Co-occurrence Matrix (GLCM) are by far the most widely used by the remote sensing (RS) community. A method for texture description based on Local Binary Patterns (LBP) has more recently been used with great success in various applications, such as facial recognition and visual inspection (Mäenpää et al., 2003). LBP have been used predominantly on image segmentation, for example, (Wang, A., Wang, S., Lucieer, 2010; Orkhonselenge, 2004; Lucieer, Stein, Fisher, 2005). Even rarer are publications on classification of RS images using LBP to characterize texture. An exception is the work of Song, Yang and Li (2010), which tests LBP on a mosaic of RS images, but the evaluation is restricted to synthetic images only.

The general objective of this study is to evaluate the performance of the LBP texture descriptor in more representative conditions of real RS applications. Specifically, in this work we applied LBP in the classification of very high spatial resolution images, following the GEOBIA paradigm.

The study is conducted upon a land-cover and a land-use classification problem, having Ikonos-2 and Quickbird-2 images as inputs. In the experiments, LBP is compared to descriptors based on Gray-Level Co-occurrence Matrices (GLCM).

2. LBP TEXTURE DESCRIPTORS

The LBP code associated to a pixel at $\mathbf{w} = (x,y)$ is computed from a set of P equally spaced samples over a circle of radius R centered at that pixel, as illustrated in Figure 1. From the intensities g_p ($0 \leq p < P$) of the P samples and the intensity g_c of the central pixel a sequence of P binary values $T_P = \{S(g_0 - g_c), S(g_1 - g_c),...,S(g_{P-1} - g_c)\}$ is computed, where S is the *sign* function, which takes the value 0 (zero) when the argument is negative and 1 (one) otherwise.



P=8, R=1 P=16, R=2 P=24, R=3

Figure 1. LBP computation for different P and R.

A simple mapping procedure converts the bit sequence T_P into a non negative integer value. Ojala et al. (2002) demonstrated empirically that only the T_P sequences containing no more than two 0 to 1 or 1 to 0 transitions are relevant for texture characterization. By imposing rotation invariance to these sequences, a texture coding ($LPB_{P,R}$) comes about, which is given by the number of 1's in the sequence. A special additional code is created for T_P sequences having more than two transitions 1 to 0 or 0 to 1. Formally:

$$LBP_{P,R}(\mathbf{w}) = \begin{cases} \sum_{p=0}^{P-1} S\left(g_p - g_c\right) & \text{for up to 2 transitions} \\ P+1 & \text{otherwise} \end{cases} \quad (1)$$

Thus, $LPB_{P,R}$, may take up to $P+2$ distinct values, which represent the gray level spatial distribution (texture) in a neighborhood of a given pixel. Clearly, $LPB_{P,R}$ is invariant to monotonic gray-scale changes. A multi-scale texture representation can be built by considering more than one $LPB_{P,R}$ code generated with multiple P and R values.

* Corresponding autor

Since the LBP descriptors are invariant to monotonic gray scale changes and, they do not capture contrast information. Ojala and co-authors (2002) propose a local contrast descriptor, denoted henceforth as $VAR_{P,R}$, which is also rotation invariant, defined as:

$$VAR_{P,R}(\mathbf{w}) = \frac{1}{P}\sum_{p=0}^{P-1}\left(g_p - \mu\right), \qquad (2)$$

where $\mu = \frac{1}{P}\sum_{p=0}^{P-1} g_p$. $VAR_{P,R}$ is an approximation of local variance, that can be computed efficiently if performed concurrently with the computation of $LBP_{P,R}$. The so called $VAR_{P,R}$ image is built by replacing each image pixel by its corresponding $VAR_{P,R}$ code.

In (Ojala et al. 2002) the texture of an image segment is described by a two dimensional histogram representing the joint distribution of $LBP_{P,R}$. and $VAR_{P,R}$ codes inside the segment. Analogously, each object class can be described by two dimensional model histogram of the $LBP_{P,R}$ and $VAR_{P,R}$ binary codes computed upon a set of segment samples belonging to the class being modelled. The comparison between the segment and the model texture is carried out by measuring the similarity between the corresponding histograms. In most of these studies the *G* statistic (Sokal and Rohlf, 1987), defined in equation (3), was used for the similarity measure between two histograms.

$$G(f_1, f_2) = 2\begin{bmatrix} \sum_{i=1}^{B} f_1(i)\log f_1(i) + \sum_{i=1}^{B} f_2(i)\log f_2(i) + \\ -\left(\sum_{i=1}^{B} f_1(i)\right)\log\left(\sum_{i=1}^{B} f_1(i)\right) + \\ -\left(\sum_{i=1}^{B} f_2(i)\right)\log\left(\sum_{i=1}^{B} f_2(i)\right) + \\ -\sum_{i=1}^{B}\left(\left(f_1(i)\right) + f_2(i)\right)\log\left(f_1(i) + f_2(i)\right) + \\ \left(\sum_{i=1}^{B} f_1(i) + \sum_{i=1}^{B} f_2(i)\right)\log\left(\sum_{i=1}^{B} f_1(i) + \sum_{i=1}^{B} f_2(i)\right) \end{bmatrix} \qquad (3)$$

where f_1 and f_2 are the segment and model histograms respectively, and *B* is the number of *bins* in f_1 and f_2. It can be easily verified that *G* is always non negative and approaches zero as the histograms being compared become more similar.

3. EXPERIMENTAL ANALYSIS

Two experiments were conducted aiming at the evaluation of the texture descriptors considered in this study.

The objective of the first experiment is to evaluate the classification accuracy associated with the descriptors $LBP_{P,R}$ and $VAR_{P,R}$, and estimate the gain from combining them into a single descriptor. The experiment also evaluates the loss of accuracy brought by concatenating histograms of $LBP_{P,R}$ and $VAR_{P,R}$, forming a one-dimensional histogram as an alternative to two-dimensional histogram representing the joint distribution of $LBP_{P,R}$ and $VAR_{P,R}$.

The objective of the second experiment is to compare the LBP-based descriptors with descriptors derived from the GLCM, the most widely used by the RS community to characterize textures. In this case, a Support Vector Machine (SVM) (Cortes and Vapnik, 1995) instead of the *G* statistic was used for classification, mainly due to its generally good performance and low demand for training samples (Huang *et al.*, 2002; Bazi and Melgane, 2006; Pal and Foody, 2010).The first experiment explores land use and the second land cover classification.

As the primary objective of the study was not to maximize the accuracy of classification, but to compare the performance associated with each descriptor, we chose in all experiments to classify the test images based solely on texture attributes. Most likely the inclusion of spectral or morphological attributes would lead to higher performances, on the other hand, it would imply an increase in the complexity of the classification stage.
The value of parameters *P* and *R* in the LBP; the gray levels number; the distance and orientation used in the construction of co-occurrence matrix, impact the classification accuracy. The optimum values of these parameters are related to the size of periodic structures that ultimately characterizes the textures. The scale of interest is therefore crucial. Thus, the parameters of each approach should be adjusted for each particular application, which in most cases requires some experimentation.

The programs used in the experiments for the calculation of LBP and VAR were obtained from University of Oulu (Oulu, 2011). The implementation of SVM was obtained in (Chang and Lin, 2001). To calculate the attributes derived from the GLCM functions available in MATLAB (Mathworks, 2009) were used.

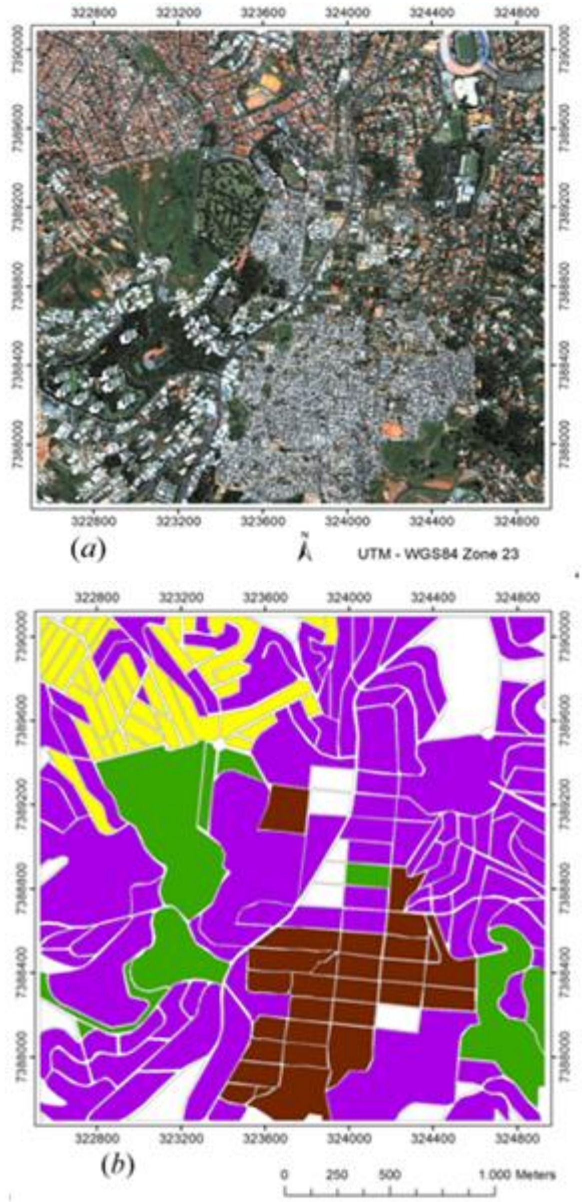
3.1 Study Areas

3.1.1 Area 1 – Land Use: Subset of a Quickbird-2 sensor image, panchromatic band, size 4000 × 4000 pixels, captured on March 31, 2002 covering an area of the city of São Paulo (coordinates North / East 322464/7389053 South / West 324872/7386671, projection UTM-SAD69). Figure 2(a) shows a color composite covering the test area.

The urban blocks layer was obtained in vector format directly from the official Urban Planning Agency of São Paulo. The land-use classes of concern are: *High standard horizontal housing, High standard residential buildings, Low standard residential housing, Slum areas* and *Unoccupied plots*. Due to the high similarity among the classes *High standard horizontal housing* and *High standard residential buildings*, we opted to merge them into a single class named hereafter *High standard horizontal or vertical residential areas*. Figure 2(b) shows the reference land-use classification of the area, which was also provided by the São Paulo Urban Planning Agency (PMSP, 2009). Table 1 indicates the number of urban blocks of each class according to the official records.

3.1.2 Area 2 - Land Cover: Ikonos-2 sensor image, panchromatic band, size 2800 × 2000 pixels, captured on May 30, 2010, covering an area of the city of Rio de Janeiro (coordinates North / South 7471911 / 669457 and East / West 7453904 / 688804, UTM-SAD 69 , WGS 1984), with size 2800 × 2000 pixels.

Figure 3a shows a color composite covering the test area (within the yellow polygons). The test area was segmented using the commercial system Definiens Developer (Definiens, 2009) and the resulting segments were manually classified by an independent group of photo-interpreters working in the framework of the PIMAR Project (PIMAR, 2010). The reference map produced is shown in Figure 3b, and it contains three classes: *Grass*; *Forest*; and *Urban*. Table 3 provides additional information about the reference data.

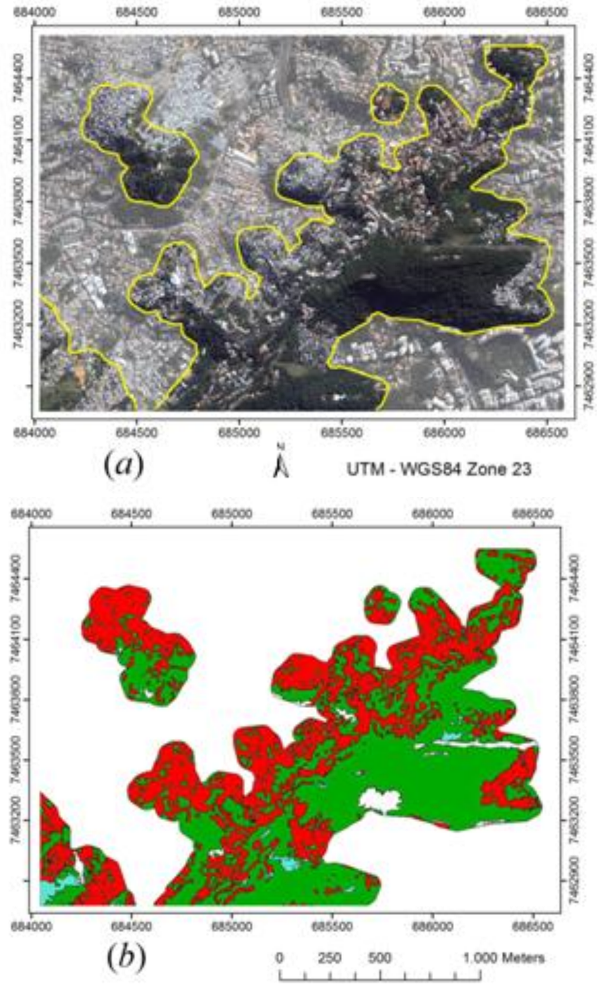


High standard horizontal or vertical areas | Slum areas
Low standard residential housing | Unoccupied plots

Figure 2. Quickbird-2 image used for land-use classification (*a*) and the corresponding land-use map (*b*).

Table 1. Number of blocks of each land-use class in experiment 1

Land-use class	Number of urban blocks
Slum areas	25
High standard horizontal or vertical residential areas	101
Unoccupied plots	8
Low standard residential housing	42



Grass type vegetation | Forested areas | Urban areas

Figure 3. Ikonos-2 image of the study site in Rio de Janeiro (*a*); land-use map (*b*).

Table 2. Number of segments assigned of each land-use class in experiment 2.

Land-cover classes	Number of segments
Grass type vegetation	5
Forested areas	57
Urban areas	26

3.2 Experiments

3.2.1 Experiment 1 – The contribution of contrast: This experiment aimed at assessing the relative performance of texture descriptors derived from $LPB_{P,R}$ e $VAR_{P,R}$ for RS image classification. Specifically, four descriptors are evaluated:

a) the $LPB_{P,R}$ histogram,
b) the $VAR_{P,R}$ histogram,
c) the histogram resulting from the concatenation of $LPB_{P,R}$ and $VAR_{P,R}$ histograms, and
d) the bi-dimensional histogram that represents the joint distribution of $LPB_{P,R}$ / $VAR_{P,R}$.

We have investigated the classification accuracy associated to $LPB_{P,R}$ and to $VAR_{P,R}$ separately (configurations *a* and *b*), as well as the improvement brought by combining them into a single descriptor (configurations *c* and *d*). The experiment also investigated if the concatenation of both $LPB_{P,R}$ and $VAR_{P,R}$ histograms (configuration *c*) is a proper replacement in terms of performance for the bi-dimensional histogram representing the joint distribution $LPB_{P,R}$ / $VAR_{P,R}$. Configuration *c* constitutes a descriptor proposed in this work. In all cases the $VAR_{P,R}$ values were quantized in 8 levels. Classification was based on the *G* statistic (equation 3).

Table 3 presents the Kappa values recorded for both applications and study areas considering only single scale versions of the texture descriptors. Table 4 shows the histogram length in each case.

For $LPB_{P,R}$ used individually, the Kappa index ranged from 0.69 to 0.81 and from 0.53 to 0.79 for study areas 1 and 2, respectively. The best and worst indexes were achieved with different combinations of *P* and *R*, in both applications. For instance, while (*P*,*R*) = (8,1) delivered the worst Kappa value for test site 1, its performance was near the maximum observed for test site 2 (Kappa = 0.78). The results indicate that the optimal setting of *P* and *R* may have an important impact in classification accuracy. It is worth mentioning that the best results in our experiments were obtained with *P* equal to 8 or 16 and with *R* between 2 and 3, which is consistent with other studies on LBP (Ojala *et al.* 2002).

In contrast, the choice of *P* and *R* did not affect substantially the performance associated to $VAR_{P,R}$. Notice that the indexes in the VAR columns of table 3 for both study areas are in most cases superior or slightly inferior to the best performance recorded for $LPB_{P,R}$ alone, although the $VAR_{P,R}$ histogram is shorter (8 bins) than the $LPB_{P,R}$ histogram (10 bins).

Table 3. Kappa indexes for single scale texture descriptors given by different combinations of $LPB_{P,R}$ and $VAR_{P,R}$.

P,R	**Kappa index**							
	Study Area 1				**Study Area 2**			
	LBP	***VAR***	***LBP+VAR***	***LBP/VAR***	**LBP**	**VAR**	**LBP+VAR**	***LBP/VAR***
8,1	0.69	0.81	0.81	0.83	0.78	0.72	0.83	0.83
8,2	0.76	0.79	0.90	0.89	0.79	0.77	0.85	0.86
8,3	0.79	0.77	0.88	0.90	0.65	0.82	0.86	0.86
16,2	0.81	0.80	0.84	0.86	0.78	0.77	0.91	0.87
16,3	0.81	0.77	0.87	0.88	0.78	0.84	0.86	0.86
24,3	0.81	0.76	0.88	0.86	0.76	0.77	0.82	0.83
24,5	0.78	0.68	0.86	0.85	0.53	0.77	0.74	0.77

Table 3 also reveals that the combined descriptors $LPB_{P,R}$+$VAR_{P,R}$, and $LPB_{P,R}$/$VAR_{P,R}$ consistently outperformed $LPB_{P,R}$ and $VAR_{P,R}$. In our experiments both combinations brought in average an absolute improvement of 0.10 to the Kappa index for both study areas, which is a significant performance gain considering automatic RS image classification. Again, these results are consistent with (Ojala *et al.* 2002).

Table 4. Histogram bins length of differents *P* and *R*.

P,R	**#bins**			
	LBP	***VAR***	***LBP+VAR***	***LBP/VAR***
8,1	10	8	18	80
8,2	10	8	18	80
8,3	10	8	18	80
16,2	18	8	26	144
16,3	18	8	26	144
24,3	26	8	34	208
24,5	26	8	34	208

It should be noted that both combined descriptors – $LPB_{P,R}$+$VAR_{P,R}$ and $LPB_{P,R}$/$VAR_{P,R}$ – achieved similar performances. Thus the descriptor $LPB_{P,R}$+$VAR_{P,R}$, proposed in this work preserved the information contained in $LPB_{P,R}$/$VAR_{P,R}$ that was relevant for class discrimination in both test applications. Additionally, Table 4 shows that the $LPB_{P,R}$+$VAR_{P,R}$ descriptor is significantly more compact than the bi-dimensional version $LPB_{P,R}$/$VAR_{P,R}$. Thus, this novel descriptor has the potential to simplify the classifier design, to reduce the demand for training samples and to improve the classifier generalization capacity.

To close this section, it must be noticed that no significant performance difference has been observed in our experiments between corresponding single and multi-scale versions of LBP descriptors.

3.2.2 Experiment 2 – Comparing $LPB_{P,R}$ and GLCM: The objective of this experiment was to compare the descriptors based in LBP with features derived from GLCM.

To make the descriptors comparable, the same classifier design should be applied for all descriptors. Clearly, the *G* statistic does not qualify for that purpose since the GLCM features are not treated as histograms. So, in this experiment we elected a SVM, working in *one-against-all* mode for all classifications, due to its generally good performance in dealing with large numbers of features.

Single scale variants of LBP combined or not with the contrast information have also been investigated. Different configurations for the GLCM computation have been considered, specifically, the number of image gray levels ($N_g \in \{128, 64, 32, 16\}$) and the distance ($d \in \{1, 2, 3\}$) characterizing the position operator. In all cases, co-occurrence matrices of four orientation angles ($\theta \in \{0°, 45°, 90, 135°\}$) were computed for each segment. Different statistics were calculated for each GLCM, bringing about four feature vectors, which were then averaged to form a single texture descriptor. Of the 14 statistics originally proposed by Haralick *et al.* (1973) for generating texture features from GLCM, only a sub-set is used in practice. Among them, entropy, energy, homogeneity, contrast and correlation are probably the most widely used (Petrou and Sevilla, 2006). In addition to them, we also used dissimilarity, variance and shade to describe textures in our experiment, as they are also quite frequently used in RS applications (Clausi and Zhao, 2002; Morales *et al.*, 2003; Liu *et al.*, 2006).

Table 5 shows the measured Kappa values. Figure 4 shows the best and the worst values obtained for each descriptor and reveals a clear superiority of LBP in comparison to GLCM descriptors.

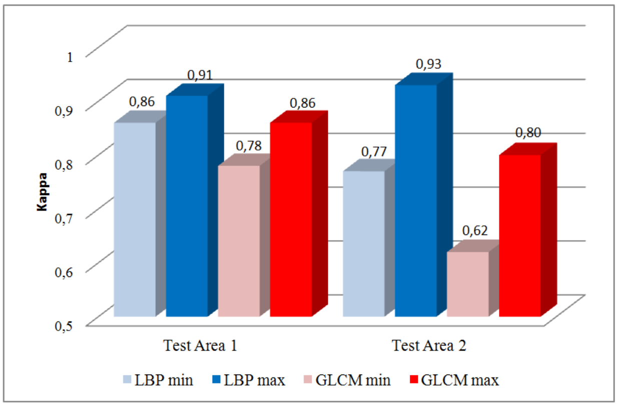


Figure 4. Kappa index for LBP and GLCM descriptor in both test areas.

Table 5. Kappa index obtained with SVM for (*a*) $LPB_{P,R}+VAR_{P,R}$ and (*b*) GLCM.

P,R	**Kappa index for *LPB+VAR***	
	Study Area 1	**Study Area 2**
8,1	**0.86**	0.86
8,2	0.89	**0.93**
8,3	0.89	**0.93**
16,2	0.90	**0.93**
16,3	0.87	0.89
24,3	0.86	0.89
24,5	**0.91**	**0.77**

(*a*)

N_g,*d*	**Kappa index for GLCM features**	
	Study Area 1	**Study Area 2**
16,1	0.80	**0.66**
16,2	0.78	0.68
16,3	**0.78**	**0.66**
32,1	**0.84**	0.75
32,2	0.82	0.73
32,3	0.82	0.78
64,1	**0.84**	**0.82**
64,2	0.80	0.77
64,3	0.82	0.67
128,1	**0.84**	0.77
128,2	0.81	0.75
128,3	0.82	0.68

(*b*)

The discrimination capacity of each descriptor can be evaluated by inspecting the maximum and minimum values measured in each case. For study area 1, 0.91 was the maximum value obtained with LBP, while the maximum performance achieved with GLCM was 0.86. For study area 2 the maximum Kappa index values was 0.93 for LBP, whereas the maximum values obtained with GLCM was 0.80. It is meaningful that the best result with GLCM for test site 1 (Kappa = 0.86) was close to the worst results measured with LBP (Kappa = 0.86). A similar behavior was observed for study area 2.

The observed superiority of LBP over GLCM descriptors is noteworthy, especially considering that they occur around high values of Kappa index. Furthermore, these results suggest that the parameter setting is more critical for GLCM (N_g, *d* and θ) than for LBP (*P* and *R*).

4. CONCLUSION

In this paper descriptors based on *Local Binary Patterns* (LBP) for texture characterization in very high resolution satellite images have been investigated. Different single descriptor variants have been tested on Ikonos-2 and Quickbird-2 images for land-cover and land-use classification.

The experiments corroborated the results found in other studies, wherein the discrimination capacity of LBP substantially increased when they are combined with the contrast information.

This paper proposed a novel texture descriptor that results from concatenating the histogram of a texture binary code and the histogram of a local variance estimate, as a replacement for the bi-dimensional histogram that represents the joint distribution of binary codes and local variance.

The experimental analysis demonstrated that the proposed descriptor, although more compact, preserved the discrimination capacity of bi-dimensional histograms.

Finally, the paper compared the LBP descriptors with textural features derived from the Gray Level Co-occurrence Matrix, which are the textural descriptors most commonly used by the Remote Sensing community. The experiments revealed a noteworthy superiority of LBP descriptors over the GLCM features.

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