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Assessment of Binary Coding Techniques for Texture Characterization in Remote Sensing Imagery

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***Abstract*—This paper investigates the use of rotation invariant descriptors based on *Local Binary Patterns* (LBP) and *Local Phase Quantization* (LPQ) for texture characterization in the context of land-cover and land-use classification of Remote Sensing (RS) optical image data. Very high resolution images from the IKONOS-2 and Quickbird-2 orbital sensor systems covering different urban study areas were subjected to classification through an object-based approach. The experiments showed that the discrimination capacity of LBP and LPQ descriptors substantially increased when combined with contrast information. This work also proposes a novel texture descriptors assembled through the concatenation of the histograms of either LBP or LPQ descriptors and of the local variance estimates. Experimental analysis demonstrated that the proposed descriptors, though more compact, preserved the discrimination capacity of bi-dimensional histograms representing the joint distribution of textural descriptors and contrast information. Finally, the paper compares the discrimination capacity of the LBP and LPQ-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 and LPQ descriptors over the GLCM features in the context of RS image data classification.**

***Keywords*— Feature Extraction, Texture, Local Binary Pattern, Urban Land Use/Land Cover, Classification.**

I. Introduction

With the advent of very high resolution (VHR) satellite imagery (up to 1 m pixels) since the late 1990s the interest for object based image analysis (OBIA), also know by the acronym GEOBIA (for Geographic Object Based Image Analysis), has increased all over the word. Traditional pixel based classification methods do not perform well for VHR images mainly due to the high within class variability of spectral features. Essentially, OBIA consists of two main steps: segmentation, which partitions the image in homogeneous regions or objects; and classification of the objects obtained in the segmentation step. Both segmentation and classification are guided by criteria based on the image objects' features. Among those features, the ones related to texture are particularly relevant, as shown in a number of applications, such as crop recognition, land-use and land-cover classification of urban areas, forest mapping, extraction of road networks, to name just a few.

Moreover, among the numerous texture descriptors proposed in the literature thus far, the features derived from the Gray Level Co-occurrence Matrix (GLCM) [1] are by far the most widely used by the RS community. More recently, a new texture descriptor based on Local Binary Patterns (LBP), proposed in [2], achieved a remarkable success in face recognition applications [3].

However, there are few published studies on the use of LBP in RS applications, most of which are related solely to segmentation [4], [5], [6]. An exception is the study of Song et al. [7], which tests LBP on a mosaic of RS images. The reported results are also encouraging, but the analysis was limited to synthetic images.

Following LBP's success, a new method for texture representation also based on local binary codes was proposed in [8]. The method, known as Local Phase Quantization (LPQ), outperformed LBP in some face recognition applications [9]. However, to our knowledge there is no published study about the use of LPQ for texture description in RS image classification.

The present paper aims at assessing LBP and LPQ texture descriptors in real RS applications following the OBIA paradigm for automatic VHR image analysis. Specifically, the analysis involve two parts: firstly we evaluate different rotation invariant LBP and LPQ descriptors and their combination with contrast information and, secondly we compare the best rated LBP and LPQ descriptor configurations with textural features derived from GLCM. The study is conducted upon a land-cover and a land-use classification problem using IKONOS-2 and Quickbird-2 images. The paper further investigates a novel textural descriptor, which combines the information carried by local binary codes with contrast information.

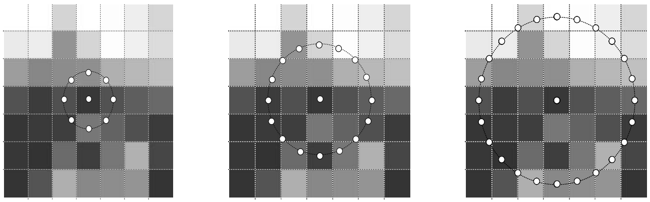
The paper is organized as follows. Section 2 presents succinctly the LBP and LPQ texture coding techniques as well as the subjacent classification strategy. Section 3 describes the experiments carried out in this study and discusses the results. Finally, in section 4 we summarize our findings.

II. Binary texture coding and classification

This section provides an overview about the texture coding and classification techniques investigated in this work. Publications containing a detailed description of those techniques are cited in the following.

A. LBP Texture Coding

The LBP code associated to a pixel at **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 Fig. 1. From the intensities g_p ($0 \le p < P$) 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*

Fig. 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 and co-authors 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 [2]. By imposing rotation invariance to these sequences, a texture coding ($LBP_{P,R}$) comes about, which is given by the number of 1's in the sequence. 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, $LBP_{P,R}$, may take up to $P+2$ distinct values, which represent the gray level spatial distribution (texture) in a neighborhood of a given pixel. Clearly, $LBP_{P,R}$ is invariant to monotonic gray-scale changes.

A multi-scale texture representation can be built by considering more than one $LBP_{P,R}$ code generated with multiple *P* and *R* values.

B. LPQ Texture Coding

LPQ is a descriptor conceived originally to outperform LBP in applications dealing with images affected by blurring or by non uniform illumination. As in LBP, a code is computed for each pixel position, which represents the texture within the $M \times M$ pixel neighborhood $N_\mathbf{w}$, centered in **w**, as shown in Fig. 2(a).

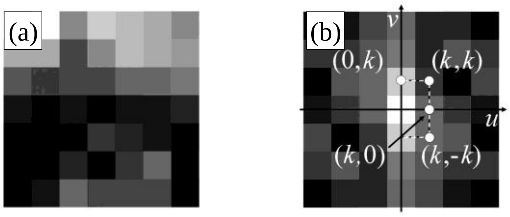


Fig. 2 The neighborhood N_w (A) and the corresponding Fourier spectrum (B).

Phase quantization takes into account only the sign of the real and imaginary components of the Fourier transform $\mathbf{F}_w(\mathbf{u})$, $\mathbf{u}$ = (u, v), in four values close to the origin of the frequency space, specifically (0,*k*), (*k*,*k*), (*k*,0) and (*k*,-*k*), as indicated by the white circles in Fig. 2(b), where $k = M^{-1}$. The eight bits generated this way are grouped into a binary code that represents the texture in $N_\mathbf{w}$. This procedure is executed for each pixel, producing the so called LPQ_M image, where $M \times M$ is the neighborhood size.

The method further includes a simple procedure that decorrelates the Fourier coefficients before the quantization step. A detailed description of the LPQ texture coding technique can be found in [10].

A rotation invariant LPQ variant is also proposed by Ojansivu et al. [11]. It involves a preliminary step that computes the angle corresponding to the so called local characteristic orientation. The neighborhood is rotated by this angle before the LPQ codes are computed. This yields a rotation invariant binary number that represents the texture in $N_\mathbf{w}$. Texture representation in multiple scales can be obtained by computing LPQ_M for different values of *M*.

C. VAR Texture Coding

The LBP descriptors are invariant to monotonic gray scale changes and, consequently do not capture the contrast information. Ojala et al. [2] propose a local contrast descriptor, denoted henceforth as $VAR_{P,R}$, which is also rotation invariant, defined as:

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

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 $LBP_{P,R}$.

D. Texture Similarity Metric

The texture of an image segment can be described by a normalized histogram of the binary codes associated to the pixels inside the segment. Analogously, each object class can be described by a specific model histogram of the binary codes computed upon a set of segment samples belonging to the class being modeled. The comparison between the segment and the model texture is carried out by measuring the similarity between the corresponding histograms. Most related works use the *G* statistic [12] for that purpose, which is given by equation (3).

$$G(f_1, f_2) = 2\left[\begin{array}{c} \sum_{i=1}^{B} f_1(i)\log f_1(i) + \sum_{i=1}^{B} f_2(i)\log f_2(i) - \left(\sum_{i=1}^{B} f_1(i)\right)\log\left(\sum_{i=1}^{B} f_1(i)\right) + \\ -\left(\sum_{i=1}^{B} f_2(i)\right)\log\left(\sum_{i=1}^{B} f_2(i)\right) + \sum_{i=1}^{B}\left(\left(f_1(i)\right) + f_2(i)\right)\log\left(f_1(i) + f_2(i)\right) + \\ \left(\sum_{i=1}^{B} f_1(i) + \sum_{i=1}^{B} f_2(i)\right)\log\left(\sum_{i=1}^{B} f_1(i) + \sum_{i=1}^{B} f_2(i)\right) \end{array}\right] \quad (3)$$

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.

III. EXPERIMENTAL ANALYSIS

This section describes the procedures and results of three experiments that aimed at the evaluation of the texture descriptors considered in this study.

A. Study Areas

1) Area 1 – Land-use Classification: This experiment aimed at classifying the land-use of a section of the city of Sao Paulo (Brazil), considering the urban blocks as the analysis units. For that purpose, a 0.6 m resolution, panchromatic image from the QuickBird-2 sensor was used. The image was captured on March 2002 and has 4000×4000 pixels. Fig. 3(A) shows a color-composite of the image. The urban blocks layer was obtained in vector format directly from the official Urban Planning Agency of São Paulo. Fig. 3(B) shows the reference land-use classification of the area.

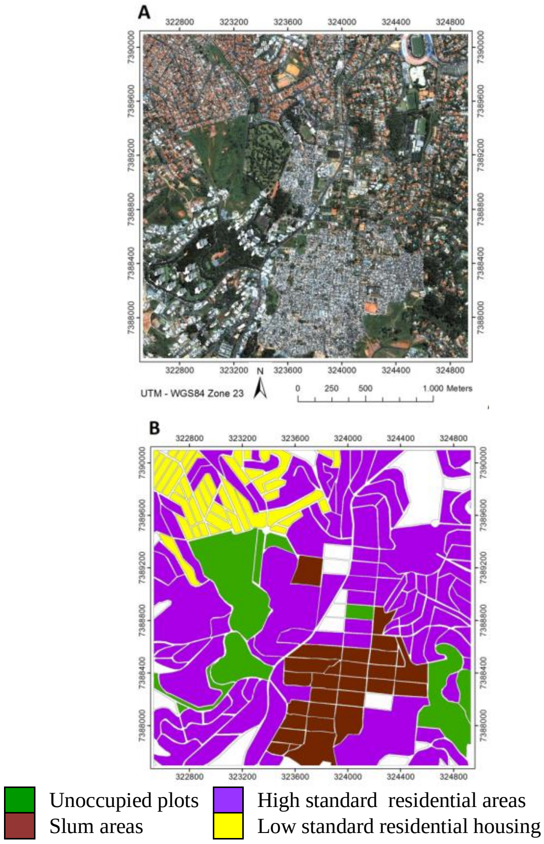


Fig. 3 Image used for land-use classification (A) and the land-use map (B)

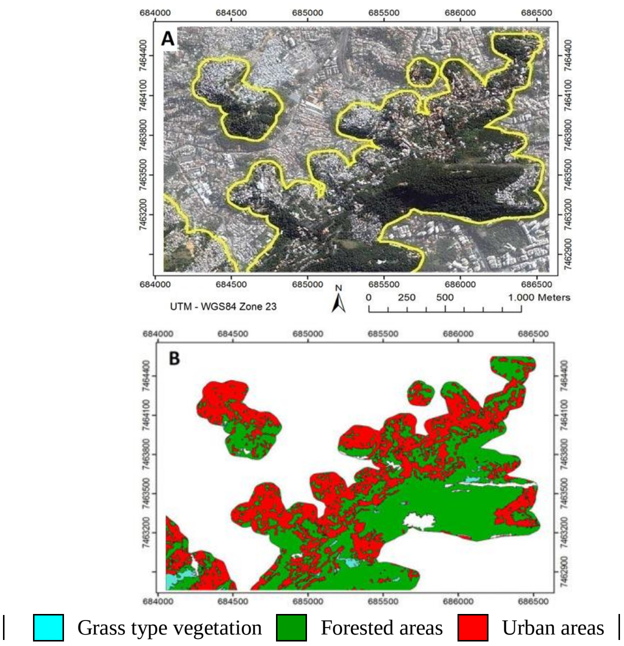


Fig. 4 Image used for land-cover classification (A) and land-use map (B)

2) Area 2 – Land-cover Classification: A second problem addressed in our experiments consisted on the land-cover classification of a section of the city of Rio de Janeiro (Brazil). A 1m resolution, panchromatic image from the IKONOS-2 sensor was used for that purpose. The image was captured on May 2010 and has 2800×2000 pixels.

Fig. 4(A) shows a color-composite of the image. The whole area was segmented using the commercial system Definiens Developer and the resulting segments were manually classified. The land-cover map obtained this way was used as reference data and it is shown in Fig. 4(B).

B. *Experiments*

The objective of this analysis is to assess the relative performance associated to textural descriptors, rather than maximizing recognition rates. Thus, we decided to use only texture features for object description although the inclusion of spectral and shape features in addition to texture would probably lead to higher performances. A number of combinations of P and R values for $LBP_{P,R}$ and $VAR_{P,R}$ descriptors, as well as different window sizes (M×M) for LPQ_M have been considered in our experiments.

1) The contribution of contrast: This experiment aimed at assessing the relative performance of texture descriptors derived from $LBP_{P,R}$ e $VAR_{P,R}$ for RS image classification. Specifically, four descriptors are evaluated: the $LBP_{P,R}$ histogram, the $VAR_{P,R}$ histogram, the histogram resulting from the concatenation of $LBP_{P,R}$ and $VAR_{P,R}$ histograms, and the bi-dimensional histogram that represents the joint distribution of $LBP_{P,R}$ / $VAR_{P,R}$.

So, we investigated the classification accuracy associated to $LBP_{P,R}$ and to $VAR_{P,R}$ separately, as well as the improvement that may be brought by combining them into a single descriptor. The experiment also investigated if the concatenation of both $LBP_{P,R}$ and $VAR_{P,R}$ histograms is a proper replacement in terms of performance for the bi-dimensional histogram representing the joint distribution $LBP_{P,R}$ / $VAR_{P,R}$. The concatenation of both $LBP_{P,R}$ and $VAR_{P,R}$ histograms 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 1 presents the Kappa values recorded for both applications and study areas. The results indicate that the optimal setting of P and R is not only application dependent, but 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 [2].

Table 1 also reveals that the combined descriptors $LBP_{P,R}$+$VAR_{P,R}$, and $LBP_{P,R}$/$VAR_{P,R}$ consistently outperformed $LBP_{P,R}$ 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 for automatic RS image classification. Again, these results are consistent with [2].

Furthermore, it should be noted that both combined descriptors – $LBP_{P,R}$+$VAR_{P,R}$ and $LBP_{P,R}/VAR_{P,R}$ – achieved similar performances. Thus the descriptor $LBP_{P,R}$+$VAR_{P,R}$, proposed in this work preserved the information contained in $LBP_{P,R}/VAR_{P,R}$ that was relevant for class discrimination in both test applications. Additionally, the $LBP_{P,R}$+$VAR_{P,R}$ descriptor is much more compact than the bi-dimensional version $LBP_{P,R}/VAR_{P,R}$. 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.

TABLE I
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

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.

2) Variants of LPQ_M : The purpose of this experiment was to compare LPQ_M descriptor separately or combined with the contrast information. As in previous experiments, contrast information was given by $VAR_{P,R}$. The results reported in this section correspond to the (P,R) combinations among {(8,1), (8,2), (16,2), (16,3)}, which produced the highest Kappa value. Once again, the G statistic was used for classification.

In this analysis we did not test descriptors representing the joint distribution of LPQ_M and $VAR_{P,R}$ because it would involve very large histograms (in our case, 2550 *bins*), what would be impractical under our test conditions as in most real applications. Thus, the analysis tested only the LPQ_M individually and concatenated with $VAR_{P,R}$.

The results for both study areas using LPQ_M and $VAR_{P,R}$ are shown in Table 2. The Kappa values ranged from 0.65 to 0.74 for study area 1 and from 0.74 and 0.86 for study area 2 when LPQ_M was used independently. Recalling table 1, the Kappa indexes for $LBP_{P,R}$ varied between 0.69 and 0.81 for the study area 1 and between 0.53 and 0.79 for study area 2.

The analysis of the results obtained when both $LBP_{P,R}$ and LPQ_M techniques were combined with the contrast information ($VAR_{P,R}$) leads to a similar conclusion. It is noteworthy that the Kappa index varied within similar ranges for LPQ_M+$VAR_{P,R}$ and for $LBP_{P,R}$+$VAR_{P,R}$ in both study areas.

In sum, a comparison with the $LBP_{P,R}$ showed that the higher computational complexity associated to the LPQ_M descriptors is not directly compensated by corresponding benefits in terms of performance.

TABLE II
KAPPA INDEXES FOR SINGLE SCALE TEXTURE DESCRIPTORS GIVEN BY DIFFERENT COMBINATIONS OF LPQ_M AND $VAR_{P,R}$

M	Kappa Index			
	Study Area 1		Study Area 2	
	LPQ	LPQ+VAR	LPQ	LPQ+VAR
3	**0.74**	0.87	0.82	**0.91**
5	**0.74**	**0.92**	**0.86**	**0.91**
7	0.65	0.89	0.74	0.86
9	0.67	0.89	**0.86**	0.84

3) Comparing $LBP_{P,R}$, LPQ_M and GLCM: In the experiments reported in the preceding sections the better tradeoff between performance and computational complexity was achieved by the descriptor $LBP_{P,R}$+$VAR_{P,R}$ followed by LPQ_M+$VAR_{P,R}$. The objective of this final experiment was to compare these descriptors with features derived from GLCM, which is widely used for texture characterization in RS image classification.

To make the descriptors comparable, the same classifier design should be applied for all descriptors to avoid possible bias introduced by different classification algorithms. Clearly, the G statistic does not qualify for that purpose since the GLCM features do not take the form of 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 and LPQ 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.* [1] 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. 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.

Fig. 5 shows the best and the worst values obtained for each descriptor and reveals a clear superiority of LBP and LPQ in comparison to GLCM descriptors. 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 and 0.93 were the maximum values obtained with LBP and LPQ respectively, while the maximum performance achieved with GLCM was 0.86. For study area 2 the maximum Kappa index values were 0.93 and 0.89, respectively for LBP and LPQ, whereas the maximum values obtained with GLCM was 0.80. It is meaningful that the study area 1 (Kappa = 0.86) is close to the worst results measured with LBP and LPQ, 0.86 and 0.85, respectively. A similar behavior is observed for study area 2.

The lowest results for each descriptor for both study areas are equally inferior for GLCM in comparison to LBP and LPQ. For study area 1, 0.78 was the minimum value for GLCM, and 0.86 and 0.85 respectively for LBP and LPQ. Similarly, for the study area 2 the minimum Kappa value observed for GLCM was 0.62, while the Kappa index was never inferior to 0.77 and 0.80 for LBP and LPQ respectively. Therefore, the observed superiority of LBP and LPQ over GLCM descriptors is remarkable, especially considering that they occur around high values of Kappa index.

To close this section, we would like to point out that the results obtained with SVM and with the *G* statistic do not differ substantially for the LBP and LPQ descriptors, which we believe supports the use of the classification approach, wherein segments are described by feature vectors that encompass the LBP or LPQ histogram values along with other non textural features.

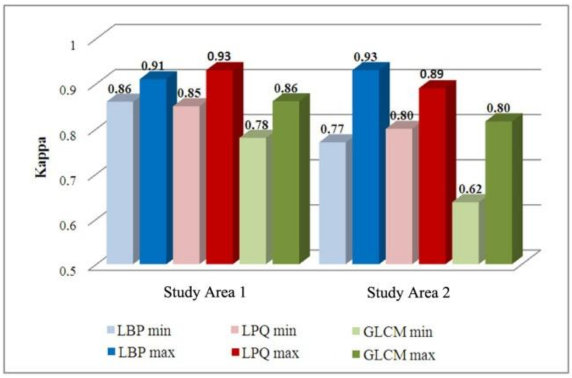


Fig. 5 Kappa index for LBP, LPQ and GLCM descriptor in both study areas

IV. Conclusions

In this paper descriptors based on *Local Binary Patterns* (LBP) and *Local Phase Quantization* (LPQ) for texture characterization in very high resolution satellite images have been investigated. Different 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 and LPQ 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 (either LBP or LPQ) and the histogram of a local variance estimate.

The experimental analysis demonstrated that the proposed descriptor, in spite of being more compact, preserved the discrimination capacity of bi-dimensional histograms that represent the joint distribution of binary codes and local variance.

Furthermore, no significant performance difference has been observed in our experiments between corresponding single and multi-scale versions of LBP and LPQ descriptors.

In contrast to works where LBP and LPQ have been used in face recognition, the performances associated to both descriptors were very close in our tests. This means that the higher complexity involved in the computation of LPQ, as compared to LBP, did not bring a corresponding improvement in terms of recognition performance.

Finally, the paper compared the LBP and LPQ 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 and LPQ descriptors over the GLCM features.

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