A comparative study of color-texture image features

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Abstract: In this work we compare two spatial and two wavelet-domain feature extraction methods that have been proposed in the recent literature for color-texture classification. The corresponding color-texture features, namely the Opponent-Color Local Binary Pattern distributions, the Chromaticity Moments, the Wavelet Correlation Signatures and the Color Wavelet Covariance features, are extracted in RGB, $I_1I_2I_3$, HSV and CIE-Lab color spaces. The classification task is realized by Support Vector Machines. Experiments are performed on two standard datasets comprising of 54 and 68 textures from the Vistex and the Outex databases respectively. The results show that in most cases color enhances texture classification. Both spatial and wavelet features can lead to an accurate representation of color-textures. The appropriateness of a color-texture feature extraction method has to be determined by considering the trade-off between the accuracy and the feature space dimensionality needs, as these are imposed by a prospective application.

Keywords: Image Analysis, Color Texture Features, Support Vector Machines.

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1 INTRODUCTION

Color texture analysis is a major field of development for new methods concerning various vision applications. Although texture perception is not directly associated with color perception, a variety of color-texture feature extraction methods have been proposed in the literature. Recent approaches to color-texture analysis focus on the exploitation of both intra- and inter-channel information, such as the estimation of chromatic correlation features (Paschos, 1998), wavelet correlation signatures (WCS) (Van De Wouwer et al., 1999), features quantifying the correlation of Gabor features between the image color channels (Jain and Healey, 1998), correlation estimates of Zernike moments between different image color channels (Wang and Healey, 1998; Al-Rawi and Yang, 2001) distributions of Opponent Color Local Binary Pattern (OCLBP) features (Mäenpää, 2003) and Color Wavelet Covariance (CWC) features (Iakovidis et al., 2004).

The effectiveness of the wavelet transform for texture representation, has been pointed out in many studies (Iakovidis et al., 2004; Unser and Eden, 1989; Randen and Husøy, 1999). Nevertheless, many researchers still persist in supporting the use of spatial-domain features (Paschos, 1998; Mäenpää, 2003; Paschos, 2000). The issue of which approach is the best for the classification of color textures has not been thoroughly investigated in the literature. Comparative studies have focused on issues such as the enhancement introduced by the inclusion of color in texture analysis (Drimbarean and Whelan, 2001), the effect of using perceptually uniform color spaces for color texture representation (Paschos, 2001) and whether color and texture information should be considered jointly or separately (Mäenpää and Pietikäinen, 2004).

In this paper, we compare recent spatial and wavelet-domain color-texture feature extraction methods under the experimental framework described in (Ojala et al., 2002), using both Vistex and Outex textures. These include the extraction of OC-LBP, CM, WCS and CWC features. The classification task has been assigned to Support Vector Machines (SVM) as these have proved to be robust, resistant to the "curse of dimensionality". Moreover, SVMs are less empirical as regards the determination of their parameters compared to standard neural networks and they have proved to provide better generalization performance than other traditional classifiers in many applications, including the classification of textures (Li et al., 2003).

The rest of this paper is organized in three sections. Section 2 includes a brief description of the feature extraction methods compared. The experimental framework and results are presented in Section 3. Finally, Section 4 summarizes the conclusions of this study.

2 FEATURE EXTRACTION METHODS

2.1 Opponent-Color Local Binary Pattern distributions

The Local Binary Pattern (LBP) method has been proposed by Ojala and Pietikainen (1998), as a two-level version of the texture spectrum method which uses three levels (0, 1 and 2) for the representation of local texture patterns. The local binary pattern of a 3×3-pixel neighborhood is estimated as follows:

1. The original 3×3 neighborhood is thresholded to two levels (0 and 1) using the value of the center pixel.
2. The values of the pixels in the thresholded neighborhood are multiplied by certain weights assigned to the corresponding pixels.
3. The values of the eight pixels are summed to obtain a single value for the corresponding pattern.

The LBP feature vectors are formed by the histogram bins of the LBP values distribution in an image region. LBP is usually combined with a contrast measure which is defined as the difference between the average intensity of "1" pixels and the average intensity of "0" pixels (LBP/C features).

An extension of the LBP method for color images, named OC-LBP, has been proposed by Mäenpää (2003) and involves the application of the LBP operator on each color channel separately. In addition, each pair of color channels is used in collecting opponent color patterns so that the center pixel for a neighborhood and the neighborhood itself are taken from different color channels. In total, 3 intra-channel LBP histograms (one histogram for each color channel C_i, i = 1, 2, 3) and 6 inter-channel histograms are extracted and concatenated into a single distribution.

2.2 Chromaticity moments

The Chromaticity Moments (CMs) have been proposed by Paschos (2000) as a simple and computationally low-cost method for color texture classification. Let X, Y, Z quantities represent the XYZ color space channels. The chromaticity trace $T(x, y)$ and its distribution $D(x, y)$ for an image of L_x, L_y dimensions are defined as follows:

$$T(x,y)=\begin{cases}1, \exists(i,j): I(i,j)\rightarrow(x,y)\\ 0, else\end{cases} \tag{1}$$

$$D(x,y)=k \tag{2}$$

where $0 \le i \le L_x$, $0 \le j \le L_Y$, k = # of pixels producing (x, y). The functions $T(x, y)$ and $D(x, y)$ are characterized by a set of moments, which form the feature vector and are defined as follows:

$$M_T(m,l)=\sum_{x=0}^{Xs-1}\sum_{y=0}^{Ys-1}x^m y^l T(x,y) \tag{3}$$

$$M_D(m,l)=\sum_{x=0}^{Xs-1}\sum_{y=0}^{Ys-1}x^m y^l D(x,y) \tag{4}$$

where $p=m+l$=1, 2,… represents their order and X_S, Y_S are the discrete dimensions of the x-y space. The discrete $X_S \times Y_S$ space is produced by rescaling and discretization: $x = \lfloor 100x \rfloor$, $y = \lfloor 100y \rfloor$.

2.3. Wavelet Energy features

The Discrete Wavelet Transform (DWT) of a gray-level image is realized by convolving the image with a low pass filter L and a high pass filter H, the output of which is then sub-sampled dyadically. This procedure produces a low-resolution image $B_0(k)$ and detail images $B_j(k)$, j = 1, 2, 3 at scale k. The repetition of this filtering procedure for k = 1, 2,…K results in a multi-scale representation of the image. By omitting the sub-sampling operation, a variation of the

DWT, the Discrete Wavelet Frame Transform (DWFT) is produced. DWFT is a redundant representation that leads to a texture description tolerant to translation (Unser and Eden, 1989). The Wavelet Energy (WE) features are estimated by summing the squares of all $b^{j,k}$ coefficients of the output images $B_j(k)$, $j = 0, 1, 2, 3$:

$$E^{B_j(k)} = \sum_i b^{j,k}(i)^2 \tag{5}$$

2.4. Wavelet Correlation Signatures

The WCS have been proposed by Van De Wouwer et al. (1999) as extensions of the DWFT energy features that take into account the correlation of the wavelet coefficients between the image color channels. They are derived from the following equation:

$$WC_{C_l,C_m}^{B_j(k)} = \begin{cases} E_{C_l}^{B_j(k)} & l = m \\ \dfrac{\sum_i b_{C_l}^{j,k}(i)\ b_{C_m}^{j,k}(i)}{E_{C_l}^{B_j(k)} \cdot E_{C_m}^{B_j(k)}} & l \neq m \end{cases} \tag{6}$$

where $b_{C_l}^{j,k}$ and $b_{Cm}^{j,k}$ are the coefficients of the detail images $B_j(k)$, $j = 1, 2, 3$, $k = 1, 2, \ldots K$ of the color channels C_l and C_m, $l = 1, 2, 3$, $m = 1, 2, 3$ respectively.

2.5. Color Wavelet Covariance

The Color Wavelet Covariance (CWC) features are covariance estimates of the 2nd order statistical information inherent in the DWFT of the color channels of an image (Iakovidis et al., 2004). The image color channels are transformed to the wavelet domain by the DWFT. The 2nd-order statistical information of the wavelet coefficients is captured by means of co-occurrence matrices. Co-occurrence matrices encode the gray-level spatial dependence based on the estimation of the 2nd-order joint conditional probability density function f(i, j, d, α), which is computed by counting all pairs of pixels at distance d having gray-levels i and j at a given direction α. The angular displacement of d = 1 is included in the range of the α-values {0, π/4, π/2, 3π/4}.

Let $M_{C_i}^{B_j(k)}(a)$ be a cooccurrence matrix estimated over a detail image $Bj(k)$, $j = 1, 2, 3$, $k = 1, 2, \ldots K$, of the color channel C_i, $i = 1, 2, 3$, for a direction $\alpha \in \{0, \pi/4, \pi/2, 3\pi/4\}$. Four representative statistical features are estimated over each detail image B_j(k), $j = 1, 2, 3$, $k = 1, 2, \ldots K$, namely the angular second moment (f_1), the correlation (f_2), the inverse difference moment (f_3) and the entropy (f_4). The resulting set of features that correspond to the different color channels C_i is $F_{C_i}^{B_j(k)}(a)$, where $i = 1, 2, 3$, $j = 1, 2, 3$, $k = 1, 2, \ldots K$, $F \in \{f_1, f_2, f_3, f_4\}$ and $\alpha \in \{0, \pi/4, \pi/2, 3\pi/4\}$.

The Color Wavelet Covariance of a Feature F (CWC), between the detail images $B_j(k)$, $j = 1, 2, 3$, $k = 1, 2, \ldots K$ of color channels C_l and C_m, $l = 1, 2, 3$, $m = 1, 2, 3$ is estimated as follows:

$$CWC_{C_l,C_m}^{B_j(k)} = Cov\left(F_{C_l}^{B_j(k)}, F_{C_m}^{B_j(k)}\right),\ l \leq m \tag{7}$$

3 RESULTS

The experimental evaluation of the four color-texture feature extraction methods was performed by using two standard publicly available color-texture datasets from the Outex database. The comparative study was based on the framework proposed in (Ojala et al., 2002).

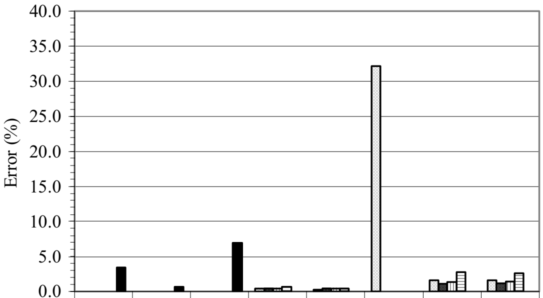
The first dataset originates from the VisTex database (Contrib_TC_00006) and consists of 54 texture images of 512×512-pixel dimensions. Each image was split into 16 non-overlapping 128×128 sub-images, forming a total of 864 samples. Half of these samples were used for training and the rest were used for testing the classification performance of an SVM classifier. The Radial Basis Function (RBF) was employed as an SVM kernel. The RBF kernel usually performs better than other non-linear kernels, such as the polynomial or the sigmoid, because it usually has a better boundary response as it allows for extrapolation, and most high-dimensional data sets can be approximated by Gaussian-like distributions similar to those used by RBF networks. Moreover it involves only one parameter, which makes it easier to search for its optimal parameters in practice.

The second dataset originates from the Outex database (Contrib_TC_00013) and it consists of 68 textures of 746×438-pixel dimensions. From each texture 20, 128×128 sub-images have been acquired. A total of 1360 samples was produced and split into a balanced training-testing dataset (Ojala et al., 2002).

The OC-LBP distribution has not been quantized, as the SVMs are tolerant to the input space dimensionality (Vapnik, 1998). The CMs were computed up to the 3rd order because only a marginal improvement was observed by the incorporation of higher-order moments. As regards the wavelet-based methods, a 4-level DWFT was applied for the extraction of WCS and WE features, whereas a 1-level DWFT was applied for CWC feature extraction. In the latter case the use of more wavelet decomposition levels would disproportionally increase the computational complexity and lead to only a marginal increase in classification accuracy. Four representative color spaces, namely the RGB, the $I_1I_2I_3$, the HSV and the CIE-Lab have been considered for color-texture feature extraction. Chromaticity moments have only been extracted from RGB images as they inherently involve the RGB to XYZ color transformation (Paschos, 2000).

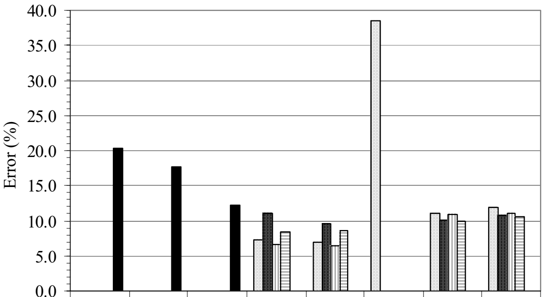
The classification results obtained for each dataset are illustrated in Fig. 1 and 2 respectively. The three leftmost columns of these figures present the performance of the corresponding gray-level features (LBP, LBP/C, WE).

All methods produce higher errors for the second dataset, as it is less diverse (Ojala et al., 2002). This also justifies the fact that the Vistex textures were classified almost perfectly even with the simple gray-level LBP/C features, resulting in only 0.7% classification error. Figure 2 shows that in most cases color-texture features perform better than gray-level features. Actually, this is not true only for the CMs, which are outperformed by all other features. However, one could argue that it might be preferable to extract 13 gray-level wavelet energies than 72 wavelet-domain color-texture features (Fig. 3), as the latter provide slightly better performance than the former for the classification of the Outex textures. This cannot be generalized as for the Vistex textures the contribution of color significantly enhances the performance of the wavelet features.



	LBP	LBP/C	WE	OC-LBP	OC-LBP/C	CM	WCS	CWC
RGB				0.5	0.2	32.2	1.6	1.6
I1I2I3				0.5	0.5		1.2	1.2
HSV				0.5	0.5		1.4	1.4
CIE-Lab				0.7	0.5		2.8	2.6
Gray Level	3.5	0.7	6.9					

Figure 1 *Classification errors obtained for the Vistex textures*



	LBP	LBP/C	WE	OC-LBP	OC-LBP/C	CM	WCS	CWC
RGB				7.3	6.9	38.5	11.1	11.9
I1I2I3				11.0	9.6		10.1	10.8
HSV				6.6	6.5		10.9	11.1
CIE-Lab				8.4	8.5		10.0	10.6
Gray Level	20.3	17.6	12.2					

Figure 2 *Classification errors obtained for the Outex textures*

Comparing the performance of the spatial OC-LBP and OC-LBP/C features with the performance of the wavelet color-texture features for both datasets, it could be concluded that the first lead to comparable or improved color texture classification accuracy regardless of the color space employed. This improvement comes with a disproportional increase of the dimensionality (Fig. 3). Moreover, the contrast feature marginally enhances the accuracy while by doubling the dimension of the OC-LBP feature vector.

Different color spaces seem to affect differently the spatial and the wavelet-domain color-texture feature extraction approaches. More specifically, the OC-LBP features work well for both RGB and HSV spaces, while the wavelet features are positively affected by the $I_1I_2I_3$ color space. The two wavelet-based approaches result in comparable classification performance.

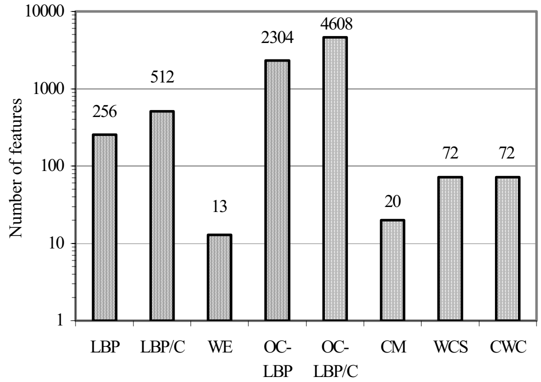


Figure 3 *Number of features feeding the SVMs for the various feature extraction methods compared*

4 CONCLUSION

We attempted a comparative evaluation of spatial and wavelet-domain color-texture features in different color spaces. The results show that color-texture features could enhance texture classification, but there are cases for which gray-level features could work as well. A major conclusion of this study is that the appropriateness of a color-texture feature extraction method has to be determined by considering the tradeoff between the accuracy and the feature space dimensionality needs, as these are imposed by a prospective application. Moreover, the choice of the color space may affect the color texture classification performance in some degree.

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