Illuminant Invariant Descriptors for Color Texture Classification

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Abstract. In this paper we present a novel descriptor for color texture analysis specially designed to deal with changes in illumination in imaging. The descriptor, that we called Intensity Color Contrast Descriptor (ICCD), is based on a combination of the LBP approach with a measure of color contrast defined as the angle between two color vectors in an orthonormal color space. The ICCD robustness with respect to global changes in lighting conditions has been experimentally demonstrated by comparing it on standard data sets against several other in the state of the art.

Keywords: Color texture classification, Illuminant invariant descriptors.

1 Introduction

Texture classification is an important computer vision problem that consists in assigning a given unknown texture to a set of known texture classes. Although a wide variety of methods have been proposed in literature, texture classification largely remains an open issue [1, 2]. Given a distance/similarity measure between textures, the success of a classification approach depends primarily on the effectiveness of the texture descriptors [2]. Due to the enormous variability of the images (e.g. variations in lighting, scale, rotation) no obvious descriptor exists for all texture classification problems [3, 2, 4].

In this paper we present the Intensity Color Contrast Descriptor (ICCD): a descriptor that combines the Local Binary Pattern approach with information related to the local color contrast of the image. For each pixel of the image the angular difference between its own color vector and the average color vector in the surrounding neighborhood is quantized to form the color contrast histogram. Being defined in terms of angular differences, the ICCD descriptor is invariant with respect to scaling and orthonormal transformations in the color space, and is therefore quite robust with respect to changes in the color and intensity of lighting.

The proposed approach has been evaluated on various image data sets collected under controlled and non-controlled acquisition conditions, and with fixed and variable illumination. Experimental results demonstrates that ICCD outperforms other descriptors in the state of the art in classifying textures images taken under variable lighting conditions.

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2 Color Texture Classification

Texture classification is usually achieved by sequencing feature extraction and classification. The performances of the classifiers mainly depend on the features [5], therefore the efforts of researchers, over the years focused on the feature extraction.

Initially the problem has been faced by considering gray-level images without taking into account color information. Then, researchers, also motivated by studies on human visual perception [6–8], have started to explicitly consider color so demonstrating that this can improve the accuracy in texture classification [9, 3].

In fact, studies on the psycho-physical properties of the human visual system have confirmed that the perception of color patterns comes from the interaction of three components processed through separate pathways [10–13]. While the first two components are processed by early visual cortical areas and are used for the extraction of color-based information, the last component comes from processing at higher level and is used for the extraction of purely texture-based information.

In computer vision, color data can be represented in different spaces, and there is no color space which is well-suited for the characterization of all kind of textures, independently on the texture descriptor adopted [3]. One way to overcome this problem is to consider multiple color spaces, or multiple feature selection methods [2].

Given a color representation of the image, associated texture features can be extracted by using one of the numerous techniques that exist in literature [14]. We can group them in four classes:

1. structural approaches. Textures are described by rules, which determine a specific arrangement of primitives textural elements (texels) [15, 16];
2. spatial-frequency or spectral approaches. Textures are represented in the frequency domain. Examples are wavelet transform, Gabor filter or discrete cosine transform [17, 18];
3. statistical approaches. Textures are considered as stochastic processes and characterized by a few statistical features [19]. Examples are co-occurrence matrices [19, 20], run-length matrix [21], sum and difference histograms [22], Markov random field models [23] or autoregressive models [24]. Methods that combine statistical and structural approaches such as local binary patterns (LBP) [3, 25];
4. fractal approaches [26]. It has been shown to be useful for modeling some natural textures [27, 28].

Whatever the color space and texture features chosen, several ways to combine color data and texture have been proposed. Following the scheme proposed in [20], we have three approaches: parallel, sequential and integrative.

The parallel approach extracts texture features from a gray scale version of the image; while color data is coded as a separate 3D histogram. In the sequential approach the color image is quantized using a clustering technique. The resulting image is subsequently processed as gray-scale texture. In the integrative approach color and texture are processed jointly performing either single- or multi-channel analysis.

As discussed above, a wide variety of solutions have been proposed in literature. Notwithstanding this, color texture classification remains an open issue. In fact, the variability to be taken into account are not only due to changes in scale, rotation, and light intensity, but also to the spectral power distribution of the light [29]. Most popular methods that cope with this problem includes the preprocessing of the image using, for example, the gray-world or Retinex normalization, or the use of illumination-invariant descriptors [30, 1]. Others methods are inspired by opponent color mechanisms in human vision [31, 32] or statistical variation in color channels [33–35].

In this work we present a novel illuminant-invariant descriptor for texture analysis mainly based on a measure of color contrast defined as the angle between two color vectors in an orthonormal color space. Such a measure has been combined in a parallel configuration with a classic texture descriptor based on the local binary pattern approach.

3 The Intensity-Color Contrast Descriptor

In this work we present a illuminant-invariant descriptor for texture analysis. The texture descriptor proposed here combines, using a parallel approach, an intensity-based feature with a local measure of the color contrast.

For the intensity information we decided to use a Local Binary Pattern descriptor [36] computed on the luminance image. After preliminary experiments, that agree with [3], we selected the $LBP^{u}_{16,2}$ operator: 16 neighbors at a distance of two pixels, uniform patterns, without rotation invariance. The distribution of the local binary patterns forms the 243-bins histogram that we used to represent intensity variations of the textures.

Concerning color, we assume that the pixels are represented by triplets $\mathbf{c} = (c_1, c_2, c_3)$ of non-negative values, and in the experiments these values will correspond to the red, green, and blue components in the RGB color space. This descriptor can be easily generalized to other color spaces. To make the descriptor robust against changes in the color of the illuminant, the local color contrast is computed in terms of angular differences between vectors in the color space. Given two vectors $\mathbf{c}_1$, $\mathbf{c}_2$, the corresponding angular difference is defined as:

$$\alpha(\mathbf{c}_1, \mathbf{c}_2) = \begin{cases} \frac{2}{\pi} \arccos \frac{\langle \mathbf{c}_1, \mathbf{c}_2 \rangle}{\|\mathbf{c}_1\| \|\mathbf{c}_2\|} & \text{if } \mathbf{c}_1 \neq \mathbf{0} \wedge \mathbf{c}_2 \neq \mathbf{0} \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where $\langle \cdot, \cdot \rangle$ denotes the inner product in the color space, and where $\| \cdot \|$ indicates the Euclidean norm. Note that $0 \leq \alpha \leq 1$ because the vectors have non-negative components. The local contrast is obtained by measuring the angular difference between the color of the pixel $\mathbf{c}(i, j)$ at the location i, j and the average normalized color $\overline{\mathbf{c}}(i, j)$ of its neighborhood:

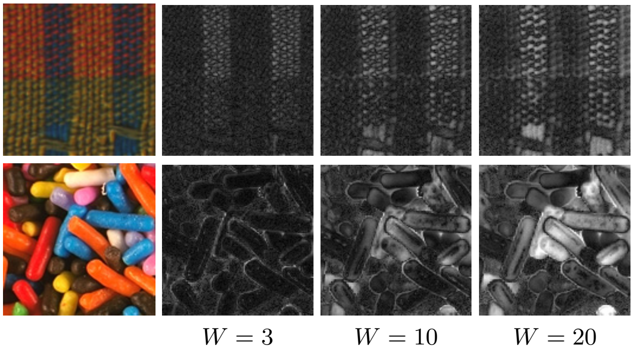

Fig. 1. Examples of color contrast maps obtained by varying the parameter W

$$\overline{\mathbf{c}}(i,j) = \frac{1}{(2W+1)^2} \sum_{x=i-W}^{i+W} \sum_{y=j-W}^{j+W} \frac{\mathbf{c}(x,y)}{\|\mathbf{c}(x,y)\|}, \tag{2}$$

where the summation is taken only over the non-zero vectors, and where W determine the size of the neighborhood. The normalization of the terms in the summation makes the average invariant with respect to scaling in the color space. Figure 1 shows some examples of color contrast maps, that is, the images of the angular differences $\alpha(\mathbf{c}(i,j), \overline{\mathbf{c}}(i,j))$, obtained with different values of W: small values produce detailed contrast maps, and the coarse structure of the texture is captured when W is large. The distribution of the angular difference in the contrast map has been uniformly quantized into Q bins and encoded by a histogram, that we called Color Contrast Histogram.

The final ICCD descriptor has been obtained by the concatenation of the two histograms (color contrast and intensity) and is formed by $N = 243 + Q$ components. Note that both the histograms are invariant with respect to monotonic transformations of the pixels' intensity, and to rotations in the color space.

To allow texture classification we need to embed our descriptor into a metric space. For this purpose, we decided to use the χ^2 distance:

$$\chi^2(\mathbf{x}, \mathbf{y}) = \frac{1}{2} \sum_{i=1}^{N} \frac{(x_i - y_i)^2}{x_i + y_i}, \tag{3}$$

where $\mathbf{x}$ and $\mathbf{y}$ are two feature vectors of non-negative values (ICCD descriptors, in this case). It has been demonstrated to provide good performance when applied to histograms [25].

4 Experimental Results

To evaluate the ICCD descriptor we replicated the three texture classification experiments that Mäenpää and Pietikäinen designed to compare several color texture descriptors [3].

Fig. 2. Exemplars of the 54 classes of textures considered in the first experiment. Images have been obtained from the photographs in the VisTex data base.

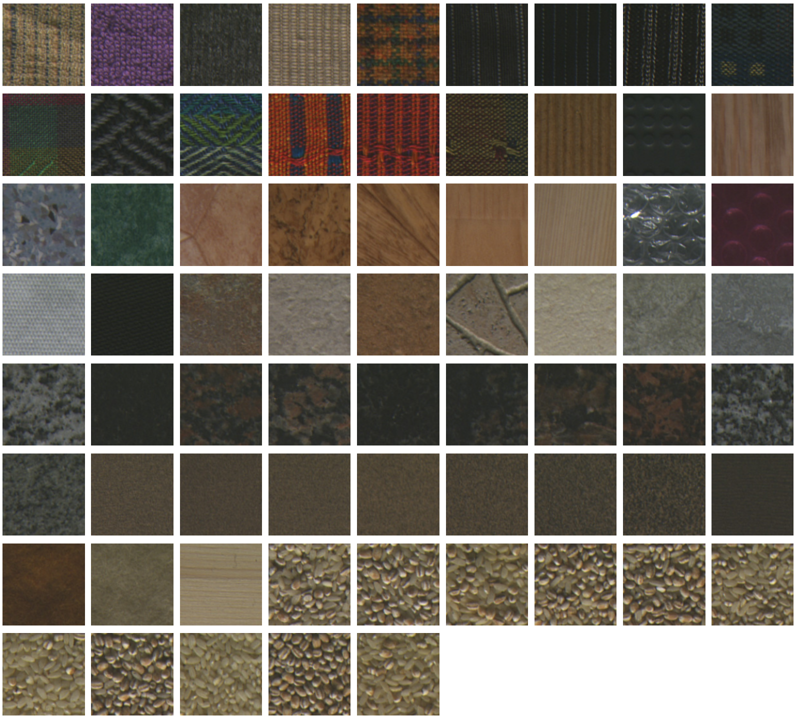

Fig. 3. The 68 classes considered in the second and third classification experiments

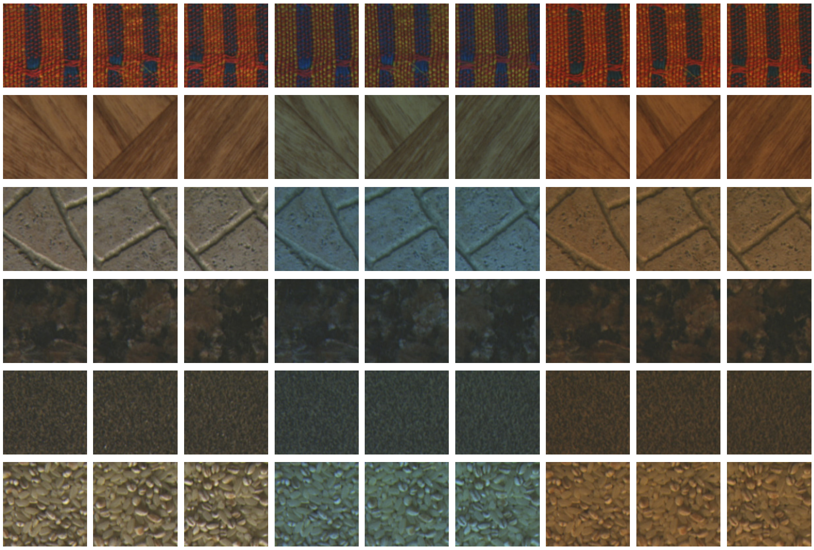

Fig. 4. Examples of images in six of the 68 classes of the third classification experiment. Each row contains images from a different class. The first three columns contain training images; the last six contain test images. Note that test images have been taken under two different illuminants, and that training images have been taken under a third illuminant.

The database used in the first experiment contains 864 images representing 54 classes (see Figure 2). These have been obtained from the VisTex [37] dataset of natural objects or scenes captured under non-controlled conditions with a variety of devices. Each photograph has been divided into 16 sub-images, half of which has been included in the training set; the remaining sub-images form the test set.

The second experiment consists in the classification of 1360 images (680 for training and 680 for test) of 68 different classes. The images (from Outex [38]) have been obtained by subdividing 68 photographs in 20 sub-images each. The photographs depict the textures of various materials, and have been obtained under controlled condition (same illumination, same acquisition device). Figure 3 shows an example for each of the 68 classes.

The third experiment uses the same 680 training images of the second experiment. While the test set is formed by 1360 images obtained from additional photographs of the same 68 surfaces taken under different illumination conditions (different illuminant color, and slightly different position of the light source). Figure 4 shows the intra-class variability for some classes.

The images of the three experiments are available from the Outex web site (`http://www.outex.oulu.fi/`) under the names `Contrib_TC_00006`, `Outex_TC_00013`, and `Outex_TC_00014`. In the following we will refer to them as 'VisTex', 'Outex 13', and 'Outex 14'.

In all the experiments we used the Nearest Neighbor classifier: given a texture image, its distance with respected to all the training images is computed. The prediction of the classifier is the class of a closest training set image. Performance

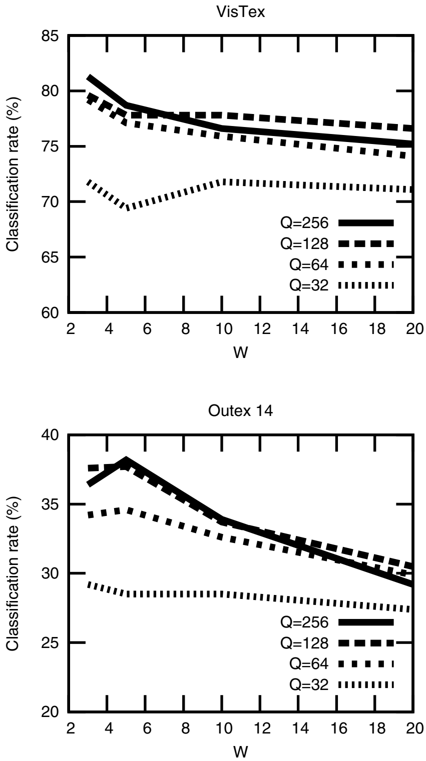

Fig. 5. Performance of the color contrast histogram on the three classification experiments, obtained by varying the parameters W and Q.

are reported as classification rates (i.e. the ratio between the number of correctly classified images and the number of test images).

In the first experiment we have studied how much the classification performance are affected by the parameters of the ICCD descriptor. In particular, we computed the classification rates obtained by varying the neighborhood size W, and the number of bins Q. Note that in this experiment only the color contrast part of ICCD is considered. The plots in Figure 5 show that the best classification rate is generally achieved by using a small value of W, and a large value of Q. Since we are particularly interested in the case of variable illumination, in the following we will consider the values $W = 5$ and $Q = 256$ which obtained the best result in the third experiment.

Table 1 reports the results obtained in the three classification experiments by using various texture descriptors. In particular we reported the classification rates corresponding to:

Table 1. Summary of the results obtained in the three classification experiments. For each experiment the best classification rate is reported in bold. The first three descriptors are the proposed ICCD descriptor and its two main components. The remaining six are the best performing color, and combined descriptors as reported in [3]. LBP operators are reported with the notation $LBP_{n,r}$ where n is the size of the neighborhood and r is its radius; the superscript u indicates than only uniform patterns are considered.

Descriptor	VisTex	Outex 13	Outex 14
Intensity-Color Contrast Descriptor	98.1	89.3	**75.6**
Color Contrast Histogram	78.7	68.4	38.2
$LBP^u_{16,2}$ on the pixels' luminance	98.1	82.6	67.6
HSV histogram	97.5	**94.7**	14.0
Histogram in the Ohta's color space	**100**	94.1	12.0
Histogram of the pixels' value (V)	89.1	75.6	39.9
$LBP_{8,1}$ on RGB	97.9	87.8	53.9
$LBP^u_{16,2}$ on L*a*b*	**100**	85.3	63.2
$LBP_{8,1} + LBP^u_{16,2} + LBP^u_{24,5}$ on L*a*b*	99.5	87.8	67.8

i) the proposed ICCD descriptor;
ii) its individual components (color contrast histogram and $LBP^u_{16,2}$);
iii) the best descriptors reported in [3], namely histograms in the HSV and Ohta's [39] color spaces, and histogram of pixels' Value;
iv) the best combinations of color and texture descriptors reported in [3] (various LBP histograms computed on the components of the RGB and L*a*b* color spaces).

The results (table 1) obtained show that the first classification experiment is quite simple: several descriptors obtained more than 97% of classification rate, and in two cases all the test images have been correctly classified. Concerning the first two experiments, when the illumination conditions do not change, color is a very important cue for texture classification. In fact, the highest classification rates have been achieved by using simple color histograms; in these experiments our descriptor is not too far from the best.

On the other hand, under variable illumination conditions (third experiment) color information, if not properly encoded, can be misleading: color descriptors often perform very bad when compared to the $LBP^u_{16,2}$ on the gray level version of the image. The computation of LBP features on the color channels did not significantly outperform $LBP^u_{16,2}$. The color contrast histogram by itself did not achieved high classification rates. However, it encodes information which is mostly orthogonal with respect to that provided by traditional LBP features. In fact, in this experiment the best performance has been achieved by our ICCD descriptor, which obtained a classification rate of 75.6%: at least 7.5% better than any other descriptor considered.

5 Conclusions

In this work we presented a novel illuminant-invariant descriptor for texture analysis. The descriptor has been obtained through a combination of local binary patterns and a histogram of the color contrast defined in terms of the angle between the color of the pixels and the average color of their neighborhoods.

To verify the effectiveness of the proposed descriptor we considered three experiments of texture classification. These experiments are based on the VisTex and the Outex data sets and have been previously considered in [3] to evaluate several strategies exploiting color information for texture classification. Classification is simply performed by a nearest neighbor classifier using the χ^2 distance. In all the three experiments the ICCD descriptor outperformed the classic LBP histograms. In particular, the improvement in the third experiment is quite evident (about 8% of classification accuracy). Note that among the experiments considered, the third is the only one that includes images having change in illumination; the results obtained confirm the robustness of our descriptor in dealing with this type of variability.

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