Textural Features in Multi-Channel Color Images

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Abstract

A set of textural features for the classification of textures in color images is presented. These color texture features are based on the color covariance texture model, a texture model of second order statistics for multi-channel color images. In the color covariance texture model, the spatial correlation of pixels in textured image segments are represented by covariance functions. The pixel arrangement within each color plane is considered as well as the interrelations of the pixel's color components between different color planes. From the covariance functions, a set of 14 moments is extracted as covariance texture features. These moments are based on specific characteristics of the covariance functions classifying different types of color textures. The new covariance texture features correspond to the human perception of texture including the substantial textural features coarseness, entropy, contrast, directionality, and color. The significance of the color covariance texture features is verified by classification tests on different image series of color micro-textures.

1. Introduction

The analysis of texture in color images has given rise to growing interest in computer vision to guarantee reliable object recognition. Objects in natural scenes are often characterized by their specific color texture. Humans observe color textures as homogeneous image segments interpreting them easily as surfaces of picture objects or the scene background. For example, humans can perceive a forest immediately but we do not explicitly recognize the amount of trees, branches, leaves, etc. The dominant texture features are coarseness, entropy, contrast, directionality, and color. However, for texture, there exists no unique definition, it is more an intuitive term. One common definition declares textures as more or less regular patterns which consist of a set of elementary components, the texture primitives. The main characteristics of textures are due to the spatial arrangement of those texture primitives. In macro-textures, the texture primitives themselves have significant features. On the other hand, micro-textures consist of small primitives which are in many cases consist of only a single pixel. Micro-textures are mostly found in pictures of natural scenes. Due to the indeterministic structure of micro-textures, statistical texture models are particularly suited. Many approaches have been developed using color information and texture features for image analysis. In the literature, color and texture are mostly discussed as independent disciplines. The proposed texture models are operating traditionally on grey-level images, see [10] for survey. But today, the restrictions placed on grey-level images are not sufficient for texture analysis as many applications of computer vision deal with color textures [9], [11].

In principle, there are two basic approaches to handle color textures, single-channel texture analysis and multi-channel texture analysis. One approach to single-channel color texture analysis is based on the extraction of texture features separately in each color channel of a color image analogous to a grey-level image. Using the *RGB* format for color images, this approach requires triple the amount of data for texture description. Another possibility for the use of single-channel texture models for color texture modelling consists of an initial transformation of a multi-channel color image into an one-dimensional feature image, e.g. into a binary image as described in [6]. In contrast to single-channel texture models, the multi-channel color texture analysis is directly based on the multi-dimensional representation of color images. This color texture analysis takes into account the textural interrelations between the different color channels. In different approaches to color texture modelling, the analysis of the spatial arrangement of color pixels is mainly based on second order statistics. The *color covariance* texture model is based on second order statistics which is described in section 2. Based on the parameters of this color texture model a set of 14 moments is defined as *covariance texture features* in section 3. In the following section 4, the significance of the color covariance texture features is verified by classification tests. In section 5, experiments on adaptive feature selection are described before some conclusions are given in section 6.

2. Color Covariance Texture Model

The following is a description of the color covariance texture model, a multi-channel texture model for colored micro-textures which has been derived from the auto-covariance texture model for grey-level textures. Like auto-covariance [3], the color covariance [5],[8] is a second order statistics about the correlation of pixel pairs for a set of topological pixel relations. In contrast to the grey-level auto-covariance texture model, the spatial relations of pixel values are calculated for the different color components of involved pixels. Not only are the spatial relations inside each color plane analysed but also the interrelations between the color components of pixels in different color planes. In figure 1, this idea is illustrated for the case of the 3-channel *RGB* color image.

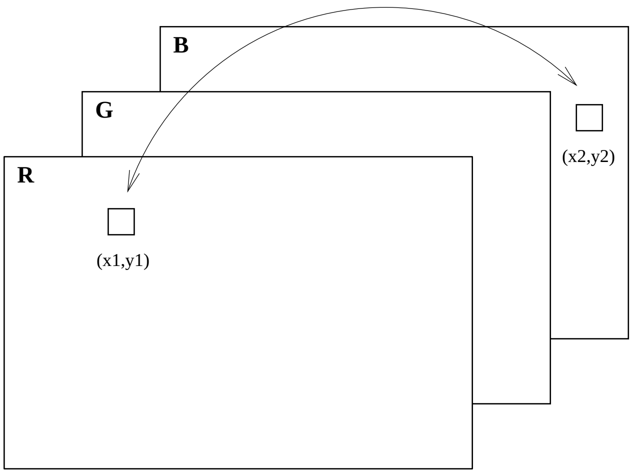

Figure 1. Illustration of color covariance in a 3-channel RGB color image.

The correlation between two color planes i and j for any multi-channel color image is defined by the color covariance functions CC^{ij} given in formula (1). $I^i(x,y)$ is used to denote the color component i of the pixel at position (x,y) in the image segment I. μ^i is the mean value, σ^i is the standard deviation of the segment I in the color plane i. For this reason, the set of pixel values in each color plane has to be an ordered set, e.g. a set of intensity values. The sum is normalized by the number $\#I$ of involved pixels in the segment I. The color covariance function is calculated for a set of different displacement vectors $\Delta = \{(\Delta x, \Delta y), \, |\Delta x| \leq D_x, \, |\Delta y| \leq D_y\}$ with maximum horizontal distance D_x and maximum vertical distance D_y according to the orthogonal image topology. Due to the restriction to a limited set of displacement vectors, a covariance function is defined by a color covariance matrix which is called CC-matrix in the following. A separate CC-matrix is defined for every combination of color channels. The CC-matrix is indexed by the topological coordinates $(\Delta x, \Delta y) \in \{-D_x, \ldots, 0, \ldots, D_x\} \times \{-D_y, \ldots, 0, \ldots, D_y\}$ as a $(2D_x + 1) \times (2D_y + 1)$-dimensional matrix. In the centre of a CC-matrix, the indices $(0,0)$ indicate zero displacement.

$$CC^{ij}(\Delta x, \Delta y) = \frac{1}{\sigma^i \sigma^j} \frac{1}{\#I} \sum_{x,y \in I} (I^i(x,y) - \mu^i)(I^j(x+\Delta x, y+\Delta y) - \mu^j) \tag{1}$$

There are some significant characteristics of CC-matrices. Due to the normalisation factor $\frac{1}{\sigma^i \sigma^j} \frac{1}{\#I}$, it holds $CC^{ij}(\Delta x, \Delta y) \in [-1,1]$ where 1 means maximum correlation, 0 no correlation, and -1 maximum anti-correlation. Inside a color plane i, we have $CC^{ii}(0,0) = 1$ because every pixel has a maximum correlation to itself (zero displacement). Note that $CC^{ij}(\Delta x, \Delta y) \in [-1,1]$ holds only if the image segment I is organized as a torus where the segment I is continued in all directions in a cyclic way. Otherwise, separate calculations of different mean values $\mu^i(\Delta x, \Delta y)$ and different standard deviations $\sigma^i(\Delta x, \Delta y)$ are needed for every color plane i and for all displacements $(\Delta x, \Delta y) \in \Delta$ to normalize the formula. However, for reasons of efficiency we use the definition in formula (1) taking into account only small divergences of the covariance values. Simple transformations lead to a more efficient calculation of CC-matrices as shown in formula (2).

$$CC^{ij}(\Delta x, \Delta y) = \frac{1}{\sigma^i \sigma^j} \left(\frac{1}{\#I} \sum_{x,y \in I} I^i(x,y) I^j(x+\Delta x, y+\Delta y) - \mu^i \mu^j \right) \tag{2}$$

The CC-matrices are inherently characterized by their symmetrical properties. CC^{ii} are symmetrical matrices themselves as shown in formula (3), and $CC^{ij}, i \neq j$ are in pairs symmetrical, see formula (4). Hence, half of the values in formula (1) are redundant. Thus, for every possible combination (i,j) of color planes, only half of the values of the CC-matrices have to be calculated explicitly.

$$\overline{CC^{ii}} = CC^{ii} \tag{3}$$
$$\overline{CC^{ij}} = CC^{ji} \tag{4}$$
$$\text{where} \quad \overline{CC}(\Delta x, \Delta y) = CC(-\Delta y, -\Delta x)$$

There is an obvious congruence between rotations of textured image segments and the rotation of their corresponding CC-matrices. However, the most important characteristic of CC-matrices depends on their independence to variations of colors in image sequences. This problem in color constancy is often caused by separate fluctuations in the brightness of the color channels. The invariance of the CC-matrices to color variations caused by separate additive and multiplicative noise is shown in the formulas (5) and (6). I_{+c} indicates the image I in which all pixels are added by a constant c, I_α is a variation of I due to a multiplication of all pixels by a factor α. Note that c and α are arbitrary vectors of independent values in the dimension of the color space.

$$CC^{ij}_{I_{+c}} = CC^{ij}_{I} \qquad (5)$$

$$CC^{ij}_{I_\alpha} = CC^{ij}_{I} \qquad (6)$$

Table 1. Color covariance texture features.

Energy $$\mathbf{m_1} = \sum_{x,y} CC(x,y)^2$$
Coarseness $$\mathbf{m_2} = \sum_{x,y} \sqrt{x^2+y^2} \quad CC(x,y)$$
Fineness $$\mathbf{m_3} = \sum_{x,y} \frac{CC(x,y)}{1+\sqrt{x^2+y^2}}$$

3. Color Texture Features

One of the most referenced approaches to texture modelling is based on co-occurrence statistics. In this texture model, the number of pixel pairs with a specific spatial relation in a textured image region is registered. The frequency distribution of every possible combination of two pixels is organized in a square matrix. The size of this co-occurrence matrix depends on the number of considered pixel values. A separate co-occurrence matrix is needed for every spatial relation causing a big amount of data for texture description. By Haralick et al. [4], a set of moments has been defined for co-occurrence matrices which leads to a considerable data reduction. The main aspect of these texture moments lies in their intuitively motivated texture description. Among others, certain moments are given for the roughness, fineness, contrast, and entropy of texture. The set of Haralick's texture features is often used for texture classification.

Table 2. Color covariance texture features.

Directionality-1 $$\mathbf{m_4} = \sum_{x,y} \frac{CC(x,y)}{1+y^2}$$ $$\mathbf{m_5} = \sum_{x,y} \frac{CC(x,y)}{1+(x-y)^2}$$ $$\mathbf{m_6} = \sum_{x,y} \frac{CC(x,y)}{1+x^2}$$ $$\mathbf{m_7} = \sum_{x,y} \frac{CC(x,y)}{1+(x+y)^2}$$
Directionality-2 $$\mathbf{m_8} = \sum_{i} CC(i,0)/sum$$ $$\mathbf{m_9} = \sum_{i} CC(i,i)/sum$$ $$\mathbf{m_{10}} = \sum_{i} CC(0,i)/sum$$ $$\mathbf{m_{11}} = \sum_{i} CC(i,-i)/sum$$
where $$sum = \sum_i CC(i,0) + CC(i,i) + CC(0,i) + CC(i,-i)$$

In contrast to co-occurrence matrices, the covariance matrices are defined independently of the number of different pixel values. Additionally, the covariance information of pixel pairs in different spatial relations are organized in only one covariance matrix. Hence, a covariance matrix provides information about the directionality of texture. The dimension of a covariance matrix depends only on the number of spatial relations of pixel pairs. The set Δ of displacement vectors takes into account the orthogonal relations of pixels with the maximum horizontal distance D_x and a maximum vertical distance D_y according to the topological maximum metric l_∞. For textures in multi-dimensional color images, separate covariance matrices for each combination of the

Table 3. Color covariance texture features.

Contrast-1 $$\mathbf{m_{12}} = \frac{\sum_{x,y} CC\text{neg}(x,y)}{\sum_{x,y} CC\text{abs}(x,y)}$$
Contrast-2 $$\mathbf{m_{13}} = \frac{\#\{CC(x,y);\ (x,y) \in \Delta, CC(x,y) < 0\}}{\#\Delta}$$
Entropy $$\mathbf{m_{14}} = -\sum_{x,y} CC\text{pos}(x,y)\ \log(CC\text{pos}(x,y))$$
where $$CC\text{abs}(x,y) = \lvert CC(x,y) \rvert\ ,\ (x,y) \in \Delta$$ $$CC\text{neg}(x,y) = \begin{cases} -CC(x,y) & \text{if } CC(x,y) < 0, \\ 0 & \text{otherwise} \end{cases}$$ $$CC\text{pos}(x,y) = \frac{CC(x,y)+1}{2}\ ,\ (x,y) \in \Delta$$

color planes are defined, e.g. 9 CC-matrices in the case of a 3-channel *RGB* color image. For the covariance matrices, we developed a set of textural features for compact texture description [7]. Fourteen moments for covariance matrices are defined in the tables 1, 2, and 3. The moments are called covariance features in the following explanations, the full set of these covariance features is named M^{14}. The moments are defined by formulas where the sum is always built over the set Δ of spatial indices $(\Delta x, \Delta y)$ of the CC-matrices. For reasons of simplicity, these indices are named (x, y) or i, the operator $\#$ specifies the size of a set. The covariance features are not restricted to multi-channel covariance functions, but also suited for single-channel covariance matrices. They have been developed intuitively like the texture features of Haralick, but they are defined in a completely different way. The moments m_1, m_2, m_3 are measurements for the resolution of a texture. High values of m_1 (*Energy*) and m_2 (*Coarseness*) indicate a rough structured texture while the contrary moment m_3 (*Fineness*) detects fine structures. The characteristics m_1, m_2, m_3 are derived by different measurements of the weight of the matrix centre. The moments m_4, m_5, m_6, m_7 (*Directionality-1*) detect the directionality of a texture in the horizontal (—), first diagonal (\ ), vertical (|), and second diagonal (/) direction, respectively. This is realized by a summation of the covariance values along cuts through a covariance matrix which are disposed according to the four specified directions. For a proper calculation, the cuts near the matrix centre are weighted stronger than the tangential ones. A more simple estimation of texture directionality is given by the moments m_8, m_9, m_{10}, m_{11} (*Directionality-2*). These moments calculate the normalized sum of covariance values along central cuts through a covariance matrix in the four main orthogonal directions. The moments m_{12} and m_{13} define measurements of a texture's contrast. m_{12} (*Contrast-1*) calculates the proportion of the negative covariance values (anti-correlation) with regard to the sum of the absolute values of all covariance matrix entries. m_{13} (*Contrast-2*) indicates the relation between the number of negative covariance values to the number $\#\Delta$ of all covariance matrix values. The moment m_{14} (*Entropy*) detects the entropy of a covariance matrix, after scaling the covariance values in $[-1, 1]$ to values in $[0, 1]$ for an accurate use of the logarithm function. A high value of m_{14} indicates a balanced distribution of the covariance matrix values which occurs with high texture entropy.

4. Color texture classification

In order to evaluate the significance of the covariance features, three image series of color textures have been chosen for classification tests. These texture series T_1, T_2, T_3 consist of color micro-textures taken from three different image databases. T_1 is an ad hoc assembled color texture series consisting of 320 color textures in 32 different texture images taken from the *VisTex* color texture database [2]. The other two color texture series are taken specially for this purpose from natural outdoor scenes. T_2 is a collection of 408 images showing the barks of 6 different tree species [1], T_3 consists of 240 images taken from 6 different kinds of ground vegetation. All images of T_2 and T_3 have been taken from different trees or plants. Every texture series was divided randomly into two disjunct subsets of the same size, a training set and a test set. The training set is used only to find out the parameters for the classification method and for normalisation of the feature spectrum as described below. The test set is dedicated exclusively to calculations of the classification performance.

For classification of the color texture series T_1, T_2, T_3, a *nearest-neighbour* classifier has been chosen. This classification method provides high robustness on test sets with non-parametric distributions and non-linear class borders in their feature spectrum. We do not claim this classification algorithm to be an optimal strategy for color texture classification. Rather the significance of different color texture features is to be compared by this traditional classification method. However, we used a special version of this classification method, the *k-nearest-neighbour* classifier, to increase its performance by using a classification parameter $k = 5$. For texture features, the set M^{14} of covariance features is used which have been derived from CC-matrices calculated on the texture series in the *RGB* color format. The strategy of the *nearest-neighbour* classifier mainly depends on calculations of distances in the feature space. In order to use the Euklidian distance function in this classification algorithm, an adaptive normalisation is performed on the covariance features of the texture series. This is done by formula (7) in which the covariance features $m_1, \ldots, m_{14} \in M^{14}$ are transformed into a new features m_i^n where the mean values μ_i and the standard deviations σ_i are derived from the training set. This normalization results in new feature values characterized by mean values 0 and standard deviations 1.

$$m_i^n = \frac{m_i - \mu_i}{\sigma_i} \ , \quad m_i \in M^{14} \qquad (7)$$

In figure 2, the classification rates for the separate covariance features $m_1, \ldots, m_{14} \in M^{14}$ on the test sets of the color texture series T_1, T_2, T_3 are given. The different classification rates of the moments are given for T_1 on the left side, for T_2 in the middle, and for T_3 on the right side, respectively. The results for the three test sets are different but consistent. In all cases, the covariance features $m_1, \ldots, m_7$ and m_{14} are significantly better than the others. The covariance features $m_8, \ldots, m_{13}$ (*Directionality-2, Contrast-1, Contrast-2*) turned out to be less significant. However, separate use of the moments is not applicable for classification, rather a clever combination of the covariance features are to be found as described in the next section.

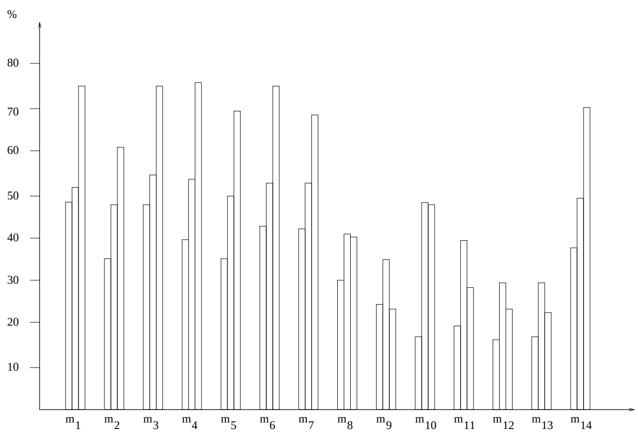

Figure 2. Classification rates of the separate covariance features.

5. Feature selection

For an efficient color texture classification, a reduction of the texture model parameters to a small set of significant texture features is essential. The number of parameters of the color covariance texture model depends originally on the size of the covariance matrices. In the case of the *RGB* color images taken from the texture series T_1, T_2, T_3, we choose the maximum covariance distances $D_x = 5$ and $D_y = 5$ which results in 9 CC-matrices of dimension 11×11. A maximum distance of 5 pixels turn out to give good results in micro-texture classification. Due to the symmetrical properties (3) and (4), half of these values are redundant leading to a number of $9 \cdot 61 = 549$ different values of CC-matrices. This full set of covariance values is called CC-11×11 in the following. In contrast to the full CC-matrices, the covariance moments of M^{14} lead to a respectable data reduction. These covariance features are invariant to symmetric matrix transformations as shown in formula (8). The covariance features have to be derived from only 6 CC-matrices because 6 of the 9 CC-matrices are symmetric in pairs, see formula (4). This leads to $6 \cdot 14 = 84$ different color covariance features called CC-M^{14}.

$$m_i(\overline{CC}) \quad = \quad m_i(CC) \ , \qquad m_i \in M^{14} \qquad (8)$$

Two adaptive methods for feature selection for further reduction of the texture model parameters have been examined. In a first approach, optimal subsets of the covariance features M^{14} have been calculated for the texture series T_1, T_2, T_3. We tested all $2^{14} - 1$ non-empty subsets of the covariance features on the training sets looking for the best classification results. For all subsets of M^{14}, the classification was performed for the covariance moments on all 6 different CC-matrices at once. In the case of the first texture series T_1, we got an optimal set CC-M^{opt_1} of 5 moments (*Energy, Coarseness, Directionality-1 (|), Directionality-2 (—), Directionality-2 (\ )*), leading, applied to the 6 different CC-matrices, to a 30-dimensional feature space. The optimal set CC-M^{opt_2} consists of the 6 moments *Energy, Coarseness, Directionality-1 (\ ), Directionality-1 (|), Directionality-2 (—), Entropy*. CC-M^{opt_3} consists of the 4 moments *Fineness, Directionality-1 (—), Directionality-1 (\ ), Contrast-1*. As a result of this adaptive feature selection, the classification can be considerably increased.

For a further reduction of data, we used the *Karhunen-Loève analysis*, another adaptive strategy for feature selection. This method calculates the coefficients of a linear transformation of the features which is performed offline on the training sets. In table 4, the classification results for the texture series T_1, T_2, T_3 are given for the feature sets CC-11×11, CC-M^{14}, and for the optimal feature sets CC-

M^{opt_1}, CC-M^{opt_2}, CC-M^{opt_3}. These feature sets were taken in their full dimension and after a feature reduction by the Karhunen-Loève transformation to a 48-, 24-, 12-, and 6-dimensional feature space. In all cases, the adaptive feature reduction down to the dimension 12 does not significantly affect the classification results. In addition, in table 4, the classification results of grey-level auto-covariance texture features taken from the color texture series are given. For this comparison, the images of the three color texture series have been transformed initially to grey-level images. AC-11×11 indicate the values of the 11×11-dimensional auto-covariance matrix, AC-M^{14} are the covariance features derived from this auto-covariance matrix. In the case of the texture series T_1, T_2, T_3, an obvious advantage of the color covariance features in contrast to the corresponding grey-level versions of these texture features can be concluded.

Table 4. Classification (in %) by different covariance feature sets.

T_1	Dim		48	24	12	6
CC-11×11	549	76.9	76.2	76.2	71.9	64.4
CC-M^{14}	84	68.1	68.1	68.1	66.9	63.7
CC-M^{opt_1}	30	74.4		74.4	74.4	69.4
AC-11×11	61	70.6	70.6	70.0	69.4	68.1
AC-M^{14}	14	56.2			56.2	54.4

T_2	Dim		48	24	12	6
CC-11×11	549	75.5	75.5	75.0	74.0	71.6
CC-M^{14}	84	68.6	68.6	68.6	68.6	68.1
CC-M^{opt_2}	36	77.0		77.0	76.0	74.5
AC-11×11	61	73.0	73.0	73.5	73.0	71.6
AC-M^{14}	14	66.2			66.2	64.7

T_3	Dim		48	24	12	6
CC-11×11	549	80.8	80.8	80.0	80.8	80.0
CC-M^{14}	84	70.8	70.8	71.7	73.3	70.8
CC-M^{opt_3}	24	84.2			84.2	68.3
AC-11×11	61	78.3	78.3	78.3	78.3	75.8
AC-M^{14}	14	68.3			68.3	65.0

6. Conclusions

A color covariance texture model has been described which is based on second order statistics for multi-channel color images. These statistics take into account the correlation of color pixels inside each color plane as well as interrelations of different color components of pixels. In order to find a compact description for color textures, a set of covariance features have been defined by moments of covariance functions. These covariance features are closely related to the human textural perception qualifying them as features for texture recognition, e.g. in image retrieval applications. The covariance features are to be used in applications of color texture classification especially in combination with adaptive strategies for feature selection. The set of covariance features turned out to be a reliable feature set for texture discrimination. At the moment, further research work is based on the segmentation of textured color images, and on the synthesis of color textures. Some encouraging results have been achieved on the syntheses of micro-textures on the basis of the color covariance texture model. Other studies deal with texture synthesis by some high-level intuitive descriptions as a discipline of virtual reality.

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