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A hybrid color texture image classification method based on 2D and semi 3D texture features and extreme learning machine

Abstract. *Color texture classification is an important step in image segmentation and recognition. The color information is especially important in textures of natural scenes. In this paper, we propose a novel approach based on the 2D and semi 3D texture feature coding method (TFCM) for color texture classification. While 2D TFCM features are extracted on gray scale converted color texture images, the semi 3D TFCM features are extracted on RGB coded color texture images. The proposed approach is tested on two publicly available datasets. Moreover, comprehensive comparisons are realized with traditional texture analysis tools. The results show the advantages of the proposed method over other color texture analysis methods.*

Streszczenie. *W artykule zaproponowano nowa metodę klasyfikacji obrazów z kolorowa teksturą wykorzystującą wykorzystującą metody kodowania tekstury 2D. Metodę testowano na dwóch przykładach baz danych i porównano z metodami dotychczas stosowanymi. (**Hybrydowa metoda klasyfikacji obrazów z kolorowa teksturą**)*

Key words: Color texture classification, Texture feature coding method, feature extraction
Słowa kluczowe: tekstura, klsyfikacja obrazów z teksturą

1. Introduction

Texture analysis is very useful for experiments of image classification and identification. Thus, it has long been an area of computer vision with active research area spanning image processing, pattern recognition, and computer vision, with applications to medical image analysis, remote sensing, object recognition, industrial surface inspection, document segmentation and content-based image retrieval. Texture classification has received significant attention with many proposed approaches, as documented in comprehensive surveys [1-5]. The ability of a human to distinguish different textures is apparent, therefore, the automated description and recognition of the texture images is in demand.

Over the years, many researchers have studied different texture analysis methods. Many of these methods represent the local behavior of the texture via statistical [6], structural [7] or spectral [8] properties of the image. A methodology is presented in [9], where second-order probability distributions [2, 4] are enough for human discrimination of two texture patterns, has motivated the use of statistical approaches. On the other hand, structural approaches describe the textures by rules, which govern the position of primitive elements, which make up the texture [10]. In addition, signal processing methods, such as Wavelet transform [11-13], Fourier analysis [8] and Gabor filters [14], were motivated by psychophysical researches, which have given evidences that the human brain does a frequency analysis of the image [15, 16]. These approaches represent the texture as an image in a space whose coordinate system has an interpretation that is closely related to the characteristics of a texture.

The texture feature coding method (TFCM) that forms the basis for texture features was first discussed by Horng [17] and later applied in various application such as tumor detection and landmine detection [18, 19]. TFCM is a new texture analysis scheme which transforms an original image into a texture feature image whose pixel values represent the texture information of the pixel in original image. The TFCM is a coding scheme that transforms an image into a feature image, in which each pixel is encoded by TFCM into a texture feature number (TFN) that represents a certain type of local texture. The TFN of each pixel in the feature image is generated based on a 3×3 texture unit as well as the gray-level variations of its eight surrounding pixels. The TFN histogram and TFN co-occurrence matrix are derived to generate many texture features for texture classification. The method has several remarkable advantages including accurate representation and record of target texture, and computational efficiency [19].

In this paper, we propose a hybrid method where both 2D and semi 3D TFCM and Extreme Learning Machine (ELM) is combined for efficient color texture classification. ELM was proposed as an alternative and effective approach for neural networks. We firstly review the TFCM and ELM methods and then we conduct several experiments on the various color textures for showing the efficiency of the proposed hybrid scheme. Experimental results are promising and the comparisons show the superiority of our proposal.

The rest of this paper is organized as follows. Section 2 reviews the related works for texture classification. Sections 3 and 4 review the TFCM based feature extraction mechanism and the ELM classifier. In Section 5, we evaluate the capabilities of the proposed features with extensive experiments on two texture datasets, and present comparisons with current methods. Finally, we conclude the paper in section 6.

2. Related works

Up to now, numerous feature extraction approaches have been proposed for texture image classification. Scale-invariant feature transform (SIFT) [20], Histogram of Oriented Gradients (HOG) feature and the related methods are some of the representative approaches that are widely used in image processing community [21, 22]. Moreover, Chellappa et al. used Gaussian–Markov random field (GMRF) based features to find some statistical relationships among adjacent pixels [23]. Kashyapand Khotanzad then proposed the isotropic circular Gaussian–Markov (ICGMRF) to achieve rotation invariant texture description [24]. Another extension was the isotropic circular GMRF (ACGMRF) designed by Deng and Clausi to encode relative orientations of adjacent pixels [25]. In addition, methods based on multi-channel filtering or wavelet decomposition [26] were also studied. Varma and Zisserman [27] introduced text on histograms in MR8 filtered response space as features. Sengur [11, 12] used the wavelet transform, entropy and energy features for color texture image classification with various classifiers. Local binary pattern (LBP), which is considered as an effective texture classification methodology, was proposed by Ojala et al. [28]. It has many properties such as rotation invariance and low computational cost [29, 30]. Karabatak et al. investigated the usage of association rules on wavelet domain for efficient texture classification [13]. Association rules are robust in modeling the relationship in a given database. Thus, the adjacent pixels interactions in texture structure are modeled in wavelet domain by association rules. A novel approach based on the fractal dimension for color texture analysis was proposed by Backes et al. [31]. The proposed approach investigates the complexity in R, G and B color channels to characterize a texture sample. The authors considered both all channels in combination and the correlations between them. Liu and Fieguth [32] introduced the use of random projections (RPs), a universal, information-preserving dimensionality-reduction technique, to project the patch vector space to a compressed patch space without a loss of salient information, claiming that the performance achieved by random features can outperform patch features, MR8, and LBP features.

3. Texture Feature Coding Method (TFCM)

The justification behind the TFCM technique, as proposed by Horng in [17], is the translation of an intensity image to a texture feature number (TFN) image via differencing in the image domain followed by successive stages of vector classification.

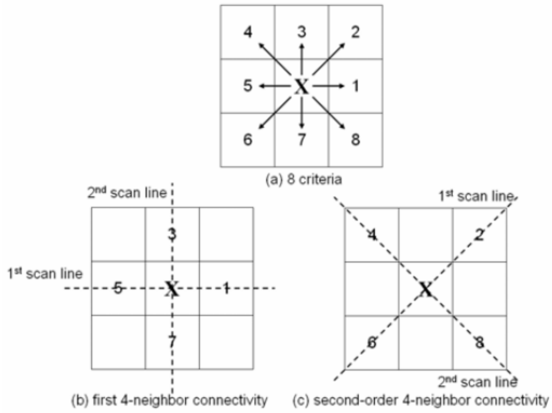

Fig. 1. 3×3 pixel neighborhood

Let's consider a pixel (i, j) in an intensity image and its surrounding 3×3 pixel neighborhood that is illustrated in Fig. 1. Horng separates the pixels in the neighborhood into horizontal and vertical and diagonal connectivity sets. Differences are then calculated along each vector in each of these connectivity sets, and the resulting two element difference vectors are thresholded at some tolerance (ε) into quantized two element vectors taking values from the set {−1, 0, 1}, corresponding to negative, no change, and positive difference values, respectively. This process maps a 3×3 pixel neighborhood to two sets of two 2×1 quantized difference vectors. After differencing and thresholding, TFCM maps the individual quantized difference vectors to gray-level class numbers based on the degree of variation in each vector. Such a classification scheme is described in [17] and reproduced in Fig. 2.

Fig. 2 Types of gray-level graphical structure variations and corresponding gray-level class numbers (1–4)

In Fig. 2, the falling lines correspond to the quantized difference vector values of −1, flat lines correspond to the quantized difference vector values of 0, and rising lines correspond to the quantized difference vector values of 1. Thus, Fig. 1 provides a mapping from each of the quantized difference vectors to gray-level class numbers taking values 1–4. Each pair of gray-level class numbers is combined into a single initial texture-feature class number using the mapping shown in Table I. This mapping takes each set of two gray-level class numbers and maps each set to an initial feature numbers taking values 1–10.

Table 1 Mapping from Gray level numbers (1-4) to initial class numbers (1-10)

		Gray Level Class #1			
		1	2	3	4
Gray Level Class #2	1	1	2	3	4
	2	2	5	6	7
	3	3	6	8	9
	4	4	7	9	10

Finally, we can then map the initial feature numbers calculated to a single class number using the mapping shown in Table II. By applying the TFCM procedure at each pixel location (i, j) in an image, the approach maps the intensity images into 2-D TFN images taking discrete values 0–54.

The extension of the TFCM technique to the 3-D data sets was proposed by Torrione et al. [19]. According to the ref. [19], a point in a 3-D data set (i, j, k) and the surrounding 26-element neighborhood was considered. Thus, the 3x3x3 data cube is comprised of 13 unique vectors passing through the point (i, j, k). By extending the TFCM approach, Torrione calculated the difference vectors along each of the 13 vectors passing through (i, j, k) and threshold each vector into the discrete values {−1, 0, 1}. Each of the 13 resulting discrete vectors can be assigned one of four gray-level class numbers in the order of increasing gray-level variation. Instead of directly calculating the initial feature number, a mapping of each texture unit vector to a texture feature number TFN was considered by Torrione. Given 13 elements, each taking a class value from 1 to 4, there are 4^{13} possible combinations. Torrione reduces this number in the following way: he considers equivalent of those vectors with equal numbers of occurrences of the class values (1, 2, 3, 4), independently to their position in the vector, thus, by considering translational and rotational invariance, the unique TFNs have the number of possibilities expressed by $\binom{13+3}{3} = 560$ by using the prime numbers [19].

Table 2 Mapping from primary (l) and secondary (2) initial feature numbers to TFN

		Initial feature number 1									
		1	2	3	4	5	6	7	8	9	10
Initial feature number 2	1	0	1	2	3	4	5	6	7	8	9
	2	1	10	11	12	13	14	15	16	17	18
	3	2	11	19	20	21	22	23	24	25	26
	4	3	12	20	27	28	29	30	31	32	33
	5	4	13	21	28	34	35	36	37	38	39
	6	5	14	22	29	35	40	41	42	43	44
	7	6	15	23	30	36	41	45	46	47	48
	8	7	16	24	31	37	42	46	49	50	51
	9	8	17	25	32	38	43	47	50	52	53
	10	9	18	26	33	39	44	48	51	53	54

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3.1. Co-occurrence Matrices

Many of the features mentioned previously are based upon the co-occurrence matrices of output TFN images. A co-occurrence value $p_\varepsilon(q,r \mid d,\theta)$ on a 2-D image can be defined as follows [19]:

$$p_\varepsilon(q,r \mid d,\theta) = \frac{N_{\varepsilon,d,\theta}(q,r)}{N_t} \tag{1}$$

where $p_\varepsilon(q,r \mid d,\theta)$ depends on the gray-level threshold ε, two discrete TFN values q and r, a distance d, an orientation θ, a counting function $N_{\varepsilon,d,\theta}(q,r)$ and a normalization term N_t. Here, θ is one of {0, 45, 90, 135, 180, 225, 270, 315} degrees.

3.2. Feature Extraction

Once an intensity image has been transformed to a TFN image by using Table 2, it is possible to apply the concepts analogous to gray-level histograms and gray-level co-occurrence matrices [19] to the TFN image and extract several features. These features are mean convergence, code variance, code entropy, uniformity, first-order difference moment, first-order inverse difference moment, second order difference moment, second-order inverse difference and four energy distribution values from the co-occurrence matrix. Thus, a 12-element feature vectors is generated based on these co-occurrence matrices and TFN histograms.

4. Extreme Learning Machine

A simple learning algorithm for single-hidden layer feedforward neural networks (SLFNs) called extreme learning machine (ELM) was firstly proposed by Huang et al. in the beginning of the last decade [33]. Beside ELM's learning speed, it also obtains better generalization performance when we consider the traditional feed forward network learning with back-propagation (BP) algorithm. The algorithm of the ELM is explained as following [33];

For a given N arbitrary input-output relation (x_i, t_i), where $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in R^n$ and $t_i = [t_{i1}, t_{i2}, \dots, t_{in}]^T \in R^m$, standard SLFNs with $\tilde{N}$ hidden neurons and activation function *g(x)* are mathematically modeled as

(2) $$\sum_{i=1}^{\tilde{N}} \beta_i g(w_i . x_j + b_i) = o_j,\ j = 1, \dots, N,$$

where $w_i = [\omega_{i1}, \omega_{i2}, \dots, \omega_{in}]^T$ is the weight vector connecting the *i*th hidden neuron and the input neurons, $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{im}]^T$ is the weight vector connecting the *i*th hidden neuron and output neurons, and $b_i$is the threshold of the *i*th hidden neuron. $w_i . x_j$ denotes the inner product of w_i and x_j. The output neurons are chosen linear in this paper.

That standart SLFNs with $\tilde{N}$ hidden neurons with activation function *g(x)*can approximate these*N*samples with zero error means that $\sum_{j=1}^{\tilde{N}} \|o_j - t_j\| = 0$, i.e., there exist β_i, $w_i$and b_i such that

(3) $$\sum_{i=1}^{\tilde{N}} \beta_i g(w_i . x_j + b_i) = t_j,\ j = 1, \dots, N.$$

The above *N* equations can be written compactly in Eq. 4:

(4) $$H\beta = T$$

where

$$H(w_1, \dots, w_{\tilde{N}}, b_1, \dots, b_{\tilde{N}}, x_1, \dots, x_N) = \begin{bmatrix} g(w_1 . x_1 + b_1) & \cdots & g(w_{\tilde{N}} . x_1 + b_{\tilde{N}}) \\ \vdots & \cdots & \vdots \\ g(w_1 . x_N + b_1) & \cdots & g(w_{\tilde{N}} . x_N + b_{\tilde{N}}) \end{bmatrix}_{Nx\tilde{N}})$$

(6) $$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N}xm} \text{ and } T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{Nxm}$$

H is called the hidden layer output matrix of neural network; the *i*th column of H is the *i*th hidden neuron's output vector with respect to inputs $x_1, x_2, \dots, x_N$.

Fig. 3 Examples of each texture class.

5. Experiments

To evaluate the validity of proposed approach, we conducted experiments using two color texture image databases. First database consists of texture images selected from [12]. A total of 1600 samples grouped into 16 texture classes were considered. Each database entry class is a set of 16 texture samples of 64x64 pixels size, each one extracted from a particular texture pattern with overlapping. Fig. 3 shows examples of texture images that are given in ref. [34]. While we used 80 % of the database for training the proposed hybrid scheme, the 20 % of the database was used for testing purposes.

Second database, called as USPTex, consists of a set of natural texture images acquired using a digital camera with 512x384 pixels resolution [31]. Texture classes considered are typically found daily, such as beans, rice, tissues, road scenes, and various types of vegetation, walls, clouds, soils, blacktop, and gravel. There are 180 different texture types (Fig. 6) and each database entry class is a set of 12 texture samples of 128x128 pixels size. Instead of using this database directly, we constructed a new database by using one of the each texture sample. Similar to the previous database, samples of 64x64 pixels size were obtained randomly for each texture class with an overlapping window. We produced 30 texture samples for each texture class. So, we have total of 5400 samples grouped into 180 classes. 66.67 % of the database (3600 samples) for training the proposed hybrid scheme, the 33.33 % of the database (1800) was used for testing the proposed methodology.

The 2D TFCM features were extracted for each texture class as described in Section 3. Moreover the semi 3D TFCM features were obtained with using the following idea.

Let's consider the 13 vectors passing through a center pixel of a 3x3x3 cube that was originally proposed by Torrione. Some of these 13 vectors passing though the center pixel are actually in the 2D plane [19]. Please refer to [35] for these 13 directions on a 3x3x3 cube. Thus, we can reduce the number of these 13 vectors to an appropriate number for reducing the size of Table II and subsequent computation cost. When we eliminate the direction of these vectors that are in the 2D plane, we have chance to reduce the number of TFN. But in this work, we just considered the diagonal vectors passing through the center pixel for extra reducing the number of vectors and constructed a similarity with the 2D TFCM procedure. An illustration is given in Fig.4 for 4 diagonal directions.

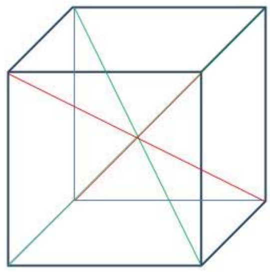

Fig. 4 3D directions

Once the diagonal directions are determined as shown in Fig. 4, similar to 2D TFCM procedure, the directions are grouped into two subsets (red and green diagonals). We assumed the red diagonals as horizontal and vertical direction and the green directions as two diagonal vectors in 2D TFCM. After determining the related vectors, the same coding and feature extraction mechanism in 2D TFCM is considered. Thus, this procedure is called as "semi 3D" feature extraction.

5.1. Evaluation

To evaluate the performance of the proposed hybrid 2D and semi 3D TFCM and ELM methodology, we designed a two-step evaluation. First, we evaluated each 2D and semi 3D TFCM feature in order to determine the number of descriptors n that best characterizes the texture and its influence on the results of both databases. In the sequence, to provide a better evaluation of the proposed methodology, we performed a comparison with other color texture methods found in the literature. For this comparison, the following methods are considered: Wavelet entropy and energy, signatures [36], and wavelet energy correlation signatures [13]. A brief description of each method is presented as follows.

The usage of Wavelet transform (WT) and Adaptive neuro-fuzzy inference system (ANFIS) for color texture classification problem was investigated [12]. The investigated scheme was composed of a wavelet domain feature extractor and an ANFIS classifier. Both entropy and energy features were combined in wavelet domain.

Van de Wouwer et al. has defined the wavelet energy correlation signatures [36]. The authors captured the energy distribution of the wavelet coefficients over the scale, sub band and color space for m = n and the others ($m \neq n$) represent the covariance between different color spaces.

Histogram ratio features (HRF) use the concept of co-occurrence in color histograms to extract meaningful information of a color texture [37]. It computes the 3D color histogram of a given texture. Then, it constructs a 1-D histogram from the 3D color histogram and extracts the ratio features as pairs of histogram bins combined with the corresponding count ratios.

Fig. 5 Examples of each texture class considered in the Natural Textures database

The Linear prediction model (LPM) used in [38] makes a quantitative comparison of auto spectra of luminance and combined chrominance channels of IHLS color space. The auto spectra is obtained using power spectrum estimator by the 2D multichannel non-symmetric half plane autoregressive (2D NSHP AR) model. To measure the similarity of two spectra the symmetric version of Kullback–Leibler divergence is used. A K-NN classifier is constructed with this distance.

The Fractal Dimension (FD) approach investigates the complexity in R, G and B color channels to characterize a texture sample [31]. Investigation of all channels in combination, taking into consideration the correlations between them is proposed. This approach uses the volumetric version of the Bouligand–Minkowski Fractal Dimension method.

6. Results

In this paper, first the discrimination ability of the proposed features is evaluated. As we mentioned in Section 3.2, there are totally 12 texture features. By visual assessment after several trials, we realized that several features are not efficient enough for discriminating the all texture classes. Therefore this redundant information is eliminated for the sake of reducing the size of the feature vector. The eliminated features are the first three energy distribution values respectively. Thus, we have 9 features for each texture image for subsequent classification stage.

For constructing the 2D TFCM features, we converted the color image to gray scale image and for constructing the semi 3D features, we considered the RGB domain texture images respectively. For both 2D and semi 3D planes, we totally have 18 features. For first texture database, we have a 1600x18 feature matrix and for second texture database, we have 5400x18 feature matrix.

There are 500 hidden nodes assigned for ELM algorithm. Various number of hidden nodes for ELM algorithm is considered but we have not recorded any significant performance improvements. 10 trials have been conducted for all the algorithms and the average results. The sigmoid activation function is considered in the hidden layer.

Table 3 presents the results provided by the proposed features in comparison to other color texture methods considered for the first texture database. For accuracy, we considered the percentage of images correctly classified in their respective classes. Its results are also impressive in terms of discrimination ability. Results clearly show that 2D and semi 3D TFCM is more accurate in the classification of the first texture datasets as it presents the higher accuracy.

Table 3 Performance comparison with Energy correlation signatures and WT and ANFIS approach

Methods	**Number of Features**	**Accuracy (%)**
Energy Correlation Signatures	18	93.50
WT and ANFIS	18	97.63
Proposed	18	98.67

We also experimented with the second dataset and the related comparisons are given in Table 4. As expected, 2D and semi 3D TFCM features present an inferior performance in comparison to Histogram Ratio Features (HRF), The Linear prediction model (LPM) and The Fractal Dimension (FD). As previously stated, this result is due to the reduced number of 2D and semi 3D features. Still, the number of 2D and semi 3D features is the one which presents the smallest number of descriptors at all. Between all methods, histogram ratio features (HRF) presented the lowest success rate in second databases. Its number of descriptors was not given as it depends on the color histogram of the image. Basically, the method considers only histogram bins with counts of more than 0.1% of the number of pixels in the given image. The linear prediction model (LPM) yielded the third best accuracy. 85.92% classification accuracy is obtained on the second database. On the hand, the FD yielded the second best result when we consider the HRF and LPM results. As we can see from Table 2, 99 features are used in FD procedure. Finally, the best accuracy is obtained with the proposed method. Average 97.82 % accuracy is recorded. Moreover, the proposed methodology yielded this high accuracy with only 18 features.

Table 4 Results yielded by the proposed method and several traditional texture analysis techniques.

Methods	Number of Features	Accuracy (%)
Histogram Ratio Features (HRF)	-	48.60
The Linear prediction model (LPM)	-	85.92
The Fractal Dimension (FD)	99	96.57
Proposed	18	97.82

7. Conclusions

In this paper, we propose a hybrid method where both 2D and semi 3D TFCM and ELM is combined for efficient color texture classification. ELM was proposed as an alternative and effective approach for neural networks. We evaluate our approach on two publicly available texture database and we give several comparisons with the traditional texture analysis techniques. According to the experimental results our proposal yielded the best accuracy for two databases. The combination of the semi 3D TFCM features constructed a robust structure for modeling the various textures.

It is worth to mention that ELM is an alternative and quite efficient approach to neural networks. It does not need any iteration to converge the minimum gradient point. It reduces the computation cost and consequent training period.

Finally, the proposed 2D and semi 3D TFCM signatures are capable of discriminating different classes with considerable quality, thus overcoming a traditional color texture analysis method.

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