Novel Method for Color Textures Features Extraction Based on GLCM

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Abstract. *Texture is one of most popular features for image classification and retrieval. Forasmuch as grayscale textures provide enough information to solve many tasks, the color information was not utilized. But in the recent years, many researchers have begun to take color information into consideration. In the texture analysis field, many algorithms have been enhanced to process color textures and new ones have been researched. In this paper the new method for color GLCM textures and comparing with other good known methods is presented.*

Keywords

GLCM, Gabor filters, features extraction, image classification, image retrieval, color textures.

1. Introduction

Human eye is perceiving image like a combination of primary parts (color, texture, shape). Therefore, our approach is oriented to finding some possibilities to create robust low-level descriptors by combination of these three primary parts of image, exactly, combination of color and texture is presented in this paper.

For features texture extraction we chose GLCM matrices and Gabor filters methods. However these methods are based on extraction of grayscale images, our approach is to improve these techniques to color extraction. For extraction of color textures features, RGB and HSV color spaces are used.

2. GLCM Based Method

The GLCM (Gray-level co-occurrence matrix) is a common technique in statistical image analysis that is used to estimate image properties related to second-order statistics. GLCM considers the relation between two neighboring pixels in one offset, as the second order texture, where the first pixel is called reference and the second one the neighbor pixel. GLCM is the two dimensional matrix of joint probabilities $P_{d,\theta}(i, j)$ between pairs of pixels, separated by a distance d in a given direction θ [4]. Haralick [1] defined 14 statistical features from gray-level co-occurrence matrix for texture classification. In this work, the homogeneity for features vector is used. Homogeneity is defined as

$$Homogeneity_{d,\theta} = \sum_i \sum_j \frac{P_{d,\theta}(i,j)}{1+|i-j|} \quad . \tag{1}$$

3. Gabor Filters

The Gabor filters (GF) are optimally localized in both space and spatial frequency and getting a set of filtered images which correspond to a specific scale and orientation component of the original texture. In this work 5 scales and 6 orientations are used in terms of Homogenous Texture Descriptor (MPEG-7 standard) [2].

The frequency space is partitioned into 30 feature channels indicated as C_i as shown in Fig. 1. In the normalized frequency space ($0 \le \omega \le 1$), the normalized frequency ω is given by $\omega = \Omega/\Omega_{\max}$. $\Omega_{\max}$ is the maximum frequency value of the image. The center frequencies of the feature channels are spaced equally in 30 degrees along the angular direction such as $\theta_y = 30°\times r$. Here r is an angular index with $r = \{0,1,2,3,4,5\}$. The angular width of all feature channels is 30 degrees. In the radial direction, the center frequencies of the feature channels are spaced with octave scale such as $\omega_s = \omega_0 \times 2^{-s}$, $s \in \{0,1,2,3,4\}$ where s is a radial index and ω_0 is the highest center frequency specified by 3/4. The octave bandwidth of the feature channels in the radial direction is written as $B_s = B_0 \times 2^{-s}$, $s \in \{0,1,2,3,4\}$ where B_0 is the largest bandwidth specified by 1/2 [3].

The Gabor function defined for Gabor filter banks is written as

$$G_{p_{s,r}}(\omega,\theta) = \exp\left[\frac{-(\omega-\omega_s)^2}{2\sigma_{\omega_s}^2}\right] \times \exp\left[\frac{-(\theta-\theta_r)^2}{2\sigma_{\theta_r}^2}\right] \tag{2}$$

where $G_{p_{s,r}}(\omega,\theta)$ is Gabor function at the s-th radial index and r-th angular index. σ_{ω_s} and σ_{θ_r} are the standard deviations of the Gabor function in the radial direction and the angular direction, respectively [3].

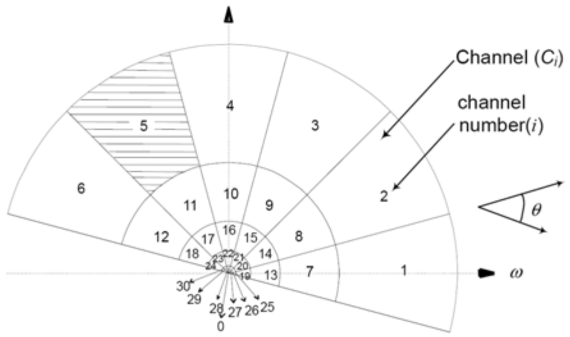

Fig. 1. Gabor filter banks (Frequency region division) [3].

For the frequency layout shown in Fig. 1, σ_{θ_r} is a constant value of $15°/\sqrt{2\ln 2}$ in the angular direction. In the radial direction, σ_{ω_s} is dependent on the octave bandwidth and is written as

$$\sigma_{\omega_s} = \frac{B_s}{2\sqrt{2\ln 2}} \quad . \tag{3}$$

The detailed description of parameters in the Gabor feature channels is given in [3].

The features vector is created by energies written as $[e_1, e_2, \ldots, e_{30}]$ indexed from 1 to 30 indicate the feature channel number defined as the log-scaled sum of the squares of Gabor-filtered Fourier transform coefficients of an image:

$$e_i = \log[1 + p_i] \tag{4}$$

where

$$p_i = \sum_{\omega=0}^{1} \sum_{\theta=0°}^{360°} [G_{p_{s,r}}(\omega,\theta) \cdot |\omega| \cdot F(\omega,\theta)] \tag{5}$$

where ω is Jacobian term between Cartesian and Polar frequency coordinates and can be written as $|\omega| = \left|\sqrt{\omega_x^2 + \omega_y^2}\right|$. $F(\omega,\theta)$ is Fourier transform of the image $f(x,y)$ [2].

4. Color Features Extraction

The GLCM and Gabor filter methods provide textures features vector from gray-level images. These methods can be also used for color images [6]. We used images represented by RGB and HSV color space.

Two types of RGB representation of image are used for color textures features extraction. The first one is RGB representation, where features vector (FV) is computed by features extraction (FE) for every R (Red), G (Green) and B (Blue) color channel:

$$FV = [FE(R), FE(G), FE(B)] . \tag{6}$$

As another type of RGB presentation, relations between all six combinations of triples of RGB are used:

$$\begin{aligned} FV = [&FE(rgb), FE(rbg), FE(gbr), \\ &FE(grb), FE(bgr), FE(brg)] , \end{aligned} \tag{7}$$

where *rgb, rbg, gbr, grb, bgr, brg* are combinations of colors computed as:

$$\begin{aligned} rgb &= round(c_1R + c_2G + c_3B) \\ rbg &= round(c_1R + c_2B + c_3G) \\ gbr &= round(c_1G + c_2B + c_3R) \\ grb &= round(cGB + c_2R + c_3B) \\ bgr &= round(c_1B + c_2G + c_3R) \\ brg &= round(c_1B + c_2R + c_3G) \end{aligned} \tag{8}$$

where the ratio $c_1{:}c_2{:}c_3$ = 100:10:1 is used.

HSV color space is a nonlinear transformation of the RGB color space. Features vector is computed for every Hue (H), Saturation (S) and Value (V) channel:

$$FV = [FE(H), FE(S), FE(V)] . \tag{9}$$

5. CGLCM Based Method

CGLCM (Color GLCM) is the special type of features extraction. In this case, FV is computed directly from 3D RGB color space, where for distance d=1 the cube of size 3x3x3 is created. By moving this cube in an image, three GLCM matrices are computed for every channel. The example of computing CGLCM for G (Green) channel is shown in Fig. 2 and described by equations (10-12).

$$GLCM_{i,j}(G) = \sum_{m=-1}^{1}\sum_{n=-1}^{1} relation\big(img(i,j,2) \,|\, img(i+m, j+n, 2)\big), \tag{10}$$

where $m \wedge n \neq 0$,

$$GLCM_{i,j}(GR) = \sum_{m=-1}^{1}\sum_{n=-1}^{1} relation\big(img(i,j,2) \,|\, img(i+m, j+n, 1)\big), \tag{11}$$

$$GLCM_{i,j}(GB) = \sum_{m=-1}^{1}\sum_{n=-1}^{1} relation\big(img(i,j,2) \,|\, img(i+m, j+n, 3)\big), \tag{12}$$

where *img* is an image represented by RGB color space, *G* is representing the G channel of RGB, and *GR* and *GB* are relations of G channel to R and G channel.

The final CGLCM vector is expressed by 9 values:

$$\begin{aligned} FV = [&FE(R), FE(RG), FE(RB), \\ &FE(G), FE(GB), FE(GR), \\ &FE(B), FE(BG), FE(BR)] \end{aligned} \tag{13}$$

where *FE* represents creating a GLCM and computing of homogeneity for this matrix.

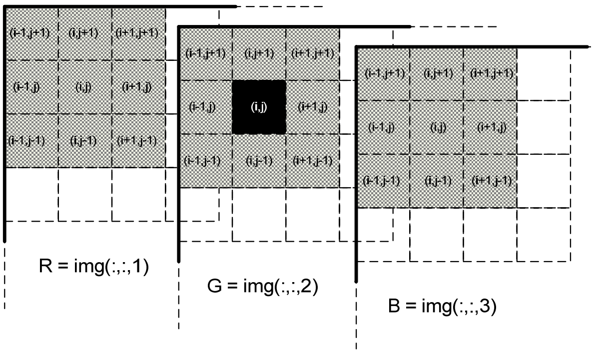

Fig. 2. The principle of CGLCM method.

6. Experimental Results

The simulation environment MATLAB was used for all experiments. We created two simple applications for annotation and retrieval. The first application is used for creating an annotated database, where the database of images is at the input and feature extraction vectors exported into XML file (Fig. 3) at the output.

The searched image and the image database are inputs for the second application. The features vector of the searched image is compared with all images in the database and similarity matching is provided by the minimal Euclidean distance (15)

$$d(x,y)=\sqrt{\sum_{i=1}^{m}(x_i-y_i)^2} \tag{14}$$

where x_i and y_i are the values of two features vectors and m is the vector size. The output of the second application is a list of images sorted by minimal distances.

```
<?xml version="1.0" encoding="utf-8"?>
<ImageList>
  <ImageFile>
    <FileName>000000.bmp </FileName>
    <FeatureVector type="CGLCM">
      0.125906 0.118667 0.048891
      0.118611 0.178479 0.074297
      0.048969 0.074304 0.200276
    </FeatureVector>
  </ImageFile>
.
.
.
```

Fig. 3. An example of XML file by the CGLCM extraction.

The features vectors are computed by the methods and the forms defined in chapters 2-5. For the rotation-invariant matching of features extraction by the Gabor filters, finding of the minimal distance for all six rotation of the feature vector is used

$$\mathrm{d}(i)=\min[\mathrm{dist}(FV_{template}(n\theta)\,|\,FV_{database}) \tag{15}$$

where $d(i)$ is the distance for the i-th image from the database, FV is the feature vector and $n\theta$ is the n-th rotation of the feature vector. For features extraction based on the GLCM and CGLCM matrices, the distance $d=1$ and all directions $\theta=\{0°,45°,90°,135°,180°,225°,270°,315°\}$ are used. Use of all direction makes these methods rotation invariant, consequently, it is not necessary to deal with the textures rotation. For better performance of GLCM, two scales (0-127 and 128-255) of intensities in an image are used.

The percentage expression of success of retrieving is provided by simply use of the method defined below

$$p=\frac{Number\ of\ truly\ found-1}{Total\ number\ of\ relevant\ textures-1}*100\% \tag{16}$$

where subtraction of 1 is used, because there was a searched image in the database.

In our experiments, 32 types of textures in 350 images (11 images for each texture) in three resolutions were used. The basic image resolution was 128x128 and others were cut to 64x64 and 32x32 as it is shown in Fig. 4. For similarity retrieval, ten textures shown in Fig. 5 were used.

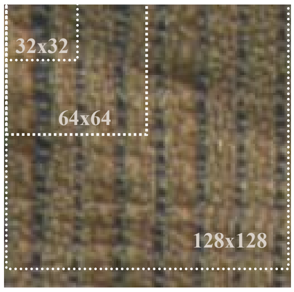

Fig. 4. Example of image resolutions in tested database.

The features vectors sizes and final results of similarity retrieval for all tested methods and image resolutions are shown in Tab.1.

Fig. 5. Textures used for similarity retrieval.

The best precision score for GLCM based methods was achieved in the RGB color space, and for GF based method in the HSV color space. From the results it is evident that GF based methods offer more effective retrieval of color textures than GLCM based methods. Utilization of simple GLCM based methods has not adequate precision of similarity retrieval; accordingly, these methods are not acceptable for image retrieval systems. On the other side, the results achieved by improved CGLCM method have same performances as GF based methods. Moreover, the precision of retrieving by CGLCM based method on smaller images (e.g. 32x32) is better in comparing to the GF based methods. In generally, the CGLCM method has rapidly lower size of feature vector.

Type of features extraction		Size of features vector	Precision of similarity retrieval		
			Images (128x128)	Images (64x64)	Images (32x32)
GLCM	Gray	2	62%	55%	35%
	RGB	6	80%	68%	57%
	6rgb	12	74%	67%	56%
	HSV	6	67%	59%	56%
GF	Gray	30	76%	63%	37%
	RGB	90	93%	76%	52%
	6rgb	180	92%	73%	58%
	HSV	90	96%	88%	60%
CGLCM		9	95%	90%	84%

Tab. 1. Results of similarity retrieval.

7. Conclusion

In the article, the comparing of gray-level and color features extraction for GLCM and GF techniques has been presented. Moreover, the new method called CGLCM has been developed, too. The results showed that use of GLCM and GF techniques for color features extraction are good way in describing the image content.

Realized experiments indicate that use of powerful GF method is more effective than GLCM. Therefore, we were finding some possibilities how to improve the GLCM based methods. We developed the CGLCM based method. This method is able to obtain similar precision of similarity retrieval like GF methods. Moreover, the smaller length of feature vector makes the new method more applied than GF methods.

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Róbert HUDEC was born in Revuca in 1974, Slovakia. He received his Ing. (M. Sc.) degree in 1998 and his PhD. degree in 2003, both at the Department of Electronics and Multimedia Communications, Technical University in Kosice. Since December 2001 he is research worker at the Department of Telecommunications, University of Zilina. His research interests include digital image processing, specially oriented on the field of filtration of mixed noise by adaptive order-statistics filters, combined low-level image description for MPEG-7 standard. Finally, since 2005 his research scopes cover systems, services and terminals of e-/m-health applications, too.