Extending GLCM to include Color Information for Texture Recognition

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Abstract. This paper proposes an automated system for texture recognition using an extended form of Grey Level Co-occurrence Matrix (GLCM). GLCM provides a popular statistical method for texture recognition, however its basic limitation is that it can only capture information from grey-scale images. To improve recognition accuracies this paper studies the possibilities of including color information from color texture images. Color information is captured by applying GLCM to each of the color channels *r, g, b*, both individually and in pairs providing 9 Color GLCM (C-GLCM) combinations i.e. *rr, gg, bb, rg, rb, gr, gb, br, bg*. Symmetrical normalized C-GLCMs computed along four directions 0º, 45º, 90º and 135º, from each of the 9 combinations are used to compute two features viz. GLCM Contrast and GLCM Mean, which are used for texture recognition. Experimental results indicate that C-GLCMs provide better recognition accuracies as compared to standard GLCMs on greyscale images.

Keywords: Texture recognition, Grey Level Co-occurrence Matrix, Color channels.
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INTRODUCTION

Texture analysis is one of the fundamental aspects of human vision by which we discriminate between surfaces and objects. In a similar manner, computer vision can take advantage of the cues provided by surface texture to distinguish and recognize objects. Texture refers to visual patterns or spatial arrangement of pixels that regional intensity or color alone cannot sufficiently describe. Many methodologies have been proposed to analyze and recognize textures in an automated fashion, some of the major approaches being energy measures [1], vertical, horizontal and diagonal masks [2], visual features like coarseness, regularity, directionality [3], fractal dimensions [4] and Gabor filters [5]. The present work proposes a scheme for texture recognition derived by extending the concept of Grey Level Co-occurrence Matrix (GLCM) proposed by Haralick [6]. GLCM provides a popular statistical method for texture analysis, which is however computed using only grey-level information while color information associated with the textures is not taken into considerations. In recent years color information has been utilized to enhance recognition accuracies [7]. The authors of [7] have however used only a single feature for recognizing textures, while the current paper attempts to improve upon it by using a combination of multiple features.

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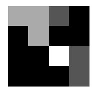
PROPOSED APPROACH

Grey Level Co-occurrence Matrix (GLCM) defines the probability of grey level i occurring in the neighborhood of another grey level j at a distance d in direction θ. These probabilities create the co-occurrence matrix $G\ (i, j \mid d, \theta)$. The *symmetrical* GLCM is formed by taking the transpose of the GLCM and adding it to the original. The GLCM is *normalized* by dividing each element by the sum of all elements. For a 4 by 4 image section A having four intensity levels the horizontal ($\theta = 0^o$) GLCM G is computed using the frequencies of occurrences of all possible combinations of intensity levels when looking along the positive x-axis and considering an offset distance d of 1 pixel. For example grey-level 0 is adjacent another 0 in A two times when looking from left to right, so the (0,0) entry in G is 2. The pictorial representation of each matrix is also shown beside it.

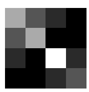
$$A = \begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 2 & 2 & 2 \\ 2 & 2 & 3 & 3 \end{bmatrix}$$

$$G = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \end{array} \begin{array}{c} \begin{array}{cccc} 0 & 1 & 2 & 3 \end{array} \\ \begin{bmatrix} 2 & 2 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{array}$$



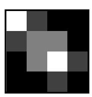
The symmetrical GLCM G_0 is formed by adding the G to its transpose G^T and dividing each element by the sum of all elements.

$$G_0 = \frac{1}{24} \begin{bmatrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{bmatrix}$$

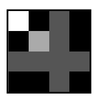


Directional GLCMs can also be computed along three other directions : vertical (θ = 90º), right diagonal (θ = 45º) and left diagonal (θ = 135º) as shown below :

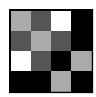
$$G_{45} = \frac{1}{18} \begin{bmatrix} 4 & 1 & 0 & 0 \\ 1 & 2 & 2 & 0 \\ 0 & 2 & 4 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$



$$G_{90} = \frac{1}{24} \begin{bmatrix} 6 & 0 & 2 & 0 \\ 0 & 4 & 2 & 0 \\ 2 & 2 & 2 & 2 \\ 0 & 0 & 2 & 0 \end{bmatrix}$$



$$G_{135} = \frac{1}{18} \begin{bmatrix} 2 & 1 & 3 & 0 \\ 1 & 2 & 1 & 0 \\ 3 & 1 & 0 & 2 \\ 0 & 0 & 2 & 0 \end{bmatrix}$$



To take color information into account each image is split into three color channels r, g, b, each channel being represented using 256 grey levels. Color GLCMs (C-GLCM) are computed first using each of the channels individually and then using two different channels simultaneously. If reference grey-tones are from channel x and neighbor grey-tones are from channel y the corresponding GLCM is denoted as G_{xy}. A texture class T consists of a set of member images : $T = \{t_1, t_2, ..., t_n\}$. For each member image, nine C-GLCMs G_{xy} [$x, y \in \{r, g, b\}$] are computed by considering each color channel individually and in pairs as shown in Eq. 1

$$G_{rr},\ G_{rg},\ G_{rb},\ G_{gr},\ G_{gg},\ G_{gb},\ G_{br},\ G_{bg},\ G_{bb} \tag{1}$$

For each C-GLCM G_{xy}, four directional GLCMs $G_{xy,\theta}$ [$\theta \in \{0°, 45°, 90°, 135°\}$] are computed as shown in Eq. 2

$$G_{xy,0},\ G_{xy,45},\ G_{xy,90},\ G_{xy,135} \tag{2}$$

A set of features derived from four directional normalized symmetrical GLCMs are used as the actual feature vector viz. GLCM Contrast (C) and GLCM Mean (M) as defined below. If $p_{i,j}$ represents the element *(i,j)* of a normalized symmetrical GLCM, and *N* the number of grey levels, then

$$C = \sum_{i=1}^{N}\sum_{j=1}^{N} p_{i,j}(i-j)^2 \tag{3}$$

$$M = M_i = \sum_{i=1}^{N}\sum_{j=1}^{N} i p_{i,j} = M_j = \sum_{i=1}^{N}\sum_{j=1}^{N} j p_{i,j} \tag{4}$$

For each directional C-GLCM $G_{xy,\theta}$, two feature values viz. Contrast (C) and Mean (M), are calculated as per Eq. 3 and Eq. 4. Each feature is averaged over the 36 directional C-GLCMs, for each member image. Thus for a specific image, Contrast C is computed as shown in Eq. 5. Mean (M) is also computed in a similar fashion.

$$\begin{aligned}
C_{rr} &= (C_{rr,0} + C_{rr,45} + C_{rr,90} + C_{rr,135})/4 \\
C_{rg} &= (C_{rg,0} + C_{rg,45} + C_{rg,90} + C_{rg,135})/4 \\
C_{rb} &= (C_{rb,0} + C_{rb,45} + C_{rb,90} + C_{rb,135})/4 \\
C_{gr} &= (C_{gr,0} + C_{gr,45} + C_{gr,90} + C_{gr,135})/4 \\
C_{gg} &= (C_{gg,0} + C_{gg,45} + C_{gg,90} + C_{gg,135})/4 \\
C_{gb} &= (C_{gb,0} + C_{gb,45} + C_{gb,90} + C_{gb,135})/4 \\
C_{br} &= (C_{br,0} + C_{br,45} + C_{br,90} + C_{br,135})/4 \\
C_{bg} &= (C_{bg,0} + C_{bg,45} + C_{bg,90} + C_{bg,135})/4 \\
C_{bb} &= (C_{bb,0} + C_{bb,45} + C_{bb,90} + C_{bb,135})/4 \\
C &= (C_{rr} + C_{rg} + C_{rb} + C_{gr} + C_{gg} + C_{gb} + C_{br} + C_{bg} + C_{bb})/9
\end{aligned} \tag{5}$$

A texture class $T = \{t_1, t_2, ..., t_n\}$ is mapped with the boundary feature values of its member images.

$$
\begin{aligned}
& T = \{C_{max},\ C_{min},\ M_{max},\ M_{min}\} \\
& where \\
& C_{max} = \max(C_1, C_2, ..., C_n); \quad C_{min} = \min(C_1, C_2, ..., C_n) \\
& M_{max} = \max(M_1, M_2, ..., M_n); \ M_{min} = \min(M_1, M_2, ..., M_n)
\end{aligned} \tag{6}
$$

A test image *s* with its computed features $\{C_s, M_s\}$ is said to belong to a specific class *T* if its feature value lies within the boundaries of the corresponding values of the training set i.e. if the following relation is satisfied

$$(C_{min} \le C_s \le C_{max}) \& (M_{min} \le M_s \le M_{max}) \tag{7}$$

EXPERIMENTATIONS AND RESULTS

The system is tested using 105 images downloaded from various Web sites [8, 9 ,10] pertaining to three texture classes *wood*, *leaves*, *rock* with 45 images as the training set and remaining 60 images as the testing set. Sample images are shown in Fig. 1 :

FIGURE 1. Sample images for three texture classes : wood, leaves, rock

The discrimination training set plots for the three texture classes are shown in Figures 2 and 3. Table 1 shows the accuracies of texture classes using C-GLCMs.

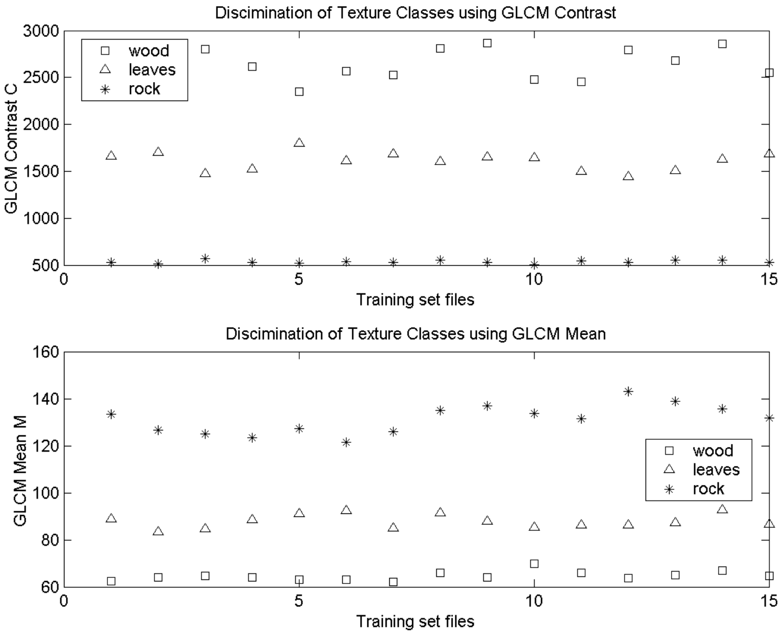


FIGURE 2. Training set plots for GLCM Contrast and GLCM Mean

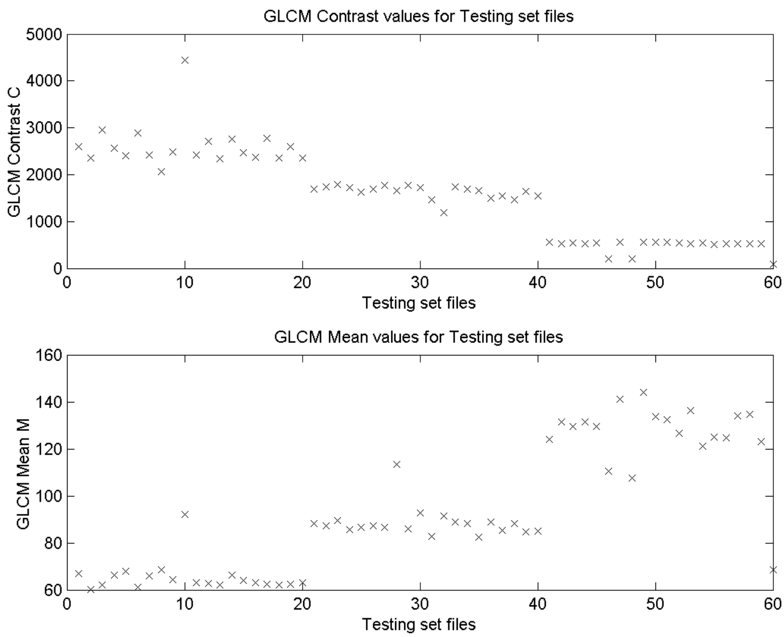


FIGURE 3. GLCM Contrast and GLCM Mean values for testing set files

TABLE 1. Texture Recognition Accuracies using C-GLCM

Texture class	GLCM Contrast	GLCM Mean
Wood	90%	95%
Leaves	95%	95%
Rock	85%	85%
Overall Accuracy	90%	91.67%

CONCLUSIONS AND FUTURE SCOPES

This work proposes a texture recognition system based on the popular technique GLCM. Previous works on GLCM have used grey-level images and computed the probability matrix based on neighboring grey-tones within the single matrix. The current work takes into account the color information by computing GLCMs based on different color channels. Unlike [7] which uses a single feature, the present work has used a combination of two features for better recognition accuracies of 90% compared to 75% reported in [7]. It may be mentioned that the recognition accuracies of the above texture samples that could be achieved using standard GLCM applied on grayscale images ranges from 60% for rock, 70% for wood and 75% for leaves. So C-GLCMs are observed to improve the recognition accuracies from around 70% to 90% from standard GLCMs. Future work will involve using a statistical classifier like a Neural Network and additional color features like histograms for improving accuracy results.

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