A New Color-Texture Approach for Industrial Products Inspection

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***Abstract*—This work presents an approach for color-texture classification of industrial products. An extension of Gray Level Co-occurrence Matrix (GLCM) to color images is proposed. Statistical features are computed from an isotropic Color Co-occurrence Matrix for classification. The following color spaces are used: RGB, HSL and La*b*. New combination schemes for texture analysis are introduced. A comparison with Local Binary Patterns (LBP) is also performed. The tests were conducted in a variety of industrial samples. The obtained results are promising and show the possibility of efficiently classifying complex industrial products based on color and texture features.**

***Index Terms*—Color vision, texture analysis, classification, statistical features extraction.**

I. Introduction

Texture and color analysis have been widely studied in the literature. Each of the two domains was studied independently. In recent years, we see an increase of interest in the use of both color and texture in image analysis. Most of these work done by the research community in these areas used simple images or available image databases. The application here is of industrial nature and the objects to analyze are made of various materials. The objective of this application is to classify these products using color and texture cues. The problem is complex because the non homogeneous nature of the products at hand. For example, roofing shingles show a difference in the spatial distribution of color and texture even for similar products.

Many methods have been proposed in order to handle machine vision problems where color and texture features serve as a cue for classification, segmentation and recognition. Various statistical descriptors have been proposed for the measure of image textures [1]-[7], [10]. Theses statistical approaches use n-order statistics to define image textures. Other approaches define textures by means of mathematical morphology operators [8], [9] or Filter Banks [10]-[13]. These techniques were first proposed for processing grayscale images, and then were extended to color texture processing.

Some authors proposed the use of a combination of color and texture features. Texture features were computed in grayscale and combined with color histograms and moments [14]-[17]. These combined features are then sent to a classifier for color-texture classification. Other authors proposed the use of color quantization to reduce the number of colors and process the resulting image as grayscale for texture extraction [18]-[24]. More sophisticated techniques use a combination in between color bands for texture features computation [25]-[29].

In this work we present a new and effective framework for color-texture classification of industrial products. The proposed Color Co-occurrence Matrix (CCM) approach uses statistical features computed from an isotropic co-occurrence matrix extracted from color bands and combined with color image entropies. A comparative study is also performed between the proposed approach [35] based on Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) texture analysis introduced in [6].

This study permits to show that some techniques are more suitable for the analysis of complex industrial products where the color and texture distribution are non homogenous and where slight variation in color for similar samples is present. These texture analysis techniques were extended to process color images. The comparison has been conducted in the following color spaces: RGB, HSL and La*b* [30], [31] with interesting results. A variety of industrial products provided by an industrial partner were used in our experiments.

The remaining of this paper is organized as follows: In section 2, we introduce the proposed framework for color-texture classification. In section 3, the theoretical background for texture analysis is prsented. In sections 4 and 5, we present the color-texture analysis and classification scheme. Experimental results are discussed in section 6. The image database and the experimental setup are presented in this section. Section 7 concludes this work.

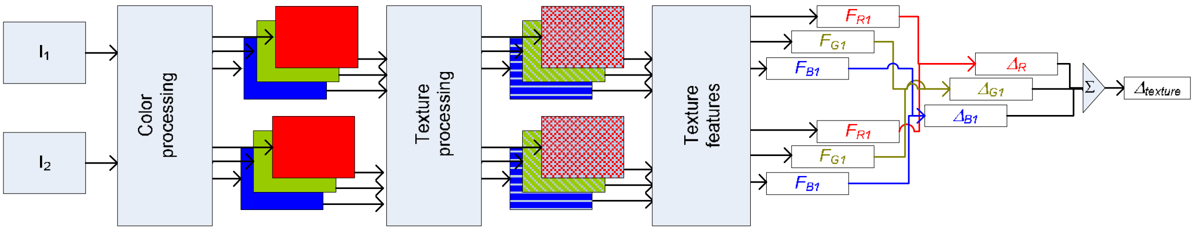


Figure 1. Framework for color-texture classification.

II. COLOR-TEXTURE CALSSIFICATION FRAMEWORK

In this work color-texture classification is performed and comparison is conducted between the proposed Color Co-occurrence Matrix (CCM) and Local Binary Patterns (LBP) texture analysis.

The Color Co-occurrence Matrix (CCM) was first proposed in [35]. This technique extends Gray Level Co-occurrence Matrix (GLCM) to process color images and combine it with color image entropies for color-texture classification. Local Binary Patterns (LBP) texture analysis was introduced in [6]. This technique is widely used by the research community for texture classification. In this work we extend the LBP approach to process color images.

For each color-texture classification technique we compare similar and non similar images. The obtained distances are normalized in order to show the discrimination power of each method. Normalization is performed by dividing each distance with the largest obtained distance.

The classification framework is given in Fig 1. The algorithm steps are given below:

1. Extract color bands from a color image (R, G, B or H, S, L or L, a*, b*) [1].
2. Apply the texture analysis technique to each band.
3. Compute the texture features F_i for each processed color band.
4. Compute the Euclidian distance between the same features in similar bands of two different images: $\Delta = \sum \left(f_i - f_j\right)^2$.
5. The final distance is the sum of the three bands distances.

The following sections show how to compute color-texture features for classification.

III. TEXTURE ANALYSIS TECHNIQUES

Texture analysis is an area of computer vision that has attracted a lot of interest. Many techniques are available in the literature. In this work we introduce a new approach for color-texture classification: Color Co-occurrence Matrix (CCM) [35] and compare its performance with the Local Binary Patterns (LBP) texture analysis technique [6].

In the following sections we present each technique and the statistical features representing texture attributes that can be extracted from the texture image.

A. Gray Level Co-occurrence Matrix (GLCM)

Gray Level Co-occurrence Matrix was proposed in [2] by Haralick and is widely used for texture analysis. It estimates the second order statistics related to image properties by considering the spatial relationship of pixels. GLCM depicts how often different combinations of gray levels co-occur in an image.

The GLCM is created by calculating how often a pixel with the intensity value *i* occurs in a specific spatial relationship to a pixel with the value *j*. The spatial relationship can be specified in different ways, the default one is between a pixel and its immediate neighbor to its right. However we can specify this relationship with different offsets and angles. The pixel at position (*i*,*j*) in GLCM is the sum of the number of times the (*i*,*j*) relationship occurs in the image.

Fig 2 describes how to compute the GLCM. It shows an image and its corresponding co-occurrence matrix using the default pixels spatial relationship (offset = +1 in x direction). For the pair (2,1) (pixel 2 followed at its right by pixel 1), it is found 2 times in the image, then the GLCM image will have 2 as a value in the position corresponding to *Ii* =1 and *Ij* =2. The GLCM matrix is a 256x256 matrix; *Ii* and *Ij* are the intensity values for an 8bit image.

The GLCM can be computed for the eight directions around the pixel of interest (Fig 3). Summing results from different directions lead to the isotropic GLCM and help achieve a rotation invariant GLCM (Fig 4).

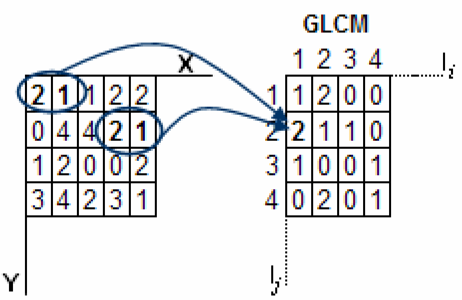
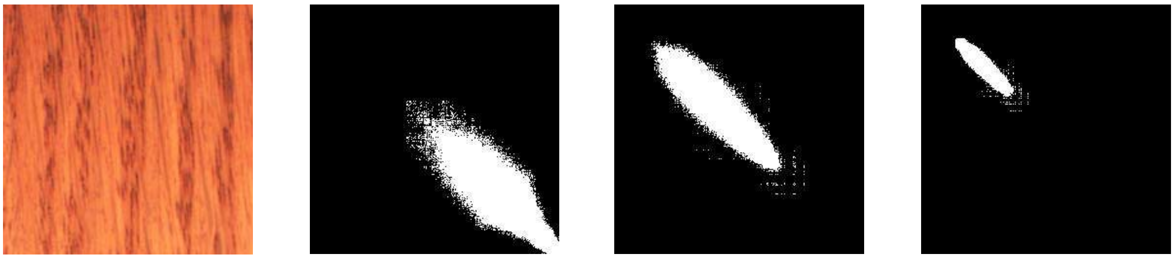


Figure 2. Description of the Gray Level Co-occurrence Matrix.

135°	90°	45°
180°	x	0°
225°	270°	315°

Figure 3. Directions used for computing isotropic GLCM.



(a) Original (b) GLCM Red (b) GLCM Green (d) GLCM Blue

Figure 4. Example of isotropic GLCM images.

B. Local Binary Patterns (LBP)

The local binary pattern (LBP) texture analysis operator was introduced in [6]. It is a gray-scale invariant texture measure computed from the analysis of a 3x3 local neighbourhood over a central pixel. The LBP is based on a binary code describing the local texture pattern. This code is built by thresholding a local neighbourhood by the gray value of its center.

The eight neighbours are labelled using a binary code {0, 1} obtained by comparing their values to the central pixel value. If the tested gray value is below the gray value of the central pixel, then it is labelled 0, otherwise it is assigned the value 1:

$$P_i^{'} = \begin{cases} 0 & \text{if } I(x_i,y_i) < I(x_0,y_0) \\ 1 & \text{otherwise} \end{cases} \tag{1}$$

$P_i^{'}$ is the obtained binary code, P_i is the original pixel value at position *i* and P_0 is the central pixel value.

With this technique there is 256 (2^8) possible patterns (or texture units).

The obtained value is then multiplied by weights given to the corresponding pixels. The weight is given by the value 2^{i-1}. Summing the obtained values gives the measure of the LBP:

$$I_{LBP} = \sum_{i=1}^{8} P_i^{'} 2^{i-1} \tag{2}$$

Fig 5 shows an example on how to compute LBP. The original 3x3 neighbourhood is given in Fig 5 (a). The central pixel value is used as a threshold in order to assign a binary value to its neighbours. Fig 5 (b) shows

6	5	2
7	6	1
9	3	7

(a)

1	0	0
1		0
1	0	1

(b)

1	2	4
8		16
32	64	128

(c)

1	0	0
8		0
32	0	128

(d)

LBP = 1+8+32+128 = 169

Figure 5. Computation of LBP.

the result of thresholding the 3x3 neighbourhood. The obtained values are multiplied by their corresponding weights. The weights kernel is given by Fig 5 (c). The result is given in Fig 5 (d). The sum of the resulting values gives the LBP measure (169). The central pixel is replaced by the obtained value. A new LBP image is constructed by processing each pixel and its 3x3 neighbours in the original image. Fig 6 shows an example of the resulting LBP images.

C. Texture statistical features

From the texture image we can compute different statistical measures. The following are used in this work:

1. Entropy:

$$Entropy = \sum_{i,j=0}^{N-1} -ln(P_{i\,j})P_{i\,j} \tag{3}$$

2. Energy:

$$Energy = \sum_{i,j=0}^{N-1} (P_{i\,j})^2 \tag{4}$$

3. Contrast:

$$Constrast = \sum_{i,j=0}^{N-1} P_{i\,j}(i-j)^2 \tag{5}$$

4. Homogeneity:

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{i\,j}}{1+(i-j)^2} \tag{6}$$

5. Correlation:

$$Correlation = \sum_{i,j=0}^{N-1} P_{i\,j} \frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{7}$$

Where:

$P_{i\,j}$ is the pixel value in position (*i,j*) in the texture image.

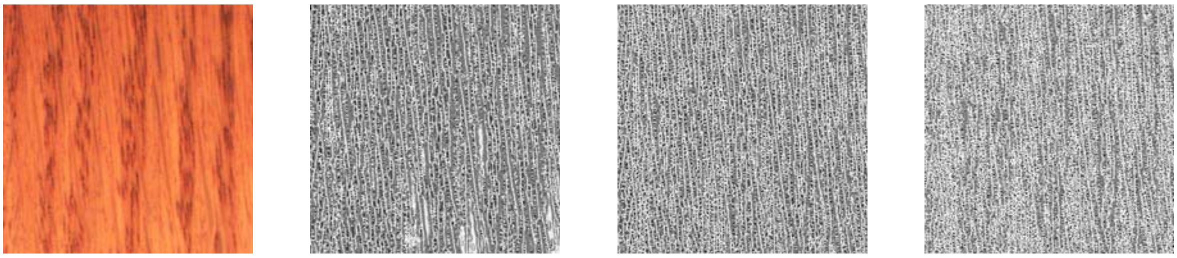
N is the Number of gray levels in the image.

$\mu = \sum_{i,j=0}^{N-1} iP_{i\,j}$ is the texture image mean.

$\sigma^2 = \sum_{i,j=0}^{N-1} P_{i\,j}(i-\mu)^2$ is the texture image variance.

D. Image entropy

In the proposed approach [35], we add original image entropy in the computation of color-texture distance. This statistical feature has shown to add more



(a) Original (b) LBP Red (b) LBP Green (d) LBP Blue

Figure 6. Example LBP images.

discrimination power to the classification scheme. The same approach is used in both texture analysis techniques: GLCM and LBP. The entropy equation is given in (3) above.

IV. COLOR-TEXTURE ANALYSIS

The texture analysis techniques presented above (GLCM and LBP) have been defined for grayscale images. We use a simple extension of these techniques to color images. In color space the texture analysis techniques and their statistical features are computed for each band. Comparisons can then be done between similar bands from two different images for classification.

Color images can be represented in different color spaces. The color model is an abstract mathematical model for color representation as vector of numbers. Many color spaces are used in computer vision. In this work, we compared the performance of these texture analysis techniques in the following color spaces: RGB, HSL and La*b*[1], [30]-[31].

RGB color space is the classical color model for color image representation. It uses an additive color mixing model of red, green and bleu colors. This color image model is provided directly by the cameras.

HSL color model represent the hue, saturation and luminance obtained form color images. HSL is obtained from RGB using color conversion equations [1], [30]-[31]. This model is widely used in computer vision for color processing.

La*b* color model is a standard color space designed by International Commission on illumination. It is perceptually uniform, and its L component closely matches human perception of lightness. This model is usually used as a reference for color difference computation [1], [30]-[31].

V. TEXTURE CLASSIFICATION

In order to classify the texture images, a distance is computed between their extracted features. This distance is obtained by computing the Euclidian distance between similar features [35]:

$$\Delta_{texture} = (F_i - F_j)^2 \tag{8}$$

Where:

$F = [Entropy, Energy, Contrast, Homogeneity, Correlation]$ is the features vector (i for image 1 and j for image 2).

The global texture distance for each color band is computed by adding to the GLCM and LBP features distance, the square difference between entropies of the original band image:

$$\Delta_b = \Delta_{texture} + (Entrop_i - Entrop_j)^2 \tag{9}$$

Where:

$Entrop_i$ is the entropy of the original band image (i for image 1 and j for image 2).

For color image classification, we extend the features distance to the color space. The distance is obtained by computing the Euclidian distance between similar features for similar bands. The global color-texture distance is the sum of each color band distance:

$$\Delta_{Color-Texture} = \Delta_{b1} + \Delta_{b2} + \Delta_{b3} \tag{10}$$

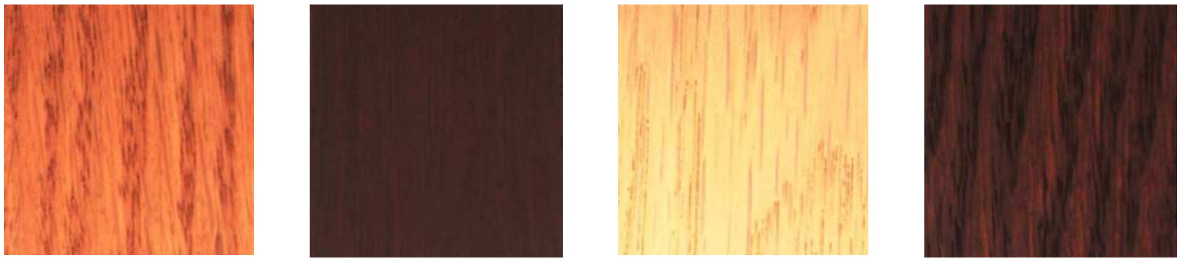
VI. EXPERIMENTAL RESULTS

For Image acquisition and processing, the following setup was used:

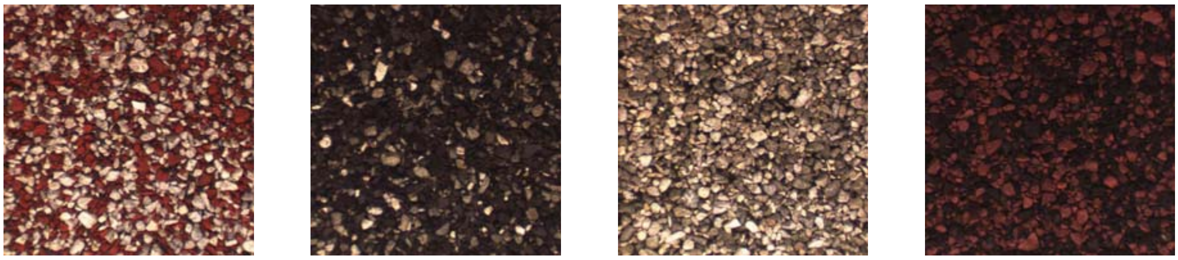
1. JAI 3-CCD high performance camera with 1024x768 resolution and a camera link interface.
2. 16mm F1.4 lens;
3. Fiber optic diffuse coaxial lighting with 200W light source;
4. A Camera link frame grabber;
5. Intel Pentium P4 processor 2.0 GHz and 2GB RAM;
6. eVision C++ library for image acquisition;
7. Matlab 7.3 (Release 2006B) and Image Processing Toolbox.

The samples were placed at approximately 20cm from the camera. The color-texture analysis algorithms were implemented using Matlab 7.3, the Image Processing Toolbox and C++. The following industrial products were used in our experiments: Roofing shingles, wood, organic fibers and fabric. About 2650 images were collected for our tests. Examples of these images are given in Fig 7.

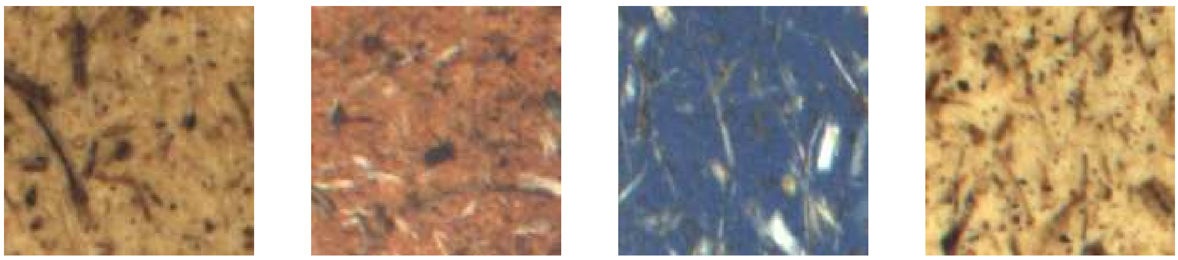
The first tests were conducted in RGB, HSL and La*b* color spaces. RGB color space gave the best results, followed closely by HSL color space (Table I) [35]. La*b* color space performed the worst. The remaining tests were done in RGB color space.



(a) Example of Wood samples



(b) Example of Roofing shingles samples



(c) Example of Organic fibers samples

(d) Example of Fabric samples

Figure 7. Example of industrial products used in our experiments.

TABLE I
PERFORMANCE OF COLOR SPACES USING GLCM FOR ROOFING SHINGLES

CCM	RGB	HSL	La*b*
Roofing shingles	94%	93%	71%

Color-texture classification experiments were conducted in the available samples, success rates are given in Table II. The obtained results show that CCM outperforms LBP color-texture classification technique.

Tests conducted in other images in the database like laminates and leather gave similar interesting results. This is very promising for our color-texture classification framework of complex industrial products.

TABLE II
SUCCESS RATE OF COLOR-TEXTURE CLASSIFICATION TECHNIQUES IN RGB COLOR SPACE

	CCM	LBP
Roofing shingles	94%	83%
Wood	90%	75%
Organic fibers	95%	85%
Fabric	91%	79%

The Color isotropic Co-occurrence Matrix (CCM) performed the best in RGB and HSL color spaces. In the La*b* color space the results does not permit to effectively discriminate between close color-texture samples. Classification between images was done successfully using a sum of color bands distances computed using isotropic GLCM. For each channel a sum of the Euclidian distance between GLCM features and the square difference between entropies of the original band images was used.

Also of importance is the lighting used during the classification. We used a fiber optic coaxial diffuse lighting that permits a uniform diffuse lighting over the inspected surface. This lighting setup gave the best result in our tests. Other lighting techniques were also tested. Diffuse high frequency stabilized full spectrum lighting provided the second best results. Poor results were obtained with fluorescent lighting.

VII. CONCLUSION

In this work we presented a new framework for color-texture classification of industrial products. A comparative study was conducted between the proposed color co-occurrence matrix (CCM) approach and local binary patterns (LBP) texture analysis approach. Also, new combination schemes for texture analysis were introduced. We conducted experimental tests with a variety of industrial samples. The obtained results are promising and show the possibility of efficiently classifying complex industrial products where non homogenous color and texture distributions are present.

The proposed CCM approach for texture analysis provide an advantageous scheme for effectively encoding complex non homogenous color and textures where irregular components are present and also textures lacking repetitive patterns.

ACKNOWLEDGMENT

This work has been supported by a grant from Quebec Ministry of Education - PART grant: PART2006N035.

Special thanks to M. Trudel, for providing product samples for our experiments and to CRVI technicians J. Poulin and L.A. Marceau (http://www.crvi.ca) who helped in building the image database.

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