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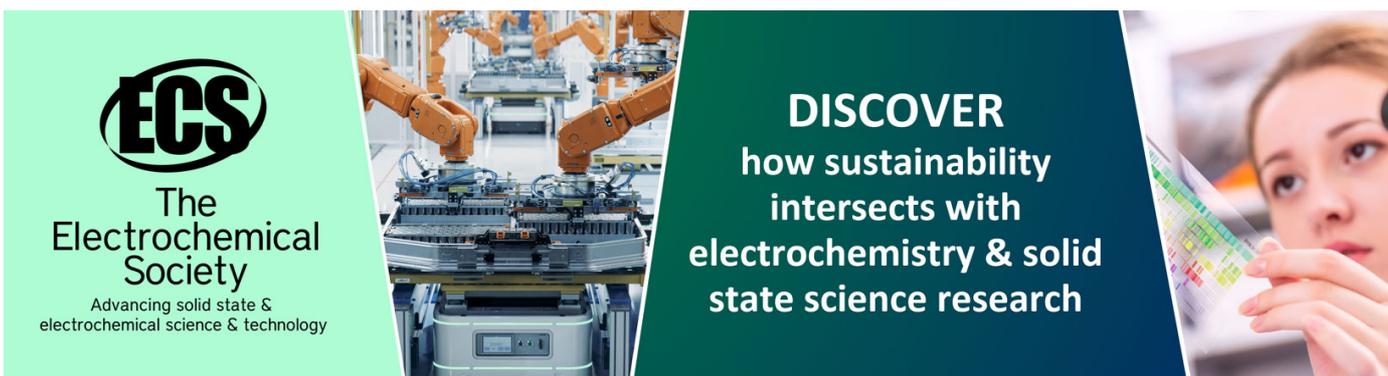
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# Wood Texture Features Extraction by Using GLCM Combined With Various Edge Detection Methods

A Fahrurozi<sup>1</sup>, S Madenda<sup>1</sup>, Ernastuti<sup>1</sup>, D Kerami<sup>2</sup>

<sup>1</sup>Computer Science Department, Gunadarma University, Indonesia

<sup>2</sup>Mathematics Department, University of Indonesia, Indonesia

Email: achmad.fahrurozi12@gmail.com

**Abstract.** An image forming specific texture can be distinguished manually through the eye. However, sometimes it is difficult to do if the texture owned quite similar. Wood is a natural material that forms a unique texture. Experts can distinguish the quality of wood based texture observed in certain parts of the wood. In this study, it has been extracted texture features of the wood image that can be used to identify the characteristics of wood digitally by computer. Feature extraction carried out using Gray Level Co-occurrence Matrices (GLCM) built on an image from several edge detection methods applied to wood image. Edge detection methods used include Roberts, Sobel, Prewitt, Canny and Laplacian of Gaussian. The image of wood taken in LE2i laboratory, Université de Bourgogne from the wood sample in France that grouped by their quality by experts and divided into four types of quality. Obtained a statistic that illustrates the distribution of texture features values of each wood type which compared according to the edge operator that is used and selection of specified GLCM parameters.

## 1. Background

In an industry that uses wood as raw material, determining the quality of the wood is very important and is known as quality control, because it is useful in the price determination and guarantee the quality of production. In the past, wood quality determination carried by experts through visual observation on a single or several sectional of wood was observed. Along with the development of technology, wood can be observed by using a digital image of a cross section of that wood that forms a particular unique texture. Wood quality is likely to be based on wood fiber density and arrangement of fibers that visualizes the annual rings on that wood. Therefore, the edge detection method used with the hope to strengthen the characteristics contained in image of wood texture. It is because these characteristics can be determined by the fibers contained in wood cross section was observed.

Recognizing of the characteristics of an image of wood texture computationally very useful because it can increase time and cost efficiency in quality control. In order that the computer can recognize the wood characteristics that represented by texture image of wood cross section, it is necessary to extract the characteristics from image of wood texture. These characteristics are usually represented by several items that commonly called features. These features will determine the characteristics of a texture. One method to obtain a texture feature that widely used are Gray Level Co-occurrence Matrices (GLCM) [1]. However in recent years, the GLCM is often combined with other methods and is rarely used individually [1], such as by combining it with Gabor filter [2], Local Binary Pattern (LBP) [3], etc.



## 2. Edge Detection Methods

Edge detection method is used to gain an edge in an image, in which the edge is meant is the boundary between the two areas that have a large enough difference in intensity. Edge detection method used in this study include first-order edge detection (Roberts, Sobel and Prewitt) and second-order edge detection (Canny and Laplacian of Gaussian). First order methods used because their simplicity and second-order used because it is claimed as the most effective edge detection methods (especially Canny), and this research aim to compare the results of first-order and second-order methods.

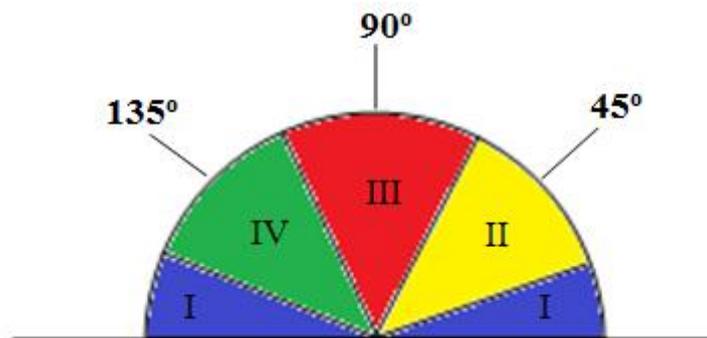
### 2.1. First-Order Edge Detection

Roberts edge detection method using a filter with the smallest size ie. 2x2, so it is known as edge simplest edge detection method. While Sobel and Prewitt edge detection method using a 3x3 filter. All of the first-order edge operator provides the results of a grayscale image, where the results of edge detection with Sobel and Prewitt operators tend to have the same characteristics [4].

### 2.2. Second-Order Edge Detection

Second-order edge detection methods using a filter with varying sizes depending on the values of certain parameters (usually denoted sigma  $\sigma$ ). Canny Operator was introduced by John Canny in 1986, and is known as the optimum edge detection operator. Canny edge detection results are a binary image that are proven to capture smooth edges or rough edges in the observed image. While the operator Laplacian of Gaussian (abbreviated as LoG) gives the grayscale or binary image, depending on the size selection and parameter (sigma) in the construction.

According to [5] Canny operator found the edge through six major procedures, ie: 1) Smoothing for noise removal. This can be done by using a Gaussian filter with a simple window. Window used much smaller than the size of the image, 2) Get a edge strength. This is done by using a Gaussian operator, 3) Find gradients use formula  $\theta = \tan^{-1}(G_y, G_x)$ , and then convert the  $\theta$  to one of four direction, which is  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$  (conversion area shown in figure 1), 4) Non-max suppression 5) Double thresholding and 6) Edge tracking by hysteresis.



**Figure 1.** Area conversion of gradients that obtained in step 3).  $\theta$  that ranges between  $0^\circ$  and  $22,5^\circ$  well as  $157,5^\circ$  and  $180^\circ$  degrees (area I) converted to  $0^\circ$ ,  $\theta$  that ranges between  $22,5^\circ$  and  $67,5^\circ$  degrees (area II) converted to  $45^\circ$ ,  $\theta$  that ranges between  $67,5^\circ$  and  $112,5^\circ$  degrees (area III) converted to  $90^\circ$ , and  $\theta$  that ranges between  $112,5^\circ$  and  $157,5^\circ$  degrees (area IV) converted to  $135^\circ$ .

The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection. The Laplacian is often applied to an image that has first been smoothed with something approximating a Gaussian smoothing filter in order to reduce its sensitivity to noise. The operator normally takes a single gray level image as input [5]. Formula Gaussian functions are used vary, one that is widely used are [6]:

$$LoG(y, x) = - \left[ \frac{x^2 + y^2 - \sigma^2}{\sigma^4} \right] e^{-\frac{(x^2 + y^2)}{2\sigma^2}} \quad (1)$$

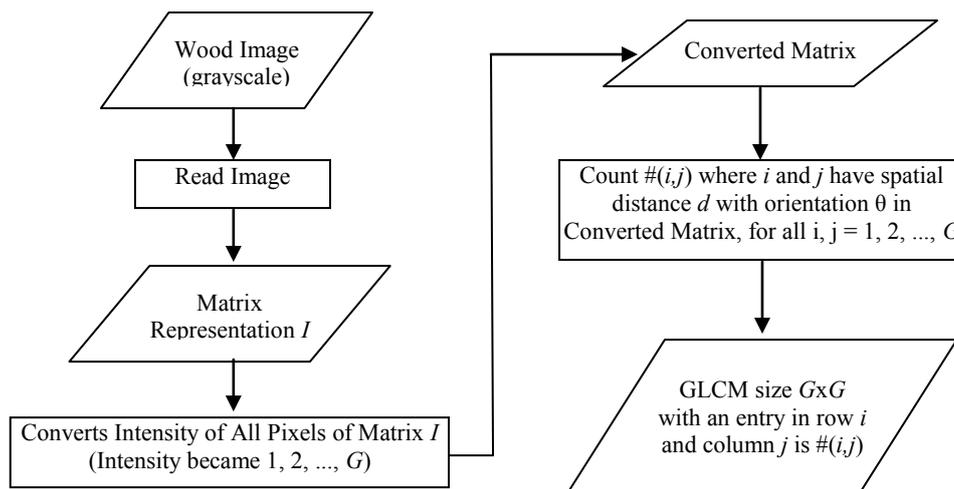
Meanwhile [8] uses the formula:

$$LoG(y, x) = \frac{1}{\pi\sigma^4} \left[ 1 - \frac{x^2+y^2}{2\sigma^2} \right] e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad (2)$$

where  $\sigma$  denote parameter of LoG operator, that can determine size of the filter and how smooth this operator filtering an input image, while  $x$  and  $y$  denotes spsial coordinate of any pixels of input image.

### 3. GLCM

GLCM introduced by Haralick [9], formed by considering the relationship of neighborhood between pixels in a matix, so often used in texture analysis. Adjacency relationship is meant is adjacency between two pixels which are determined by the spatial distance and angles between the two pixels that considered. Thus the spatial distance and angles are parameters of GLCM. Besides the spatial distance and angles, another parameter that determines the construction of GLCM (also called co-occurrence matrice) is a gray limits, which can be interpreted as a parameter that determines the size of the resulting matrix and also determine the rules for conversion of the intensity values for each pixel in original image. The algorithm of co-occurrence matrice construction of a grayscale image can be summarized in figure 2 below.



**Figure 2.** Construction of GLCM from some grayscale image

#### 3.1. Gray Limits Parameter

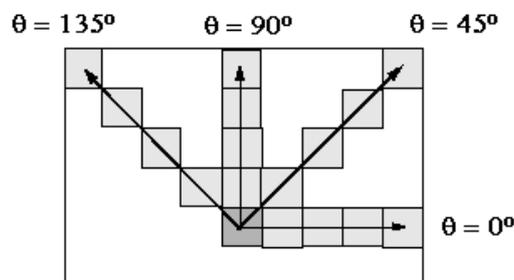
Parameter Gray limits (denoted  $G$ ) specify the size of the co-occurrence matrix that generated, as illustrated in Figure 3. Selection of parameters  $G$  determine the rules "grouping" intensity values of the pixels of digital image. Thus the value selection of  $G$  is based on the characteristics of the given image. Suppose that a grayscale image has an intensity of between 0-255, which means there are  $2^8 = 256$  gray levels, then the value of  $G$  that is generally used has the form  $2^k$ , where  $k = 3, 4, \dots, 8$  ( $k=1$  for binary image). In general, such an image has  $S = 2^m$  gray levels with a matrix representation  $I$  size  $M \times N$  and selected parameter  $G$  are  $2^k$ ,  $3 \leq k \leq m$ , then the rules of "grouping" the intensity values in matrix  $I$  are as follows:

1. Determine the divisor factor  $p = 2^m/2^k$
2. The Conversion of intensity value for each pixel in the matrix image representation provided that all pixels with intensity values between  $h*p$  to  $(h+1)*p-1$  converted to  $(h+1)$ , with  $h = 0, 1, 2, \dots, (G-2), (G-1)$ .
3. Obtained matrix  $I$  has an intensity of between 1 to  $G$ .

The Selection of parameter values for  $G$  relies on the case at hand and the data they hold. If the data contains imagery that has a texture that is formed due to small differences in intensity between neighboring pixels constituent, then the selection of small value of  $G$  is feared would "eliminates" the texture of image. So it is better to choose the value of  $G$  is large enough. However, if the image of textured owned had a very clear edge between the pixels forming the texture, it is possible the selection of  $G$  value is small, it aims to reduce the size of the resulting matrix GLCM, thus speeding up the process of computing  $G$ .

### 3.2. Angle and Direction Parameter

The values of parameter angle ( $\theta$ ) that proposed by Haralick and often used in studies on the analysis and classification of texture are  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$ . The determination of adjacency relationship between pixels of the co-occurrence matrix is generated is illustrated in figure 3. For simplicity of writing, the co-occurrence matrices obtained from spatial distance parameter  $d$  and angles  $\theta$  denoted  $M_{d,\theta}(i,j)$ .



**Figure 3.** The direction angles that determines the adjacency to obtain ordered pairs of gray level

Another angle that corresponding to the four angles in Figure 4 are  $180^\circ$ ,  $225^\circ$ ,  $270^\circ$  and  $315^\circ$ . The meaning of the corresponding here can be explained as follows: suppose the  $d$  parameter specified fixed, then the matrix co-occurrence  $M_{d,0^\circ}(i,j)$  dan  $M_{d,180^\circ}(i,j)$  are matrix that has the entries exactly the same on the main diagonal, and each reflecting the other entries with the main diagonal as axis of symmetry. Mathematically it can be written:

$$\begin{aligned} m_{d,0^\circ}(i,j) &= m_{d,180^\circ}(i,j) && \text{for } i = j \\ m_{d,0^\circ}(i,j) &= m_{d,180^\circ}(j,i) && \text{for } i \neq j \end{aligned} \quad (3)$$

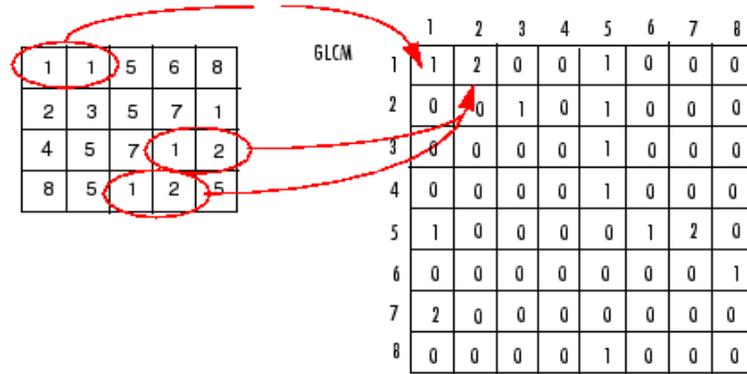
Likewise for another angle that corresponding each other, and because the co-occurrence matrix are a square matrix so we have:

$$M_{d,\theta}(i,j) = (M_{d,(\theta+180)^\circ}(i,j))^T \quad (4)$$

with  $(M_{d,(\theta+180)^\circ}(i,j))^T$  denoted the transpose of matrix  $M_{d,(\theta+180)^\circ}(i,j)$ .

The value of  $d$  determines the spatial distance to decide whether the two pixels are neighboring or not. Spatial distance ( $d$ ) that is used depending on the case at hand, widely 1, 2, 3, 4, 5, and the maximum limits for value of  $d$  are  $L = \min(R-1, K-1)$ , where  $R$  is the number of rows and  $K$  is number of columns of the matrix representation of image  $I$ . The smaller the value  $d$ , then the adjacency relationships are considered more detail, and vice versa.

Based on the above discussion, if it is determined  $G = 8$ , the value of  $d = 1$ , and the direction is determined by the angle  $\theta = 0^\circ$ , then the entries in the co-occurrence matrix produced was obtained in a manner as illustrated in figure 4 below.



**Figure 4.** Illustration of co-occurrence matrices construction. Left: Matrix representation of grayscale image I size 5x5 with gray level 1 to 8. Right: Co-occurrence matrix  $M_{1,0}^0(i,j)$  size 8x8 where the entries  $m_{1,0}^0(i,j)$  indicates the number of occurrences of gray values  $i$  and  $j$  being a neighbor with distance  $d = 1$  in the direction of  $0^\circ$  in the matrix  $I$ .

### 3.3. GLCM Features

Haralick proposed 14 features in “Statistical and structural approaches to texture” in 1979 to characterize texture [9]. GLCM produces features which describe well the relationship of adjacency among pixels in an texture image. These features extracted from a co-occurrence matrices by some formulas, depend on properties that wants to observed. Selection of features to be extracted depends on the case and texture data encountered. Features GLCM frequently used in research and analysis related to the texture of which are Contrast, Correlation, Energy, Entropy, Inverse Difference Moment (IDM) and Homogeneity. In this study, we use four of Haralick texture features, i.e. Contrast, Correlation, Energy and Homogeneity.

**3.3.1. Contrast.** Contrast is a measure of the intensity contrast between a pixel and its neighbor over the whole image [10]. Contrast is 0 for a constant image [11]. The formula is:

$$\sum_{i=1}^G \sum_{j=1}^G (i - j)^2 * P_{ij} \tag{5}$$

where  $P_{ij}$  denote the probability of an entry  $m_{d,\theta}(i,j)$  in GLCM  $M_{d,\theta}(i,j)$ , and computed with formula:

$$P_{ij} = m_{d,\theta}(i,j) / \sum_{i=1}^G \sum_{j=1}^G m_{d,\theta}(i,j) \tag{6}$$

**3.3.2. Correlation.** Correlation measures the linear dependency of grey levels of neighboring pixels. This is often used to measure deformation, displacement, strain and optical flow, but it is widely applied in many areas of science and engineering [12]. Calculated by the formula:

$$\frac{\sum_{i=1}^G \sum_{j=1}^G (i-1)(j-1) * P_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{7}$$

where:  $\mu_x = \sum_{i=1}^G \{(i - 1) * \sum_{j=1}^G P_{ij}\}$   
 $\mu_y = \sum_{j=1}^G \{(j - 1) * \sum_{i=1}^G P_{ij}\}$   
 $\sigma_x = \sum_{i=1}^G \{(i - 1 - \mu_x) * \sum_{j=1}^G P_{ij}\}$   
 $\sigma_y = \sum_{j=1}^G \{(j - 1 - \mu_y) * \sum_{i=1}^G P_{ij}\}$

**3.3.3. Energy.** Energy is also known as Angular Second Moment or Uniformity, is the sum of squares of entries in the GLCM. Energy measures the image homogeneity. Energy is high when image has very good homogeneity or when pixels are very similar [12]. Energy calculated with the formula:

$$\sum_{i=1}^G \sum_{j=1}^G (P_{ij})^2 \tag{8}$$

where  $P_{ij}$  indicated the intensity value of pixel in spatial coordinate  $(i,j)$  whole GLCM and  $G$  is the value of gray limits parameter of GLCM.

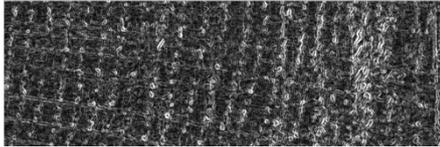
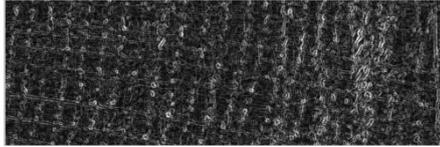
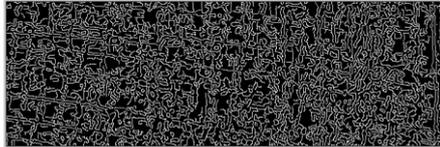
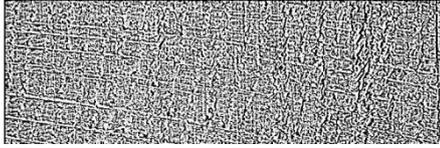
3.3.4. *Homogeneity*. Homogeneity is meant here is the local homogeneity in the observed image. It is high when local gray level is uniform and inverse GLCM is high [12]. Homogeneity, also known as Inverse Different Moment (IDM), that also large if big values are on the main diagonal. The formula is:

$$\sum_{i=1}^G \sum_{j=1}^G \frac{P_{ij}}{1+|i-j-2|} \tag{9}$$

#### 4. Results and Discussion

There are 80 images from 80 samples of wood, which are grouped into four types of quality (determined by expert) and each group consists of 20 samples, provided by LE2i laboratory, Université de Bourgogne, France. The fourth quality of the wood are: (a) very good (type Tres Fin/TF), (b) good (type Fin/F), (c) medium (type Medium/M) and (d) poor (type Gros Grain/GG). The next stage are to apply several methods of edge detection in each image of the sample of wood with the aim of strengthening the appearance of wood fiber that can be used as a measuring tool in determining the quality of the wood. Table 1 below gives an example image of a variety of edge detection that is applied to an image of type F.

**Table 1.** Image of several edge detection method applied to an image of wood sample from type F.

Original Image	Operator	Edge Detection Image
	Roberts	
	Sobel	
	Prewitt	
	Canny	
	LoG	

Based on the table above, it can be seen that the results of edge detection from several edge detection methods give the expected result, ie strengthen the characteristics of wood image were observed, particularly the fibers that visualizes the annual rings. The results of edge detection using Sobel and Prewitt operator have the same characteristics, while the result of Roberts operator gives the

impression that is darker than the other edge detection results. The image produced by Canny operator provides the number of edges that relatively much more than the edges in image produced by using another operators, as mentioned in [5] that this is due Canny can capture the strong and weak edge.

Table 2 below provides the extracted texture features of all types of wood were observed in this study that obtained by using Roberts operator as edge detection method, sets specific GLCM parameters to build co-occurrence matrices the use equation (5), (7), (8) and (9) to compute the texture features.

**Table 2.** Texture features of Roberts operator image with GLCM parameters  $d = 1, \theta = 45^\circ$ , and  $G = 8$

Wood Type	Sample	Features				Wood Type	Sample	Features			
		Contrast	Corr	Energy	Hom			Contrast	Corr	Energy	Hom
TF	01	0.4513	0.2048	0.2408	0.7818	M	01	0.409	0.1944	0.2703	0.7978
	02	0.4263	0.3308	0.2353	0.7964		02	0.3766	0.2813	0.2886	0.8159
	03	0.4522	0.2072	0.2403	0.7816		03	0.4084	0.197	0.2702	0.7981
	04	0.4203	0.3571	0.2356	0.8008		04	0.3402	0.2923	0.3163	0.8313
	05	0.4449	0.2137	0.2421	0.7844		05	0.409	0.1944	0.2703	0.7978
F	01	0.3821	0.1908	0.3034	0.8103	GG	01	0.4214	0.2424	0.2538	0.7966
	02	0.3198	0.2714	0.3683	0.8416		02	0.2805	0.2591	0.4284	0.8604
	03	0.3261	0.2435	0.368	0.8386		03	0.4258	0.2428	0.2532	0.7956
	04	0.3825	0.1856	0.3046	0.8101		04	0.265	0.2532	0.4556	0.8679
	05	0.3877	0.19	0.2994	0.8077		05	0.3861	0.2064	0.2917	0.8083

Suppose it is assumed that the data texture features is the Normal distribution, then the 95% confidence intervals for each values of features obtained can be calculated by the formula [13]:

$$[\bar{x} - (1.96 * s / \sqrt{n - 1}), \bar{x} + (1.96 * s / \sqrt{n - 1})] \quad (10)$$

where  $\bar{x}$ ,  $s$  and  $n$  respectively denotes samples means, samples standard deviation, and number of samples. By paying attention to the confidence intervals were obtained, it can be analyzed related to the distribution of texture features values that can be used to distinguish wood type. If the confidence interval for mean of a feature between each type of wood has a fairly large intersection, it can be said that the texture features aren't good enough to used to characterize, or even further to distinguish between one wood texture image and another. Table 3 presents confidence interval for means of the Contrast feature of the whole image of Roberts operator on four types of wood in this paper, where each type has 10 wood texture image.

**Table 3.** Contrast of Image by Roberts Operator with GLCM parameters:  $d = 2, \theta = 135^\circ$ , and  $G = 8$

Sample	Wood Type			
	TF	F	M	GG
01	0.5024	0.4289	0.4513	0.4857
02	0.5452	0.3747	0.4418	0.3311
03	0.5033	0.3739	0.4524	0.4859
04	0.5561	0.4229	0.4207	0.3085
05	0.5003	0.4258	0.4587	0.4311
06	0.5642	0.381	0.4454	0.3436
07	0.5027	0.3758	0.4366	0.4135
08	0.5619	0.4256	0.4376	0.3775
09	0.5337	0.3788	0.4547	0.4881
10	0.2655	0.351	0.4403	0.3383
Mean	0.50353	0.39384	0.44395	0.40033
Std Deviation	0.087667	0.028712	0.011123	0.070116
Int Confidence	0.446255; 0.560805	0.375081; 0.412599	0.436683; 0.451217	0.354521; 0.446139

Due GLCM has some parameters that determine its construction, we then can analyze the effect of changing of GLCM parameters to changes of the distribution of pre-determined texture features. Table 4 presents the effect of changing the spatial distance parameter to confidence interval for the

Energy features in the whole sample of wood (each type of wood has 20 pieces of wood texture images).

**Table 4.** Confidence interval for means of feature Energy of each type of wood depend on various spatial distance (Fixed parameters  $\theta = 0^\circ$  and  $G = 8$ , except for operator Canny  $G = 2$ )

Edge Detection Operator	Wood Type	Spatial Distance				
		1	2	3	4	5
Roberts	TF	0.2247 ; 0.3110	0.2006 ; 0.2818	0.2000 ; 0.2775	0.2002 ; 0.2750	0.2002 ; 0.2732
	F	0.3503 ; 0.3949	0.3153 ; 0.3574	0.3116 ; 0.3514	0.3090 ; 0.3465	0.3065 ; 0.3426
	M	0.2951 ; 0.3113	0.2645 ; 0.2785	0.2621 ; 0.2749	0.2609 ; 0.2727	0.2596 ; 0.2707
	GG	0.3162 ; 0.4588	0.2845 ; 0.4219	0.2812 ; 0.4140	0.2787 ; 0.4088	0.2766 ; 0.4051
Sobel	TF	0.0306 ; 0.0543	0.0242 ; 0.0444	0.0237 ; 0.0428	0.0238 ; 0.0422	0.0237 ; 0.0415
	F	0.0716 ; 0.0827	0.0598 ; 0.0692	0.0585 ; 0.0674	0.0580 ; 0.0663	0.0573 ; 0.0652
	M	0.0555 ; 0.0598	0.0456 ; 0.0490	0.0446 ; 0.0477	0.0443 ; 0.0473	0.0438 ; 0.0467
	GG	0.0607 ; 0.1001	0.0504 ; 0.0841	0.0494 ; 0.0814	0.0489 ; 0.0800	0.0481 ; 0.0788
Prewitt	TF	0.0565 ; 0.0896	0.0455 ; 0.0743	0.0444 ; 0.0719	0.0444 ; 0.0711	0.0441 ; 0.0702
	F	0.1241 ; 0.1398	0.1057 ; 0.1196	0.1036 ; 0.1168	0.1027 ; 0.1150	0.1016 ; 0.1132
	M	0.0976 ; 0.1042	0.0815 ; 0.0871	0.0796 ; 0.0848	0.0792 ; 0.0842	0.0782 ; 0.0832
	GG	0.1064 ; 0.1604	0.0902 ; 0.1373	0.0884 ; 0.1332	0.0876 ; 0.1313	0.0863 ; 0.1297
Canny	TF	0.4906 ; 0.5093	0.4570 ; 0.4755	0.4569 ; 0.4756	0.4657 ; 0.4850	0.4704 ; 0.4879
	F	0.4757 ; 0.4816	0.4394 ; 0.4448	0.4377 ; 0.4429	0.4449 ; 0.4501	0.4452 ; 0.4506
	M	0.4866 ; 0.5038	0.4517 ; 0.4695	0.4510 ; 0.4691	0.4595 ; 0.4784	0.4633 ; 0.4804
	GG	0.4820 ; 0.5000	0.4464 ; 0.4617	0.4452 ; 0.4593	0.4522 ; 0.4673	0.4533 ; 0.4676
LoG	TF	0.1390 ; 0.1577	0.0961 ; 0.1112	0.0949 ; 0.1107	0.0945 ; 0.1103	0.0941 ; 0.1100
	F	0.1150 ; 0.1189	0.0767 ; 0.0811	0.0741 ; 0.0789	0.0740 ; 0.0787	0.0744 ; 0.0793
	M	0.1233 ; 0.1289	0.0839 ; 0.0889	0.0828 ; 0.0876	0.0821 ; 0.0871	0.0820 ; 0.0872
	GG	0.1156 ; 0.1385	0.0787 ; 0.0971	0.0746 ; 0.0948	0.0749 ; 0.0948	0.0755 ; 0.0956

The effects of changes the parameters spatial distance to a observed feature can be further analyzed by calculating the percentage of intersection of confidence interval for the mean between each types of wood, as presented in table 5. The percentage is calculated by the following formula:

$$PI_{ij} = \frac{I_{ij}}{U_{ij}} \times 100\% \tag{11}$$

with:

$PI_{ij}$  = percentage of intersection of class  $i$  and class  $j$ ,

$I_{ij}$  = length of intersection between the confidence interval for the mean of the data set of the features of class  $i$  and class  $j$ ,

$U_{ij}$  = length of union between the confidence interval for the mean of the data set of the features of class  $i$  and class  $j$ .

**Table 5.** Intersection percentage of each confidence interval for mean of feature Energy with fixed GLCM parameters  $\theta = 0^\circ$  and  $G = 8$  (except for operator Canny  $G = 2$ )

	Wood Type	Spatial Distance														
		1			2			3			4			5		
		TF	F	M	TF	F	M	TF	F	M	TF	F	M	TF	F	M
Roberts	TF	100	-	-	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-	0	100	-
	M	18.29	0	100	17.24	0	100	16.4	0	100	15.75	0	100	15.23	0	100
	GG	0	31.29	0	0	30.61	0	0	29.97	0	0	28.81	0	0	28.07	0
Sobel	TF	100	-	-	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-	0	100	-

	M	0	0	100	0	0	100	0	0	100	0	0	100	0	0	100
Prewitt	GG	0	28.3	0	0	27.94	0	0	27.9	0	0	26.73	0	0	25.61	0
	TF	100	-	-	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-	0	100	-
	M	0	0	100	0	0	100	0	0	100	0	0	100	0	0	100
Canny	GG	0	29.11	0	0	29.3	0	0	29.4	0	0	28.13	0	0	26.92	0
	TF	100	-	-	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-	0	100	-
	M	58.19	0	100	52.65	0	100	49.63	0	100	49.59	0	100	40.83	0	100
LoG	GG	34.47	0	61.52	16.12	0	43.13	7.86	0	34.41	4.83	0	29.78	0	0	15.54
	TF	100	-	-	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-	0	100	-
	M	0	0	100	0	0	100	0	0	100	0	0	100	0	0	100
	GG	0	14.17	24.7	3.16	12.1	27.52	0	20.6	23.82	0.86	18.63	24.88	4.46	17.76	26.01

Based on the calculation results in the foregoing table, shows that the percentage of slices are almost always stable for each operator, except Canny operator. This is presumably because Canny operator generates a binary image with a black background and white edges, and caught a lot of edges that not important so that between the type of wood has almost similar look and co-occurrence matrix. The influence of changing of parameter angle to confidence interval for the mean of the features Energy given in table 6.

**Table 6.** Intersection percentage of each confidence interval for mean of feature Energy with fixed GLCM parameters  $d = 1$  and  $G = 8$  (except for operator Canny  $G = 2$ )

Operator	Wood Type	Angle											
		0			45			90			135		
		TF	F	M									
Roberts	TF	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-
	M	18.29	0	100	20.88	0	100	18.83	0	100	13.52	0	100
	GG	0	31.29	0	0	31.79	0	0	32.33	0	0	30.15	0
Sobel	TF	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-
	M	0	0	100	0	0	100	0	0	100	0	0	100
	GG	0	28.3	0	0	29.79	0	0	28.9	0	0	25.64	0
Prewitt	TF	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-
	M	0	0	100	0	0	100	0	0	100	0	0	100
	GG	0	29.11	0	0	31.03	0	0	29.86	0	0	26.4	0
Canny	TF	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-
	M	58.19	0	100	41.37	0	100	16.75	0	100	1.24	0	100
	GG	34.47	0	61.52	1.94	0	36.36	0	9.28	6.31	0	13.08	0
LoG	TF	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-
	M	0	0	100	0	0	100	0	0	100	0	0	100
	GG	0	14.17	24.7	1.19	16.45	30.57	0	16.96	21.58	0	22.27	24.43

Can be seen in the table above that intersection percentage is also quite stable, except Canny operator. This is because the Canny operator produces edges with a random pattern as shown in table 1. While the influence of changing of parameter Gray Limits to confidence interval for the mean of Energy features are presented in table 7. Canny operator is not loaded because Canny generates binary image.

**Table 7.** Intersection percentage of each confidence interval for mean of feature Energy with fixed GLCM parameters  $d = 1$  and  $\theta = 0^\circ$

Wood		Gray Limits														
		8			16			32			64			128		
		TF	F	M	TF	F	M	TF	F	M	TF	F	M	TF	F	M
Roberts	TF	100	-	-	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-	0	100	-
	M	19.28	0	100	0	0	100	0	0	100	0	0	100	0	0	100
	GG	0	31.29	0	0	27.62	32.82	0	26.54	0	0	25.54	0.53	0	25.3	0.94
Sobel	TF	100	-	-	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	4.06	100	-	4.43	100	-
	M	0	0	100	5.56	0	100	16.83	0	100	19.78	0	100	0	0	100
	GG	0	28.3	0	0	27.66	0	0	26.66	0.04	19.95	27.08	0.08	36.17	28.61	1.09
Prewitt	TF	100	-	-	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-	0	100	-
	M	0	0	100	0.07	0	100	2.95	0	100	4.12	0	100	5.14	0	100
	GG	0	29.11	0	0	27.35	0	0	26.99	0	0	26.37	0	0	26.63	0
LoG	TF	100	-	-	100	-	-	100	-	-	100	-	-	100	-	-
	F	0	100	-	0	100	-	0	100	-	0	100	-	0	100	-
	M	0	0	100	0	0	100	0	0	100	0	0	100	0	0	100
	GG	0	14.17	24.7	0	16.45	23.88	0	16.28	23.9	0	16.27	23.79	0	16.21	23.65

In the table above shows that the intersection percentage of Roberts operator and especially Sobel operator suffered considerable changes with increasing values of gray limits parameter than other operators.

### 5. Conclusion

Based on the experimental results, it was found that edge detection method can strengthen the characteristics of the image of wood texture who want to observed, in particular the appearance of the wood fiber. Feature extraction performed by GLCM provide statistical variation value for each edge detection method that applied. Changes GLCM parameters affect the level differences in the characteristics of the four types of wood that are observed. Based on the features Energy experiments, it was found that greatest affect occur when changes are made in the Graylimits parameter, especially on Sobel operator. A combination that gives the best traits to characterize the type of wood, which is indicated by the number of the smallest intersect (relative to the interval) is Sobel operator and angle parameters. While distributions of data features with worst intersection is a combination of Canny operator and angle parameters. So as to feature Energy, the operator that most appropriate to be used to extract classification feature is the Sobel operator, while the graylimits value used is 8, with the aim of improving accuracy and reducing the size of GLCM used. For other features it is necessary to analyze and further research. The results of this research can then be used to perform classification of four types of wood were observed, by determine the classification method according to the characteristics of the data.

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