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Knots timber detection and classification with C-Support Vector Machine

Fakhira Iwani Muhammad Redzuan[1], Marina Yusoff[2]
[1,2]Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia
[2]Advanced Analytic Engineering Center (AAEC), Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia

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ABSTRACT

Timber knots recognition is of prime importance to further determine the timber grade. The recognition is normally based on the human expert's eyes in which can lead to some flaws based on human limitations and weaknesses. The use of X-ray can cause emits radiation and can be dangerous to the workers. This paper addresses the employment of computational methods for knot detection. A pre-processing and feature extraction methods include contrast stretching, median blur and thresholding, gray scale and local binary pattern were used. More than 400 datasets of knot images of the tropical timbers, namely Acacia and Hevea Brasiliensis have been tested using C-support vector machine as a knot classifier. The findings demonstrate different performances for three types of kernel. Linear kernel function outperformed both radial basis function and polynomial kernel functions for Acacia and Hevea Brasiliensis species. Both species classifications using linear kernel have managed to achieve a promising accuracy. Knots classification with the used of support vector machine has shown a promising result to improve the classifier and test with different types of tropical timbers.

Corresponding Author:

Marina Yusoff,
Faculty of Computer and Mathematical Sciences,
Universiti Teknologi MARA,
Shah Alam, Selangor, Malaysia
Email: marinay@tmsk.uitm.edu.my

1. INTRODUCTION

Timber is the only natural material structural that fully renewable and recyclable material. Furthermore, it does not contribute to greenhouse gas emissions. Timber can be formed in a various of shapes and sizes [1]. Timber has been a high strength to weight ratio. Thus, it makes the timber bear a lot of its own self-weight and the most efficiently used in structures [2]. However, the strength of timber can be affected by defects. The timber defects occurred naturally such as knots, slope of grain, gum veins and reaction wood. Due to this property, timber can be graded according to defects. The defects can be identified through knot identification as it is one of the criteria for timber grading stated in Malaysian Standard [3]. The knot is used to measure the straightness of the timbers. The diameter can affect the grade of timber, more bigger knots leads to the lower quality of timber grade [4]. Thus, identification of timber knot timber the procedure of timber grading.

Timber expert recognized knots on timber surfaces based on what he\she saw with his/her naked eyes [5]. However, because this requires human works, sometimes it will lead to some flaws based on human limits and weaknesses. The performance of this method is inconsistent because the judgement of human is very subjective [5-6] and led to low accuracy in classification of knot for timber grading because of eye fatigue [7]. Moreover, it is tedious and time consuming [8]. Currently, the most used method for automatic timber grading is based on grading machine, where it uses a scanning method to detect the knots based on timber image. Some machines use X-ray method to detect knots in the timber, however, because X-ray is well-known to emit radiation, it is dangerous to the workers [9]. Also, enlargement of image from X-ray become less sharp and more noise [10]. Hence, it caused less accuracy and efficiency in classifying the knot's type [7]. Despite of all these problems and limitations, classification of knot in timber grading process is an imperative in the manufacture of the end product [11-12]. Delays and inaccurate classification of knots will affect the subsequent process [11].

For the past decades, there have been many developments of system regarding the timber such as detection and classification of defects on plant [13-15] on timber's surface [7]. Using visual information about timber defects is reasonable for detection techniques because the color and texture of timber's defects are different [9]. A few of previous studies have been discussed about the knots on timber's surface. Timber's knots are the first defects considered by the timber's company for timber price and visual timber grading [4].

There are many detection methods used to detect on timber's surface. Song et al. used image block for replacement of image pixels. Image block applied for defect detection [9]. Most past, researchers used segmentation algorithm, but it is one of the hardest tasks in the image processing field. Hence, they used image block. Gu et al. applied simple edge detection algorithm and edge chaining to detect the outer boundary of knots [7]. For the unconnected boundary is closed by B-spline. The outer boundary of knots is important as knot image divided into three parts based on its which is interior, exterior and boundary region. Stretching contrast and thresholding method in pre-processing used by [16]. Stretching contrast is darkened the dark area and brightened the bright area. The thresholding with the Otsu's method and morphological operations is applied to detect the knots timber. However, another study from [13], the defects are detected by threading with entropy maximization and followed by median filtering. The false negative rate is lower than thresholding with Otsu's method and Morphological operations with the same data. Median filtering and Sobel operator to detect edges is employed [20].

Various of techniques are applied for color and texture extraction of timber as such percentile color image histogram to extract the color features and eigenvector to extract the texture features of an image block matrix [9]. Despite that, HSV (Hue, Saturation, Value) is applied to overcome the sensitivity of the percentile color histogram to the intensity in RGB color spaces. However, the value of these two techniques needs to normalize before combine the techniques for input in Support Vector Machine (SVM) classifier. Gu et al. pseudo colour to filter images and average of pseudo color values computed by non-linear order statistic filters [7] meanwhile Hittawe et al. used extraction of Speed Up Robust Features (SURF) and another study used both SURF and Local Binary Pattern (LBP) to extract the features [16].

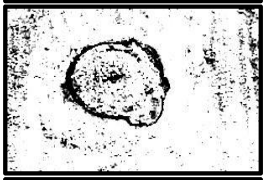
Many machine learning methods employed in improving timber utilization as an initiative in the direction towards industrial 4.0. Some of the methods such as genetic algorithm, particle swarm optimization and Monte Carlo were used in assisting the timber structural design research for tropical timbers [17-19]. However, generally most of classifiers applied from the previous studies are SVM, Artificial Neural Network and few hybrid systems for non-tropical timber knot classification. There was research use a few machine learning techniques to define quality of wood based on knots timber with the same technique of image processing. Vieira segmentation technique [5] and followed by Haralick Descriptor to extract the features. It shows SVM got the highest accuracy with 87%. SVM non-linear Gaussian kernel to detect knots and other defects with average accuracy 78% [9]. However, 90% for the knot detection alone. Both researches by [13] used Bag of Words to represent features extraction and as an input data in linear SVM classifier to detect knots and identify the number of knots. It was found that combination of feature extraction SURF and LBP got more than 90% [7] achieved 96% with tree-structure SVM technique to classify types of knots. Another research conducted by [20] used Backpropagation Artificial Neural Network with average accuracy 86.7%, but 80% for knot detection only. Therefore, this paper discusses on the identification on timber's surface and evaluation of knot classification using SVM for tropical timbers.

2. DATA ACQUISITION AND IMAGE PRE-PROCESSING

Three species of tropical hardwood timber namely Hevea Brasiliensis, Meranti and Acacia tree were collected. The data collection conducted at Konsortium Peka Sdn Bhd, Lanchang, Pahang and Woodsfield Resources Sdn Bhd Pasir Gudang, Johor State, Malaysia. All of knots timber images data sets have been processed with image processing technique. Image processing is to let the system to understand the data and detect the knots timber. The selected features have been extracted from the input in the classifier.

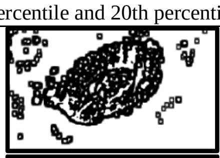
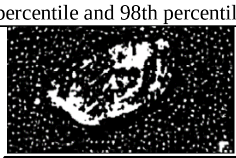
All original images have been cropped to get the knot image only. All of the cropped images were resized by using ImageMagicDisplay tool. All knot images are resized to 300x150 pixels. Table 1 demonstrates the image processing steps.

Table 1. Image processing

Process	Result
Convert image into grayscale.	
Image enhancement by using Contrast Stretching.	
Reduce image's noise by using Median Blurr.	
Segmentation of image has been done by using thresholding with Otsu's method.	
Texture has been extracted by using Local Binary Pattern.	

Texture has been extracted by Local Binary Pattern (LBP) to distinguish sounds and unsound knots. There are two experiments conducted for both images. Table 2 shows the images being extracted after reduce noise image and segmentation. The value of LBP for each pixel of the image become as an input into SVM classifier. Then, the image processing steps have been done, all the finalized data were saved into a .csv file. This data then been used as an input for SVM.

Table 2. Result of image after extracted by LBP

Process	Contrast Stretching: 5th percentile and 20th percentile	Contrast Stretching: 10th percentile and 98th percentile
LBP after reduce noise image:		
LBP after segmentation:		

3. C-SVM EMPLOYMENT

The value from feature extraction is stored in csv file. After that, the data was split into two sections which are data for training and data for testing. Split the data was then fed into SVM classifier to train and test purposes. For the output, SVM trained model was used to determine the type of knots which are sound knot and unsound knot. The steps in SVM implementation is shown in Figure 1.

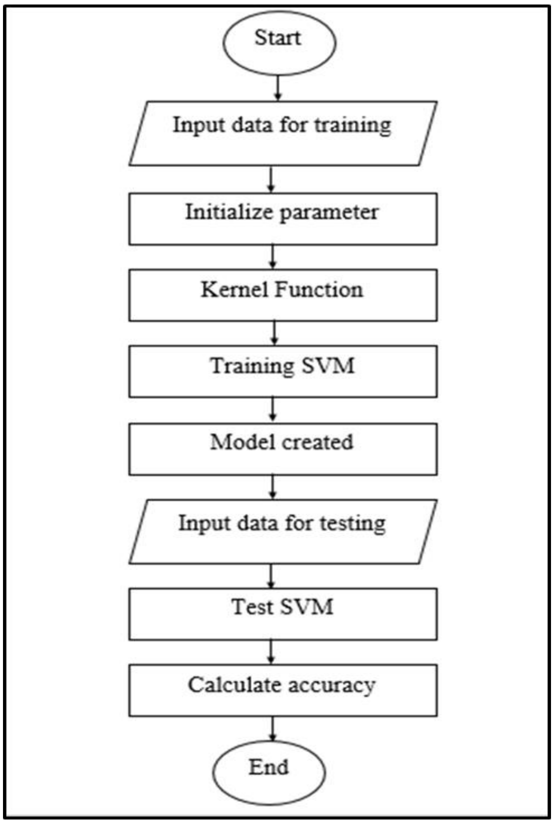


Figure 1. SVM Implementation steps

For this type of SVM, training involves the minimization of the error function to solve the following the primal optimization:

$$\frac{1}{2}w^T w + C \sum_{i=1}^{1} \xi_i \tag{1}$$

Subject to the following constraint (2):

$$y_i\left(w^T \phi(x_i) + b\right) \geq 1 - \xi_i \text{ and } \xi_i \geq 0, i = 1,\ldots, N \tag{2}$$

where C is the regularization parameter, w is the vector of coefficients, b is a bias that constant, and ξ_i represents parameters for handling non-separable data. The index i labels the N training cases. Furthermore, $y \in \pm 1$ represents the class labels and x_i represents the independent variables. The ϕ represent kernel applied. Due to the possible high dimensionality of the vector variable w, the following dual problem is solved.

$$\frac{1}{2}\alpha^T Q\alpha - e^T \alpha \tag{3}$$

Subject to

$$\begin{aligned} &y^T \alpha = 0 \\ &0 \leq \alpha_i \leq C \quad i = 1,..l\# \end{aligned} \tag{4}$$

where $e = [1,\ldots,1]^T$ is the vector of all ones, Q is an l by l positive semidefinite matrix, $Q_{ij} = y_i y_j K(x_i, x_j)$, and $K(x_i, x_j) \equiv \varphi(x_i)^T \varphi(x_j)$ is the kernel function.

$$w = \sum_{i=1}^{l} y_i \alpha_i \phi(x_i) \tag{5}$$

After problem (3) and 4) is solved, using the primal-dual relationship, the optimal w satisfies and the decision function is shown in (6).

$$sgn\,(w^T\,\varphi(x)+\,b\,)=sgn\left(\sum_{i=1}^{l}y_i\alpha_i\;K\left(\,x_i\,,\,x_j\,\right)+\,b\,\right)\#\qquad(6)$$

4. COMPUTATIONAL RESULTS AND FINDINGS

There were experiments have been done on Acacia and Hevea Brasiliensis species to get the accuracy for each kernel function. Table 3 indicates all parameters were setting up for the data. There were 50 experiments conducted to find the highest accuracy for each species. The splitting data were 70% for training and 30% for testing.

Table 3. Parameter settings

	Linear Kernel	RBF Kernel	Polynomial Kernel
C	1,3,5	1,3,5	1,3,5
Gamma	-	0.01	-
Degree	-	-	30

4.1. Results for Acacia species

Several tests were performed to see the accuracy of the knot detection for Acacia Species using linear, RBF and polynomial kernel. The evaluation was based on the application of LBP as an extraction feature. Noise reduction and segmentation using different contrast values were performed prior to the extraction process. Table 4 shows the performance of knot detection using linear kernel function, where the parameter, C are 1, 2, and 3. It is demonstrated that the highest accuracy of 76% is reported, when using the percentile of contrast 10^{th} and 98^{thn}, C=5 and based on the extract the texture by LBP after segmentation.

Table 4. Performance of knot detection for acacia species using linear Kernel function

Linear kernel function, C	Contrast (5,20)		Contrast (10,98)	
	Reduce noise (%)	Segmentation (%)	Reduce noise (%)	Segmentation (%)
1	59	62	62	72
3	60	75	65	69
5	65	69	62	**76**

Meanwhile, the results of RBF kernel using gamma=0.001 has shown lower accuracy compared to linear kernel as demonstrated in Table 5. most have highest accuracy is 65%. Meanwhile, as shown in Table 6, the performance of Polynomial Kernel seems better that RBF with the highest accuracy of 71%.

Table 5. Performance of knot detection for Acacia species using RBF Kernel

RBF Kernel	Contrast (5,20)		Contrast (10,98)	
	Reduce noise (%)	Segmentation (%)	Reduce noise (%)	Segmentation (%)
1	65	63	65	65
3	65	65	65	62
5	62	65	65	65

Table 6. Performance of knot detection for Acacia species using Polynomial Kernel

Polynomial Kernel, C	Contrast (5,20)		Contrast (10,98)	
	Reduce noise (%)	Segmentation (%)	Reduce noise (%)	Segmentation (%)
1	65	69	71	69
3	68	65	65	71
5	66	65	65	62

4.2. Result for Hevea Brasiliensis species

Tests were also performed to see the accuracy of the knot detection for Hevea Brasiliensis Species for the three kernels. The testing was based on noise reduction and segmentation using different contrast values after the extraction processes. Table 7 shows the performance of knot detection using linear kernel function, where the parameter, C are 1, 2, and 3. It shows that the highest accuracy of 76% when using parameter C=5 and with segmentation and a contrast percentile of images of 5^{th} and 20^{th}.

Table 7. Performance of knot detection for Hevea Brasiliensis using linear Kernel function

Linear kernel	Contrast (5,20)		Contrast (10,98)	
	Reduce noise (%)	Segmentation (%)	Reduce noise (%)	Segmentation (%)
1	71	73	68	68
3	68	74	68	68
5	71	76	66	63

Table 8 shows the accuracy with the highest 73% with parameter C=3 when the contrast percentile of the image was 5^{th} and 20^{th} and the texture extracted by LBP after segmentation.

Table 8. Performance of knot detection for Hevea Brasiliensis using RBF Kernel function

RBF Kernel	Contrast (5,20)		Contrast (10,98)	
C	Reduce noise (%)	Segmentation (%)	Reduce noise (%)	Segmentation (%)
1	1	68	71	71
3	3	68	73	68
5	5	68	68	69

Table 9, it shows that the accuracy is harder to achieve more than 60%. However, 59% is the highest accuracy with C=3 when LBP after reduce noise and the contrast percentile at 5^{th} and $20t^{h}$.

Table 9. Performance of knot detection for Hevea Brasiliensis using polynomial Kernel function

Polynomial	Contrast (5,20)		Contrast (10,98)	
Kernel,	Reduce noise (%)	Segmentation (%)	Reduce noise (%)	Segmentation (%)
1	53	48	48	50
3	59	50	55	52
5	56	50	53	58

Overall, Linear Kernel function is outperformed than other functions in which the highest accuracy was performed by Linear Kernel function for the two species. Both species offered the same accuracy value of 76% as the highest accuracy. The differences only on the percentile used.

5. CONCLUSIONS

This paper addresses the comparison of knot detection capability with the use of SVM for two species of the tropical timbers namely Acacia and Hevea Brasiliensis. Prior to performed detection, all images of the two species have gone through several pre-processing steps such as contrast stretching, median blur, thresholding with the Otsu's method and feature extraction using Local Binary Pattern algorithm were used. C-SVM is used to perform the classification process. Overall, the achievement is only76% for knot detection. However, it can be seen as a good effort for knot detection for tropical timber at initial stage. With the improvement in pre-processing methods and experiment with recent classification methods, the solution has a big potential to aid timber expert or timber grader in recognizing types of knot with a better accuracy.

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