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Evaluation of Feature Extraction and Selection Techniques for the Classification of Wood Defect Images

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Abstract: The main objective is to evaluate different feature extraction and selection techniques as well as classification performances for the wood defect images. This study presents a classification system to classify the defect images from a database provided by a wood factory. This database consists of 1498 defect images and they are classified using Support Vector Machine (SVM), J48, random forest and K-NN classifiers. The features for each defect image are extracted using six types of feature extraction techniques. Feature selection methods are used to choose the features according to their significance. From the findings, it can be observed that Ranker method produced the best performance for most of the feature extraction techniques and classifiers. This directly indicates that all the extracted features have significant contribution. For SVM, it is tested with three different settings: linear, RBF and polynomial. The highest classification rate is obtained by using Gray Level Co-occurrence Matrix (GLCM) with SVM polynomial. For J48 and random forest classifier, features computed using Colour Coherence Vector (CCV) yielded the best measure, whilst for K-NN, it is Gabor features which performed best. Besides 89.85% of case crack are correctly classified, 38.63% for fungus, 16.48% for knot, 88.06% for worm holes and 51.61% for watermark case. For defect cases other than crack, it is observed that the number of misclassification cases is biased on crack case. The proposed methodology can be applied to create an automated visual inspection system for detection of semi-finished wood defect in the wood industry.

Key words: Wood defect, classification, feature extraction technique, GLCM, CCV

INTRODUCTION

Automatic detection of wood defects has become a great demand to the wood industry. The automated process saves a lot of cost and proven to provide consistent outcome. There has been a massive growth of interest in work related to the detection and classification of wood defects since the past years. Recently, Hashim *et al.* (2015) has reviewed previous research related to the automated vision inspection of timber surface defect. The inspection was done using various sensors namely the vision sensor, ultrasound, vibration sensor and infrared thermography. There are approaches using multi sensor where several different sensors are fused together.

A survey of the recent work in wood image segmentation, detection and classification for wood defects is summarized in Table 1. Type of defects and wood used in the studies are identified and listed in the table, along with the features and methods implemented by each work. The most common wood defects in the studies are wood knot (Gu *et al.*, 2010; Mahram *et al.*, 2012; Mohan and Venkatachalapathy, 2012; Hashim *et al.*, 2013; Yuce *et al.*, 2014; Breinig *et al.*, 2015; Mu *et al.*, 2015a, b; Song *et al.*, 2015; Hua and Jin-Cong, 2015) and crack (Breinig *et al.*, 2015; Mu *et al.*, 2015a, b; Song *et al.*, 2015). Various types of wood and wood products were studied in the literature such as sugi (Hu *et al.*, 2003) lumber boards timber (Mohan and Venkatachalapathy, 2012; Hashim *et al.*, 2013; Hittawe *et al.*, 2015; Chen *et al.*, 2014) wood veneer (Yuce *et al.*, 2014) board from many different sources (Mahram *et al.*, 2012; Breinig *et al.*, 2015; Song *et al.*, 2015; Hua and Jin-Cong, 2015) and x-ray of wood (Mu *et al.*, 2015a, b).

For the wood feature extraction, it is interesting to note that the textural features were commonly used by previous researchers. The most favored technique is Gray Level Co-occurrence atrix (GLCM)

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Table 1: Recent works related to wood defect segmentation, detection and classification

Researchers	Type of defects	Type of wood	Features	Methods
Hu *et al*. (2003)	Split and hole	Sugi	8 recognition rules based on 4 features	Non-segmenting Laser displacement sensor to detect the splits and holes based on their thickness Method based on pixel model to compute area of the defect
Gu *et al*. (2010)	Four types of wood knots (sound knots, dead knots rotten knots, pin knots)	Lumber boards 800 wood knot images	Novel order statistic filter to obtain average pseudo color feature for each knot area	Segmentation Partition the knot images into 3 areas Trained 800 wood knot images using SVM classifier About 96.5% classification rate
Mahram *et al*. (2012)	Wood knots and cracks	U Oulu wood and knots database	GLCM, LBP and statistical moments Hybrid features: GLCM+ LBP, GLCM+statistical moments, LBP+ statistical moments	Non-segmenting Principal Components Analysis (PCA) and Linear Discriminate Analysis (LDA) to reduce FV dimension Classification using SVM and K-NN
Mohan and Venkatachalapathy (2012)	Knots (dry knot, sound knot, horn knot, edge knot)	Timber-400 images of wood knots	Hilbert transform features	Non-segmenting Feature reduction by gabor filters classification using Naive Bayes, radial basis function, bagging using naïve bayes, KNN, REP trees and random forest
Hashim *et al*. (2013)	Knots and bark pockets	Timber-500 clear, 500 with defects	Texture features: energy, contrast, correlation	Segmentation Rotation invariant texture feature Based on spatial Dependence matrix
Chen *et al*. (2014)	Sub, bug, cleat decay	Timber	N/A	Segmentation of defects based on color and mathematical morphology Seed points were automatically selected using boundary information
Yuce *et al*. (2014)	Bark, colored streaks, discoloration, pin knots, rotten knots, roughness, sound knots, splits, streaks	Wood veneer	17 statistical features of the gray-level distributions	Non-segmenting Defects classification using feed-forward ANN with a Back-propagation (75% dataset for training, 25% testing) Feature selection using PCA
Breinig *et al*. (2015)	Pith and knot	Board from Norway spruce sawlogs	30 variables describing the knot and pith pattern on the board face are used as wood feature data	Segmentation Classification of wood surfaces according to visual appearance by multivariate analysis of wood feature data
Mu *et al*. (2015)	Cracks, knots, rotten	X-Ray of wood	13 eigenvalues of images are extracted using GLCM and Normalized GLCM to obtain the joint probabilities	Non-segmenting Using fuzzy BP neural networks for automatic identification of wood defects
Hittawe *et al*. (2015)	Cracks and knots	Timber from Epicea and Pine datasets (100 images for each dataset)	LBP and SURF features and combination of both	Non-segmenting Using dictionary based on bag-of-words approach SVM classifier to detect knots and cracks Precision/recall: 0.92/0.94 and 0.91/0.96 for Epicea and Pine
Mu *et al*. (2015)	Crack and decay	X-Ray of wood	GLCM-features are selected to reflect perimeter, area, length-width ratio and gray average of defect shape	Non-segmenting Preprocess image using mean, median and secondary wiener filtering Detect wood defect based on RBF neural network Accuracy of above 85%

Table 1: Continue

Researchers	Type of defects	Type of wood	Features	Methods
Song *et al.* (2015)	Sound knot, dry knot, black knot crack, resin pocket	120 images of pine wood board surface	Image block percentile color histogram and eigenvector texture feature	Segmentation Divide wood image into several same size image blocks, calculate color feature and Singular Value Decomposition (SVD) to extract k-max eigenvectors as texture feature Using SVM classifier to determine the defected wood
Hua Jin-Cong (2015)	Dead knots, poles, living knots	Softwood and hardwood features, GLCM and combination of both	Tamura texture features, GLCM and combination of both	Non segmenting Classification using BP neural network Highest accuracy using combination of Tamura and GLCM (92.67%)

(Mahram *et al*., 2012; Mu *et al*., 2015a, b; Hua and Jin-Cong, 2015) due to its good performance in discriminating textures, followed by statistical features (Mahram *et al*., 2012; Hashim *et al*., 2013; Yuce *et al*., 2014) and Local Binary Pattern (LBP) (Mahram *et al*., 2012; Hittawe *et al*., 2015). Other preferred features are the recognition rules (Hu *et al*., 2003) pseudo color feature Hilbert transform features (Mohan and Venkatachalapathy, 2012) variable description features (Breinig *et al*., 2015) SURF features (Hittawe *et al*., 2015) color histogram and eigen vector texture feature (Song *et al*., 2015) and Tamura texture features (Hua and Jin-Cong, 2015). However, the choice of features are depends on the defect problem and image itself, hence there is no exact technique or solution that could exclusively represent defect features. Other additional approaches applied in the literature in exploiting the features are reduction of Feature Vector (FV) using Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA) (Mahram *et al*., 2012) Gabor filters (Mohan and Venkatachalapathy, 2012) and feature selection using PCA (Yuce *et al*., 2014).

According to Hashim *et al*., (2015) there are two general approaches in the wood defect detection namely the segmentation method (Hashim *et al*., 2013; Breinig *et al*., 2015) and the non-segmentation method (Mahram *et al*., 2012; Mohan and Venkatachalapathy, 2012; Yuce *et al*., 2014; Hittawe *et al.*, 2015; Mu *et al.*, 2015a, b; Hua and Jin-Cong, 2015; Hu *et al*., 2003). For the segmentation method, the defect area or images will be segmented or partitioned prior to extracting the features and the extracted features will be fed into a classifier to produce a classifier model with referring the training set. For the non-segmentation approach, either whole wood image will be classified or the images have been manually divided into defect or non-defect objects. The classifiers used in previous work include Support Vector Machine (SVM) (Mahram *et al*., 2012; Hittawe *et al*., 2015; Song *et al*., 2015) K-NN (Mahram *et al*., 2012; Mohan and Venkatachalapathy, 2012) Naive Bayes (Mohan and Venkatachalapathy, 2012) Radial Basis Function (RBF) (Mohan and Venkatachalapathy, 2012; Mu *et al*., 2015) REP Trees (Mohan and Venkatachalapathy, 2012) Random Forest (Mohan and Venkatachalapathy, 2012) ANN (Yuce *et al*., 2014) and BP Neural Network (Mu *et al*., 2015; Hua and Jin-Cong, 2015). In this study, feature extraction and selection techniques with the aim to classify wood defect images are evaluated and the classification performances for these techniques are presented.

MATERIALS AND METHODS

The proposed methodology is illustrated in Fig. 1. Firstly, the input wood image will be automatically segmented using a Fuzzy C-Means (FCM) approach adapted from (Ahmad *et al*., 2016) to get the defect images. The segmented images, which are the wood defect images are then labelled according to the type of defects. The features of each defect images are extracted using six low level feature extraction techniques. Before going to classification process, these features will be selected using three feature selection methods in order to get the most useful features sorted or chosen accordingly. After the classification process using four different classifiers the defect images will be categorized into their respective class.

Feature extraction methods: Prior to classification, six different types of features are employed. The adopted features are Gray Level Co-Occurrence Matrix (GLCM) Local Binary Pattern (LBP), wavelet based features using Discrete Wavelet Frame (DWF) and Gabor Transform and colour-based features using Colour Histogram (CH) and Colour Coherence Vector (CCV).

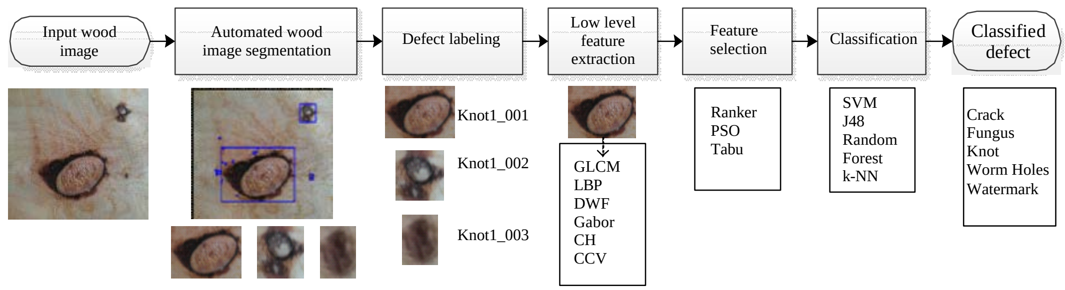

Fig. 1: Flow diagram of the proposed methodology

Gray Level Co-Occurrence Matrix (GLCM): GLCM is a texture-based technique where the co-occurrence matrix is calculated for each image on how often a pixel with a certain intensity i occurs in relation with another pixel j, at a certain orientation θ and distance d. This study uses θ = 0°, 45°, 90° and 135° and d = 1, resulting 16 number of features for GLCM. The first 4 features are the angular second moment, contrast, correlation and entropy features for θ = 0°, followed by θ = 45°, 90° and 135°, respectively. These features were calculated based on method proposed by Haralick *et al.* (1973).

Local Binary Pattern (LBP): The basic operator of LBP is used to describe the local textural patterns. It was introduced by Ojala *et al.* (1996) and the spatial domain version for still images was discussed in detail in (Pietikainen *et al*., 2011). LBP uses a circular neighbourhood where the pixel values are bilinearly interpolated whenever the sampling point is not at the center of a pixel. To obtain a label for the center pixel, the neighbourhood pixels are thresholded by its center pixel value and then will be multiplied by powers of two followed by summation. In this study, a neighbourhood of 8 pixels with radius 1 is used, resulted a total of $2^8 = 256$ different labels. A histogram with 256 bin will be generated from the interpolated image and the pixel count of each bin is taken as the FV thus, the FV length for LBP is 256.

Gabor transform: Gabor transform extracts texture data from an image. It was introduced by Manjunath and Ma (1996) where the best parameters found from the experiment for total number of scales, S and orientations, K are 4 and 6, respectively. Gabor transform will produce S×K response images and only the mean of each response are taken as the feature. Thus, there will be a total of 24-dimensional features for each defect image.

Discrete Wavelet Frame (DWF): DWF is applied to produce four wavelet coefficient images that are the same size as the input image due to an over-complete wavelet decomposition. It is called an over-complete decomposition because the filtered images are not sub sampled. The coefficient images produced are from these channels: Low-Low (LL) Low-High (LH) High-Low (HL) and High-High (HH). The next decompositions are just as with other wavelet transforms where it is done on the LL channels. In this research, a three-level decompositions with the Haar wavelet basis is used, resulting in a 10 wavelet features and an additional of another 10 features are produced by calculating the standard deviation of the wavelet features. There will be a total of 20-dimensional FV for each defect image.

Colour Histogram (CH): CH is the most common way of describing low-level colour properties of images. Introduced by Swain and Ballard (1991) CH is represented by a set of bins where each bin represents a particular colour. It is obtained by counting the number of pixels that fall into each bin based on their colour. Colour histogram can be generated either as three independent colour distributions (one for each of the Red-Green-Blue (RGB) primary colours) or more commonly, as a joint distribution of all three primary colours (the so-called 3D colour histogram). Usually, the obtained histograms are normalized with respect to the total number of image pixels. In this study, we experimented with 3D colour histogram using 64 colour bins, resulting in 64 dimensional feature vectors.

Colour Coherence Vector (CCV): CCV is a colour based method which integrates some spatial data in an image and each pixel in a given bin is classified as either coherent or incoherent. It was proposed by Pass *et al.* (1996). A pixel will be considered as coherent if it belongs to a large connected group of similar pixels; else it is incoherent. Firstly, the process is to obtain the 3D colour histograms with n number of bins. Next, every pixel in all the bins are analyzed for their coherency by comparing the size of the region the pixels belong to with a predefined threshold value, o. For this study as in the colour histogram, 64 colour bins are used. Several values of θ were tested and it is found that the optimal value of τ is 1% of the total number of pixels in the image. The feature vector for CCV for each defect image is therefore, 128-dimensional (64 bins×2 categories).

Classifiers and feature selection methods: The experimental research was carried out using SVM, J48 Random Forest and K-NN classifiers. In order to reduce the dimensionality of the extracted features, features selection was carried out before the feature vectors were passed on to a classifier. In this research work, PSO search, Tabu search and Ranker were used to identify those extracted features that contributed positively in the classification process. PSO search (Moraglio *et al*., 2007) explores the attribute space by means of the PSO algorithm. It is initialized with a population of random potential solutions namely called particles, are flown through the problem space. PSO search seeks for optima satisfying performance or the best recognition rate in the search algorithm.

Tabu search (Hedar *et al*., 2006) conducts a search through the space of extracted features. Tabu search is evading local maximums by accepting bad and diverse solutions and make further search in the best solutions. It search process stops when there is not more improvement in the iterations.

Ranker (Hall and Holmes, 2003) ranks extracted features in conjunction with correlation attribute evaluator. It evaluates the worth of an attribute by measuring the correlation between it and the subject. It treats each nominal extracted feature as the individual significance indicator on a merit basic. The overall correlation for the nominal extracted features is established by a weighted average.

RESULTS AND DISCUSSION

This study describes the wood image database used the experimental setup and also discusses the obtained results.

Wood image database: A total of 1498 defect images were obtained from an industry source (Infinity Creations Enterprise). The dimensional size of these images is varies from 6×15 pixels up to 1600×831 pixels. The respective number of images per defect class is listed in Table 2. These images were manually grouped into the classes based on the ground truth provided by expert from our collaborative partner. Examples of images for each type of defects are shown in Fig. 2.

Experimental setup: The experiment consisted of two phases; training and testing. The training was carried out to obtain the models for classification, by optimizing parameters for each classifier. Derived from the heuristic f results attained from the training, the parameter values were established as the models for testing phase which are shown in Table 3. In the testing phase, the models

Table 2: Number of images for each defect class

Type of defects	Crack	Fungus	Knot	Worm holes	Watermark
No. of images	591	44	91	670	62

Table 3: Parameters of classifiers

Classifiers	Parameters
RF	No. of attributes = 1, Seed = 2, No. of instances = 200
K-NN	k = 1
SVM with ln kernel	Cost = 32
SVM with poly kernel	Cost = 256, γ = 0, degree = 3, coefficient = 1.4
SVM with RBF kernel	Cost = 256, γ = 0.5

Fig. 2: Example of defect images. From left to right: crack, fungus, knot, worm holes and watermark

Table 4: Wood defect classification results

	CCR						TPR						FPR					
Variables	GLCM	LBP	Gabor	DWF	CH	CCV	GLCM	LBP	Gabor	DWF	CH	CCV	GLCM	LBP	Gabor	DWF	CH	CCV
SVM linear																		
Ranker	75.65	66.46	72.02	72.97	65.70	68.45	75.70	66.50	72.00	73.00	65.70	68.50	17.60	25.60	21.00	19.50	26.70	23.60
PSO	65.91	63.79	70.64	70.91	62.80	62.96	65.90	63.80	70.60	70.90	62.80	63.00	26.50	28.70	22.50	21.40	29.90	29.70
Tabu	65.91	63.51	71.12	71.40	62.96	64.47	65.90	63.50	71.10	71.40	63.00	64.50	26.50	29.80	22.10	21.10	29.90	28.20
SVM RBF																		
Ranker	80.45	68.51	75.44	72.36	71.60	73.73	80.50	68.50	75.40	72.40	71.60	73.70	11.50	21.10	13.30	14.90	18.70	16.30
PSO	73.18	70.23	75.86	69.27	70.64	72.43	73.20	70.20	75.90	69.30	70.60	72.40	18.70	21.90	16.00	17.30	20.90	18.50
Tabu	73.18	69.13	75.86	68.29	70.99	72.77	73.20	69.10	75.90	68.80	71.00	72.80	19.00	23.50	16.00	17.20	20.60	17.00
SVM poly																		
Ranker	81.96	69.54	74.14	72.09	72.63	73.87	82.00	69.50	74.10	72.10	72.60	73.90	10.90	18.90	14.10	14.70	17.90	15.20
PSO	73.05	71.40	74.55	70.51	71.05	72.63	73.00	71.40	74.60	70.50	71.10	72.60	19.50	20.50	17.50	16.70	20.80	18.80
Tabu	72.98	68.24	75.10	72.29	70.85	73.25	73.00	68.20	75.10	72.30	70.90	73.30	19.40	24.60	16.90	15.20	20.70	17.00
J48																		
Ranker	70.44	67.90	71.26	67.07	70.64	73.94	70.40	67.90	71.30	67.10	70.60	73.90	16.80	16.00	14.40	19.30	18.10	15.50
PSO	65.84	67.96	71.00	67.69	68.52	70.85	65.80	68.00	71.00	67.70	68.50	70.90	20.70	16.60	15.70	18.40	19.60	17.40
Tabu	64.47	64.47	71.60	67.97	69.41	71.74	64.50	64.50	71.60	68.00	69.40	71.70	20.80	20.80	15.00	18.60	18.90	17.00
Random forest																		
Ranker	77.06	77.50	78.26	75.86	74.14	78.60	77.20	77.50	78.30	75.90	74.10	78.60	14.70	15.90	14.80	16.60	16.80	14.30
PSO	70.64	77.16	76.27	74.07	70.78	73.59	70.60	77.20	76.30	74.10	70.80	73.60	19.00	15.90	15.80	17.70	18.60	17.20
Tabu	70.16	77.43	76.20	74.28	71.33	76.47	70.20	77.40	76.20	74.30	71.30	76.50	19.60	15.50	15.90	17.70	18.50	15.90
K-NN																		
Ranker	73.53	73.19	77.51	73.39	70.37	74.35	73.50	73.20	77.50	73.40	70.40	74.30	16.50	18.90	14.30	16.20	20.70	16.60
PSO	68.86	75.38	74.55	71.33	68.52	71.12	68.90	75.40	74.60	71.30	68.60	71.10	19.50	16.90	16.20	18.00	22.20	19.20
Tabu	67.97	75.51	74.42	72.36	70.23	72.98	68.00	75.50	74.40	72.40	70.20	73.00	20.00	16.00	16.70	16.90	20.10	18.20

Table 5: Confusion matrix

Classified as	a	b	c	d	e	Total
a = crack	531	7	13	35	5	591
b = fungus	12	17	0	4	1	44
c = knot	66	2	15	6	2	91
d = worm holes	65	7	0	590	8	670
e = watermark	20	2	0	8	32	62

obtained from the training phase are utilized for class classification for the wood image dataset.

Experimental results and discussion: Full experimental results are summarized in Table 4 where the values for Correct Classification Rate (CCR), True Positive Rate (TPR) and False Positive Rate (FPR) are compared for all feature extraction techniques, classifiers and feature selection methods.The highest measure for each category is highlighted. From the results, it is seen that features processed using Ranker method gave the best performance for most of the feature extraction techniques and classifiers. For SVM, it is tested with three different settings: Linear, RBF and Polynomial (Poly). The highest classification rate is obtained by using GLCM with SVM poly (81.96% and 82% for CCR and TPR) with the lowest FPR measure (10.9%). For J48 and Random Forest classifier, features computed using CCV gave the best measure, whilst for K-NN, it is Gabor features which performed best.

Table 5 listed the confusion matrix for each defect cases. Based on the result, 89.85% of case crack are correctly classified, 38.63% for fungus, 16.48% for knot, 88.06% for worm holes and 51.61% for watermark case. For defect cases other than crack, it is observed that the number of misclassification cases is biased on crack case. This scenario is very obvious for knot case, due to the nature of knot images that we received from our collaborative partner where most of the knot cases are having crack at the knot. Nevertheless, the highest TPR of 82% is a promising result where the image database is formed from wide variety of defects.

GLCM scored the highest CCR due to the adopted textural features (angular second moment, contrast, correlation and entropy) better represented the defect regions. On the other hand, CH and CCV obtained the lower CCR as the extracted colour features are not quite well described the defects.

CONCLUSION

An evaluation on feature extraction and selection approaches for classification of wood defect images has been presented in this study. The evaluation was performed on a collection of 1498 wood defect images which include crack, fungus, worm holes and watermark. The highest CCR (82%) was obtained using SVM polynomial classifier, together with the GLCM technique and ranker.

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