



Study of Neural Network Training Algorithms in Detection of Wood Surface Defects

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(Received 19 August 2018; Accepted 25 September 2018; Published on line 1 September 2019)

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DOI: 10.5875/ausmt.v9i3.1924

Abstract: Accurate detection of defects through machine vision improves the economical growth of wood industry. In this paper six common defects on wood surface are considered for study. Quality of wood image is enhanced by Histogram Equalization method. Contrast enhanced images are subject to Thresholding segmentation which examines the objects in the image and identifies the defect. The segmented images are cropped in to small blocks. Segmentation-based Fractal Texture Analysis (SFTA) feature extraction method is accomplished to extract 21 texture features from the wood images. The extracted features are fed in to the training algorithms such as Levenberg-Marquardt, Scaled Conjugate Gradient, Gradient Descent with Adaptive Learning Rate, Bayesian Regularization and Resilient Backpropagation. The Performance of training algorithms are analyzed with several performance metrics. The result obtained shows a considerable improvement in accuracy of 98.2 % by Bayesian Regularization tool.

Keywords: Bayesian Regularization; Histogram Equalization; Levenberg-Marquardt; Gradient Descent with Adaptive Learning Rate; Resilient Backpropagation; Scaled Conjugate Gradient; Segmentation-based Fractal Texture Analysis (SFTA); Thresholding.

Introduction

Wood is an important renewable natural resource in our everyday lives and economy. Wood supplies raw material for many products. Many wood products can be recycled and reused. Wood provide us measurable health benefits and is a durable material lasting for a number of years. It is important to prevent it from defects. No tree is said as perfect. It is subject to defect from the seedling to its last stage. There arise several defects on wood. This paper examines six defects namely bark pockets, bird pecks, burls, fungal damage, insect defects and knots. Manual detection of defects is time consuming. Automatic detection using image processing technique is done in the proposed work. 600 wood images with 100 per class are considered for study. The captured images are resized and their contrast is improved using histogram equalization

method. Thresholding segmentation method is applied on the enhanced wood images to differentiate the defect from the surface of wood. This identifies the defect accurately through machine vision. These segmented images are cropped into small blocks and Segmentation-based Fractal Texture Analysis (SFTA) feature extraction approach is implemented to extract 21 features from each image. The dataset obtained is fed in to various neural network training tools such as Levenberg-Marquardt (trainlm), Scaled Conjugate Gradient (trainscg), Gradient Descent with Adaptive Learning Rate (traingda), Bayesian Regularization (trainbr), Resilient Backpropagation (trainrp). The performance of the training algorithm in detection of wood defect is furnished through the performance measures like accuracy, precision, recall etc. The same can be visualized by means of the ROC curves plotted. The accuracy obtained is greater than 83% and Bayesian Regularization Backpropagation training tool is superior among others by an accuracy of 98.2%.

Related Work

[1] Shows that good accuracy and precision could be obtained with Naive Bayes classifier applied to wood test images. Gray Level Co-occurrence Matrix (GLCM) was used to get wood texture features. In [2] the natural pattern of veneer was removed by applying morphological enhancement and defects were estimated by a decision function based on Gaussian mixture. An accuracy of 90% was obtained. The authors of [4] implemented a Compressed Sensing framework approach to detect and localise defects in grayscale textures. Gaussian Mixture model was applied to train the features extracted from defect-free texture samples. The real time defect detection and localization was enabled by embedding the inspection stage with a multi-scale framework. Two independent datasets were used to evaluate the performance of compressed grayscale patches for texture error detection. The performance was stated in terms of accuracy and speed. In [7] the optimization method for detection of defects in wooden species was evaluated to detect the wooden knot defect. The NSGA II algorithm was used to obtain the features which identify the defects.

Time Delay Neural Network (TDNN) was trained [6] using various training algorithms with a set of speech data to analyze the performance of algorithms. Otsu's thresholding method was used to extract the features of speech data. The extracted features were fed into TDNN with 8 different training algorithms. The synaptic weights were adjusted to minimize the error between the output computed and the desired output. Half of the speech data were used for training and the remaining were used to test the network. As a result, the performance of scaled conjugate gradient is better than other algorithms.

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Conjugate Fletcher-Reeves Update achieves average accuracy 95% for unknown and 99% of known speech word.

The color features were extracted [10] by removing L channel in L*a*b* color space, and taking only a* and b* channel. The texture features were extracted using Segmentation-based Fractal Texture Analysis (SFTA). The combination features which consists of color features (10) and texture features (48) were given as input in k-Nearest Neighbor (k-NN) classifier with cosine distance. The classification of flower gives the best result with accuracy 73.63%.

Proposed Work

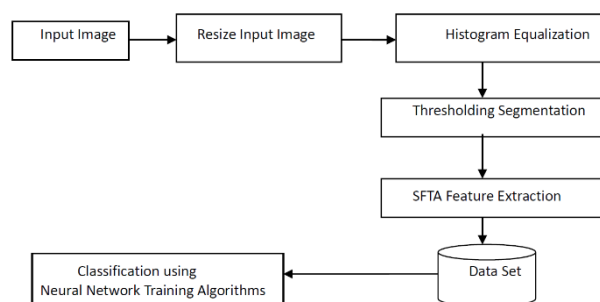


Figure 1. Framework of Wood Defect Detection System.

Wood Image Acquisition

600 wood images with 100 per class are acquired from the databases of www.stephenfinch.co.uk, help.timberlake.com, www.ee.oulu.fi, www.shutterstock.com. The acquired color images are resized in to 256 X 256. Figure 2 depicts the sample wood images used for classification.

Contrast Enhancement

Contrast is the change of color and brightness with other objects. This factor is important in evaluating image quality. Histogram Equalization method is applied to improve the contrast of the wood images. The histogram spreads out the most frequent intensity values and specifies the occurrence of a color in an image. Now the contrast enhanced wood images are ready for segmentation.

Thresholding

Image Thresholding is a kind of pixel based segmentation. Thresholding is a way of partitioning the image in to foreground and background. This method is most effective for images with high contrast. Color is considered as a strong tool for segmentation. The color



Figure 2. Sample Wood Images a) Bark Pockets b) Bird Pecks c) Burl d) Fungal damage e) Insect defects f) Knot.

difference is one of the easiest clues to tell different objects apart. First color conversion is to be done on the wood images. The RGB image is to be converted in to YCbCr image (Y : Luminance; Cb : blue chroma component; Cr : red chroma component) and threshold is applied only to Cb component. The Y and Cr components are unaltered. This may differentiate the defect surface of the wood image from normal region as shown in Figure 3.

The segmented images are then cropped in to small patches of 55 x 55. Now the wood images are subject to feature extraction.

SFTA Feature Extraction

Segmentation-based Fractal Texture Analysis feature extraction algorithm is used to extract the texture features of the wood image. The algorithm decomposes the given input image in to a set of binary images. Compute the fractal dimensions of the resulting regions from binary images. This in turn describes the segmented texture patterns.

Algorithm:

To extract features the following steps are to be followed.

Step 1: sfta (IM, N)



Figure 3. Original and Thresholded Image.

IM - the input grayscale image

N - parameter that defines the size of a feature vector

Step 2: $T = \text{otsurec}(IM, N)$

Returns a set of thresholds T for the given image using the multi-level otsu algorithm. Recursively this algorithm is applied to each image region until total thresholds are found.

Step 3: $I = \text{FindBorders}(IM)$

Return the binary image with region boundaries of the given image IM. The returned image I holds the value 1 if the corresponding pixel in IM contains the value 1 and at least one neighboring pixel having the value 0. Otherwise I took the value 0.

Step 4: $DD = \text{hausdim}(IM)$

Returns the Hausdorff fractal dimension DD of an object represented by the binary image IM. Non-zero pixels belong to an object and 0 pixels contain the background.

In the above algorithm, considering N to be 4, 21 texture features are obtained for each image and stored as a .mat file. The size of the feature vector can be varied, thereby yielding redundancy in case of larger sizes.

Training Algorithms

The procedure to carry out learning process in neural network is called training algorithm. In this work 5 different algorithms such as Levenberg-Marquardt algorithm (trainlm), Scaled Conjugate Gradient algorithm (trainscg), Gradient Descent Adaptive Learning algorithm (traingda), Bayesian Regularization (trainbr) and Resilient

Backpropagation (trainrp) are examined with the dataset of 6 classes of wood defects. According to the algorithm the network training function updates the bias and weight.

Levenberg-Marquardt algorithm (trainlm)

The Levenberg-Marquardt algorithm is also called as damped least-squares method. It is designed to work with loss functions that take the form of sum of squared errors. It works with gradient vector and Jacobian matrix.

Scaled Conjugate Gradient algorithm (trainscg)

Scaled Conjugate Gradient (trainscg) will not require line search at each iteration. Step size scaling mechanism is used. This avoids time consuming line search per learning iteration.

Gradient Descent with Adaptive Learning Rate algorithm (traingda)

Gradient Descent with Adaptive Learning Rate (traingda) is very sensitive. The initial network output and error are to be calculated first. The current learning rate is used at each epoch so that new weights are calculated. New errors and outputs are calculated next.

Bayesian Regularization Backpropagation algorithm (trainbr)

Bayesian Regularization Backpropagation (trainbr) algorithm minimizes a linear combination of weights and squared errors. The linear combinations are also modified to get good generalization qualities at the end of the training network.

Resilient Backpropagation algorithm (trainrp)

Resilient Backpropagation (trainrp) algorithm, here the direction of the weight update is determined by the sign of the derivative. A separate update value is used to determine the size of the weight change.

Experimental Results

This research can identify 6 types of defects that occur on wood surface namely bark pockets, bird pecks, burls, fungal damage, insect defects and knots. Thresholding segmentation is used to segment the wood images. In segmentation process the RGB image is first converted in to YCbCr. A threshold is applied to Cb component and Y and Cr components are unaltered. This may segment the image to represent the damaged region to conclude which network tool is well suited for the detection of wood defects.

Total Number of surface defect wood images : 600 with 100 per class.

of the wood as shown in Figure 4.

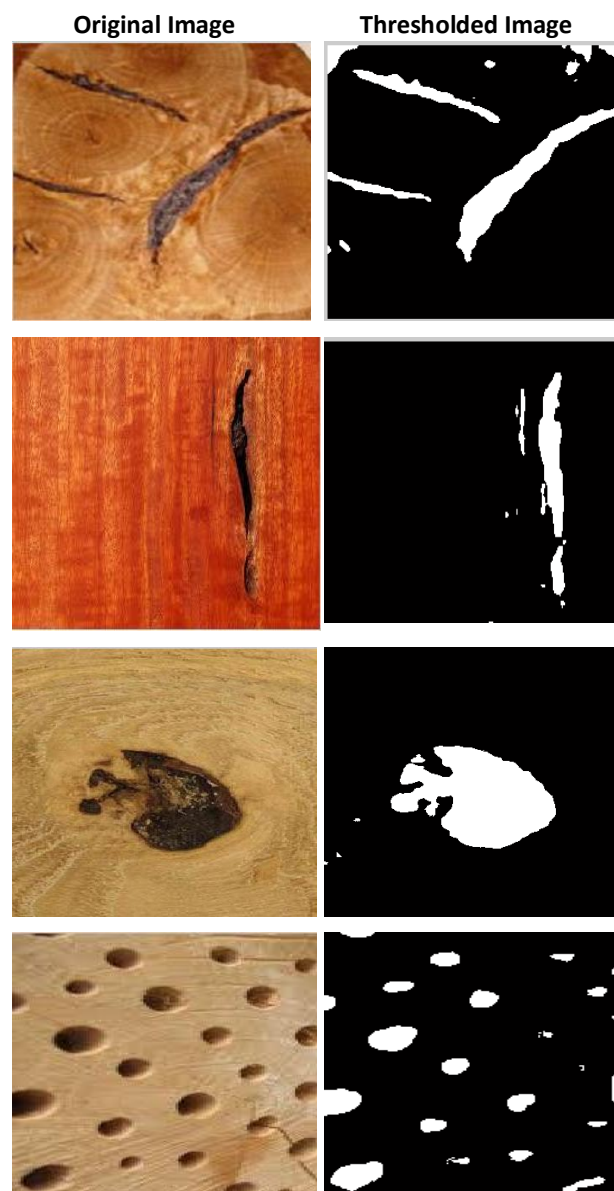


Figure 4. The original and Thresholded applied image.

After segmentation the wood images are cropped in to small patches and SFTA feature extraction algorithm is applied. This extracts 21 texture features from the wood surface and is now stored as a dataset. The extracted features are subject to training and testing with the Feedforward neural network training algorithm such as Levenberg-Marquardt, Scaled Conjugate Gradient, Gradient Descent with Adaptive Learning Rate, Bayesian Regularization and Resilient Backpropagation. These algorithms are analyzed with various performance metrics

Number of Inputs considered for training and testing in the network: 21.

Number of outputs obtained in the network: 6.

The confusion matrix is plotted as in Table 1 for each

Table 1. Confusion Matrix for SFTA with Training algorithms.

Wood Surface Defects	Levenberg-Marquardt				Scaled Conjugate Gradient				Gradient Descent with Adaptive Learning Rate				Bayesian Regularization				Resilient Backpropagation			
	TP	FN	FP	TN	TP	FN	FP	TN	TP	FN	FP	TN	TP	FN	FP	TN	TP	FN	FP	TN
Bark Pockects	58	42	32	468	79	21	36	464	45	55	70	430	92	8	6	494	59	41	57	443
Bird Pecks	65	35	34	466	82	18	22	478	42	58	40	460	97	3	1	499	43	57	24	476
Burls	66	34	15	485	80	20	18	482	62	38	59	441	93	7	8	492	64	36	39	461
Fungal Damage	91	09	44	456	89	11	12	488	64	36	45	455	94	6	4	496	75	25	44	456
Insect Defects	79	21	34	466	71	29	14	486	63	37	50	450	93	7	7	493	66	34	23	477
Knots	56	44	26	474	76	24	21	479	23	77	37	463	99	1	6	494	54	46	52	448

network tool to compare among them. The values of True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN) are mentioned through which the accuracy is calculated.

After evaluation with the dataset the performance measures such as Accuracy, Precision, Mean Square Error, Recall, F-Score and Misclassification Rate is obtained for each training algorithm as shown in Table 2. All algorithms keep on par with each other yielding a considerable accuracy. The Bayesian Regularization algorithm

illustrates the true positive rate (TPR) against false positive rate (FPR). In assessment of the performance of the ROC curve, trainbr algorithm is visualized best to other algorithms.

Conclusion

This work identifies the defects on the wood surface by Thresholding segmentation. The Cb component is

Table 2. Performance Measures of Training Algorithms in Detection of Defects on Wood Surface.

Training Algorithm	MSE	Accuracy	Precision	Recall	F-Score	Misclassification Rate
Levenberg-Marquardt	0.998	89.72	69.16	69.16	69.16	0.102
Scaled Conjugate Gradient	0.732	93.15	79.58	79.5	79.53	0.068
Gradient Descent with Adaptive Learning Rate	0.804	83.3	49.83	49.83	49.83	0.167
Bayesian Regularization	0.529	98.2	94.6	94.6	94.6	0.017
Resilient Backpropagation	1.02	86.72	60.16	60.16	60.16	0.132

outperforms the others with 98.2%.

The class wise performance of the algorithms is represented by means of Receiver Operating Characteristic (ROC) curve as shown in Figure 5. This

subject to Thresholding. Then the texture features of 600 images with 100 per class are extracted through SFTA feature extraction algorithm. The features extracted are subject to training and testing with Feedforward neural

network training algorithms such as trainlm, trainscg, traingda, trainbr and trainrp. The performance measures of the algorithms are analyzed and trainbr (Bayesian Regularization) gives an accuracy of 98.2% which works best in identification of defects on wood images.

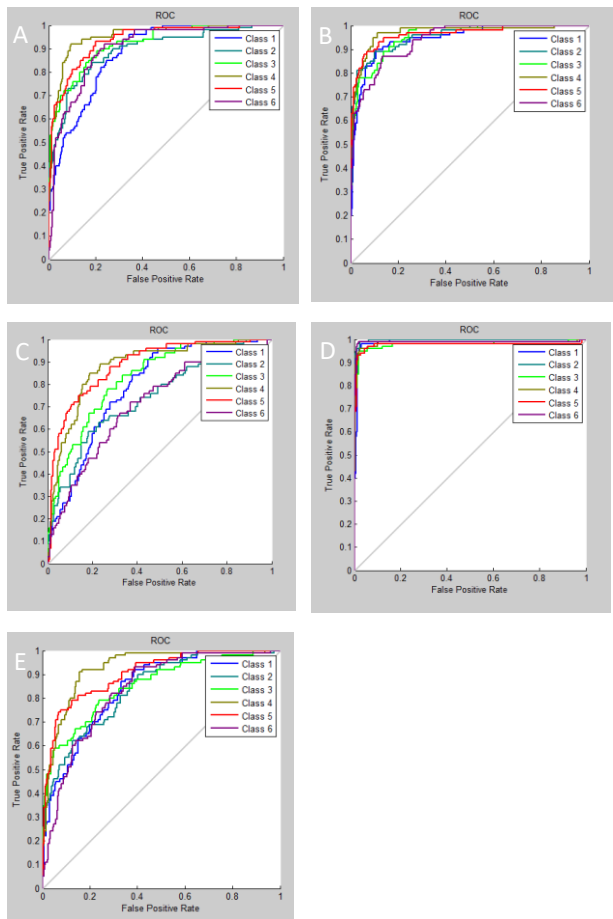


Figure 5. ROC Curves a) trainlm curve b) trainscg curve c) traingda curve d) trainbr curve e) trainrp curve.

of the algorithms are analyzed and trainbr (Bayesian Regularization) gives an accuracy of 98.2% which works best in identification of defects on wood images.

In the future work, the number of features extracted from SFTA algorithm can be increased and applied with other training algorithms to see further improvements in their performance.

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