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HYBRID OPTIMIZATION FOR CLASSIFICATION OF THE WOOD KNOTS

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ABSTRACT

Knots are common wood defects. A knot is a specific imperfection in timber, reducing its strength which can be exploited for artistic effect, resulting in knot selection being an important matter in the wood industry. The value of wood is related to its quality, and this in turn is determined by defect numbers and distribution. This is challenging as in some instances, selection/classification is manual. In this paper, it is proposed to detect and classify the knots in timber boards. Hilbert transforms and Gabor filters are used for pre-processing the image of knots. The features obtained from preprocessing were classified using Multi Layer Perceptron (MLP) and Neural Network (NN) with Particle Swarm Optimization (PSO) and Invasive Weed Optimization (IWO) for momentum and learning rate.

Keywords: *Wood Knots, Hilbert Transforms, Gabor Filter, Multilayer Perceptron, Neural Network, Particle Swarm Optimization, Invasive Weed Optimization.*

1 INTRODUCTION

An orthotropic material is one that has mechanical properties that are independent as well as unique in each of the three mutually perpendicular directions i.e. longitudinal, radial and tangential axes. Wood is one such material. Knots are that portion of the branches of a tree that become one with the bole of the tree. These knots induce changes in the mechanical properties of the wood. This happens due to the disruption in the continuity of the direction of the fibers of wood linked with the knots. The changes, thus induced by the knots depend on the size of the knots, the location, and the shape of the knots, their soundness, the grain's attendant local slope and the kind of stress pressured on the wood member.

The direction taken by the exposing cut is what determines the shape or the form of a knot on sawn surfaces. When lumber is sawn from logs and branches are sawn perpendicular to their length, nearly round knots are produced. Similarly, if the cuts are diagonal to the length, we observe oval knots. Spiked knots occur when the sawn cuts are lengthwise to the branches.There is always continuous growth at the intersection of the limbs and the bole of the trees, provided the limb is alive the knots that result from such a situation are called inter-growth.Once the branches die, there is additional growth of the tree, encasing the dead limbs which result in encased knots. [1]

The need for wood increased with development, in contrast to the fact that its availability is limited. It is years before a tree produces good timber. Also, all parts of timber cannot be used as wood has an undesirable feature for some applications. These are considered defects. They are of economic concern for producers and lumber users as grade, structural integrity, and price are based on location, defect size and type. With shortages/prices of wood increasing, industry spend time/money to inspect lumber and remove features which impact final product quality negatively. This ensued that industry used lower grade material with more defects that affect wood material's overall strength [2].

Knots frequency/size is the first depreciation factor considered by wood suppliers to estimate the timber price. This is a criterion considered in visual lumber grading. Knots in a piece of wood have many technological drawbacks, due to grain angle deviation in/around knots. Surface quality around knots is deprecated due to grain deviation in wood matching, while tools life expectancy is greatly shortened by shocks against knots. Also, knots depreciate the wood's aesthetic quality. Knot geometry knowledge and location are

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valuable in saw mills to optimize cutting decisions/improving logs/lumber grading [3].

Classification is a decision making task of human activity. Classification problems occur when an object is assigned to a predefined group/class depending on many related observed attributes. Problems in industry, science, and business and medicine are classification problems. A limitation of statistical models is their working well when underlying assumptions are satisfied. Their effectiveness depends on various assumptions/conditions on which models are developed. Users should possess knowledge of data properties and model capabilities before successful application of models.

Neural networks are important classification tools [4]. Recent neural classification research proved that Neural Networks (NN) are good alternatives to many traditional classification procedures. Their advantage is due to the following theoretical aspects. First, NN is data driven, self-adaptive methods adjusting for data without specification of the functional / distributional form of the underlying models. Also, they are universal functional approximates as NN can approximate any function accurately [5].

Timber is inspected to remove knots to improve wood quality and value. Manual knots selection/classification process is tedious and time consuming. Cleavability, cracking/warping and timber working ease are affected by knots. It is difficult to build up a system to automatically find defects in the classification of wood knots. The many aspects known for the difficulty in the origin of wood materials are the texture and color on the surface of the wood, and the non-uniformity in the surface of the wood. In this paper, a wood knot classification system based on hybrid optimization is proposed.

2 LITERATURE SURVEY

The robustness of different color spaces against spectrally varying illumination in industrial wood defect inspection was examined by Kauppinen and Silvén (1996) when inspection systems were not adapted to illumination variations. Spectral changes were accomplished through a digital transformation of color temperature illuminating wood images. The authors concluded that original RGB color space was the best under varying illumination and that XYZ and CIELuv spaces were also promising.

Tree-Structured Support Vector Machine was proposed by Stove (2006) for wood knot classification. Tree structures SVM splits a big classifier into smaller/simpler ones lowering computational time. Pin knot has smallest size compared to other knots. Classifier using size feature X distinguishes between pin knots and remaining knots. The feature vector in remaining classifier levels reduces. Similarly, dead knots with a prominent dark boundary curve against interior/exterior area are seen as black and non black knots by two levels of a classifier, the process being repeated for all classes. At the last level, "not recognized knot" not belonging to the 4 designed classes are not classified. Experiments reveal the suggested SVM classifier achieving average 96.5% classification rate of 400 test knot images.

The issue of automatic classification of wood defects was looked into by Gu, et al., (2009). There was increasing interest in R and D, for automatic wood defect detection / classification methods/systems, especially in wood-rich Scandinavian countries. Presently, lumber board inspections/wood grading is undertaken by trained human experts. Long hours of exposure to wood inspection leads to eye fatigue resulting in reduced efficiency and inspection accuracy. It has been seen that human visual inspections very rarely achieved more than 70% performance in large lumber grading due to eye fatigue. Increasing imaging techniques, available wood images, databases and sophisticated computer vision techniques have made online automatic wood inspections a reality with performances exceeding those by human inspectors.

Schmidt, et al., (1997) revealed an approach operated through the use of local pixel neighborhoods primarily, and which integrated segmentation/labeling in one classification step. A trained feed-forward Artificial Neural Network (ANN) accepted CT values from small 3D neighborhood about target pixel classifying each pixel as either split, knot, decay/clear wood or bark. To accommodate different hardwood types, a histogram-based preprocessing step normalizes CT density values before ANN classification. Morphological post-processing refined the detected image region shapes.

Estevez, et al., (2003) proposed characteristics (features) set for radiate pine board's

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defect classification automatically; the proposed method uses a genetic algorithm. The method used low-cost machine vision system including color video camera, frame grabber, and microcomputer. The following 10 defects were classified: live knot, hole, dead knot, pith, blue stain, split, wane, stain, plus clear wood: birds eye & freckle and bark & pitch pockets. Database designs of 2,958 boards face color images were used. From them, 16,800 feature vectors were obtained/divided into test, training and validation sets. Totally 182 features were observed in every vector measured in windows around objects/segmented objects. 64 from 182 original features were chosen/applied as inputs in a multilayer perceptron NN classifier with a feature selection algorithm. No decrease in classification performance was allowed. Best off-line performance was 74.5% of exact classifications in test set when the genetic algorithm developed features were used. Classification performance of 87.8% was achieved in reduced database involving 7 defect types. With 10 defect types plus clear wood, an online system calculation obtained 80% correct classification.

An image processing, feature extraction and artificial neural networks based automatic wood recognition system was introduced by Khalid et al., (2008). The PC-based wood recognition system prototype can classify 30 different tropical Malaysian woods, according to species based on macroscopic wood anatomy. Image processing was carried out through the use of author's new in-house image processing library called "Visual System Development Platform". Textural wood features were extracted with a co-occurrence matrix approach, called grey-level co-occurrence matrix. A multi-layered neural network based on popular back-propagation algorithm was trained to locate wood samples for classification. The system identifies wood in seconds, eliminating human recognition. Results revealed high recognition accuracy, ensuring that the technique suits commercial purposes.

A FMM neural networks based color image segmentation method was suggested by Ruz, et al., (2005) called Fuzzy Min-Max neural network for Image Segmentation (FMMIS), its first step was an automatic selection of starting pixels from defective regions. A histogram based color intensities study of defective regions/grain line regions of radiate pine boards was performed. Next, rectangular boxes were grown from initial pixels set with the aim of enclosing defective regions. FMMIS method's performance on pine board images test set was measured under the criteria: Area Recognition Rate (ARR), confusion matrix, segmentation quality and average processing time.

3. METHODOLOGY

This section provides the algorithm for feature extraction, texture feature extraction and classifiers in the study

3.1 Hilbert Transforms

The Hilbert transform $H[g(t)]$ of a signal $g(t)$ is defined as

$$H[g(t)] = g(t) * \frac{1}{\pi t} = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{g(\tau)}{t-\tau}\,dT = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{g(t-\tau)}{\tau}\,d\tau \quad (1)$$

The Hilbert transform of $g(t)$ is convolution of g(t) with signal $1/\pi t$. It is response to $g(t)$ of a linear time-invariant filter (called a Hilbert transformer) with impulse response $1/\pi t$. The Hilbert transform $H[g(t)]$ is denoted as $\hat{g}(t)$ or as $[g(t)]^{\wedge}$

$$H[g(t)] = \frac{1}{\pi}\lim_{\varepsilon\to 0}\left(\int_{t-\frac{1}{\varepsilon}}^{t-\varepsilon}\frac{g(\tau)}{t-\tau}\,dT + \int_{t+\varepsilon}^{t+\frac{1}{\varepsilon}}\frac{g(t-\tau)}{\tau}\,d\tau\right)$$

The Cauchy principal value is got by considering a finite integration range that is symmetric about point of singularity, but excludes symmetric subinterval, taking limit of integral as length of interval approaches ∞ while, simultaneously, length of excluded interval approaches zero. Hence, when written as an integral as in (1), it means Cauchy principal value of its integral [13].

3.2 Gabor Filter

Gabor filter was introduced by Dennis Gabor. A one-dimensional filter, it is defined as multiplication of a cosine/sine (even/odd) wave with Gaussian windows

$$g_e(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-x^2}{2\sigma^2}} \cos(2\pi\omega_0 x)$$

$$g_e(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-x^2}{2\sigma^2}} \sin(2\pi\omega_0 x)$$

Where ω_0 defines centre frequency (frequency in which filter yields greatest response) and σ spread of Gaussian window [14].

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Gabor filters are wavelet groups, with each wavelet capturing energy at specific frequencies and direction. Expanding a signal provides a localized frequency description capturing the signal's local features/energy. Then texture features are extracted for energy distribution. Gabor filter's scale (frequency) and orientation tunable property makes it fit for texture analysis [15]. A two dimensional Gabor function g(x,y) and its Fourier transform G(u,v) are given by:

$$g(x,y)=\left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right]$$

$$G(u,v)=\exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\}$$

Where $\sigma_u = 1/2\pi\sigma_x$ and $\sigma_v = 1/2\pi\sigma_y$ [16]

3.3 Multi Layer Perceptrons (MLP)

MLP neural networks include units in layers, each layer being composed of nodes and in a fully connected network each node connect subsequent layer nodes. Each MLP has 3 layers minimum including an input layer, one/more hidden layers and output layer. The input layer distributes inputs to other layers. Input nodes have a linear activation without thresholds. Every hidden unit node and output node have thresholds in addition to weights. Hidden unit nodes have nonlinear activation functions and outputs linear activation functions. So, each signal feeding a subsequent layer node has original input multiplied by weight with added threshold and is passed through a linear or nonlinear (hidden units) activation function. Fig.1 reveals a typical 3 layer network. Only 3 layer MLPs are considered in this work as they approximate a continuous function. For actual 3 layers MLP, all inputs are connected to all output directly [17].

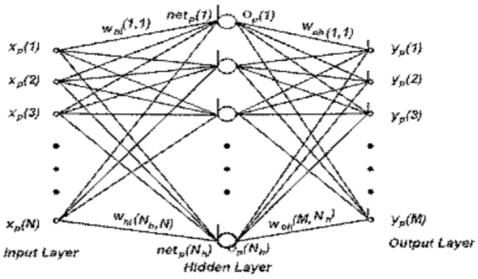

Figure 1 : Typical Three Layer Multi Layer Perceptron Neural Network

Forward pass: The input vector x^0 is transformed into the output vector x^L, by evaluating the equation

$$x^l(i) = f(u_i^l) = f\left(\sum_{j=1}^{n_{l-1}} W^l_{ij}x^{l-1} + b^l_i\right)$$

for l = 1 to L.

Error computation: The difference between the desired output d and actual output x^L is computed

$$\delta_i^L = f'(u_l^L)(d_i - X^L{}_i)$$

Backward pass: The error signal at the output units is propagated backwards through the entire network, by evaluating

$$\delta_i^{L-1} = f'(u_l^{L-1})\sum_{i=1}^{n_j}\delta_i^l w_{ij}^l$$

from l = L to 1.

Learning updates: The synaptic weights and biases are updated using the results of the forward / backward passes

$$\Delta w_{ij}^l = \eta\delta_i^l x_j^{l-1}$$

$$\Delta b_i^l = \eta\delta_i^l$$

These are evaluated for l = 1 to L. The order of evaluation doesn't matter [18].

3.4 Particle Swarm Optimization (PSO)

PSO originated from simulation of birds flock social behavior. In PSO, every particle flies in the search space with velocity adjusted by own flying memory and companion's flying experience. Every particle has objective function value decided by a fitness function:

$$V_{id}{}^t = wXV_{id}{}^t + c_1Xr_1(P_{id}{}^t - X_{id}{}^t) + c_2Xr_2(P_{gd}{}^t - X_{id}{}^t)$$

where i represents i^{th} particle and d is the dimension of solution space, c1 denotes cognition, learning factor, and c2 indicates social learning factor, r1 and r2 are random numbers uniformly distributed in (0,1), pid^t and pgd^t stand for position with best fitness found so far for ith particle and best position in neighborhood, vid^t and vid^{t-1} are velocities at time t and time t − 1, respectively, and xid^t is position of ith particle at time t. Each particle moves to a new potential solution based on following equation:

$$X_{id}{}^{t+1} = X_{id}{}^t + V_{id}{}^t, d=1, 2\ldots D$$

$$f(x) = \begin{cases} 1, & rand() < s(V_{i,d}) \\ 0, & otherwise \end{cases}$$

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$s(v) = \frac{1}{1+e^{-v}}$ [19]

3.5 Invasive Weed Optimization

Invasive Weed Optimization (IWO) is a meta-heuristic algorithm mimicking weeds colonizing behavior. Weeds basic characteristic is a population growing totally in a geographically specified area which is either large or small. The algorithm's 4 steps are described below:

1. Initialization a population: A specific number of weeds are randomly spread over entire search space. This initial population of each generation is termed as $X = \{x1; x2, \ldots x_m\}$

2. Reproduction: Each population X member produces seeds in a specified region centered at its own position. The seed number produced by $x_i, i\epsilon\{1,2 \ldots\ldots m\}$ depends on its relative fitness with respect to best and worst fitness. The number of seeds which produce a weed varies linearly from min seed to max_seed with min seed denoting worst member and max_seed the best population member.

3. Spatial Dispersal: Generated seeds are randomly distributed over d-dimensional search space through normally random number distribution with zero mean and variance σ. If σ max and σ min are maximum and minimum standard deviation, then the standard deviation in a specific generation (or iteration) is given by, where nmi represents the non-linear modulation index.

4. Competitive Exclusion: When a plant leaves no offspring, it would become extinct, or else they can take over the world. So, some competition between plants is required to limit the number of plants in a population [20].

$$\sigma_{iter} = \sigma_{min} + \left(\frac{iter_{max} - iter}{iter_{max}}\right)^{nmi} (\sigma_{max} - \sigma_{min})$$

4 RESULTS AND DISCUSSION

Evaluation was carried out using 400 images of wood knots. The types of knots chosen were dry knot, sound knot, horn knot and edge knot. The dataset consisted of 100 images of each class of knot. The images are preprocessed using Hilbert transform for feature extraction and Gabor filter for feature reduction. Experiments are conducted using various classifiers like Naïve Bayes, MLP Neural Network and Proposed Neural Network.

Table 1: Classification Accuracy and RMSE for Different Classification Techniques

Technique	Classification Accuracy	RMSE
Naïve Bayes	79%	0.3207
Multi layer perceptron Neural Network	86%	0.2865
Proposed Neural Network	91%	0.2163

It is observed from Table 1 and Figure 1 that Classification Accuracy of the proposed Neural Network increases by 13.18% when compared to Naïve Bayes and by 5.49% when compared to Multilayer perceptron Neural Network.

It is observed from Table 1 and Figure 3 that RMSE of the proposed Neural Network decreases by 32.55% when compared to Naïve Bayes and by 24.5% when compared to Multilayer perceptron Neural Network.

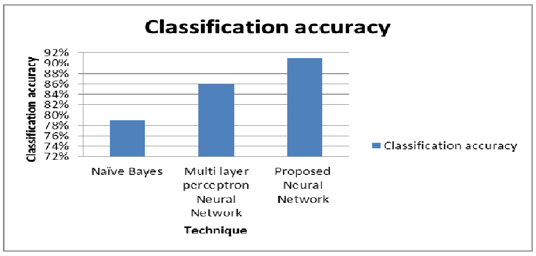

Figure 2 : Classification Accuracy

5 CONCLUSION

A knot is a particular imperfection in timber which reduces its strength. Knot selection is very important in the wood industry. The value of wood is directly proportional to its quality, and this in turn is dependent on the knots (imperfection) in the timber. This research proposes to detect and classify the knots in timber boards using Hilbert transform and Gabor filters for pre-processing the image of knots. The features obtained from preprocessing were classified using Multilayer Perceptron (MLP) and Neural Network (NN) with Particle Swarm Optimization (PSO) and Invasive

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Weed Optimization (IWO) for momentum and learning rate. The classification accuracy is greatly increased, and RMSE is significantly decreased with the proposed Neural Network.

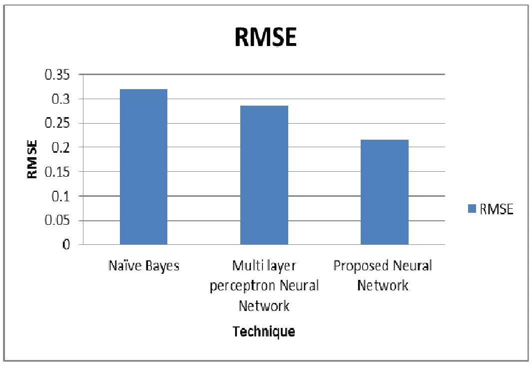

Figure 3: RMSE

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