Automatic Sapstain Detection in Processed Timber Through Image Feature Analysis

Jeremiah D. Deng, *Member, IEEE*

Abstract

Sapstain is considered a defect that must be removed from processed wood. So far, research in automatic wood inspection systems has been mostly limited to dealing with knots. In this paper, we extract a number of colour and texture features from wood pictures. These features are then assessed using machine learning techniques via feature selection, visualization, and finally classification. Apart from average colour and colour opponents, texture features are also found to be useful in classifying sapstain. This implies a significant modification to the domain understanding that sapstain is mainly a discolourization effect. Preliminary results are presented, with satisfactory classification performance using only a few selected features. It is promising that a real world wood inspection system with the functionality of sapstain detection can be developed.

I. Introduction

Sapstain is caused by fungus infection in wood and can subsequently damage the wood quality, especially for soft woods such as Radiate Pine, Corsican Pine, Ponderosa Pine and Douglas Fur. Depending on temperature and moisture conditions, timber can be infected at any time during manufacturing. The onset of the fungus can be very rapid, with discolourization of timber appearing within 5 or 6 days in the right moisture conditions [5]. Sapstain can penetrate deep into the timber, which means the removing the surface stain will not eliminate the sapstain from the wood. It is a real problem for the timber industry as it can cause the wood to lose its strength over time, and is generally considered a defect that must not appear in finished products.

The visual discolourization caused by sapstain can vary from completely covering the sapwood to appearing as specks, streaks or patches of various intensities of colour [5]. The colour of the stain can vary depending on the infecting organism, species and moisture condition of the wood. The most common fungal stain is blue-stain as can be seen in Fig. 1. The colour of blue-stain typically varies from blue to bluish black and grey to brown, but can also have shades of yellow, orange, purple and red.

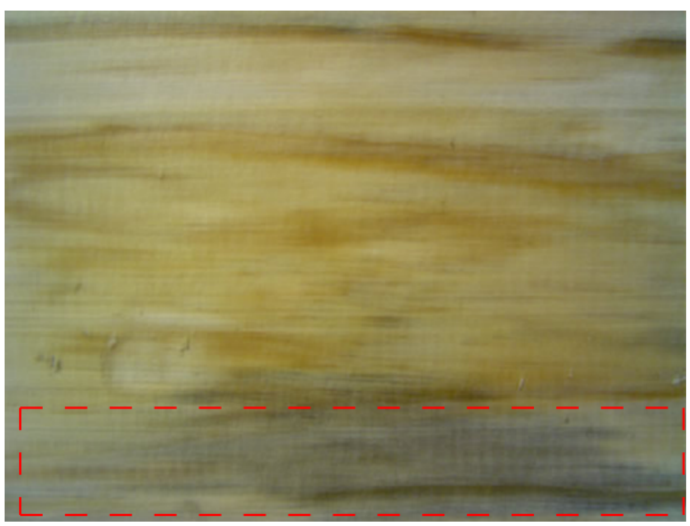

Fig. 1. A blue-stain region is marked by the dashed rectangle at the bottom of the image.

Human inspection of defects in timber is the typical method of classifying defects from clear wood with timber manufacturers. Although humans are good at pattern matching in general, our performance is not perfectly reliable and sometimes even fails to maintain a satisfactory level. For instance, human inspection of defects achieved a 68% detection rate in locating and identifying defects in red oak timber [6]. In a comparative study [9], human inspection achieved an 80% detection rate of knots in pine timber. In an experiment conducted by Gronlund in 1995 [4], timber boards were graded into four grades by

J. D. Deng is with the Department of Information Science, University of Otago, PO Box 56, Dunedin 9054, New Zealand. E-mail: jeremiah.deng@otago.ac.nz.

two different experts, only 60% of the boards were put into the same grade. This further exemplifies how inconsistent and inaccurate human inspection can be.

While prior research into methods for automatic timber inspection systems have focused on the detection of defects such as knots, there has been a lack of research focus on the automatic detection of sapstain. Like other timber defects such as knots, sapstain can greatly vary in its appearance, ranging from a distinctive greyish area that penetrates deep into the timber, to a very light sporadic blue colour appearing on the surface on the timber. It is this vast range of visual appearance that challenges both human performance and automatic methods of inspection.

In this article, we will present a machine learning based approach in dealing with automatic sapstain detection. After considering a few potentially useful image features extracted from timber board images, we conducted feature analysis in ranking and selecting the features. Classification algorithms were then employed to work on selected features, achieving rather satisfactory in cross validation experiments.

The rest of the paper is organized as follows. Our experimental setting is first introduced in Section II, where data acquisition and our general experimental approach are explained. An introduction to feature extraction then follows in Section III. Visualization, feature analysis, and classification results are then presented and discussed in Section V. Finally we conclude our study in Section VII.

II. Experiment settings

To our knowledge there is no publicly available image data of sapstain defects. Our image data were taken from 20 different timber boards using a Sony Digital Still Camera (Cybershot DSC-P93). The 20 boards were provided by the Kiwi Wood Processing Ltd., and an experienced defect inspection employee from the same company then identified the clear and sapstain regions within the 120 images. The images are 1280×960 pixels in size. The regions were then extracted from the images and split into 30×30 pixel blocks. Thus we obtained 2,500 blocks from each class (either 'clear' or 'sapstain'), forming a data set of 5,000 sample images in total.

Several feature schemes were considered for the classification of clear and sapstain image data. These include colour averages, colour histogram centiles, colour opponents, and texture features such as Gabor filter energy and local binary patterns. Experiments were then conducted to evaluate various feature schemes and find out the most effective feature combination that can be used for classification. A number of feature ranking and selection techniques were involved. Further classification results were obtained by using a reduced feature set. Good classification accuracy was achieved with a number of classifiers.

Finally we consider an approach using self-organzing maps, where the visualization user interface and the classification process can operate within the same framework. Because of its convenience and good performance, We propose to use this framework in online inspection of wood images for sapstain detection.

III. Feature extraction

A. Colour means

Because sapstain is related to a discolourization process, a set of colour features were first taken into consideration. Since sapstain dominantly appears as a discolouring defect, using colour means of image blocks is a relevant choice. This image feature is computationally very light-weight. In calculating colour means, we considered the RGB space, as well as other colour spaces with colour opponents:

1) Ohta colour opponents [14], expressed as

$$\begin{pmatrix} I_1 \\ I_2 \\ I_3 \end{pmatrix} = \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & & -1/2 \\ -1/4 & 1/2 & -1/4 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{1}$$

2) Wandell colour opponents. Wandell colour opponents are thought to reflect the representation of colour in the central visual system [22]. Each of the colour channels are adjusted linearly for each of the colour opponents: lumination (L), Red versus Green (R/G), and Yellow versus Blue (Y/B), as follows.

$$\begin{pmatrix} L \\ R/G \\ Y/B \end{pmatrix} = \begin{pmatrix} .281 & .694 & .064 \\ -.097 & .146 & -.025 \\ -.093 & -.253 & .466 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{2}$$

The colour opponent features have been shown to be most useful when the texture contains significant differences in colour, and they have been successfully used for texture classification along with texture features.

B. Colour centiles

Colour centiles are colour histogram features that were proposed for wood inspection [9]. For a cumulative histogram $\mathrm{CH}(x)$ defined over a discrete range of N, a p-percentage centile c is defined as $c = \min(k) : k \in N$ and $\mathrm{CH}(k) \geq p$.

As a colour histogram feature, colour centiles have also been proven to be consistent despite different colour shades due to varying illumination conditions. Through some trial with the p value, we find that 30% centiles are most useful and give robust classification results.

C. Visualization of the feature spaces

The colour features given above are all based on the 3-dimensional RGB colour space. To visualize them together with the class labels of the data samples, we produced some 2-D scatter plots, as shown in Fig. 2. Note that only the first and the second dimensions are used for the X- and Y-axis of each graph, but other combinations give similar appearance. It can be seen that while the discriminant ability of each feature scheme is to some extent satisfactory, none of them is ideal but bearing some significant overlapping between the 'clear' and 'sapstain' classes. No obvious preference of a feature scheme can be concluded from these scatter plots, although the overlaps between samples of two classes seem to be less obvious in the opponent colour models (Ohta and Wandell) than in the other two feature spaces.

As an artificial neural network model, self-organizing maps (SOMs) [8] conduct data clustering and dimension reduction simultaneously. It has been used frequently in various data visualization tasks. Fig. 3 gives the feature map generated on the average Wandell colour features using the SOM Toolbox [1]. Image blocks of both 'clear' and 'sapstain' classes are used to label the feature map units. There was a clear boundary between the clear (lower and left) and sapstain (upper and right) zones, despite some minor folding effect. This demonstrates the usefulness of the colour opponent features.

D. Texture features

1) Gabor filtering: Gabor filters are a set of Gaussian modulated sine functions defined on a few spatial orientations. Gabor filtering has been widely used in image segmentation, object classification, and image retrieval [10], and is often referred to as the Homogeneous Texture Descriptor in the MPEG-7 core experiments [11]. The two dimensional Gabor function is defined as

$$g(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jfx\right], \tag{3}$$

where σ_x and σ_y are spatial spreads of the Gaussian on x- and y-directions respectively, and f the spatial frequency. A set of self-similar Gabor filters are generated through dilation and rotation of this mother function [10]. The filtering process was conducted in frequency domain for speeding-up and the filtered image was obtained through fast Fourier transform. The mean values of filtered images, obtained by filters of 3 frequency levels and 5 orientations, were used in our study and resulted in a 15-dimension feature for each sample image.

2) Local Binary Patterns (LBP): LBPs have been shown to be a simple but effective method of texture discrimination based on a simplification of directional grayscale difference histogram [15] [16]. The basic idea of LBP is quite straightforward. Consider the local 3×3 window centered at the current pixel, as shown in Fig. 4. A binary weight is assigned to the neighbouring cell using the given index if the corresponding grayscale value is greater than that of the centre pixel. For instance, the pattern in the figure will give a LBP of $1+8+32+128=169$. Denote LBP histogram vectors as $h_i=[h(1),h(2),...,h(L)]$ ($L=256$), the Chi-square distance can be used to calculate the dissimilarity between feature vectors h_1 and h_2:

$$d_{\mathcal{X}^2}=\sum_{k=1}^{L}\frac{[h_1(k)-h_2(k)]^2}{h_1(k)+h_2(k)} \tag{4}$$

IV. Feature evaluation and selection

Given a set of features $F=f_1,f_2,...,f_n$, it is often the case that the features can be redundant and noisy at the same time. Hence it makes sense to evaluate the features and obtain a reduced feature set S, so that further data analysis processes, such as classification, can benefit from it. We can define the mutual information of two variables x_1 and x_2 as follows:

$$I(x,y)=\int\int p(x,y)\frac{p(x,y)}{p(x)p(y)} \tag{5}$$

To rank a feature f_i, we need to calculate $I(f_i,c)$, i.e., the mutual information between the feature and the class label. In fact $I(f_i,c)$ is often referred to as 'information gain' (IG), denoted as $\mathrm{IG}(f_i|c)$, indicating the amount of additional information about a feature f_i once the class label c is given. A modified measure based on IG is defined as 'symmetric uncertainty':

$$\mathrm{SU}(f_i|c)=\frac{\mathrm{IG}(f_i|c)}{H(f_i)+H(c)}, \tag{6}$$

where $H(.)$ is the entropy. A straightforward approach would be selecting the first features that have the top-ranked IG or SU measures. This is however sub-optimal, since not only these selected features can be rather relevant, making the selection redundant in itself, but also other features, which are less relevant but still useful for classification, lose the chance to be selected. Therefore, methods have been investigated in order to guide the search process to find feature subsets with the minimum mutual relevance between features. In the minimal-redundancy-maximal-relevance (mRMR) approach [17], both the relevance to class

$$D=\frac{1}{|S|}\sum_{f_i\in S}I(f_i,c), \tag{7}$$

TABLE I
PERFORMANCE OF INDIVIDUAL FEATURE SCHEMES AND THEIR COMBINATIONS

Accuracy (%)	k-NN	NB	RBF	SVM
RGB	89.5	77.3	87.8	88.5
RGB Centile	89.1	79.1	89.3	89.1
Wandell	90.4	86.5	88.4	88.6
Ohta	90.2	86.0	89.2	88.5
Gabor	82.3	70.5	75.3	76.4
LBP	72.7	65.9	63.9	65.3
Ohta + Gabor	93.6	80.8	87.6	89.5
Wandell + Gabor	93.7	74.8	87.7	89.5
Wandell + LBP	92.6	83.5	65.3	89.0
ALL	93.8	83.3	89.7	89.4

and the mutual relevance between features

$$R = \frac{1}{|S|^2} \sum_{f_i, f_j \in S} I(f_i, f_j) \tag{8}$$

are taken into consideration, and the optimization criterion for the search process is

$$\max(D - R). \tag{9}$$

Besides the above approach that employs numeric measures to selection features, another major approach in feature selection practice is the so called *wrapper* method, using classifiers in this context to evaluate feature selections generated from random or guided search. Various classification algorithms can be used, e.g., support vector machines (SVM) and *k*-nearest neighbours (*k*-NN).

V. ANALYSIS AND CLASSIFICATION RESULTS

A. Feature selection and classification

To assess the quality of the features, we assessed the performance of the feature schemes, each individually and also in combination, for classification. Four classifiers are used: *k*-nearest neighbour with $k = 11$ and distance weighting; Naive Bayes with kernel estimation; radial basis functions (RBF) with 24 or 32 Gaussian clusters; and SVM with complexity value of 20. Results are listed in Table I.

It seems that among the colour features, Wandell colour opponents work the best almost for all classifiers, although the margin to the performance of Ohta colour components is quite small. The average colours and centiles in the RGB space does not perform the best.

As with texture, Gabor features seem to outperform the LBP. Furthermore, experiments conducted using Chi-square distance measure on the LBP data did not give better results than using euclidean distance. The results presented above were obtained using euclidean distance only for all kinds of features.

The best combination of colour and texture features is 'Wandell + Gabor', which is as high as 93.74 and comparable to that of using all the features in a k-NN classifier.

To achieve good performance, joint feature schemes such as 'Wandell+Gabor' are favoured in the results given above. However, these joint feature schemes, especially because of the inclusion of texture features, have large dimensionality. To explore the reducibility of the feature scheme, we further used a few feature selection methods to extract the best seven feature components. Feature ranking and selection methods used include: IG, SU, and mRMR. SVM was used in a wrapper approach to select its version of the best seven. The selection results using different methods are given in Table II. Although there exist some minor variations among these different selection outcomes, there are a few notable similarities:

- Colour features are most important. All four selections pick 'avgR' (average R) and 'avgOhta2' (average I_2 in the Ohta model) as the first two best features.
- All selections also include texture features. Interestingly, although the first three selections pick Gabor filter coefficients, mRMR picks more LBP features instead.

While we considered blue sapstain only in this study, it is interesting to see that the most important colour features are actually the average red, and average red versus blue. On the other hand, with the facts that multiple texture features selected using various methods, as shown in Table II, and that the inclusion of texture features helped to achieve higher accuracies, these results suggest that fungi also cause significant changes to texture appearance on the wood, despite the domain knowledge suggests sapstain is merely a discolourization effect.

Other frequently used dimension reduction techniques include random projection [2], and principal component analysis (PCA). We also test the performance of the selected features and compared the results. Here we give the k-NN ($k = 11$)performance, shown in Table III.

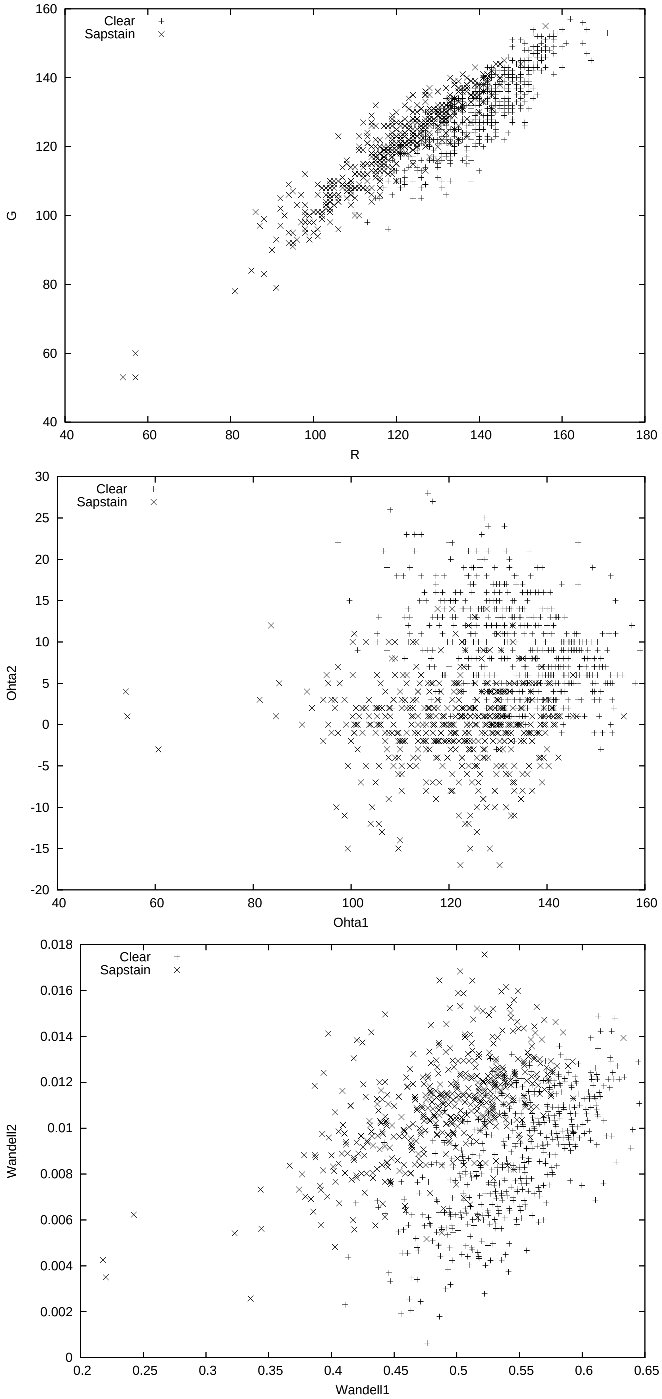

Fig. 2. Scatter plots of different colour feature schemes. (a) Average RGB colour, shown with R vs G; (b) 30% colour centiles, shown with R vs G; (c) Average Ohta colour, shown with the first two components; and (d) Average Wandell colour, shown with the first two components.

TABLE II

THE BEST SEVEN FEATURES SELECTED BY DIFFERENT ATTRIBUTE SELECTORS.

Method	Selected Features						
SVM	avgR	avgOhta2	Gabor8	Gabor9	Gabor1	Gabor2	avgWand3
IG	avgR	avgOhta2	Gabor2	avgWand1	avgOhta1	Gabor9	Gabor5
SU	avgR	avgOhta2	Gabor2	avgWand1	Gabor5	avgOhta1	Gabor9
mRMR	avgOhta2	avgR	LBP1	LBP3	avgOhta3	Gabor5	LBP2

Fig. 3. Feature map generated on average Wandell colour features.

P_1	P_2	P_3
P_4		P_5
P_6	P_7	P_8

70	44	43
67	65	44
66	45	66

1	0	0
8		0
32	0	128

Fig. 4. A example of LBP computation.

TABLE III

PERFORMANCE OF REDUCED FEATURE SETS SELECTED BY SVM, IG, RANDOM PROJECTION (RP), PCA, AND MRMR.

Performance	IG	RP	PCA	mRMR	SVM
Accuracy	90.7	91.6	93.5	93.6	94.2
Kappa	0.81	0.83	0.87	0.87	0.88

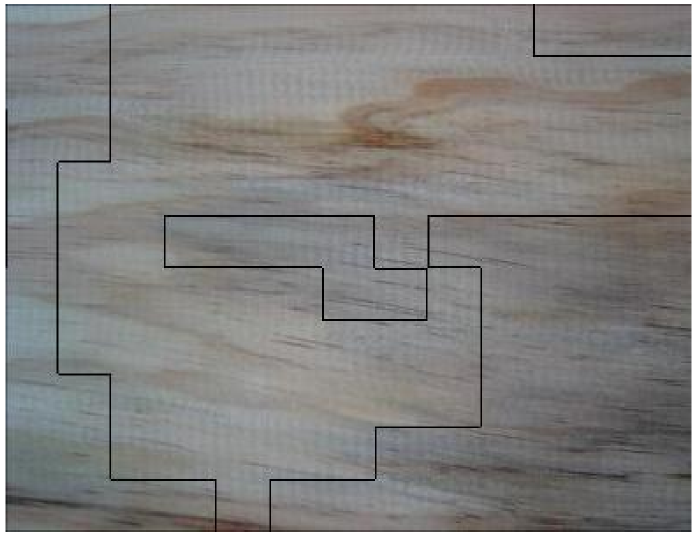

Fig. 5. An board cutting example based on sapstain classification.

A little surprisingly, all reduced feature sets can achieve very good classification accuracies. It is noted that the results using both PCA and SVM feature selection can get better or almost the same accuracy as that of using the whole feature set.

B. Post-processing

Another problem that arose which could potentially cause frustrations in practical application is the occurrence of single regions being classified as sapstain. If a region surrounded by clear regions is classified as sapstain, it would be cut and removed from the timber board. This would cause valuable lengths of clear board to be lost. To overcome this, the neighbours of each classified region were inspected; if no neighbours within a 1-block distance of the current region were also classified as sapstain, it meant the region was an isolated sapstain region and was thus re-classified as clear wood. An example of board cutting based on sapstain classification is shown in Fig. 5.

VI. RELEVANT WORKS

There is a growing trend in employing machine vision and image analysis techniques in wood processing applications. In [12], an approach of evaluation of wood strands arrangement on oriented strand board was proposed, using image analysis to automatically compute the number of strands, strand area, and fibre directions. For inspection of timber, a number of studies have been conducted [9] [19] [13]. Self-organizing maps were employed to visualize and classify sound wood and defects, e.g. in [13] [20]. Although there was a recent study on the the detection of sapstain caused by two kinds of fungi, it used a biological method [7]. To our knowledge, there has been no computational solutions proposed for sapstain detection. Besides, there seem to be no machine learning based studies to analyze the effectiveness of the feature schemes used in solving wood inspection problems.

Centiles have been widely used in defect inspection in timber with good results [9] and again are computationally light suiting the practical application of colour centiles with automatic wood defect systems.

Although not found very effective in this case study, as a texture feature LBP has been successfully used in surface defect detection [23], face recognition [3], face expression recognition [18], and medical image categorization [21]. Some of these incorporated multi-resolution features in consideration, but we restricted ourselves in small region inspection and used the basic LBP feature only.

VII. CONCLUSION

Building reliable automatic wood inspection systems is a meaningful topic for the wood industry. So far systems for the detection of wood defects such as knots have been developed. Various colour and texture features have been proposed for the purposes. In this paper, we presented the first computational approach on sapstain detection. Our approach is first to conduct machine learning experiments on the colour and texture features extracted from blue sapstain images. Features as few as seven are found to be effective in later building classifiers, whose performance is assessed with cross validations. Feature analysis and selection methods reveal that although average colour components and colour opponents are the most important features, texture features are among the best features too. This implies that sapstain is not a discolourization effect alone but bears significant texture variation on wood appearance.

Colour features provide the best results for classifying sapstain and clear wood. RGB colour means, colour-opponent combinations and centiles all had an adequate classification rate of greater than 80%. Among these it is the colour-opponent models that give the best classification performance, suggesting that they are most sensitive to the discolourization in sapstain images. Colour opponents are most frequently present among the selected features obtained using various feature selection methods. On the other hand, texture features have much poorer classification performance. However, when being combined with colour features, they can produce superior performance that outruns using colour features or texture features alone.

Furthermore, by either conducting feature selection, or using dimension reduction algorithms such as PCA and random projection, it is found that the effective dimensionality of the feature sets can be as low as seven. This allows efficient classification models to be trained and tested.

Automatically detecting sapstain would be of a great value to automatic defect inspections systems in the timber industry. The results of this study could be incorporated into exiting automatic detection systems using SOM [20] for visualization and a stronger classifier to improve the classification performance of sapstain within processed timber. Future work also needs to look into developing automatic systems for the detection of multiple defects, such as knots, cracks and other kinds of sapstain.

Acknowledgment. The author thanks Matthew Gleeson for his work in collecting the sapstain image data and conducting some initial experiments.

References

[1] [Online]. Available: http://www.cis.hut.fi/projects/somtoolbox/

[2] D. Achlioptas, "Database-friendly random projections," in *PODS '01: Proceedings of the twentieth ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. New York, NY, USA: ACM, 2001, pp. 274–281.

[3] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037–2041, 2006. [Online]. Available: http://dx.doi.org/10.1109/TPAMI.2006.244

[4] O. Groenlund, "Quality improvements in forest products industry," Master's thesis, Lulea University of Technology, Sweden, 1995.

[5] T. Highley, *Wood Handbook - Wood as an Engineering Material*. Forest Products Laboratory, 1999.

[6] H. Huber, C. McMillin, and J. McKinney, "Lumber defect detection abilities of furniture rough mill employees," *Forest Products Journal*, vol. 35, pp. 79–82, 1985.

[7] S. Kim, A. Uzunovic, and C. Breuil, "Rapid detection of ophiostoma piceae and O. quercus in stained wood by PCR," *Applied and Environmental Microbiology*, vol. 65, 1999.

[8] T. Kohonen, *Self-organizing maps*. Springer-Verlag, 1997.

[9] J. Lampinen and S. Smolander, "Wood surface inspection system based on generic visual features," in *Proc. of ICANN*, 1995.

[10] B. Manjunath and W. Ma, "Texture features for browsing and retrieval of image data," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, no. 8, pp. 837–842, 1996.

[11] B. Manjunath, J. Ohm, V. Vasudevan, and A. Yamada, "Colour and texture descriptors," *IEEE Trans on Circuits and Systems for Video Technology*, vol. 11, no. 6, pp. 703–715, 2001.

[12] T. Nishimura, M. Ansell, and N. Ando, "Evaluation of the arrangement of wood strands at the surface of osb by image analysis," *Wood Science and Technology*, vol. 36, pp. 93–99, 2002.

[13] M. Niskanen, O. Silven, and H. Kauppinen, "Color and texture based wood inspection with non-supervised clustering," in *Proc. 12th Scandinavian Conference on Image Analysis*, 2001, pp. 336–342.

[14] Y. Ohta, T. Kanade, and T. Sakai, "Color information for region segmentation," *Computer Graphics and Image Processing*, vol. 13, pp. 222–240, 1980.

[15] T. Ojala, M. Pietikainen, and D. Harwood, "A comparative study of texture measures with classification based on feature distributions," *Pattern Recognition*, vol. 29, pp. 51–59, 1996.

[16] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, 2002.

[17] H. Peng, F. Long, and C. Ding, "Feature selection based on mutual information: Criteria of max-dependency, max-relevance, and min-redundancy," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 8, pp. 1226–1238, 2005.

[18] C. Shan, S. Gong, and P. W. McOwan, "A comprehensive empirical study on linear subspace methods for facial expression analysis," in *Computer Vision and Pattern Recognition Workshop*. Los Alamitos, CA, USA: IEEE Computer Society, 2006, p. 153.

[19] O. Silven and H. Kauppinen, "Color vision based methodology for grading lumber," in *Proceedings of the 12th ICPR*, 1994, pp. 787–790.

[20] O. Silven, M. Niskanen, and H. Kauppinen, "Wood inspection with non-supervised clustering," *Machine Vision and Applications*, pp. 275–285, 2003.

[21] G. Tian, H. Fu, and D. D. Feng, "Automatic medical image categorization and annotation using lbp and mpeg-7 edge histograms," in *Technology and Applications in Biomedicine, 2008. ITAB 2008. International Conference on*, 2008, pp. 51–53.

[22] B. Wandell, *Foundations of Vision*. Sinauer Associates, 1995.

[23] X. Xie, "A review of recent advances in surface defect detection using texture analysis techniques," *Electronic Letters on Computer Vision and Image Analysis*, vol. 7, no. 3, pp. 1–22, 2008.