Genetic input selection to a neural classifier for defect classification of radiata pine boards

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Abstract

A genetic algorithm was used to determine an appropriate set of features for automatic defect classification of radiata pine boards. The study was performed using a low-cost machine vision system composed of a color video camera, a frame grabber, and a microcomputer. The following 10 defect categories were considered, plus clear wood: birds eye & freckle, bark & pitch pockets, wane, split, blue stain, stain, pith, dead knot, live knot, and hole. A database was built containing color images of 2,958 board faces. A total of 16,800 feature vectors were extracted from these images, and partitioned into training, validation, and test sets. Each vector was composed of 182 features measured in the segmented objects and in windows around the objects. By using feature selection algorithms, 64 out of 182 original features were selected and used as inputs to a multilayer perceptron neural network classifier, without reducing the classification performance. Using the set of features evolved by a genetic algorithm, the best off-line performance obtained was 74.5 percent of correct classifications on the test set. The classification performance on a reduced database with 7 defect categories reached 87.8 percent. An online system evaluation yielded 80 percent of correct classifications with 10 defect categories plus clear wood. The study shows that the genetic selection of features allows us to identify the most relevant features for complex classification problems, such as wood defect classification, where the best features are unknown.

Automatic detection of defects on wood boards and grading of the products into quality categories is one of the key areas of interest in the forest products industry. A defect is considered to be any characteristic that makes wood unsuitable for a given use. With the aim of improving yield and increasing productivity, in the last decades several automated visual inspection systems for lumber have been proposed. In the early 1980s, Conners et al. (1983) and McMillin et al. (1984) proposed an automated lumber processing system that combined computerized axial tomography and computer vision, to locate internal knots in logs and surface defects in wood boards.

Kline et al. (1998) evaluated the performance of a color camera machine vision system for lumber processing in a furniture rough mill. The study used 134 red oak boards and five defect categories: wane, knot, split, hole, and void (false defects). The performance criteria was the yield of dimension parts that can be obtained from lumber. Automated rough mill yield using the prototype lumber inspection system was found to be 56.3 percent compared to 69.1 percent (estimated optimum) and 65.6 percent (observed yield from a furniture rough mill).

A review of methods for automated defect detection and grading has been provided by Szymani and McDonald (1981) and Pham and Alcock (1998). **Figure 1** shows an automated visual inspection framework to detect wood surface defects, which is subdivided into five modules: image acquisition, image segmentation, feature extraction, feature selection, and classification.

The most common data-acquisition method is based on optical cameras. Several studies have shown that color vision offers advantages over grayscale images for automated visual inspection of wood. According to the literature, adding color information to black and

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The authors would like to thank Research Assistants, Gerardo Bühler, Rodrigo Caballero, Marcelo Fernández, Pedro Ortega, Patricio Reinoso, Gonzalo Ruz, and Michel Tesmer, for their valuable help with the experiments and software implementation. This research was supported by Conicyt-Chile under grants Fondecyt 1980909 and Fondef 1022; and by Forestal Mininco S.A. This paper was received for publication in March 2002. Article No. 9468.
*Forest Products Society Member.

Forest Prod. J. 53(7/8):87-94.

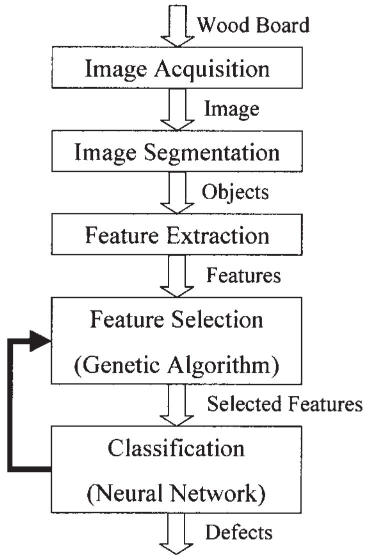

Figure 1. — Automated visual inspection system for wood boards. A feature selection stage based on a genetic algorithm is added to the conventional framework to select an appropriate feature subset as inputs to a neural network classifier.

white data enhances the recognition rate from 5 to 20 percentage points (Conners et al. 1985, Lampinen et al. 1994, Funck et al. 2000). Conners et al. (1985) showed that almost all of the useful color information could be retained using only two of the three color components (the red and blue channels).

Besides optical scanners, a variety of different sensors have been investigated to detect wood defects. These include radio-frequency (Steele et al. 2000), microwave (Szymani and McDonald 1981), infrared camera (Quin et al. 1998), x-ray (McMillin et al. 1984, Conners et al. 1997), gamma ray (Karsulovic et al. 1999) and ultrasound (Karsulovic et al. 2000). Most of these sensing technologies remain experimental. Recent developments have used a multiple sensor approach to scanning, since all grading features cannot be consistently detected with a single sensing mechanism (Conners et al. 1997, Astrand and Aström 2000, Kline et al. 2000, Nyström 2000).

Low-cost systems, based on general purpose computers including a video camera, an image capture board, and a microcomputer, are flexible and allow many different algorithm options for image segmentation, feature extraction, feature selection, and defect classification. The aim of the image segmentation stage is to divide the image into clear wood and defects. Pham and Alcock (1996) found that a major weakness in the process is segmentation. This is often the most time-consuming part of the process. Segmentation usually does not locate all defects properly, especially defects such as sound knots, which have a similar appearance to clear wood. There are a wide variety of segmentation algorithms to choose from. Histogram-based thresholding is a simple and fast method; however, grain lines in clear wood can appear to be as dark as defects. Funck et al. (2000) analyzed the performance of a wide range of segmentation algorithms on images of Douglas-fir veneer, concluding that region-based algorithms have the greatest promise.

After the image segmentation stage, defect areas called objects are isolated. Windows are defined as square- or rectangular-shaped areas of the image centered in the object geometrical center. The process of calculating features from the objects or windows is called feature extraction. Most often features describe shape, size, and intensity levels, including color.

Feature selection is the process of forming a smaller subset of features from the original feature set that satisfies a certain error classification criterion. Genetic algorithms (GAs) seem suitable for solving the feature selection problem due to their inherent parallelism, their guided search of the most promising regions, their ability to find and maintain multiple optima, and their ability to optimize a non-analytical criterion (Mitchell 1996). The use of GAs for selecting features for defect classification of wood boards has been reported elsewhere (Estévez and Caballero 1998; Estévez et al. 1998, 1999). In a different approach, Patton and King (2000) have applied GAs to optimize the location of knot anomalies in wood using infrared images.

The classification module has features as inputs and defect categories as outputs. There are many types of classifiers that have been employed to classify wood products. Among the most common are multilayer perceptron (MLP) neural networks (Haykin 1994). Learning results from the repeated presentation of a training set of examples to the MLP. The presentation of the entire set of training examples to the learning algorithm is called an epoch (Haykin 1994). Cho et al. (1991) compared an MLP, a rule-based system, and a k-nearest neighbor classifier. The MLP obtained the best classification results (81%). Pham and Alcock (1999a) combined several neural classifiers to improve the performance achieved with individual classifiers in wood defect identification.

Pham and Alcock (1999b) compared the usefulness of different features for classifying nine classes of defects on images of birch wood boards. Thirty-two features were implemented and compared using an MLP neural network. Features were extracted from segmented objects and from windows around the objects. When used individually, the object features and the window features were comparable to one another with performances of around 74 percent. The best performance was achieved when all features were employed together, reaching 85.2 percent.

In this paper, a feature selection study is made to determine an appropriate set of features in the inputs to a neural network classifier for automatic defect classification of radiata pine boards. The study is based on a low-cost machine vision system composed of a color video camera, an image capture board, and a microcomputer.

Methods

Wood sample

A sample of about 1,500 dry radiata pine (*Pinus radiata* D. Don) board specimens was selected. The lumber was ob-

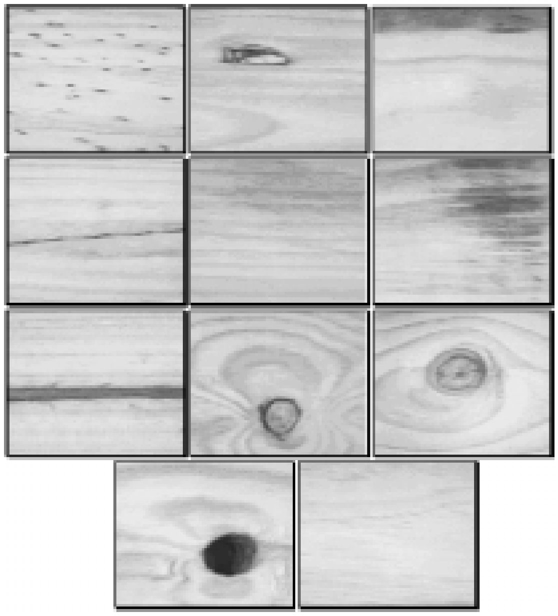

Figure 2. — Image samples of each of the 11 categories considered. In the top row, left to right, birds eye, pocket, and wane; in the second row, left to right, split, blue stain, and stain; in the third row, left to right, pith, dead knot ,and live knot; in the bottom row, left to right, hole and clear wood.

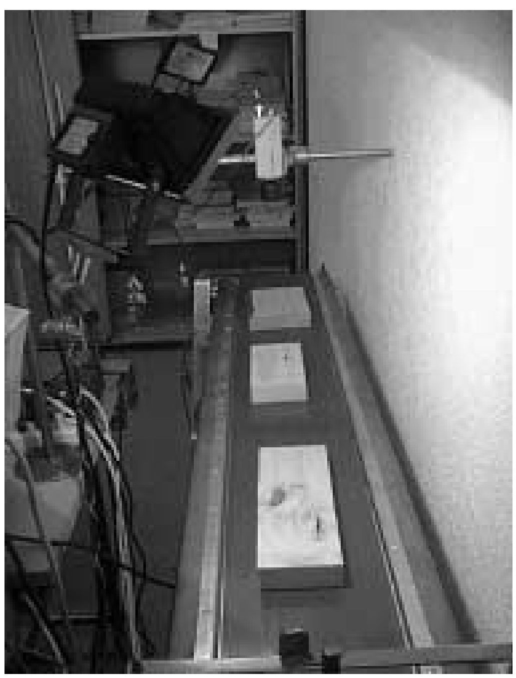

Figure 3. — Automated visual inspection system with a view of the video camera, illumination system, and conveyor belt.

tained from a rough mill in southern central Chile. Sample board thicknesses were 2.15 cm or 3.3 cm; board widths ranged from 6 cm to 15 cm; and board lengths were between 10 cm and 30 cm. Although at the rough mill board lengths are over 2 m, shorter samples were provided for this study, each one representing a particular defect. Each board face was manually labeled, according to its largest defect, into one of the following 10 categories: birds eye & freckle, bark & pitch pockets, wane, split, blue stain, stain, pith, dead knot, live knot, and hole (**Fig. 2**). Defect-free boards were grouped into the clear wood category. An identifier was marked on one side of the board along with an arrow pointing to an arbitrary forward direction. A forward direction was defined in order to distinguish between 180-degree rotations of boards while being processed through the system. At least 100 board specimens were collected per each of the 11 categories just mentioned.

Hardware

The imaging system was composed of a National Television Standard Committee (standard television video signal format used in the United States) (NTSC) color video camera, a frame grabber IM-PCI-AM-CLR from Imaging Technology, and a 333-MHz Pentium-II PC with 128 MB RAM, running under Windows NT. Lighting was a mixture of two frontal halogen lights and ceiling fluorescent lamps. The halogen light sources were located on one side of the conveyor belt, with an angle of approximately 45 degrees (**Fig. 3**). On the other side of the conveyor belt a white wall acted as a light diffuser, as shown in **Figure 3**, and lights were adjusted to obtain a uniform illumination over the board samples. The available hardware allowed us to scan only one side per run.

Software

The image-processing system software was written in C++ and consisted of image acquisition, image segmentation, feature extraction, and classification modules. The image-acquisition module acquired images, detected the boards on the conveyor belt, and eliminated the background. The system acquired images using the frame grabber with a resolution of 640 by 480 pixels, but only odd lines were considered to avoid interlacing. Therefore, resolution of the image was reduced to 320 by 240 pixels. Images were in red, green, and blue (RGB) containing 256 intensity levels in each channel. The camera was configured for a 16.4-cm field of view, covering completely the board width on the conveyor belt. The camera produced color images with 14.6 pixels per cm both cross-board and down-board resolution. The conveyor belt speed was fixed at about 0.3 m/sec. There were no fences to ensure straight movement through the scanning system. To introduce invariance to small displacements and to 180-degree rotations in relation to the camera field of view, every board face was fed through the system six times, three times in the forward direction and three times in the reverse direction (180-degree rotation). Thus six scanned color images for each board face were stored in the computer for further processing. As many of the boards were not truly rectangular, in order to completely avoid void defects, the image segmentation algorithm for eliminating the background cut out 1 mm to 2 mm on each board boundary, generating images with no void defects.

The image segmentation module performed the following five steps for each of the four channels (RGB + Gray): edge detection, image binarization, Boolean OR operation of the previous images, morphological closing (dilation-erosion), and selection of the five largest objects detected. Segmentation was performed by histogram-based multiple thresholding.

The feature extraction module extracted features from objects and windows of 64 by 64 pixels centered in the object geometrical center. There were 182 features extracted, including: 35 object geometrical features measured on the binarized gray image (e.g., area, perimeter, average radius, aspect ratio, first and second order moments, etc.); 100 object color features (25 features measured in each of the four channels, e.g., object histograms were divided into 5 fixed parts according to their intensity levels: very bright, bright, midrange, dark and very dark); and 47 window color features (e.g., mean and variance of window histograms, mean and variance at the edge of windows). This set of 182 features served as the basis for our feature selection study.

The classification module employed MLP neural networks as classifiers. All networks had one hidden layer with an N_i-N_h-N_o architecture, where N_i is the number of inputs, N_h is the number of hidden units, and N_o is the number of outputs or categories. Networks were trained by a second-order Back-Propagation Quasi-Newton learning algorithm (BPQ) (Saito and Nakano 1997), which uses an adaptive step-length. The objective function minimized was the sum of square errors plus a penalty term consisting of the sum over all squared weights. The penalty term was weighted by a regularization factor. For each simulation, the weights were randomly initialized. The data were normalized in the range [0,1] and randomly split into training, validation, and test sets. To avoid overfitting and to achieve good generalization, all networks were trained using the training data and tested on the validation data every 10 epochs. The set of weights giving the minimum validation error was saved and tried on an independent test set. To improve the performance achieved with individual classifiers, the combination of three or five neural classifiers was carried out by simple averaging of their outputs (Sharkey 1999).

Feature selection

The GA-based feature selection method proposed by Estévez and Caballero (1998) was used in this study. Each individual in the GA population represents a feature subset as a binary string, where a "0" in the i-th position indicates that the i-th original feature is excluded from the feature subset, and a "1" indicates that the feature is present. To evaluate the fitness of an individual, the selected feature subset is fed into a neural network classifier of fixed architecture, and trained by BPQ learning. The GA fitness function combined two optimization criteria: 1) minimization of the error rate of the classifier; and 2) minimization of the number of features. The following parameters were used (see Estévez and Caballero 1998 for details): P = 20 (population size); ς = 0.01 (weighting factor in fitness function that penalizes the number of features); M = 3, ν = 0.6, and ι =10 percent (mutation parameters); p_c =1 (probability of crossover); G = 20 (number of generations). MLP networks with 20 hidden units were trained for 300 epochs by using BPQ learning, with a regularization factor κ= 0.1.

The GA method, although very effective in finding a global optima, is computationally expensive since at each generation a population of P neural networks have to be trained until convergence. The search space of the feature selection problem faced in this work was large with a 182-dimensional feature space. For these reasons, the original feature space was reduced by using the Mutual Information Feature Selection (MIFS) algorithm (Battiti 1994), before employing the GA search. The mutual information method offers advantages over other methods based on linear dependence (e.g., correlation), since it can measure arbitrary relations between variables and is invariant under a variable transformation. The MIFS algorithm ranks features from the most informative to the less informative, based on the mutual information between input features and output classes. The parameter η used by MIFS was set to 0.7 (Battiti 1994). The F most informative features according to MIFS were selected, with F = 10, 20, ..., 170; and tried as inputs to an MLP neural classifier. MLPs of architecture F-20-11 were trained by using BPQ learning for 2,000 epochs and a regularization factor κ = 0.1. The performance of the MLP classifier was measured as the average percentage of correct classifications on the validation set, using two trials for each combination of parameters.

Image database

A database containing color images (640 by 480 pixels) of radiata pine boards was developed at the University of Chile. **Table 1** shows the number of board faces and the total amount of images in the database. As explained in the software section, six color images were acquired for each board face. In total, 17,748 images (2,958 Δ 6) were collected.

The segmentation module delivered the five largest objects detected in each image, ordered by their area size. Each object (potential defect) was visually compared with the actual object, identified as one of the 10 defect categories or as clear wood, and manually labeled. The clear wood category contained segmented objects as dark as defects, mostly grain lines. For each image stored in the database, a target file was created identifying each object detected.

In the feature extraction stage, 182 features were extracted from each object. Out of the more than 70,000 segmented objects in the 17,748 images, a total of 16,800 feature vectors were extracted. As some defect categories were more frequent than others, the number of samples per category ranged from 1,400 to 11,000. To obtain an unbiased classifier, 1,400 samples were randomly chosen per each of the 10 defect categories. By random selection, 12,000 feature vectors were assigned to the training set, 2,400 to the validation set, and 2,400 to the test set. The samples on the

Table 1. — Image database.

Category	Board faces	No. of images
Birds eye & freckle	237	1,422
Bark & pitch pockets	269	1,614
Wane	208	1,248
Clear	255	1,530
Split	222	1,332
Stain	244	1,464
Blue stain	292	1,752
Pith	202	1,212
Dead knot	295	1,770
Live knot	471	2,826
Hole	263	1,578
Total	2,958	17,748

Table 2. — Simulation results on the validation and tests sets, using all original features and the GA best-evolved individual.

		All	GA
	No. of features	182	64
Validation set	Mean (%)	75.2	75.0
	Standard deviation	0.67	0.63
	p-value		0.35
Test set	Mean (%)	72.4	72.1
	Standard deviation	0.84	0.35
	p-value		0.26

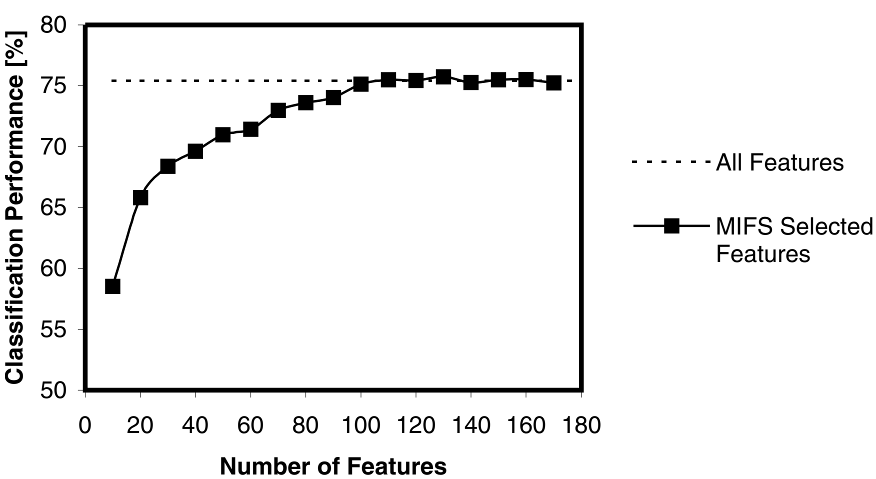

Figure 4. — Classification performance on the validation set with all the original features (--), and as a function of the number of selected features by the mutual information feature selection algorithm (—■—).

test set corresponded to different boards from those used for training or validation. Each defect category had 1,000 samples for training, 200 samples for validation, and 200 samples for test. However, the clear wood category had 2,000 samples for training, 400 samples for validation, and 400 samples for test. As the primary distinction should be between defect areas and clear wood, the correct identification of dark grain lines as clear wood is of the highest importance. By using more data for the clear wood category than for the other categories, a bias of the classifier towards clear wood was introduced.

The feature selection study was performed using the database just described, which is composed of 16,800 feature vectors for 11 categories (10 defect categories plus clear wood). The best features evolved by the GA were tested on the classification of the 11 categories and also with a reduced database representing 7 defect categories. The reduced database contained 1,400 samples of the categories birds eye & freckle, wane, split, blue stain, pith, dead knot, live knot and hole; but for classification purposes dead knots and live knots were merged into one category: knots. As before, each defect category had 1,000 samples for training, 200 samples for validation, and 200 samples for test.

Results

As explained in the methods section, the MIFS algorithm was used first to reduce the search space. **Figure 4** shows the classification performance as a function of the number of features selected by MIFS. The classification performance grew from 58.5 percent with 10 features to 75.5 percent with 110 features. Increasing the number of features over 110 did not improve the classification performance. In fact, when all features were used, the classification performance was 75.4 percent. To verify the effective dimensionality of the data, principal components analysis was performed. It was found that at least 110 principal components are needed to reach a classification performance of 75.5 percent. The MIFS results indicate that 72 out of 182 features appear to be redundant or irrelevant for the classification task. By eliminating those 72 features, the search space was reduced to 110 features.

The GA method was applied to the reduced search space. As explained in the methods section, each individual represented a subset of input features to the MLP classifier. With the GA procedure, 46 out of 110 features were eliminated. About half of the eliminated features presented very low mutual information with the categories (classes), as measured by the MIFS method, which is

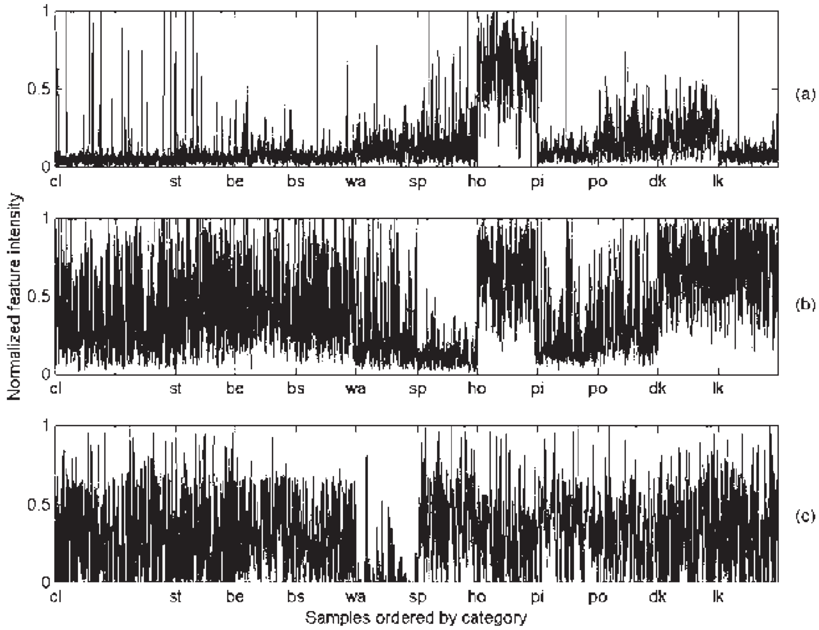

Figure 5. — Normalized intensity of three selected features as a function of the number of samples ordered by category: a) intensity variance in red channel; b) aspect ratio; c) minimum distance to one of the horizontal edges of the board image. Letters on the x-axes mark the beginning of one of the 10 defect categories: stain (st), birds eye (be), blue stain (bs), wane (wa), split (sp), hole (ho), pith (pi), pocket (po), dead knot (dk), and live knot (lk). Each defect category has been represented with 1,000 samples. The clear wood category (cl) has been represented by the first 2,000 samples.

Table 3. — Percentage of correct classifications on the test set for 10 defect categories plus clear wood, obtained with a combination of 5 neural classifiers.

Category	Test
	(%)
Birds eye & freckle	77.0
Bark & pitch pockets	60.5
Wane	72.5
Clear	77.0
Split	86.0
Stain	40.0
Blue stain	89.0
Pith	81.5
Dead knot	75.0
Live knot	61.0
Hole	99.5
Total	74.5

based on information theory. **Figure 5** shows the characteristics of three selected features that are useful to discriminate between categories.

The best-evolved individual had 64 features comprised of 13 object geometrical features, 30 object histogram features, and 21 window histogram features. **Table 2** shows the simulation results on the validation and test sets, using the entire set of features (ALL) and the best-evolved individual (GA). Ten runs were carried out in each case, with random initializations of weights. Pairwise two-tailed t-tests showed that the means obtained by GA and ALL were not significantly different at the 0.01 level of significance (p-value > 0.01), both in the validation and test sets.

Table 3 shows the classification results on the test set with 11 categories, using a combination of 5 neural classifiers. MLP networks with 20 hidden units were trained for 5,000 epochs, with regularization factors κ = 0.01; 0.03; 0.1; 0.1; 0.1. The classification performances of the individual classifiers on the test set were 73.3, 71.9, 72.3, 72.6, and 73.0 percent. By averaging the outputs of the five classifiers, a gain of 1.2 percentage points was obtained to reach a 74.5 percent classification performance. Results in **Table 3** show that 4 out of 11 categories had a performance over 80 percent of correct classification in the test set: split, blue stain, pith, and hole. The worst performance was stains, followed by pockets and live knots. Most confusions within the stain category occurred with clear wood and birds eye; most confusions within the pocket category occurred with dead knots and splits; most confusions within the live knot category occurred with dead knots. **Table 4** shows the classification performance on the test set for the reduced database with seven defect categories, using a combination of three neural classifiers. MLP networks with 60 hidden units were trained for 5,000 epochs, with regularization factors κ = 0.001; 0.01; 0.05. The classification performance of the individual classifiers on the test set were 87.2, 87.0, and 87.1 percent. By averaging the outputs of the three classifiers, a gain of 0.6 percentage points was obtained to reach 87.8 percent. In **Table 4**, all categories except wane have a classification performance over 80 percent, showing that the selected features are adequate to identify them.

To evaluate the defect detection rate of the system, a sample of 55 board faces, 5 per each of the 11 categories, was randomly chosen. On this set, 145 real defects were visually found. The system correctly detected 95 percent of these defects. Non-detected defects included small and bright birds eye, very thin splits, and some stains. This high defect detection rate was achieved at the expense of increasing the detection of false-positives, i.e., dark grain lines segmented as defects. On the same set of boards, the system automatically seg-

Table 4. — Percentage of correct classifications on the test set for seven defect categories, obtained with a combination of three neural classifiers.

Category	Test
	(%)
Birds eye & freckle	83.0
Wane	75.5
Split	89.5
Blue stain	95.5
Pith	90.0
Knot	81.8
Hole	99.0
Total	87.8

mented 231 objects, 60 percent of which corresponded to real defects. The correct classification rate of false-positives was 77 percent and were classified as clear wood.

In **Table 5**, preliminary online evaluation results of the current system are presented. For this evaluation, a sample of 33 board faces, 3 per each of the 11 categories, was randomly chosen. Each board was fed through the system three times in the forward direction and three times in the reverse direction. The system automatically acquired an image of the board moving on the conveyor belt, and then started the serial execution of the segmentation, feature extraction, and classification stages. The online system evaluation yielded 80 percent of correct classifications with 10 defect categories plus clear wood. The scanning results were inmediately displayed on the computer monitor.

Summary

A database was developed containing 17,748 images of wood board faces, corresponding to 10 categories of defects plus clear wood. A total of 16,800 feature vectors were extracted from these images for system training, validation, and test. By using feature selection algorithms, approximately 65 percent of the original 182 features was eliminated, without reducing the classification performance. A mutual information feature selection algorithm was used first to reduce the dimensionality of the original search space from 182 dimensions to 110 dimensions (about 40%). The GA-based feature selection algorithm was employed to find out the best subset of features, which was reduced to 64 features. The best overall off-line performance obtained by a combination of neural classifiers on a test set was 87.8 percent of correct classifications with 7 defect categories, and 74.5 percent with 10 defect categories plus clear wood. In addition, the system was evaluated online, yielding a performance of 80 percent of correct classifications with 11 categories. Results here include the effect of misaligned wood boards through the system.

Conclusions

Contrary to linear projection methods such as principal components, feature selection algorithms can reduce the computational requirements of online inspection systems by eliminating redundant or irrelevant features. The GA-based feature selection algorithm, as well as the mutual information feature selection algorithm, employed in this work, can be directly applied to enhance other automated visual inspection systems based on different technologies or multiple-sensors.

Improvement of the recognition rate of the stain, pocket, live knot, and clear wood categories is needed. This could be done by creating new features with higher information content and also by enhancing the segmentation process, which is a key factor to correctly distinguish clear wood from defects. Enhancing the system illumination and adding color constancy should improve defect identification.

Although the current state of the art seems to indicate that automated visual inspection of wood should combine multiple sensors to get a performance at the level required by the industry, rapid technological advancements both in computer and optical cameras may help

Table 5. — Percentage of correct classifications for images acquired online.

	Board 1		Board 2		Board 3		Average		
Category	Forward	Reverse	Forward	Reverse	Forward	Reverse	Forward	Reverse	Total
	(%)								
Birds eye & freckle	0	0	67	100	0	33	22	44	33
Bark & pitch pockets	100	100	100	67	100	67	100	78	89
Wane	100	100	100	100	100	100	100	100	100
Clear	100	33	100	100	100	100	100	78	89
Split	100	100	100	100	100	100	100	100	100
Stain	100	100	0	33	100	100	67	78	73
Blue stain	100	33	100	100	100	33	100	55	78
Pith	100	100	100	100	100	100	100	100	100
Dead knot	0	0	100	100	100	67	67	56	62
Live knot	100	67	0	0	100	67	67	45	56
Hole	100	100	100	100	100	100	100	100	100
Total							84	76	80

to introduce low-cost visual inspection systems for improving yield in the forest products industry.

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