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Camera based lumber strength classification system

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Abstract

In this paper, a new camera based lumber strength classification solution using solely knot features is presented. Two alternative classifiers, k-NN and SVM, are applied to classifing pinewood boards based on their breaking strength. Features for classification are formed using knot properties, which are extracted from four sides of the board using machine vision algorithms. Extracted properties include size, x,y,z-coordinates and the type of knot. These properties are used as such as features. They are also used to form different combination features like length or volume of the knot. In experiments, ground truth breaking strength of the boards was determined using a three point bending test. Our evaluation shows that when knots are present it is possible to classify pinewood boards with over 70% accuracy using a combination of knot based features.

1 Introduction

Machine vision has been widely employed in many quality control applications in the wood products industry. As vision systems have become more capable with advances in sensor, microprocessor, and lighting technologies, solutions have emerged that perform many wood inspection tasks automatically. Since the cameras are already available in production lines, there is an attractive opportunity for utilizing the information provided by images to also estimate the lumber strength grade.

Strength grading is needed to ensure lumber is strong enough for structural applications. The ability of lumber to resist loads depends on several factors [9]. One of the single most important factors is knots since they distort the grain patterns of wood, altering the grain orientation. Changes in orientation can cause severe reduction in strength properties since load resisting capabilities in a radial or tangential direction can be tens of times lower than in the longitudinal direction. Therefore, knots can be directly used to estimate the strength of the lumber [6].

Conventionally, mechanical stress grading machines have been used for bending lumber to measure the strength grade. Obviously, alternative approaches for obtaining this information without physical contact with the wood have been sought. Existing non-destructive methods utilize x-ray [11], microwave [7] or ultrasonic [8] imaging. A common charasteristic for these techniques is that the equipment used is expensive compared to cameras. Camera based systems can also utilize existing quality inspection equipment that is already present in many wood processing facilities.

Not much research has been done regarding non-destructive camera based strength grading of sawn wood. One proposed solution is to use grain based features for strength estimation [10]. The test material in their work was sawn near the core of the stem so no large knots were present. Therefore, knots did not introduce major grain distortions and the usage of knot based features did not provide any improvement over grain angles.

In this paper, we present a new camera based lumber strength classification solution using solely knot data available in images. Our work shows that a feature as simple as the size of the knot alone can have the same coefficient of determination (0.41) as an xray-system coupled with an FEM prosessor presented in [11]. Compared to a multi-sensor lumber classifier system [1], the proposed k-NN classifier performs equally well when only one type of wood is being classified.

The actual extraction of knot data from images was not in the scope of this research. Many existing visual quality control systems used in the wood industry alredy produce the basic knot properties like location and size. In this paper we focus on the use of those readily available features.

2 Lumber strength grading

In our contribution, we propose two alternative solutions to classifing boards to three different strength classes, based on knot features. In the first approach, a k-NN classifier is applied to these features. The second technique is to utilize an SVM classifier on those same features. Knot data used in feature vectors in classifiers is extracted from images captured from four sides of the board using machine vision algorithms.

2.1 Features

As mentioned earlier, all features used for the classification were based on knot properties. The main focus of this work was to find a combination of knot attributes that correlate best with the breaking strength of the board. Figure 1 illustrates how wood grain behaves around live knots. Changes in the direction are notable.

The upper two boards and the lower two boards in Figure 2 have similar knot patterns if the y-coordinate and the size of the knot are used as features for strength grading. These two features are considered usually as the most important strength affecting qualities in lumber. Still, the upper boards have almost a 10 MPa difference in breaking strength, so other features also need to be considered. On the other hand, the breaking strength of the lower two boards is exactly the same, so in some situations those two features alone can work exceptionally well.

Figure 1. Grain behavior around a knot.

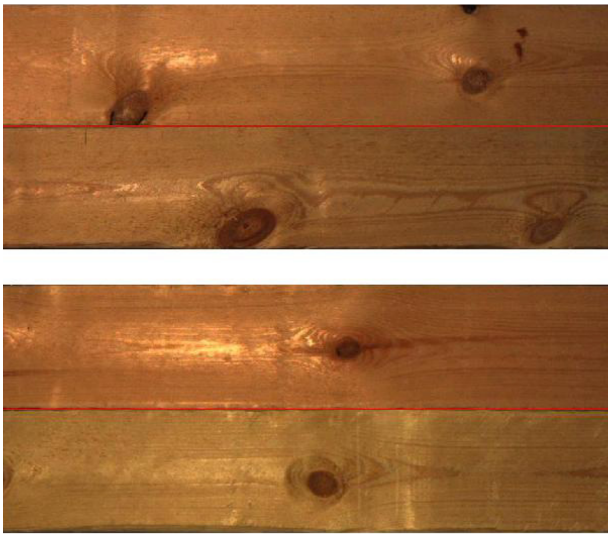

Figure 2. Two board pairs with similar knot patterns.

With the data extracted from the images, the following features can be used:

- Size of knot (larger end, smaller end)
- Average size of knot
- x,y,z-coordinates of knot (larger end, smaller end)
- yz-angle between knot ends
- Length of knot
- Volume of knot
- Sum of the size of the bigger end of the knot and knot length
- Strength reduction factor (SRF)
- Type of knot

To form a feature vector, knots are first ordered using an ordering criteria. This criteria decides which knots are the most significant and need to be included in the vector. The Size of the larger end of the knot, the average size of the knot, the volume of the knot and the strength reduction factor were used as the ordering criteria.

Strength reduction factor a is special feature formed by using the y,z-coordinates of the knot, the size of larger end of knot and the knot length. It is loosely based on the critical knot concept in Foley's doctoral thesis [6].

After the knots have been sorted using the selected ordering criteria, feature vector F can be formed. The Vector is defined as

$$F = \{f_{11}, f_{12}, f_{13}, ..., f_{1m}, f_{21}, f_{22}, f_{23}, ..., f_{nm}\} \quad (1)$$

where n is the number of features and m is the number of the most significant knots taken into consideration.

According to the National grading rule for softwood dimension lumber interpretations [2], when visually inspecting lumber the size of knots must be taken into account from a length of six inches, and the sum of sizes may not exceed the largest allowed knot. In Table 1 r^2-values between some features and breaking strength of test samples are listed. Summation of features over a six inch distance was also tested with these features. This improved r^2-values for volume and SRF but not for size. Summation means the maximum sum of selected feature taking all knots into consideration. A Stepsize of 20 mm was used while moving the six inch window across the board. Values for features without summation were calculated using two knots and the size of the larger end as ordering criteria.

Feature	r^2-value
Knot size (larger end)	0.41
Knot size (larger end, six inch sum)	0.40
Knot size (average)	0.40
Knot size (average, six inch sum)	0.38
Knot volume	0.32
Knot volume (six inch sum)	0.33
SRF	0.41
SRF (six inch sum)	0.48

Table 1. Best r^2-values for some of the features.

2.2 k-NN Classifier

The first classifier used in our system is based on the k Nearest Neighbors (k-NN) rule. This decision rule has been extensively used in pattern recognition systems because of its good performance and simple algorithm. In k-NN, unknown samples are classified by counting the labels of the k-closest training samples (prototypes) according to some similarity measure such as Euclidean distance [5]. This rule has nice properties: 1) the recognition error rate approaches twice the Bayesian error rate as the number of prototypes and the value of k becomes large, 2) the classifier can still be designed even if training samples are few and 3) it can be implemented when classes overlap with each other [5].

We use the easiest implementation of the k-NN rule when the Euclidean distance between the sample and each prototype in the training set has been computed, and then the sample is classified into the majority class of its nearest neighbors. This exhaustive search is suitable for our method due to the small number of training samples.

The best feature vectors for the k-NN method were determined by first testing all the possible combinations of features for every ordering feature using Leave-One-Out-Cross-Validation to calculate the classification accuracy. At this stage, the features were scaled to [0,1] and given weight of 0 or 1.

When the best combination was found, an iterative search to find the best possible weights for the selected features was conducted. At this stage, the features were also scaled to [0,1] first, but the weight range was changed to [0,5] and the step size was set to 0.1. The final vector then was a product of feature vector the F and the coefficient vector A, $F_{final} = F \times A$. The two best feature vectors were sought for every ordering feature, one for the best classification accuracy and one for the best coefficient of determination among the k nearest neighbors.

Classification accuracy for all four ordering criteria was consistent, and performance with the best found feature vectors varied only by a few percent. The best results were achieved by using the size of the bigger end of the knot as ordering criteria, taking the two most significant knots in the calculations and using five for the value of k, giving an almost 72 percent correct classification.

2.3 SVM

Support Vector Machine (SVM) classifiers [4] have been successfully employed for various challenging pattern recognition problems. The SVM algorithm tries to find a separating hyperplane that optimally splits the training data set. Bounds between these data classes and the hyperplane are called Support Vectors. In many cases, the input space is mapped onto a higher dimensional space using kernel functions to perform a nonlinear separation.

In this work, SVM classification was performed using the LibSVM software package [3]. The best results were achieved by using the RBF kernel. To find the best features for the SVM classifier, the data was split into two groups: training samples and test samples. The classifier was optimized by finding the best C and γ parameters. This procedure was run repeatedly for different feature vectors, randomly splitting samples into two groups each time. The feature vector with the best mean accuracy was chosen. As with k-NN classification, the best results were achieved using the two most significant knots.

3 Experiments

Test material available for this research consisted of 194 pine (*pinus sylvestris*) boards with dimensions of 3900 x 100 x 50 mm sawn near the stem core. The breaking limit was measured by bending the boards in a three-point bending machine until the point of breakdown. The limit was chosen to be the maximun amount of force directed to the board.

The knot count in the tested boards was 1-10 live and/or dead knots. Categorization of knots to live and or dead was done by the researchers themselves. This leaves a possibility of human error. The largest single knot in the test material was 44.68 mm in diameter.

The material was divided to three classes based on the breaking limit. Breaking limits for classes were lower than 29 MPa for Class I, 29 - 43 MPa for Class II and greater than 43 MPa for Class III. By choosing class limits in this way, the distribution of boards among the three classes was almost equal: 60 samples in Class I, 67 samples in Class II and 64 samples in Class III.

The type of the knot proved to be highly critical factor for classification. If live and dead knots were treated in the same way, the classification accuracy dropped by 10-20%. We found that a good way of increasing classification performance was to multiply the size of the dead knots by a factor of less than one. This way they had less impact than the live knots. The best value of this factor was dependant on the ordering criteria used. This result is consistent with the theory on how knots affect the grain flow patterns around them. Grains grow into live knots altering their orientation by as much as 90 degrees, whereas dead knots are encased by the grains, and grain flow distortions remain small. Grain behavior around a knot is illustrated in Figure 1.

The volume of the knot was the most common single feature that appeared in the best feature vectors found. The size of the knot (larger end or average size) was also included in many of the best vectors found. The y-coordinate of the larger end of the knot was not included in any of the best vectors found, but the y-coordinate of the smaller end was in almost everyone one. Test samples are sawn near the stem core, so their smaller ends are all very similar in size and y-coordinate. The reason why the y-coordinate of larger end was not selected to best features could be result of not dividing y-coordinate to three possible classes: 1) larger side is at top of the board 2) larger side is on either side of the board 3) larger side is at the bottom of the board. When the larger side of the knot is at the top or at the bottom, the z-coordinate needs to be taken into consideration. The fact that SRF was present in many of the best vectors, and SRF is formed using y,z-coordinates, among other things, also supports this theory.

One important thing to note in this work is that the moisture content was the same in all of the boards. If there would have been major variations between the moisture content of the boards, the results for classification accuracy would have undoubtedly been lower.

3.1 k-NN

Table 2 presents the best classification accuracies achieved for the four different ordering criteria using a k-NN classifier. The r^2-value in the table is calculated between the measured breaking strength and a weighted sum of $k = 5$ nearest neighbors, using $1/D$ as weight, where D is the Euclidean distance between the classified sample and its neighbor. The feature vector F that yielded the best classification accuracy was

$$F_{kNN} = \{f_{avg1}, f_{avg2}, f_{ys1}, f_{ys2}, f_{len1}, f_{len2}, f_{vol1}, f_{vol2}, f_{sl1}, f_{sl2}, f_{srf1}, f_{srf2}\} \quad (2)$$

where f_{avg} is the average size of the knot, f_{ys} is the y-coordinate of the smaller end of the knot, f_{len} is length of the knot, f_{vol} is volume of the knot, f_{sl} is sum of the size of the bigger end of the knot, and the knot length, and f_{srf} is the strength reduction factor.

With uneven class distribution, the classification accuracy was significantly lower, being only 62%. Class limits in this case were chosen to be 24 and 40 MPa, which are some of the typical limits used in wood the industry for lumber strength classification instead of

29 and 43 MPa. The sample distribution was 32 samples in Class I, 78 samples in Class II and 81 samples in Class III.

Ordering feature	Accuracy %	r^2-value
Knot size (larger end)	71.73	0.51
Knot size (average)	70.68	0.50
Knot volume	70.16	0.51
SRF	70.16	0.52

Table 2. k-NN classification results for even class distribution.

3.2 SVM

The best mean accuracy with SVM classification was achieved with the same feature vector and ordering criteria as with the k-NN.

In Figure 3 is presented 100 SVM classification test runs using the best found vector. The mean value of the optimized accuracy is 68.5%, the minimum value is 56.6% and the maximum value is 83.0% in classification accuracy. This suggests that using SVM classification the overall performance is similar compared to k-NN classification.

In some of the tests, classification accuracy was remarkably lower than with the k-NN classifier. This is probably due to randomly selecting most of samples from one of the classes to be the test samples, and the samples from the other two classes were left as training samples.

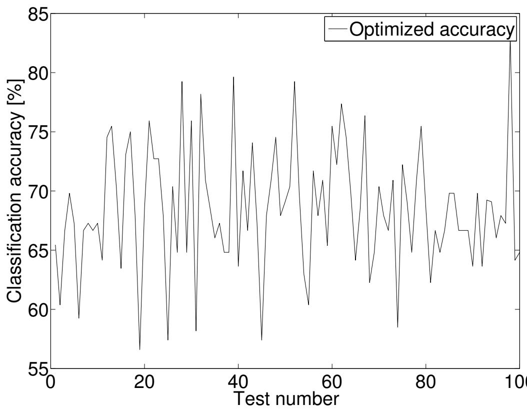

Figure 3. 100 SVM tests using the best features found.

With uneven class distribution, the mean value for optimized accuracy was 68.7%, the minimum value was 55.4% and the maximum value was 81.5% in classification accuracy. Unlike with the k-NN, the mean classification accuracy did not decrease despite the uneven sample distribution among classes.

4 Conclusions

The test results show that knot based features can be used to classify pinewood boards with good accuracy when the number of different classes is small. The two largest knots were the most critical for classification purposes in this work.

The SVM classifier seems to outperform the k-NN classifier due to the fact that it works much better in situations where the class distribution of available samples is uneven. When sample distribution between classes is even the k-NN has about 72% and SVM has about 68% classification accuracy. Both are also computationally low cost to implement, even in real-time systems. Much work remains to be done to find the best training set for SVM without overfitting the system.

It must,however, be kept in mind that only one type of wood was tested, and the data available for testing contained under 200 samples. Knot based classification may not be suitable for all wood types, or for boards that contain only very small knots. Similar features may also not work for every wood type. Nevertheless, for existing camera based lumber inspection systems, automated visual strength classification offers a potential field of development in the future. One possible improvement could be to combine knot and grain data to be used in the same classifier.

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