# 5—1 Visual Inspection of Parquet Slabs by Combining Color and Texture

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## Abstract

The goal of this research was to find out if the performance of color based wood inspection systems could be improved by combining color and texture information. This paper describes a wood surface inspection method that combines color percentile features with texture features based on simple spatial operators. The proposed method is tested with images from an application environment developed for detecting and recognizing defects in parquet slabs. The results indicate that the performance obtained with a state of the art color based method can be improved by using additional texture information.

## 1 Introduction

Visual inspection plays an important role in the quality control of many manufacturing processes. Traditionally, this job has been mainly carried out by human inspectors. The use of human labour in routine tasks like this should be avoided if possible. Results in manual inspection are often worse than one could expect, because the performance of a human inspector has a strong tendency to drop radically in uninteresting jobs. A human inspector is also quite insensitive to gradually occurring small changes. On the other hand, human inspector's ability to handle unexpected situations is difficult to achieve with machine vision systems. For a good survey on automated visual inspection, see [1].

Visual inspection of smooth uniformly coloured surfaces can be automated quite easily. The presence of texture in the image makes the automating problem much more complex. Classification of wood surfaces is especially challenging because of the strongly varying appearance of wood.

The benefits of automated inspection in wood industry are easily demonstrated. In lumber production the product volumes are huge and therefore even small improvements in quality result in considerable savings. High grade wood is considerably more expensive than low grade or non-graded wood and visual inspection is often the most laborous part in otherwise highly automated process.

Human made grading is often inconsistent. There have been observations that the correspondence between different graders is surprisingly low. In a test of four grades two different graders gave the same grade for only 60% of the boards [2]. This inconsistency is a problem when training material for visual inspection system is gathered. Good performance cannot be achieved with poor training material. Therefore the training material should be selected with special care.

Various systems for automated visual inspection of wooden surfaces have been developed [2,3]. Almost every pattern recognition technique has been tried. It would be interesting to compare the performance of these methods, but the differences in imaging environments make this quite difficult. There are applications using normal grey level and color cameras, but there are also numerous applications where special sensors like X-ray, laser profile, microwaves and electronic colorimeter are used.

Usually the color is considered to be important in wood surface inspection. Many of the defects have quite distinctive color properties compared to sound wood. For more information on color properties of wood defects, see [4]. First order color percentile features were successfully used for describing the color information in [2,3]. However, there are defects like sound knot, which have similar color and are therefore difficult to recognise. Shape or texture properties are needed to discriminate these defects.

Our goal was to find out if the performance of color based wood inspection systems could be improved by combining color and texture features. The performance of the proposed approach was tested in parquet slab inspection. The easy generalization to another wood inspection problems was also one of the targets in research.

## 2 Parquet inspection problem

The grade of a parquet slab is determined by measuring the sizes, types and number of defects. The slab is classified to the best grade whose requirements it fulfills. Of course human graders seldom follow strict numerical definitions about the defects. Instead the grading is based mainly on the general visual appearance of the parquet slabs. Therefore the results are difficult to compare to the ones achieved by human graders.

The image set used is the same as Kauppinen used in [2]. It is from the ESPRIT–P21023 (CATIE) project and consists of 150 images of beech wood parquet slabs. The images were taken with a 12-bit color line-scan camera. The training areas were marked by creating images, where the pixels belonging to the selected training class were marked with colors by hand. The images were divided into non-overlapping samples sized 32x32 pixels. Examples of parquet slab images and corresponding training images are shown in Fig 1.

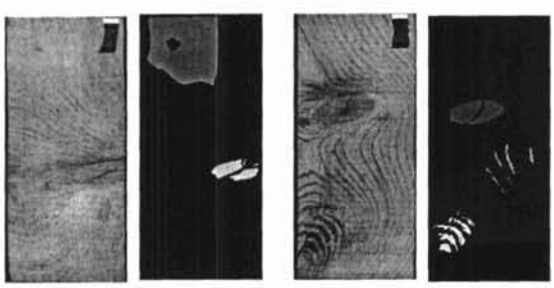

**Figure 1.** Two parquet slab images and corresponding painted training images.

The total number of these samples was 26855, and 1498 of them were used as training set. The distribution of samples to different classes is shown in Table 1. Approximately half of the training samples present good wood. The small number of streaks is compensated by increased number of splits, which are considered to be visually quite similar to the streaks.

**Table 1.** The number of samples in each class

| Class | All samples | Training set |
|---|---|---|
| Good wood | 16027 | 763 |
| Sknot (sound knot) | 430 | 47 |
| Bknot (black knot) | 102 | 51 |
| Rpith (red pith) | 788 | 49 |
| Bpith (black pith) | 380 | 47 |
| Bark pocket | 392 | 49 |
| Grain | 1129 | 51 |
| Streak | 12 | 12 |
| Crack | 1009 | 50 |
| Split | 73 | 73 |
| Lhydrolysis (light hydrolysis) | 1542 | 51 |
| Dhydrolysis (dark hydrolysis) | 1632 | 49 |
| Discoloration | 1737 | 51 |
| Lglucose (light glucose spot) | 215 | 53 |
| Dglucose (dark glucose spot) | 574 | 52 |
| Water stain | 813 | 50 |
| TOTAL | 26855 | 1498 |

Two types of classification tests were performed. First, a two-class defect detection test was performed, in which all the different defect types were considered to belong in a class called defects. In order to test the ability to recognise types of defects we made another classification test using all the 16 classes. In practise, the defect recognition would be done only for those regions that have been classified as defects in the defect detection stage. In order to have comparable results, the defect recognition was tested using all the test samples. First the color percentile features and texture features were all used individually and then color percentile features were combined with texture features.

## 3 Features used in this study

### 3.1 Color percentile features

Recently, a method based on color percentile (CP) features for wood inspection has been proposed [2,3]. The method is computationally very simple and has performed very well in various inspection problems. The color percentile features are calculated from cumulative color channel histograms $C_k(x)$, which is the sum of normalized histogram $P_k(x)$ of color channel $k$ for all the values that are smaller than or equal to $x$. The value for the percentile feature is the value of $x$ when $C_k(x)$ is known. If the color percentile feature value is denoted with $F_k(y)$ the relationship is described as

$$F_k(y) = C_k^{-1}(y) = x \qquad (1)$$

where $y$ is a value of the cumulative histogram value in the range [0%, 100%]. As can be seen, the concept of percentile is extended to have any real value between 0 and 100, so the name percentile might be misleading.

Percentile features are sensitive to intensity changes because they measure direct values of color channels. Invariance against the shift of the histogram can be achieved by calculating differences of two percentiles.

$$F_k(y_1) - F_k(y_2) \tag{2}$$

These percentile difference values can be computed also for different color channels, which gives information about the relative positions of histograms of different channels. This can be useful in recognising certain color defects.

Invariance against the width of the histogram can be achieved by normalising percentile differences. This is done by scaling with the difference of maximum and minimum percentile values.

$$\frac{F_k(y_1) - F_k(y_2)}{F_k(100\%) - F_k(0\%)} \tag{3}$$

Maximum and minimum percentile values may be unreliable because of saturated noise in the images. Therefore it is safer to use, for example, 95% and 5% percentiles.

It should be noted that color percentile features can be used in other color spaces than RGB as well. The only requirement is that the values measured cannot be circular, i.e. the smallest value is close to the largest value. This is the case for example with the hue in HSI color space. In this kind of situation the starting point for calculating the cumulative histograms cannot be defined.

Percentile differences give some invariance against the changes of illumination and reflectivity properties of the inspected surface. However, they cannot distinguish two histograms from each other if the only difference between them is the histogram's position. Usually it is reasonable to have both original and difference percentiles in the feature vector.

In this paper 117 different types of percentile features were calculated. These features included both single percentiles for different color channels and differences of percentiles. If all of them were used the calculations needed would be too time consuming. In addition, these 117 features contain much redundant information and therefore the performance would not be optimal. In order to find the optimal feature vector all the possible combinations should be tested. That is not reasonable and therefore some search procedure must be used. In this study, the final 13 features were selected using forward and backward search.

In feature selection there is a danger that the feature vector becomes too optimized for the training material. This can be avoided by not trying to achieve the best possible result. Instead one has to select feature vector of lower dimension giving a satisfactory result.

### 3.2 Features based on grey level cooccurrences and differences

The cooccurrence method (CO) is one of the best -known and widely used approaches to texture. A GxG gray level cooccurrence matrix $P_d$ is defined for a displacement $d = (dx,dy)$ as follows. The entry $(i,j)$ of cooccurrence matrix $P_d$ is the number of occurrences of the pair of gray levels $i$ and $j$ which are a distance $d$ apart.[5]

Conventionally, the second order statistics are accumulated into a set of 2-dimensional matrices, which are computed for displacements in different directions and displacements. Cooccurrences for several distances can be computed to form a multidimensional cooccurrence matrix [6]. In this paper, the following distances were used: (0,1), (1,1), (1,0), (-1,0), (-1,1), (1,-1)(0,-1)and (-1,-1).

The produced coocurrence matrix is in this case 9-dimensional. $P_{co} = (g_0, g_1, g_2, g_3, g_4, g_5, g_6, g_7, g_8)$.

| | | |
|---|---|---|
| $g_4$ | $g_2$ | $g_3$ |
| $g_5$ | $g_0$ | $g_1$ |
| $g_6$ | $g_7$ | $g_8$ |

When we calculate the difference between pixel value distance d apart and the center pixel, we get the corresponding signed gray level difference. In this case $P_{sd} = (g_1 - g_0, g_2 - g_0, g_3 - g_0, g_4, - g_0, g_5 - g_0, g_6 - g_0, g_7 - g_0, g_8 - g_0)$. Recently, Ojala et al. [7] showed that an approach based on multidimensional distributions of signed gray level differences of neighboring pixel values (SDIFF) is very powerful for texture classification. An advantage of gray-level differences over the traditional cooccurrence method is that the differences fall mainly within a narrower range than the gray levels, due to the high correlation between gray levels of adjacent pixels, consequently providing a more compact description of texture. Another advantage is that the signed differences are not affected by changes in mean luminance.

### 3.3 LBP features

Ojala *et al.* [8] have suggested the use of the Local Binary Pattern (LBP) texture operator shown in Fig. 2. The original 3x3 neighborhood is thresholded by the value of the center pixel. The values of the pixels in the thresholded neighborhood are multiplied by the weights given to the corresponding pixels. Finally, the values of the eight pixels are summed to obtain a number for this neighborhood. The LBP histogram computed over a region is used for texture description. Because there are $2^8$ possible LBP values the produced histogram consists of 256 bins

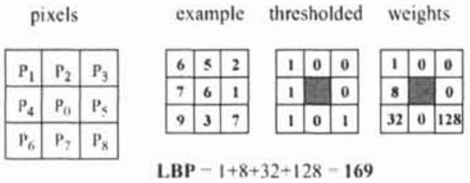


**Figure 2.** Computation of LBP operator

LBP provides us with knowledge about the spatial structure of the local image texture. LBP is invariant against any monotonic gray scale transformation. It does not address the contrast of texture, which is important in the discrimination of some textures. For this purpose, LBP could be combined with a simple contrast measure C, which is the difference between the average gray levels of those pixels which have value 1 and those pixels which have value 0, and consider joint occurrences of LBP and C. The contrast measure was not used in these experiments, because the contrast information is included in the color percentile features.

## 4 Classification methods

The performance of different classifiers varies depending on the application. There is no superior general purpose classifier. The selection of the used classifier depends on the required accuracy, complexity of training and classification and the easiness of adjusting classification rate by the user. In this paper, the KNN-classifier was used.

### 4.1 KNN-classifier

The KNN-classifier is based on the fact that if two elements are close in their representation space, they probably belong to the same class. The color features of each sample are represented by a feature vector, which represents its coordinates in the multidimensional representation space. Textural properties are represented by a feature distribution, which is similarly represented in the representation space. The sample is classified to the class where most of the nearest neighbors belong.

The reliability of a KNN-classifier increases with *k*. A strict rule is to impose that the k nearest neighbors belong to the same class to take a decision. It can be smoothed by weighting the voting of each neighbor according to its rank or distance. However, this increases the complexity of the classifier and therefore the standard version was used.

When distance-based classifiers like KNN-classifier are used, the features must be scaled properly. All features should have a similar value range in order to have equal weights in the distance calculation. Typically all the feature values are scaled to have certain maximum and minimum values, or to have a certain mean and deviation. In order to calculate the distances and to define the nearest neighbors, a metric must be selected. With color percentile features the standard euclidean distance was used. Distances between textural feature distributions were calculated using a log-likelihood distance, which is described in Section 4.2.

### 4.2 Classification based on feature distributions

Most of the approaches to texture classification quantify texture measures by single values (means, variances etc.), which are then concatenated into a feature vector. This is the case when color histogram percentile features are used. In this way, much of the important information contained in the whole distributions of feature values might be lost. There are many different ways of measuring the dissimilarity between sample and model histograms. In our experiments we used log-likelihood measure:

$$L(S,M) = -\sum_{n=0}^{N-1} S_n \ln M_n \qquad (4)$$

where $N$ is the number of bins. $S_n$ and $M_n$ are the sample and model probabilities of bin $n$ [7].

Because multidimensional histograms are too large to be used as such, they must be quantized. Usually the quantization is done by reducing the number of gray levels. Instead of reducing number of gray levels, for example, by a simple requantization of each coordinate, we partition the k-dimensional space using learning vector quantization as described in Ojala *et al.* [9]. Quantization for cooccurrences and signed differences using 256, 64 and 32 codevectors was used in experiments.

### 4.3 Combining feature distances

For each sample two different properties are calculated. A feature vector containing color percentile features and a distribution of either signed grey level differences or local binary patterns. Euclidean distance was used for feature vectors and log-likelihood distance measure for distributions. The sum of these two distances is then used in KNN-classification. In order to have equal weights, the distances must be scaled to have similar value range. For this purpose distances between all the samples in the training set were calculated and minimum, maximum and average distances defined. The scaled distances are then obtained using equations

$$d = \frac{d - d_{\min}}{d_{\max}} \qquad \mathrm{d} = \frac{\mathrm{d}}{\mathrm{d}_{\mathrm{avg}}} \tag{5}$$

## 5 Experimental results

As could be expected, the role of color information in the defects of the wood material is very significant. When defect detection was done using features separately, the error rates varied from 3.5% (with color percentile features) to 25.2 (with LBP) as can be seen in Table 2. The results obtained with percentile features represent the state of the art in wood inspection [2]. The cooccurrence method provided better results than the other texture features. This is because these features are correlated to image intensity, whereas the other texture methods used are not.

**Table 2.** Defect detection and recognition error rates for different features

| | | CP | SDIFF 32 bins | SDIFF 256 bins | LBP 256 bins | CO 256 bins |
|---|---|---|---|---|---|---|
| Detection | false alarm | 2.0 | 10.8 | 11.2 | 14.4 | 3.5 |
| | error escape | 5.8 | 41.6 | 39.9 | 41.2 | 13.4 |
| | Total error | 3.5 | 23.2 | 22.7 | 25.2 | 7.5 |
| Recognition | total error | 14.1 | 33.8 | 32.6 | 39.8 | 30.1 |

When color and texture features were combined the scaling with average values gave a little better results in defect detection test. On the other hand, in defect recognition the scaling with minimum and maximum seems to work better. Now the cooccurrence method performed worse than LBP and SDIFF. The results for scaling with average are shown in Table 3, and the results for scaling with minimum and maximum values are presented in Table 4. The error rates for classification with color percentiles only are shown for comparison.

**Table 3.** Error rates for scaling with average.

| | | CP | CP + SDIFF 32 | CP + SDIFF 256 | CP + LBP | CP + CO 256 |
|---|---|---|---|---|---|---|
| Detection | false alarm | 2.0 | 1.1 | 1.3 | 1.2 | 1.8 |
| | error escape | 5.8 | 5.6 | 4.9 | 6.0 | 5.9 |
| | total error | 3.5 | 2.9 | 2.8 | 3.1 | 3.4 |
| Recognition | total error | 14.1 | 11.2 | 11.2 | 12.3 | 14.0 |

**Table 4.** Error rates for scaling with minimum and maximum values.

| | | CP | CP + SDIFF 32 | CP + SDIFF 256 | CP + LBP | CP + CO 256 |
|---|---|---|---|---|---|---|
| Detection | false alarm | 2.0 | 1.0 | 1.6 | 0.8 | 1.7 |
| | error escape | 5.8 | 5.8 | 4.9 | 6.1 | 6.8 |
| | total error | 3.5 | 2.9 | 2.9 | 3,0 | 3.8 |
| Recognition | total error | 14.1 | 11.0 | 10.5 | 11.6 | 14.9 |

## 6 Conclusions

As our results indicate, the role of color information in the defects of the parquet material is very significant. When defect detection was done using features separately, the error rate was much lower with color percentile features than with the texture features. The cooccurrence features outperformed the signed differences and LBP, which indicates that the intensity information is very descriptive. A problem with color percentile features is that they do not describe the dependencies between neighboring pixels.

The performance of classification can be improved if the color information is combined with textural properties. When color percentile features were combined with cooccurrence matrices, the performance dropped, but combining with signed differences and LBP improved the results. Cooccurrences and color percentiles are highly correlated because they both contain intensity information. Therefore, the addition of cooccurrence features does not bring much new information. When illumination invariant texture features like LBP and signed differences are added, the results improve.

Texture features are computationally more complex than color percentile features. However, the LBP operator used in this study is computationally very simple. It can be realized with a few operations in a small neighborhood and a lookup table. It is also very encouraging that roughly quantized signed difference histograms perform well. The computation of color and texture features could be done in parallel to further speed up the process.

The results achieved in defect detection and recognition are difficult to compare to the ones achieved by human graders. The final grade for a parquet slab is assigned according to the number and the types of defects. As tests described in [2] performed by Junckers and DTU indicate, these defect detection and recognition rates form a good basis for the development of an automated inspection system.

The information on the position of the inspected regions was not used in this study. It is obvious that adjacent regions are more likely to have same type of defects. Especially the recognition accuracy of the defects could be improved if also the location information were used.

Our experiments show that the performance of a wood inspection system can be improved by combining color information with texture information. The use of KNN-classifier and similar feature calculations for the whole surface makes this approach quite easily applicable to other visual inspection problems.

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