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A colour assessment methodology for oak wood

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Abstract
· *Context* Customers have limited tolerances for colour
differences between oak wood elements in parquetry or
furniture, whereas manufacturers are in need of an objective
method to communicate possible differences in their
products.
· *Aims* This study is aimed at grading oak wood boards in
objectively defined colour classes in correspondence with
the visual assessment by an expert panel.
· *Methods* First, the most suitable spectrophotometer for
measurements approximating the perception of the human
eye was selected. Then, three colour grading algorithms were
evaluated: one based on the smallest distance towards the
centre of the colour subspaces, the second using a classification

tree and the last implementing the CIEDE2000 colour differ-
ence formula to determine tolerance ellipsoids.
· *Results* Statistical analysis using a classification tree and
CIEDE2000 tolerance ellipsoids classified the specimens in
good accordance with visual assessment, with a 6 and 5 %
misclassification, respectively.
· *Conclusions* The colour grading methodology can be
adapted to particular grading purposes and is proposed as
a basis for development of an inline colour grading system
to be added to commonly used defect detection scanners.

Keywords Colour measurement · Oak wood · Colour
grading · CIEDE2000

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1 Introduction

Although colour variations are inherent to a biological ma-
terial such as wood, customers do have certain tolerance
limits for colour differences within a product. To meet the
wishes of the end users, the manufacturing process may
include a visual colour assessment; however, sorting colour
manually is labour intensive and prone to the limits of
subjective perception regarding colour uniformity of wooden
elements in a product.

Objective colour measurements of wood have been used
in several research projects. Janin et al. (1990), Klumpers
and Janin (1992) and Winnock et al. (2010) for example
studied the colour of oak wood, related to the age and
annual ring width. Stokke et al. (1995) and Phelps et al.
(1994) used colour measuring to select lighter white oak,
which is commercially preferred, and the latter also devel-
oped a technique for improving colour matches in panel
batches. The effect of weathering and thermal treatments
on colour changes was the subject of several studies (among

others Brischke et al. 2007; Pandey 2005; Stenudd 2004; Sundqvist 2002; Temiz et al. 2005). Unfortunately, most reports lack detailed description of the methodology used, whereas a general methodology to determine wood colour would be a useful addition to existing research.

A standardized objective assessment based on an automated colour grading system could enhance the manufacturer's turnover, reduce the loss of raw material by better selection, anticipate on customer expectations and increase the use of wood of lower quality to reach a higher yield. Automated scanners or cameras for defect detection are available and commonly used in the woodworking industry, but colour grading systems are not common. Researchers at the Virginia Tech University (Department of Electrical and Computer Engineering and Department of Wood Science and Forest products), together with members of NOVA Technologies (North Carolina), developed an automated colour sorting system for hardwood edge-glued panel parts (Srikanteswara et al. 1997). The software of this system used 3D colour histograms of red, green, blue (RGB) values obtained by colour cameras, which needed data reduction to allow real-time operations risking loss of essential colour information. Furthermore, Katuščák and Kucera (2000) consider the RGB colour model less appropriate and selected the CIE $L*a*b*$ space as the most suitable for wood colour communication.

The industry active in oak wood parquetry and furniture production indicated that customers not only prefer lighter oak wood, but also often complain about a differing hue of adjacent elements, e.g. a more pinkish element in a rather brownish product. Therefore, the goal of this study was to develop an objective grading algorithm to classify oak wood in more homogeneous classes according to a measuring methodology that can be used as a basis for automation. Defining such algorithm requires in the first place that colour differences observed with the human eye are detectable in objectively measured colour data. The measuring methodology includes the selection of the most favourable measuring device as well as optimising a grading technique to find the best accordance with the visual classification.

2 Materials and methods

2.1 Oak wood material

One hundred thirty-nine specimens of quarter- and intermediate-sawn and planed parquet strips of European oak wood (*Quercus* sp.) were selected from various production batches. The air-dry strips measured $400 \times 70 \times 10$ mm and were graded as belonging to the best quality class according to the Benelux classification, which is even more stringent than in the European standard EN 13227

(2002). At a parquet production factory, the organisers of the visual assessment observed specimens in a light cabinet (see Section 2.2) to select a similar amount of specimens with a brownish and pinkish hue for the assessment, and a typical brownish and pinkish reference specimen was also chosen. The specimens were shielded from light to prevent colour changes until colour measurements started.

2.2 Visual assessment

To assess surface colours in a defined and reproducible way, a standardized light cabinet with a neutral grey background (Munsell N7) and equipped with a D65 standard illuminant perpendicular to the surface was used. The observer assessed the specimens parallel to the longitudinal direction of the specimens and at an angle of 45° without interference from the outside environment. Five adequate observers having knowledge of wood were trained and classified the strips in the brownish or the pinkish group in accordance with the reference specimens. Each observer assessed all specimens three times, and all specimens had to be classified into one of the groups. After the visual classification was achieved, the variability between observers was determined by calculating Siegel and Castellan's fixed-marginal multirater kappa (Siegel and Castellan 1988). As the authors consider the visual classification to be 'correct', specimens are labelled correct or incorrect by the grading algorithms, respectively, when there is or there is no agreement with visual classification.
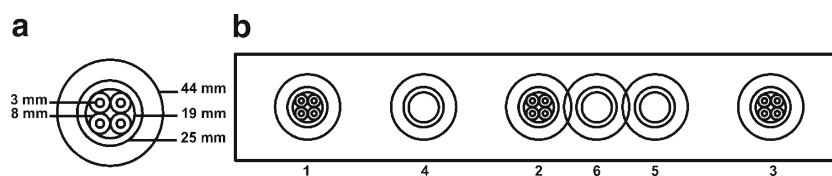
2.3 Spectrophotometer measurements

As spectrophotometers register more detailed information compared to tristimulus colorimeters, they are usually preferred for research (Stokke et al. 1995). The object is illuminated with a standard light source, and the intensity of reflected light is measured in discrete wavelength intervals of the spectrum. The device software calculates the coordinates of the CIE $L*a*b*$ or CIE $L*C*h_{ab}$ colour space starting from the determined tristimulus values for the

Table 1 Spectrophotometers used in this study with their specific aperture size and measuring geometry

Spectrophotometer	Diameter measuring aperture (mm)	Measuring geometry
Labscan XE	44	0°/45°
	25	0°/45°
Ultrascan Pro	19/25[a]	d/8°
Konica Minolta CM2600-d	3/6[a]	d/8°
	8/11[a]	d/8°

[a] Diameter of measured circle/diameter of measuring aperture

Fig. 1 Position of the measurements: **a** in relation to other apertures, **b** on the parquet strips

specific illumination used. Detailed information about these colour spaces is given in ISO 11664-4 (2008). All spectrophotometers mentioned in Table 1 were used to measure the parquet strips, using the same D65 standard illuminant and a standard observer of 10°, but differing in measuring aperture and geometry. A specific position of the measurements (Fig. 1) allowed the comparison of several measurements with small aperture to one measurement with a large aperture. Statistical comparison of different apertures or geometries was done on $L*a*b*$ or $L*C*h_{ab}$ values with paired t tests or with non-parametric Wilcoxon signed-rank tests. For the correspondence with visual assessment, a multivariate hierarchical clustering (agglomerative nesting with Ward's method) of these values was performed, and the spectrophotometer having the highest correspondence with visual classification was retained for further analyses in this paper. A multivariate analysis of variance with Wilk's lambda test showed whether the measurements of the pinkish and brownish colour groups differed significantly. Furthermore, a principal component analysis (PCA, Jolliffe 2002), which transforms the variables into principal components, reveals the colour parameters explaining the largest variance in the dataset. All statistical tests were performed in S-PLUS 8.0 using a significance level of 5 %.

A colour space of European oak wood and the pinkish and brownish subspaces within the CIE $L*a*b*$ and CIE $L*C*h_{ab}$ colour space could be determined. Therefore, the mean colour of each strip was computed with the least square method as the theoretical centre that has the smallest sum of distances to all measurements on the strip. The centre of the oak colour spaces was then determined as the point with the smallest sum of distances to all centres of the strips. Analogously the centres of the pinkish and brownish subspaces were calculated considering respectively the pinkish and brownish strips. The standard deviation of $L*$, $a*$, $b*$, $C*$ and h_{ab} was also determined to describe the subspaces.

2.4 Grading according to colour

Three different colour grading algorithms were tried to label the parquet strips. First, the smallest distance to one of the centres of the subspaces was used to classify the colour. Secondly, statistical classification by means of a classification tree, a non-parametric technique, divided the space of the multivariate results (variables $L*$, $a*$, $b*$, $C*$ and h_{ab}) into groups based on the homogeneity of the newly composed groups. The probability of a strip to belong to one of the two groups can be calculated by the mean and standard deviation of the measurements as

$$P(p \leq x) = P\left(\frac{x - m}{s} \leq Z\right)$$

with p the parameter determining the first condition split in the classification tree, x the level of p at the split, m and s the mean and standard deviation of the measurements on the strip, respectively, and Z the corresponding value on the standard normal probability density function curve. The probability to belong to the other group is then $1 - P(p \leq x)$.

Third, classification was accomplished by calculating an acceptable ΔE_{00} value with respect to the colour group centre. The CIEDE2000 colour difference equation defines a colour difference ΔE_{00} that weighs the colour parameters according to their visual importance in human colour perception. In contrast with the simple $\Delta E*$, ΔE_{00} is independent of the position in the colour space and calculated as follows:

$$\Delta E_{00} = \sqrt{\left(\frac{\Delta L'}{k_L S_L}\right)^2 + \left(\frac{\Delta C'}{k_C S_C}\right)^2 + \left(\frac{\Delta H'}{k_H S_H}\right)^2 + R_T \left(\frac{\Delta C'}{k_C S_C}\right)\left(\frac{\Delta H'}{k_H S_H}\right)}$$

with S_L, S_C and S_H as adjustment factors for $L*$, $C*$ and h_{ab}, respectively, which improves the lack of uniformity of the CIE $L*a*b*$ colour space and k_L, k_C and k_H as parametric weighting factors considering variation in experimental conditions such as luminance level, background colour, texture, etc. R_T is the rotation term that is different from zero only in the blue region (Huertas et al. 2006; Luo 2002; Kandi and Tehran 2009). For a complete description of all parameters, we refer to the publications of CIE (2001) and Sharma et al. (2005).

In the present study, the optimal parametric factors k_L, k_C and k_H as well as the optimal ΔE_{00} level that separates the pinkish and brownish specimens were searched for. For homogeneous materials, the parametric factors are all set to 1, whereas the texture of textiles requires k_L to be 2 (Kandi and Tehran 2009). As the appearance of wood is also strongly determined by its texture, most likely, not all parametric factors are equal to 1. Hauptmann et al. (2011) had better results with $\Delta E_{00}(2:1:1)$ than with $\Delta E_{00}(1:1:1)$ in their study with oak wood. The common determination of the parametric factors, by comparing visual colour differences with the corresponding ΔE_{00} (Xin et al. 2001), is unfeasible for wood as a visual colour difference scale is difficult to compose. Therefore, the ΔE_{00} between all visual

assessed specimens and the pinkish centre ($\Delta E_{00,pink}$) as well as the brownish centre ($\Delta E_{00,brown}$) were calculated for several combinations of parametric factors, and those two variables were used to make a classification tree to determine the ΔE_{00} level at which pinkish and brownish specimens are separated. The $\Delta E_{00,pink}$ or $\Delta E_{00,brown}$ level that determined the split of the tree was considered as the general ΔE_{00} to be used. For each combination of parametric factors and ΔE_{00}, the success rate (i.e. objective classification agreeing with visual classification) was calculated, and the best combination was selected.

3 Results

3.1 Visual assessment

It is obvious that the degree of consensus was inversely proportional to the number of observers taken into account (Table 2). Specimens classified three times in the same class by all observers are model specimens for their colour class, whereas specimens classified in the same class by only 60 % of the observers are mostly located at the borders of their colour class, as such in close vicinity to the borders of another colour class. The dataset containing the specimens which were classified equally by 60 % of the observers (108 samples) was the one used for further statistical analysis as groups with sufficient within variation were formed with this assessment. Siegel and Castellan's fixed-marginal multi-rater kappa was 0.75 which is above the limit of 0.70 that indicates adequate interrater agreement.

3.2 Spectrophotometer measurements

There was a considerable effect of the used measuring aperture for the measurements (Table 3). Clustering $L^*a^*b^*$ values showed less similarity with visual classification than clustering the $L^*C^*h_{ab}$ values. When larger tolerance limits were allowed (i.e. less observers had to agree upon a classification), measurements performed with a larger aperture showed more similarity and on a higher cluster level with the visual classification (Fig. 2). On the contrary,

Table 2 Number of specimens of each colour class according to 100, 80 and 60 % of the observers (fractions between brackets)

	Fraction of the observers (%)		
	100	80	60
Consensus: brownish	26 (19 %)	50 (36 %)	59 (42 %)
Consensus: pinkish	21 (15 %)	31 (22 %)	49 (36 %)
No consensus	92 (66 %)	58 (42 %)	31 (22 %)

Table 3 Comparison of various spectrophotometer apertures

Compared apertures	Significantly different colour parameters
<10 vs. >10 mm	L^*, a^*, b^*, C^*, h_{ab}
3 vs. 8 mm	a^*, b^*, C^*
25 vs. 44 mm	L^*, a^*, C^*, h_{ab}

when only a small tolerance limit was allowed (i.e. only those specimens were considered for which all observers agreed on their colour class), small measuring apertures seemed to be more appropriate. Another measuring geometry also caused significant differences in the measured information, but the clustering gave no evidence for any preference. However, colour technologists report that 0°/45° or 45°/0° geometry simulates the visual experience better (Chrisment 2004; Hunter and Harold 1987).

Within the framework of this study, the use of a larger measurement aperture was preferred as division into only two groups was intended, and therefore, relatively large tolerances were used. A classification in more groups was not requested by the industry nor by the consumers. Therefore, statistical analysis discussed in the rest of this paper refers to measurements with the Labscan XE.

Centres and standard deviations of the measured oak colour space and the pinkish and brownish subspaces are listed in Table 4. A significant difference between the pinkish and brownish group was statistically discernible, which means that these objectively determined colour parameters can be used for an automated colour grading in accordance with visually detectable differences. In PCA analyses with L^*, a^*, b^*, C^* and h_{ab}, two components explained 89 % of the total variance in the dataset. These components are:

$$\text{component } 1 = 0.85L^* + 0.47h_{ab} - 0.21a^* - 0.09C^* - 0.02b^*$$
$$\text{component } 2 = -0.78h_{ab} + 0.53L^* + 0.33a^* + 0.07C^* - 0.03b^*$$

and the biplot (Fig. 3) shows that a^*, b^*, C^* and h_{ab} were closely correlated (small angles between the arrows) and that L^* and h_{ab} had the largest variability (longest arrows). The biplot also shows that the two colour groups were distinguishable, even though there was a transition zone. The distinction followed the variation in h_{ab}, increasing from pinkish to brownish specimens.

3.3 Grading according to colour

Classification according to the smallest distances to the subspace centres classified only 72 % of the specimens correctly. Secondly the first split condition of the classification tree defined strips with a mean h_{ab} value smaller than 71.14 as pinkish (Fig. 4), although this branch still contained 10 % of the brown specimens. The power of the
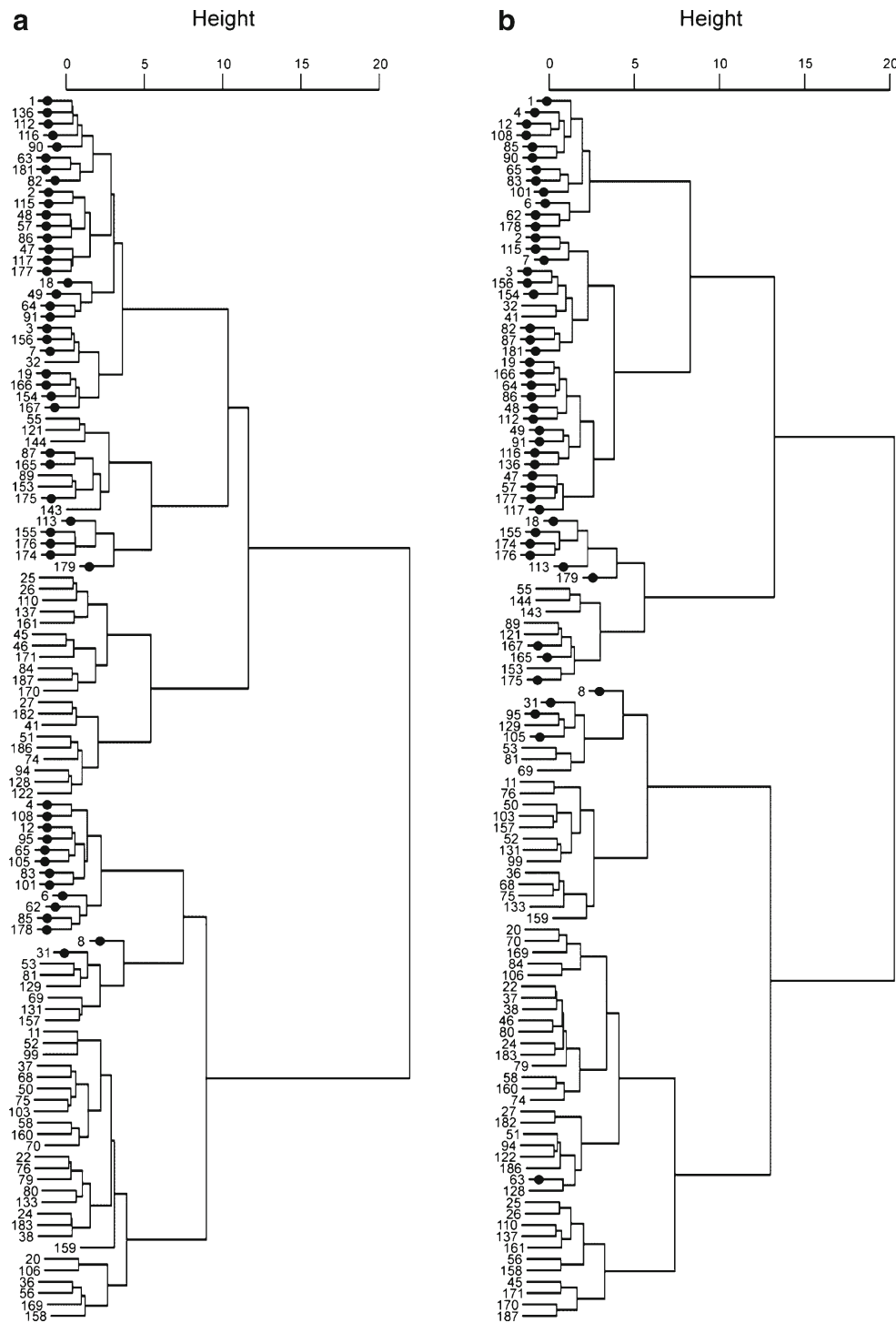
Fig. 2 Clustering of 108 specimens based on the L^*, C^* and h_{ab} values measured with spectrophotometers: **a** Konica Minolta with 8-mm aperture, **b** Labscan with 25-mm aperture; visual assessment (60 % of the observers considered) is indicated: pinkish specimens have *dots*, brownish specimens have no dots

tree was evaluated by calculating the probabilities of the strips to be smaller or larger than 71.14. Ninety-eight percent of the strips had a probability higher than 75 % to be pinkish or brownish, and 91 % even had a probability higher than 95 %. With this second classification method, only 6 % of the specimens were wrongly classified.

The best results for the CIEDE2000 method were obtained with the combination of the parametric factors $K_L=6$, $K_C=4$, $K_H=1$ and a ΔE_{00} level of 0.5 for separating pinkish and brownish groups. Figure 5 illustrates the CIEDE2000 approach. Eighty-four percent of the specimens were included in the correct ellipsoid, and 5 % were falsely labelled pinkish.

Table 4 European oak colour space and subspace centres and standard deviations of the colour parameters

Colour space	L^*	a^*	b^*	C^*	h_{ab}
Oak	67.0±1.8	7.6±0.4	22.2±0.5	23.4±0.6	71.1±0.8
Pinkish oak	66.7±1.9	8.1±0.4	22.0±0.5	23.5±0.6	69.8±0.8
Brownish oak	67.1±1.8	7.2±0.4	22.2±0.6	23.4±0.7	72.1±0.9

Another 5 % of the specimens were situated outside the ellipsoids, but far away from the transition zone between pinkish and brownish samples. So although these specimens had another colour according to the CIEDE2000 theory, they could clearly be attributed to the pinkish or brownish group in accordance with the classification tree if h_{ab} was either 0.5 degree larger or 0.5 degree smaller than 71.14. Other excluded specimens (6 %) were real borderline cases and thus difficult to classify.

4 Discussion

The spectrophotometer used for colour grading was a Labscan XE, using a 10° standard observer, D65 standard illuminant and 45°/0° measuring geometry. Other standard observers (2° in Katuščák et al. 2002), standard illuminants (C in Stenudd 2004) and device geometries (d/8° in Pandey 2005; d/0° in Katuščák et al. 2002) are used for wood colour determination. Often, these instrument settings, which are indispensable for comparing results, are missing in publications. Furthermore, a rather large measuring aperture (25 mm) seemed more appropriate for classification into two groups. This device parameter is not always mentioned in the literature. Reported apertures vary from 8 mm up to
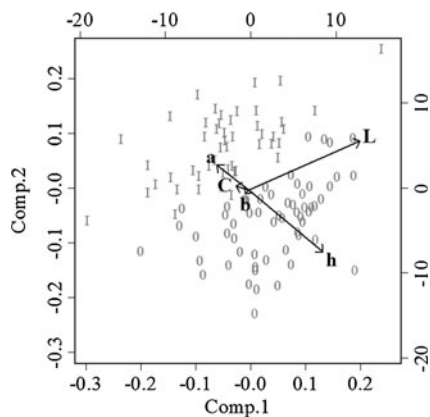

Fig. 4 Classification tree based on L^*, a^*, b^*, C^* and h_{ab} values of 108 visually assessed parquet strips

50 mm (Katuščák et al. 2002; Stenudd 2004; Sundqvist 2002), but the choice of the aperture is mostly not explained.

Concerning the grading algorithms used in this study, the training phase includes visual assessment of a representative set of material to define the desired colour subspaces. Alternatively, the visual assessment could be replaced by an objective tool-chain: as an experiment, the labelling of the training specimens was done by clustering the specimens according to the spectrophotometer measurements. For the latter, the weighing factors of the CIEDE2000 method were taken into account as they describe the mutual importance of the colour parameters. The clustering was thus performed with the $L^*/6$, $C^*/4$ and h_{ab} values. Based on this labelling of the training set that had 94 % accordance with the visual grading, the centres of the subspaces were calculated as well as a classification tree (similar to Fig. 4) indicating that the two groups were divided by the same h_{ab} limit value of 71.14. Evaluation of this fully objective grading was done according to the visual assessment available in this study: classification by the latter tree had 94 % of the specimens labelled correctly, and 86 % of the specimens were situated in the tolerance ellipsoids around the subspace centres in accordance with the visual assessment, with only

Fig. 3 Biplot of the principal component analysis of the colour parameters measured on visually assessed parquetry strips: *I* pinkish and *O* brownish specimens. The principal components are a linear combination of the measured variables L^*, a^*, b^*, C^* and h_{ab} indicated on the plot
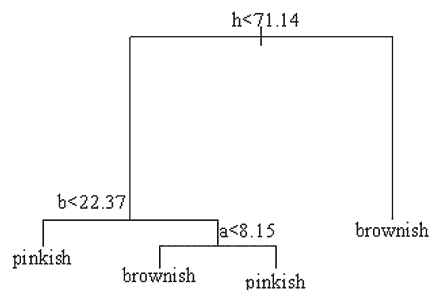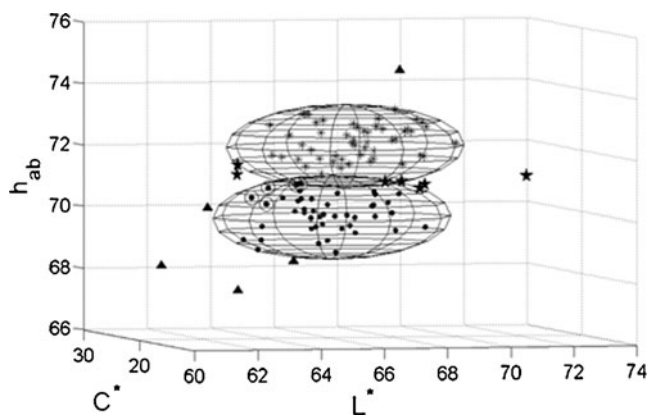

Fig. 5 Visually assessed parquet strips situated in relation to the ΔE_{00} ellipsoids around the pinkish and brownish centres; strips in the ellipsoids: *asterisks* brownish, *dots* pinkish—specimens not in accordance with visual assessment are circled; strips outside the ellipsoids: *triangles* obviously at one colour side, *stars* difficult to classify

5 % in the 'wrong' ellipsoid. Six percent of the specimens were outside the tolerance ellipsoids but clearly positioned at one colour side or the other (h_{ab} more than 0.5 degree smaller or larger than 71.14). Five percent were located in between the two ellipsoids and therefore hard to classify. In this test case, starting from objectively determined colour groups did not lower the number of correctly labelled specimens compared to the grading methodology that was based on visually determined colour groups.

In conclusion, implementation of the developed grading systems in a processing facility could be done as follows: A training set is sorted into colour groups by visual assessment or clustering of the weighed spectrophotometer measurements, and a classification tree is constructed and/or the ΔE_{00} tolerance ellipsoids are calculated. Then, the evaluation set is sorted into colour groups according to the classification tree and/or the position with respect to the ΔE_{00} tolerance ellipsoids. Moreover, one could even think of an interactive tool to define an individual colour subspace preferred by a customer, adding colour as an extra dimension for tailor-made pieces.

Some issues concerning the grading algorithm with CIEDE2000 and the implementation need more refinement in the future. The approach for wood shows some similarity with the application of the method on textiles. The texture of the sample is one of the most important parametric criteria linked to the parametric factors of the equation (Kandi and Tehran 2009). Montag and Berns (2000) found that for textiles, texture increases the L^* tolerance threshold by a factor of almost 2 compared to uniform stimuli, and Huertas et al. (2006) showed that for random-dot textures, the tolerance on L^* is increased the most, but also warned that the influence of texture on C^* and h_{ab} tolerances is in general not negligible. The latter also report that each texture or sort of texture should be studied separately in this context. The proposed parametric factors determined in the present study surely need confirmation by more research on other datasets, but they are in accordance with human perception as being most tolerant in L^*, intermediately tolerant in C^* and least tolerant for h_{ab} deviations (Malacara 2002). Furthermore, the determined ΔE_{00} level is open to discussion. The chosen level had the best accordance with the visual assessment, which forced the observers to choose between the brownish and pinkish hue. Enlarging the ΔE_{00} tolerance level would make specimens currently located outside the tolerance ellipsoids but clearly at the brownish or pinkish side of the colour space, included in the larger tolerance ellipsoids. On the other hand, more specimens situated at the transition zone could then be included in the overlap of both tolerance ellipsoids meaning that they fit into both colour groups. In contrast, a choice of smaller ellipsoids would cause specimens clearly at the brownish or pinkish side of the colour space but too far away from the centres of the ellipsoids to be excluded. The

possibility to adapt the ΔE_{00} level to each particular purpose makes CIEDE2000 a very strong tool.

Implementation as a continuous inline system, such as the sorting system developed at the Virginia Tech University and NOVA Technologies (Srikanteswara et al. 1997), must be feasible. This requires the combination of a well known and stable light source and an appropriate camera system. Exploratory experiments (unpublished results) consisted in the calibration of a scanning system using standard colour charts that were scanned and measured with a spectrophotometer as described in Léon et al. (2006). Promising first results demonstrated that it is possible to use a scanner or camera that registers RGB values and transform these values to $L^*a^*b^*$ or $L^*C^*h_{ab}$ values used for colour grading as described in this paper. As camera or scanner systems are already used in production processes for defect detection, the addition of an extra inline scanner unit for colour grading or additional software in combination with existing scanner systems would be useful for manufacturers.

5 Conclusion

The aperture of the spectrophotometer influences the measured results significantly, but as the objective in this study was a coarse classification between only two classes, a relatively larger aperture was preferred. Concerning the measuring geometry of the spectrophotometers, no preference could be determined. Differences between the visually distinct groups were significant in the objectively assessed colour parameters, with more correspondence when $L^*C^*h_{ab}$ values were considered. The most important parameters for grading were L^* and h_{ab}. The importance of h_{ab} was confirmed, as the first split condition in the classification tree used the h_{ab} values. Using the classification tree resulted in a misclassification of 6 %, whereas using a $\Delta E_{00}(6:4:1)$ level of 0.5 to define tolerance ellipsoids classified 5 % wrongly. The ΔE_{00} level may be adapted to each particular purpose and is as such a very strong and flexible approach for colour classification. This study demonstrates the potential for automated colour grading of oak wood in the woodworking industry and suggests that even the use of a camera system added to common defect detection scanners would make grading pre-sawn elements possible as well as colour-guided sawing of larger elements.

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