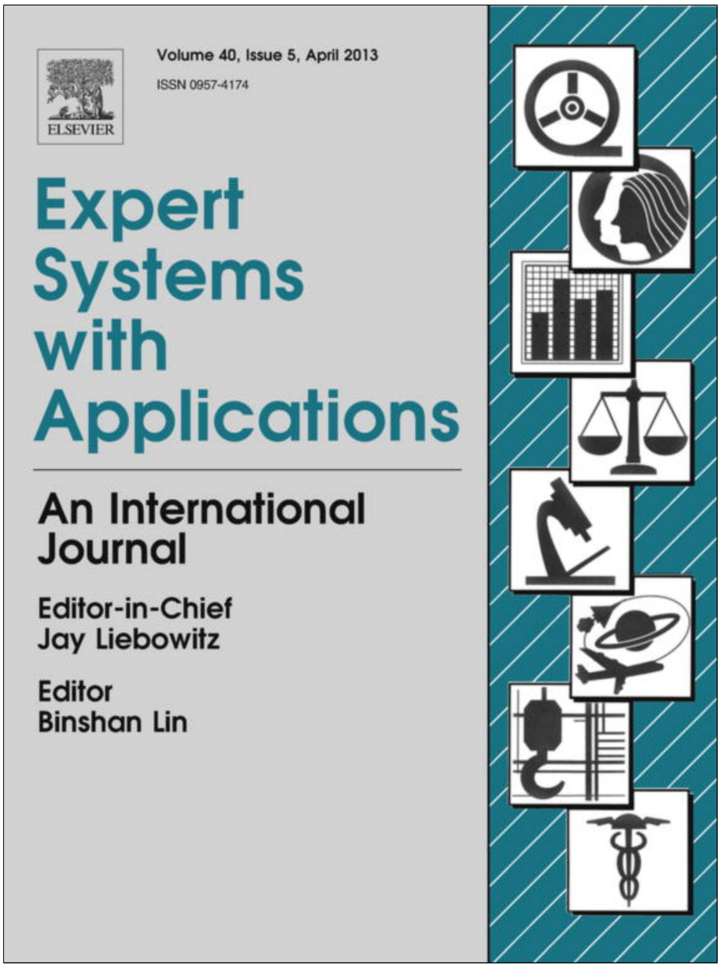
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Performance analysis of colour descriptors for parquet sorting

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ABSTRACT

In this paper we consider the problem of colour-based sorting hardwood parquet slabs into lots of similar visual appearance. As a basis for the development of an expert system to perform this task, we experimentally investigate and compare the performance of various colour descriptors (i.e.: soft descriptors, percentiles, marginal histograms and 3D histogram), and colour spaces (i.e.: RGB, HSV and CIE Lab). The results show that simple and compact colour descriptors, such as the mean of each colour channel, are as accurate as more complicated features. Likewise, we found no statistically significant difference in the accuracy attainable through the colour spaces considered in the paper. Our experiments also show that most methods are fast enough for real-time processing. The results suggest the use of simple statistical descriptors along with RGB data as the best practice to approach the problem.

1. Introduction

Wood is a widely used and greatly appreciated material. Countless are its applications in various industrial sectors including construction, interiors, furniture and shipbuilding. Like other products such as natural stone, ceramics, leather and similar, wood is mostly appreciated for its appearance; a feature that determines, to a great extent, its price. When wood is used for flooring, decking or façade cladding (in this case we usually refer to it as *engineered wood*), strict selection procedures are needed to assure satisfactory aesthetic results. To obtain beautiful and uniform surfaces, wood has to be carefully graded by fibre type and colour tone. In an increasingly globalised and competitive market, it is mandatory that wood products – particularly those of high range – be virtually extent of any defects. In an endeavour to meet such requirements and increase market shares, producers are trying to drastically improve their quality standards. In this context quality inspection plays a central role.

As noted by Bombardier and Schmitt (2010), wood quality inspection involves two different and clearly separated problems: (1) detection, localization and classification of surface defects; and (2) sorting products into lots of similar appearance. In the parquet industry the two processes are usually carried out sequentially and in this order. Both can be performed either manually or automatically. Technically speaking the first problem is referred to as *grading* and is related to detecting, measuring and counting superficial defects like knots, pockets, stains, veins, cracks, etc. Domain-specific standards (DIN-1611, 2002; DIN-EN-975-1, 2011; DIN-EN-975-2, 2004) define different wood grades on the basis of the number and size of such defects along with procedures to their measurement and detection.

As for the second problem, we can find it referred to as *sorting* (Lu, Conners, Kline, & Araman, 1997), *colour classification* (Kurdthongmee, 2008), or, again, *grading* (Faria, Martins, Ferreira, & Santos, 2008; Vienonen, Asikainen, & Eronen, 2002). To avoid confusion, throughout this paper we use the term grading to refer to the first problem and sorting for the second.

When performed manually, grading is stressful and time consuming, though, in general, not particularly demanding, since defects are usually quite evident. In contrast, sorting products into groups of similar appearance is more subtle, since products of the same class may have differences in tone which can be very slight and difficult to detect even to a trained eye. In addition this process requires more than one slab to be observed at the same time. Subjective and environmental conditions, tiredness, boredom and other factors can significantly affect the outcome of the process. To this we should add that recent studies showed how colour perception can be significantly influenced by age and socio-economical level of the subject (Kose, 2008). Our personal experience indeed confirms that different operators can produce very dissimilar results. Beginning with these considerations, it is therefore no surprise that the agreement between different operators can be as low as 60% (Rožman, Brezak, & Petrovic, 2006). As a consequence, manual inspection procedures can produce batches of products with significant variations of the visual appearance, causing sales returns and significant economical losses.

Parquet producers are therefore more and more concerned with the development of computer vision systems capable of carrying

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out automatic quality control procedures. In this paper, in particular, we are concerned with the second problem, that of measuring and comparing the visual appearance of parquet slabs in order to sort them according to suitable similarity criteria. More specifically we focus on the problem of colour sorting slabs of the same grade and quality. This consists of dividing a previously graded batch of parquet hardwood into different colour tones, among which differences in colour are usually very slight, yet noticeable. To this end we experimentally compare the effectiveness of a set of colour descriptors and spaces. We also discuss issues related to image acquisition and processing including computational time, which are of primary importance when it comes to designing and implementing practical, real-time solutions.

The remainder of the paper begins with a brief survey of related research (Section 2). In the following sections we give a description of the materials (Section 3) and methods (Section 4) used in our research. In Section 5 we present the experimental activity followed by results (Section 6) and conclusions (Section 7).

2. Related research

The first applications of computer vision to the wood industry date back to the 1980s (Conners, McMillin, & Lin, 1983; Sobey & Semple, 1989). Literature review shows that, since then, research has mostly focused on the problem of grading. Studies have confirmed that it is possible to replace manual graders with automatic systems improving production effectiveness and product quality (Kline, Surak, & Araman, 2006; Lycken, 2006). A preliminary step to automatic grading is defect detection and characterization. This has been typically approached using spectral features (Åström, Åstrand, & Johansson, 1999), spectral and X-ray features (Bond, Kline, & Araman, 2002), colour features (Ciccotelli & Portala, 1992; Conners et al., 1992) and combinations of colour and texture features (Gu, Andersson, & Vicen, 2010; Kyllönen & Pietikäinen, 2000). Other authors focused on how to deal with the grading problem once defects have been detected and located (Castellani & Rowlands, 2009; Lycken, 2006). For an up-to-date survey on automatic wood grading readers are referred to the work of Jabo (2011).

A more recent application of computer vision to wood products is the automatic identification of wood types (Labati, Gamassi, Piuri, & Scotti, 2009). This is about identifying the different types of wood that make up wood shipments; a procedure that has been used to detect illegally-traded timber (Hermanson & Wiedenhoeft, 2011).

Herein we are concerned with the problem of sorting parquet hardwood into different colour tones. We therefore assume that hardwood has been already graded, either automatically or manually. A round-up of the methods presented in this paragraph can be found in Table 1. Piuri and Scotti (2010) noted that approaches to colour-based sorting can be divided into two groups: *image-based* and *spectrum-based* processing systems. Both groups have pros and cons. Spectrum-based systems have the advantage of relying on device-independent data, but the disadvantage of a limited inspection area, which does not allow for full-field measurements. Conversely, image-based systems enable full-field inspection, but need colour calibration to produce device-independent data. Vienonen et al. (2002) described a spectrophotometric system which takes four circular samples of approximately 20 mm radius from each parquet block. A 56-bin spectrum (from 275 to 965 nm) is computed from each block and used as feature vector. Classification is based on two approaches: minimum distance classifier and a subspace classifier. Likewise, Buchelt and Wagenführ (2012) used a spectrophotometer to evaluate colour differences of native wood surfaces. In their approach spectral data are converted into CIE Lab to estimate the intra-class colour difference (ΔE^{*}_{ab}) of different species. In the same way, Schnabel, Zimmer, and Petutschnigg (2009) use spectrophotometric data and convert them into CIE Lab to model colour changes that wood undergoes during its lifetime.

Methods based on image processing work with the output of industrial cameras, which is usually a set of RGB triplets. These can be either used 'as is' or converted into different colour spaces, such as HSV, CIE Lab, etc. In both cases the aim is to extract global statistical descriptors that characterize the colour content of the images. In the design of an expert system for wood sorting based on image processing, one has to deal with the choice of the right colour space and the appropriate descriptor. Related literature shows that various solutions have been proposed in the past. Lu et al. (1997) described a system based on 3D RGB histograms and minimum distance classifier for real-time colour sorting of edge-glued panel parts reporting an accuracy ranging from 83.0% to 99.1%. Kurdthongmee (2008) described an approach for colour-based classification of rubberwood boards for fingerjoint manufacturing in which a neural network is fed with a normalized histogram of hue (H). In a qualitative study Hrčka (2008) investigated the use of colour features to classify between common beech and European spruce, showing that colour coordinates in the CIE Lab space separate the two species rather well. Faria et al. (2008) employed both device-dependent (HSV) and device-independent (CIE Lab) colour coordinates for sorting three different types of wood, namely cherry tree, beech tree and oak. Their method employs a fuzzy classifier based on a bell membership function for each of the colour coordinates. More recently Bombardier and Schmitt (2010) used mean and homogeneity extracted from CIE Lab and HSV channels as colour features, and a fuzzy reasoning classifier as the building blocks of an expert system for wood colour recognition.

This review of image processing-based methods shows that a wide variety of approaches have been proposed in literature, but, at the same time, leaves the reader uncertain about which is the 'best practice' when it comes to designing and implementing an automatic sorting system. The results presented in the papers cited above look in fact rather scattered, inhomogeneous and therefore difficult to compare to each other. Even more difficult is to reproduce the results presented in them, for data and algorithms used in the experiments are not available. Lastly, it is worth noticing that

Table 1
Summary list of methods for colour-based wood sorting.

Reference	Method	Colour descriptor	Colour space
Arden (1991)	Image-based	Marginal histograms	RGB
Lu et al. (1997)	Image-based	3D histogram	RGB
Vienonen et al. (2002)	Spectrum-based	Spectral histogram	Spectrum
Kurdthongmee (2008)	Image-based	One marginal histogram (hue)	HSV
Hrčka (2008)	Image-based	Mean + standard deviation	CIE Lab
Faria et al. (2008)	Image-based	Approx. marginal histograms	HSV, CIE Lab
Schnabel et al. (2009)	Spectrum-based	Mean	CIE Lab
Bombardier and Schmitt (2010)	Image-based	Mean + homogeneity	CIE Lab + HSV
Buchelt and Wagenführ (2012)	Spectrum-based	Mean	CIE Lab

none of the above cited works provides a comparative analysis of methods on a statistical basis. As a consequence it is difficult to provide sensible answers to questions like: Which colour descriptor gives the best accuracy? Is there a colour space superior to the others? What is the trade-off between accuracy and computational payload? In the following sections we try to answer these questions on the basis of a comparative experimental analysis.

3. Materials

We considered 14 classes of common parquet hardwood of different type, treatment and finish, as detailed in Table 3. The number of colour tones for class ranges from two to four, whereas the number of samples for tone ranges from six to eight. All the materials considered in the experiment are top-quality, therefore containing none to very few minor defects. Preliminary subdivision of the samples of each class into the different colour tones ('ground truth') has been carefully performed by a pool of experienced workers.

Images of the hardwood parquet specimens have been captured through an imaging system composed of a dome illuminator (Monster Dome Light 18.25″), an industrial CMOS camera equipped with a 6 mm fixed focal length lens and three pins to support the dome (Fig. 1). Characteristics and settings of the camera and lens are reported in Table 2. This solution leaves enough space for the specimen to pass below the dome and the camera, as if it were carried by a conveyor belt, a set-up which closely resembles the industrial conditions in which the system is supposed to operate. The camera is attached to the dome through a custom-designed support which permits relative rotation between the camera and the dome around the focal axis of the camera. The imaging system is patent pending (Bianconi, González, Fernández, & Saetta, 2012a).

The voltage of the illuminator has been set to 18 V and maintained constant throughout the image acquisition procedure. This provides a light level of about 78,600 lx at the center of the field of view. In order to avoid colour artifacts arising from image binning and/or undersampling, images have been taken at the native resolution of the camera (2560 × 1920 pixels), which corresponds to a spatial resolution of approximately 180 dpi. Preliminary white balance has been carried out to adjust colour rendition.

4. Methods

In the following two subsections we review the colour descriptors (Section 4.1) and spaces (Section 4.2) considered in this paper.

Fig. 1. The imaging system.

Table 2
Characteristics and settings of the camera and lens.

Camera	
Model	Edmund Optics 5012C LE
Red gain	1.78 ×
Green gain	1.00 ×
Blue gain	1.33 ×
Gamma correction	No
Resolution	2560 × 1920
Debayering quality	High
Image format	RGB24 (`.bmp`)
Lens	
Model	Pentax H614-MQ
Focal length	6 mm (fixed)
Aperture value	5.6
Focus	≈30 cm

In Section 4.3 we also discuss the problem of converting colour data from a device-dependent space into a device-independent one.

4.1. Colour descriptors

Colour descriptors are statistical parameters that summarize the colour content of an image irrespectively of the spatial distribution. Consequently, they are invariant to translation and rotation, and only slightly dependent on the viewing angle. By contrast, they are highly sensitive to changes in illumination. It is therefore mandatory that this be kept constant during the acquisition process, a condition that can be obtained, for instance, through the imaging device used in our experiments (Fig. 1). In real working conditions we can safely assume that similar devices can be adopted to produce invariable illumination conditions.

4.1.1. Soft colour descriptors

López, Valiente, Prats, and Ferrer (2008) introduced the term *soft colour descriptors* to refer to different combinations of the following simple statistical parameters:

- Mean

$$\mu_c = \frac{1}{n}\sum_{i=1}^{n} I_{c,i} \tag{1}$$

- standard deviation

$$\sigma_c = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}(I_{c,i}-\mu_c)^2} \tag{2}$$

- k-th moment

$$m_{c,k} = \sum_{i=1}^{n}(I_{c,i}-\mu_c)^k h_c(I_{c,i}) \tag{3}$$

In the above equations n is the number of pixels in the input image, $I_{c,i}$ the intensity of the i-th pixel in the c-th colour channel, $h_c(x)$ the probability of the intensity value x in the c-th channel (usually estimated through a discrete histogram – hence the symbol h_c, as in Eq. (4)) and μ_c the average intensity value of the c-th channel. Throughout the paper we assume that $I_{c,i} \in [0,1]$ in any colour space. In our implementation this is obtained through appropriate normalization of the input data.

Soft descriptors are easy to implement and fast to compute, therefore particularly suitable for real-time processing. Different combinations of soft colour descriptors proved effective in applications ranging from grading of stoneware tiles (López et al., 2008) to sorting of recyclable paper (Rahman, Hussain, Scavino, Basri, & Hannan, 2011). In particular, mean values of the R, G and B channels alone showed surprisingly good performance in many tasks including automatic grading of ceramic tiles (Kukkonen, Kälviäinen, & Parkkinen, 2001) and banknote recognition (Garcıa-Lamont, Cervantes, & López, 2012). Recently, Bombardier and Schmitt (2010) approached the problem of wood colour recognition by combining mean and homogeneity in the CIE Lab space. As for homogeneity, herein we used the following definition:

$$hom_c = \sum_{l=1}^{L} \frac{h_c[x(l)]}{x(l)} \tag{4}$$

where $x(l)$ represents the intensity value corresponding to the l-th bin of the histogram h_c. In our implementation the value $x(l)$ is measured at the centroid of each bin. Since bins' edges are monotonically-increasing values in $[0,1]$, this approach ensures that Eq. (4) generates no division by zero. For this reason the definition of homogeneity used here is slightly different from the one proposed in the original references (Bombardier & Schmitt, 2010; Schmitt, 2007). In that case, in fact, a division by zero may occur when $i = 0$ (see Schmitt, 2007, Eq. 3.24).

4.1.2. Colour percentiles

A percentile is the value that cuts the distribution of a random variable into two parts so that a given percent of observations fall below that value. Colour percentiles are generally computed from each colour channel. In wood grading they have been used both alone and in combination with textural features. Kauppinen (2000) employed colour percentiles alone in a non-segmenting method for grading parquet slabs. Niskanen, Silvén, and Kauppinen (2001) used colour percentiles in combination with either co-occurrence features or Local Binary Patterns for identification of knots in wood inspection. Recently Bianconi, González, Fernández, and Saetta (2012b) proved the method effective also in automatic classification of granite tiles. In the experiments presented herein, we used quartiles and quintiles of each colour channel. These are the values that cut the probability distribution of the intensity into equally-populated groups each containing 1/4 and 1/5 of the population, respectively.

4.1.3. Marginal histograms

Marginal histograms estimate the colour content of an image through the probability distribution of colours as a function of each channel separately, thus discarding any information about the other channels. Marginal histograms can be considered as projections of the 3D colour histogram (discussed in the following subsection) into three one-dimensional subspaces. Herein we considered histograms composed of 8, 16 and 32 bins for each channel, giving 24, 48 and 96 features, respectively (see Table 4). Marginal colour histograms performed well in practical applications such as classification of printed colour paper (Pietikäinen, Nieminen, Marszalec, & Ojala, 1996), natural rocks (Lepistö, Kunttu, & Visa, 2005) and generic colour textures (Bianconi, Harvey, Southam, & Fernández, 2011a). In colour-based wood sorting their use has been propounded by Arden (1991) and, more recently, by Kurdthongmee (2008).

4.1.4. 3D colour histogram

The 3D colour histogram estimates the joint probability distribution in the colour space. The method, which was originally proposed by Swain and Ballard (1991), consists of dividing the colour space in parts of equal volume and counting how many times each part is represented in the input image. Lu et al. (1997) used the 3D colour histogram for colour sorting edge-glued wooded panels. In our experiments we adopted the implementation proposed by Mäenpää and Pietikäinen (2004) in which the colour space is partitioned by dividing each colour channel into segments of equal length. Since we used eight subdivisions for each channel, the method generates $8^3 = 512$ features.

4.2. Colour spaces

Critical to the application studied herein is the choice of the right colour space. This can be either a device-dependent or a device-independent one. Device-dependent spaces are not directly related to how the human vision system perceives colours: they simply encode device-specific data at the device level (Kang, 2006). Device-dependent spaces include additive spaces, such as RGB and HSV, and subtractive spaces (not considered here). In contrast, device-independent colour spaces (also called *colorimetric* spaces) are directly related to the human vision system. Their main objective is in fact to define colour coordinates that are universally valid for the group of normal observers (Wyszecki & Styles, 1982). The basic colorimetric space is CIE XYZ. Any colour space that can be directly transformed into CIE XYZ is device-independent. A colour space is said *uniform* when the Euclidean distance between colours in that space is proportional to colour differences as perceived by humans. CIE Lab and CIE Luv are examples of device-independent and uniform colour spaces.

Related literature for a long time has debated about whether there is a colour space superior to the others. Device-independent and uniform colour spaces should be preferable – at least in principle – since they are intimately related to the way humans perceive colours. This assertion, however, has not been clearly confirmed by the experiments. Comparison of different colour spaces for image classification has in fact led, so far, to contradictory or inconclusive results. Paschos (2001) found that perceptually uniform/approximately uniform colour spaces (CIE Lab and HSV, respectively) outperform RGB in many cases. By contrast, other authors found no significant difference among the colour spaces considered in their works: in a texture classification experiment Drimbarean and Whelan (2001) showed that none of the RGB, HSI, CIE XYZ, CIE Lab and YIQ proved sufficiently superior; likewise, Brunner, Maristany, Butler, VanLeeuwen, and Funck (1992) found no practically important differences in performance among RGB, HSV, CIE Lab, CIE Luv and YIQ for defect detection in Douglas-fir veneer. Finally, Qazi, Alata, Burie, Moussa, and Maloigne (2011) recently showed that CIE Lab outperforms RGB and IHLS with textured images, but the trend is reversed for pure colour feature cues.

In this paper we considered the same colour spaces studied by Paschos (2001), namely two device-dependent spaces (RGB and HSV) and one device-independent space (CIE Lab). We believe these represent sensible and viable choices for the problem studied herein. In practical applications the use of RGB data is dictated by the availability of such data as direct output of the imaging system. This avoids the computational overhead required to convert RGB data into other colour spaces. RGB, however, is not perceptually uniform. HSV, in contrast, is approximately uniform and decouples colour data into an intensity (V channel) and a chromatic part (H and S channels). RGB colour data are converted to HSV through simple equations (Kang, 2006). Finally, CIE Lab is a device-independent and uniform colour space closely related to the human vision system. To obtain Lab colour coordinates from RGB, one needs to colour calibrate the image acquisition system. The procedure adopted here is described in the following section.

4.3. Colour calibration

Colour calibration consists of determining a function that maps device-dependent colour data into device-independent ones (León,

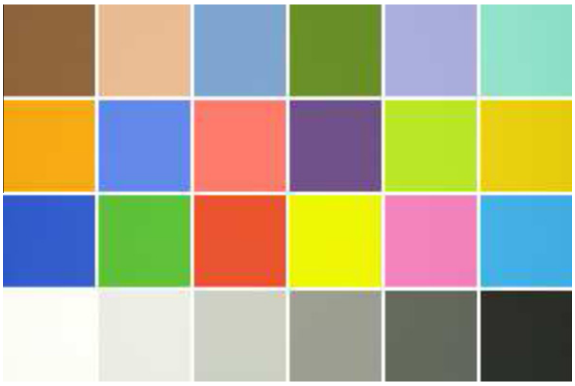


Fig. 2. The 24 reference colours of the X-Rite® color checker.

Mery, Pedreschi, & León, 2006). The form of the function is established a priori. Most commonly this is a polynomial, but other methods, such as lookup tables (Po-Chieh, 1993) and neural networks (Schettini, 1995) have been proposed as well. In our experiments we adopted a simple linear model, which can be expressed in the following way:

$$\begin{bmatrix} \widehat{L}^* \\ \hat{a}^* \\ \hat{b}^* \\ 1 \end{bmatrix} = \begin{bmatrix} M_{11} & M_{12} & M_{13} & M_{14} \\ M_{21} & M_{22} & M_{23} & M_{24} \\ M_{31} & M_{32} & M_{33} & M_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \\ 1 \end{bmatrix} \tag{5}$$

where $\widehat{L}^*$, $\hat{a}^*$ and $\hat{b}^*$ represent the estimated CIE Lab colour coordinates. This approach has some advantages: it is fast, easy to implement and requires the estimation of few parameters. Moreover, previous experiments showed that linear models perform as well as higher-degree models in colour calibration (Bianconi, Saetta, Sacchi, Asdrubali, & Baldinelli, 2011b). In order to determine the parameters of the model (the M_{ij} coefficients), we need a set of reference colour patches of which both the device-dependent $[R,G,B]^T$ and the device-independent coordinates $[L^*,a^*,b^*]^T$ are known. The first are the raw output of the imaging system, the second can be measured through a colorimeter or any other colour measuring device. Most commonly device-independent colour data come with the reference patches. Here we used a standard calibration set (X-Rite® Color Checker) which contains 24 colour patches (Fig. 2). The corresponding device-independent data are available online (BabelColor, 2012).

The unknown parameters are estimated through a least-squares procedure:

$$\mathbf{M} = \underset{M_{ij} \in \mathbb{R}}{\operatorname{argmin}} \left\{ \sum_{r=1}^{R} \left[\left(\bar{L}_r^* - \widehat{L}_r^* \right)^2 + \left(\bar{a}_r^* - \hat{a}_r^* \right)^2 + \left(\bar{b}_r^* - \hat{b}_r^* \right)^2 \right] \right\} \tag{6}$$

where $\bar{L}^*$, $\bar{a}^*$ and $\bar{b}^*$ are the 'true' CIE Lab colour coordinates of the reference colour patches, R is the number of the patches (24, in this case) and $\mathbf{M}$ the matrix of M_{ij} coefficients (Eq. (5)).

5. Experiments

In the experimental part we estimated the accuracy of the methods presented in Section 4. The experiments have been designed to replicate the manual sorting process usually adopted in industry. In our experience this works as follows: As a first step one or more workers select one representative wood sample for each tone of the class of wood which is going to be produced thereafter (in our experiments tones range from two to four per class). The samples are then passed to the worker in charge of the sorting process (let us refer to him as the 'selector'), whom in general is given a short time to familiarize with the grades before the selection process begins. During the selection process the selector takes a position from which he can see both the tables to select (which are usually carried on a conveyor belt) and the samples of each grade. Whenever a table arrives, the selector diverts the slab to the storage bin corresponding to the sample that the specimen resembles most. In practice the whole process is clearly a supervised classification task in which the samples represent the training set. Therefore, in order to comparatively evaluate the performance of the colour descriptors and spaces presented in the preceding sections, we submitted them to a supervised classification task. For each wood class we considered all the classification problems that can be generated by choosing one sample per tone for training while leaving the others for validation. This procedure provides a deterministic estimation of the classification accuracy. The accuracy estimated this way is also very realistic, in our view, because the appraisal procedure matches the real working conditions quite well.

Given T the number of tones for each wood class and S the number of samples for each tone (see Table 3), the classification accuracy a can be expressed in the following way:

$$a = \frac{1}{PT(S-1)} \sum_{p=1}^{P} C_p \tag{7}$$

where P is the number of problems ($P = S^T$) and C_p the number of correctly classified samples in the p-th problem. $T(S-1)$ represents the number of samples to classify in each problem.

5.1. Classifier

The selection of the appropriate classifier is always a crucial and difficult step in the design of an expert system. In this work two conditions limit this choice drastically: (1) the need for a classifier that works even with one training sample only (see the considerations reported at the beginning of Section 5), and (2) the absence of tuning parameters, which may significantly modify the relative performance of the colour descriptors and spaces. This considered, we thought that the 1-NN classifier would be the most appropriate solution for the problem studied herein (in our implementation we used the Euclidean (L_2) distance). Absence of tuning parameters, easiness of implementation and other desirable asymptotic properties make this classification strategy particularly suitable for comparative purpose. Furthermore the 1-NN can work even with few training samples (as few as one, like in this case), whereas other classifiers, such as SVM, cannot. Finally, recent literature strongly supports the use of the 1-NN for performance comparison of image analysis algorithms (Crosier & Griffin, 2010; Guo, Zhang, & Zhang, 2010; Kandaswamy, Schuckers, & Adjeroh, 2011; Liu, Fieguth, Clausi, & Kuang, 2012).

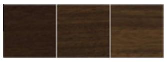
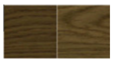
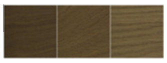
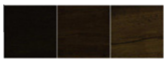
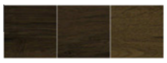
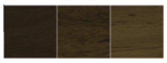
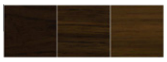
5.2. Implementation, execution and reproducible research

Methods and algorithms have been implemented in Matlab® R14. Image acquisition and classification have been performed in the Department of Industrial Engineering, at the University of Perugia, on a laptop PC equipped with Intel® T2300, 1 GB RAM, and Windows™ XP – 32 bits, Service Pack 3. For reproducible research purposes, all the data required to replicate the experiments (i.e.: source code, images and subdivisions into train and validation sets) are available in Ref. PG (2012).

6. Results

Classification accuracies for each colour descriptor, wood class and colour space are reported in Table 5. On average the results

Table 3
Summary list of the hardwood parquet samples used in the experiments.

Wood class	Botanical name	Treatment	Tones	Samples/tone	Image resolution
1	*Clorophora excelsa*	None		8	1200 × 600
2	*Quercus petrea*	Painted		8	1500 × 500
3	*Quercus petrea*	UV-treated, painted		8	1300 × 1000
4	*Quercus petrea*	Painted		8	1400 × 480
5	*Quercus petrea*	None		6	1300 × 480
6	*Quercus petrea*	UV-treated, brushed		8	1400 × 1300
7	*Quercus petrea*	Oil-treated, hand-planed, painted		7	1400 × 1300
8	*Quercus petrea*	Oil-treated, hand-planed		8	1500 × 1300
9	*Quercus petrea*	Thermo-treated		8	1500 × 1300
10	*Quercus petrea*	Thermo-treated		8	1500 × 1300
11	*Quercus petrea*	Brushed		8	1400 × 1300
12	*Quercus petrea*	Oil-treated		8	2000 × 600
13	*Tectona grandis*	None		8	1600 × 600
14	*Tectona grandis*	None		8	1200 × 600

confirm the effectiveness of the methods considered in the paper, with most methods attaining an accuracy close to 90%.

For comparison purposes we have computed the 95% confidence intervals of the mean classification accuracy attained by each colour descriptor in each of the three colour spaces (Fig. 3). Since data (average accuracies) are not normally-distributed, confidence intervals for the means have been estimated through percentile bootstrap (Schmidheiny, 2012). The procedure consist of drawing a number B of bootstrap samples, computing the distribution of the mean over the bootstrap samples and deriving the lower and upper bounds of the confidence interval as the 2.5 and 97.5 percentiles of such distribution. Parameter B needs to be set by the user: Schmidheiny (2012) recommends using 1000 or more replications; herein we used 2000, as suggested by Wang (2001).

We observe that in none of the three colour spaces there is a colour descriptor significantly superior to the others. Indeed Fig. 3 clearly shows large overlap among all the confidence intervals. It is interesting to notice that the simplest descriptor (mean of each colour channel) performs as good as the others. In contrast, the performance of 3D colour histograms is appreciably lower – though, as we mentioned above, this difference does not reach statistical significance. This result is logical and stems from the intrinsic structure of colour histograms (Bianconi, Fernández, González, Caride, & Calviño, 2009): since colour differences between grades are very subtle (see Fig. 3) colours tend to spread over a limited portion of the colour space. Therefore, while different colours can be assigned to the same bin of the 3D histogram, many other bins remain empty. The same considerations apply to marginal histograms: here we notice that accuracy improves as the number of subdivisions increases, as one would expect, since a finer subdivision of each colour axis allows for better discrimination between tones. Soft colour descriptors show very similar performance, suggesting that it is not much use adding higher-order statistical descriptors to the simple mean. Likewise, colour percentiles do not represent a significant improvement on soft colour descriptors (see Fig. 4).

As for colour spaces, the results show that there is very little difference among RGB, HSV and CIE Lab: none of them proved significantly superior. These findings confirm the conclusions obtained by Brunner et al. (1992) and Drimbarean and Whelan (2001). These results suggest that RGB data are better employed with no changes or modifications: converting them into other colour spaces only adds unnecessary overhead without appreciable beneficial effects. We also notice that the general trend is very similar for the three colour spaces, showing no appreciable interaction effects between colour descriptor and colour space.

Finally, it is worth mentioning that the overall processing time (feature extraction + classification) is rather contained, with most descriptors completing the task in less than 1 s. (see Table 4). We can see that most of the variability in computing time is due to feature extraction, whereas 1-NN classification requires almost the same amount of time for all descriptors. Furthermore, we should not forget that these figures have been obtained using a scripting language running on low cost hardware; therefore they largely overestimate the real computing time that can be achieved through dedicated hardware and optimized code.

7. Conclusions

In this paper we have presented a performance analysis of different colour descriptors and spaces for sorting parquet slabs into

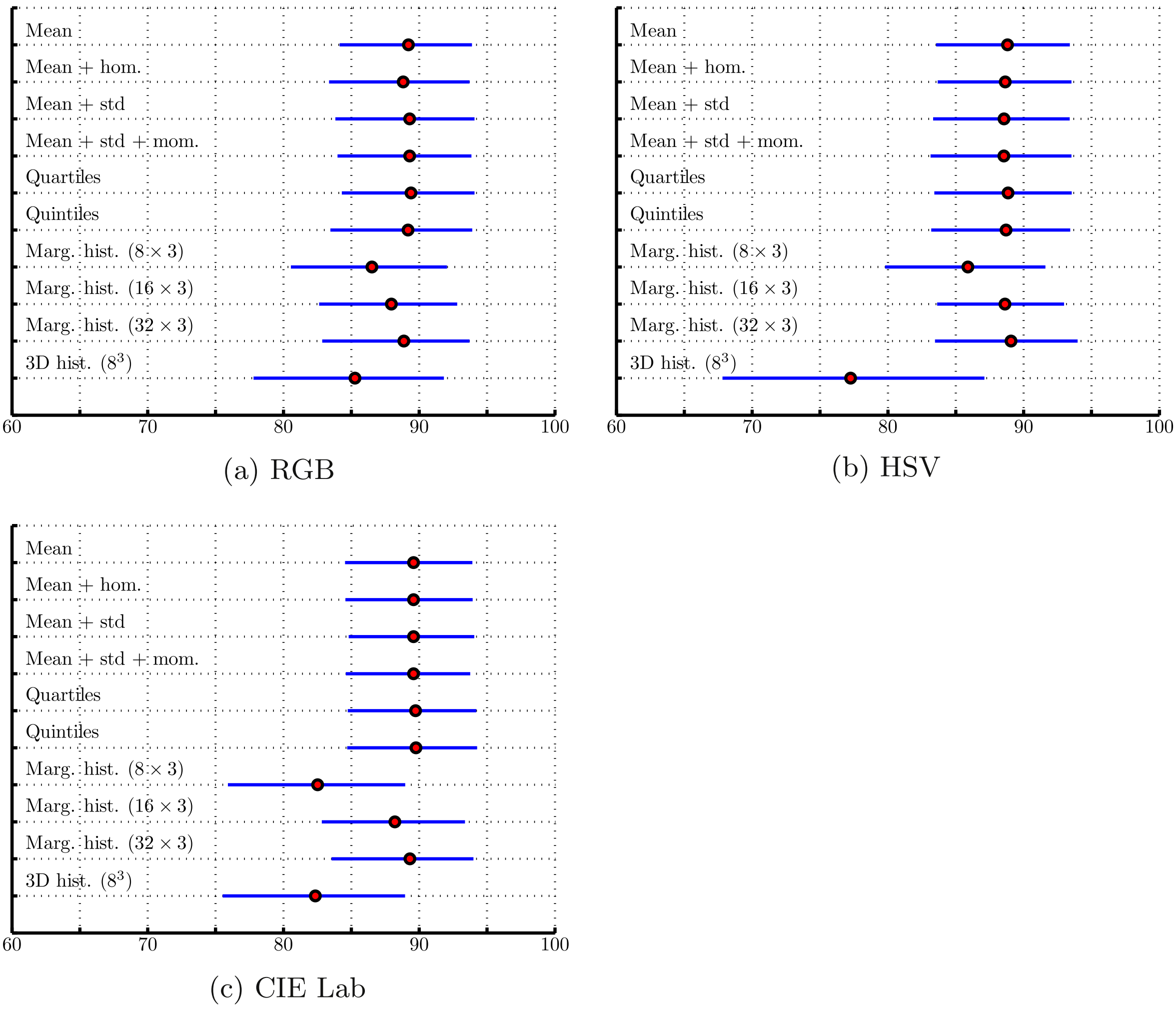


Fig. 3. Confidence intervals for the average classification accuracy (%) in the three colour spaces.

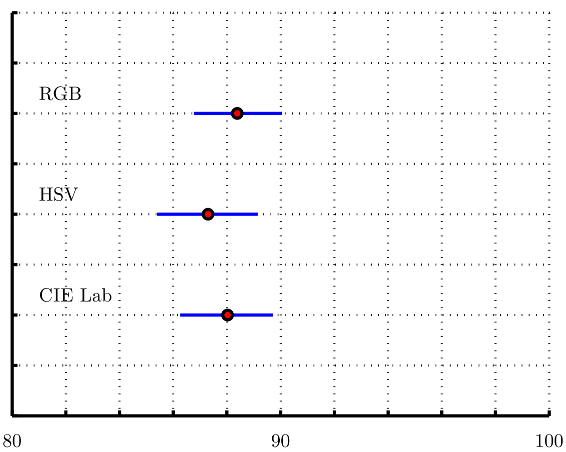


Fig. 4. Confidence intervals for the average classification accuracy (%) for each colour space.

Table 4
Colour descriptors used in the experiments. Average extraction and classification time (in seconds) refer to the equipment described in Section 5.2.

Color descriptor	No. of features	Avg. extraction time (a)	Avg. classification time (b)	(a + b)
Mean	3	0.236	0.029	0.265
Mean + hom.	6	0.863	0.030	0.894
Mean + std	6	0.439	0.028	0.468
Mean + std + mom.	15	8.059	0.028	8.087
Quartiles	9	2.218	0.028	2.246
Quintiles	12	2.234	0.028	2.263
Marg. hist. (8 × 3)	24	0.542	0.029	0.571
Marg. hist. (16 × 3)	48	0.571	0.029	0.600
Marg. hist. (32 × 3)	96	0.610	0.029	0.639
3D hist. (8^3)	512	0.705	0.029	0.734

classes of similar visual appearance. To the best of our knowledge, this is the first comprehensive study on the subject based on statistical analysis and reproducible experiments.

The overall results show, on average, a low error classification process with about 90% accuracy. Most methods are also computationally inexpensive, therefore suitable for real-time processing. This outcome is satisfactory, considering that the results have been obtained with standard industrial equipment – specifically a single-sensor camera – and a very simple classifier (1-NN). We believe that the overall accuracy could be significantly increased by adopting higher-level imaging devices (i.e.: 3-sensor camera) and more sophisticated classifiers. The comparative analysis showed no significant difference between the descriptors and colour spaces

Table 5
Average classification accuracy.

Colour descriptor	Wood class														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	*Avg.*
RGB															
Mean	94.9	87.9	69.0	97.7	94.8	100.0	86.8	86.2	71.4	89.9	97.3	100.0	91.9	81.2	*89.2*
Mean + hom.	94.7	87.7	69.0	97.7	94.8	100.0	87.2	86.2	69.6	86.6	97.3	100.0	91.8	81.1	*88.8*
Mean + std	95.1	88.3	67.6	97.7	95.0	100.0	87.9	86.1	72.2	90.2	97.3	100.0	91.5	81.4	*89.3*
Mean + std + mom.	95.1	88.3	67.6	97.7	95.0	100.0	87.9	86.1	72.2	90.2	97.3	100.0	91.5	81.4	*89.3*
Quartiles	95.1	87.9	68.9	97.9	95.6	100.0	88.3	87.1	70.8	90.0	97.5	100.0	91.2	81.3	*89.4*
Quintiles	94.6	86.5	67.4	97.7	95.0	100.0	88.3	87.2	71.9	90.3	97.4	100.0	91.1	80.9	*89.2*
Marg. hist. (8×3)	91.2	83.5	67.1	97.0	90.4	100.0	85.3	86.9	57.9	83.8	97.9	100.0	84.7	85.5	*86.5*
Marg. hist. (16×3)	87.7	89.4	65.5	98.7	90.9	100.0	87.1	86.5	67.3	90.0	97.7	100.0	88.1	82.5	*88.0*
Marg. hist. (32×3)	94.0	87.6	64.6	98.4	94.4	100.0	91.6	87.6	68.6	89.5	98.1	100.0	89.1	80.5	*88.9*
3D hist. (8^3)	88.5	82.8	65.3	99.4	87.8	100.0	85.5	85.9	53.0	80.4	98.3	100.0	80.9	85.9	*85.3*
Avg.	*93.1*	*87.0*	*67.2*	*98.0*	*93.4*	*100.0*	*87.6*	*86.6*	*67.5*	*88.1*	*97.6*	*100.0*	*89.2*	*82.2*	*88.4*
HSV															
Mean	94.1	86.0	68.8	97.9	94.4	100.0	90.5	74.9	77.3	93.3	95.3	100.0	86.5	84.2	*88.8*
Mean + hom.	94.4	84.5	68.9	97.9	94.4	100.0	88.0	75.6	77.5	93.5	95.3	100.0	86.6	84.5	*88.6*
Mean + std	94.7	86.4	67.3	97.9	94.3	100.0	89.3	73.9	76.2	93.6	95.3	100.0	85.7	85.1	*88.6*
Mean + std + mom.	94.7	86.4	67.3	97.9	94.3	100.0	89.3	73.8	76.1	93.6	95.3	100.0	85.7	85.1	*88.5*
Quartiles	95.6	85.6	67.9	98.0	95.6	100.0	89.8	74.7	77.5	93.2	95.9	100.0	86.8	83.4	*88.8*
Quintiles	94.6	84.6	67.3	98.1	94.6	100.0	90.4	74.4	77.8	94.0	95.5	100.0	87.1	83.4	*88.7*
Marg. hist. (8×3)	90.6	88.7	66.5	100.0	87.0	100.0	89.1	74.1	63.6	88.5	97.3	98.4	74.4	84.3	*85.9*
Marg. hist. (16×3)	89.3	86.6	64.8	97.8	89.6	100.0	88.3	85.4	79.5	92.0	97.2	100.0	84.2	86.0	*88.6*
Marg. hist. (32×3)	95.2	86.2	64.1	97.3	94.4	100.0	93.3	83.8	77.9	92.4	98.5	100.0	83.6	80.2	*89.1*
3D hist. (8^3)	89.2	63.2	62.8	100.0	87.6	100.0	59.6	58.3	46.5	77.6	97.7	98.3	59.9	80.7	*77.2*
Avg.	*93.2*	*83.8*	*66.6*	*98.3*	*92.6*	*100.0*	*86.8*	*74.9*	*73.0*	*91.2*	*96.3*	*99.7*	*82.1*	*83.7*	*87.3*
Lab															
Mean	94.7	87.9	68.9	96.4	95.0	100.0	87.1	85.3	76.1	91.7	97.7	100.0	91.9	81.4	*89.6*
Mean + hom.	94.7	87.9	68.9	96.4	95.0	100.0	87.1	85.3	76.1	91.7	97.7	100.0	91.9	81.4	*89.6*
Mean + std	95.0	88.1	67.7	96.4	95.0	100.0	88.2	85.0	75.7	92.0	97.7	100.0	91.7	81.5	*89.6*
Mean + std + mom.	95.0	88.1	67.7	96.4	95.0	100.0	88.2	85.0	75.7	92.0	97.7	100.0	91.7	81.5	*89.6*
Quartiles	95.5	88.5	67.6	96.4	96.3	100.0	88.0	85.9	75.4	91.5	98.4	100.0	91.7	80.9	*89.7*
Quintiles	95.1	87.5	67.4	96.9	94.8	100.0	88.8	86.5	75.8	91.5	98.4	100.0	92.4	81.6	*89.8*
Marg. hist. (8×3)	87.7	65.3	65.0	86.4	94.6	100.0	79.7	87.4	70.4	88.3	90.1	100.0	78.6	61.9	*82.5*
Marg. hist. (16×3)	95.8	81.5	63.4	96.3	91.7	100.0	82.5	83.9	78.5	92.5	99.0	100.0	89.8	80.0	*88.2*
Marg. hist. (32×3)	96.2	87.7	62.6	90.0	95.4	100.0	92.4	79.1	81.3	94.9	99.8	100.0	91.1	80.0	*89.3*
3D hist. (8^3)	87.7	64.7	65.1	85.5	96.7	100.0	79.9	87.4	70.4	88.2	86.5	100.0	79.0	61.9	*82.4*
Avg.	*93.8*	*82.7*	*66.4*	*93.7*	*94.9*	*100.0*	*86.2*	*85.1*	*75.5*	*91.4*	*96.3*	*100.0*	*89.0*	*77.2*	*88.0*

considered in the paper, therefore suggesting – from both standpoints of accuracy and computational efficiency – the use of simple statistical descriptors along with RGB data as the best practice.

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