Detection of various characteristics on wooden surfaces, using scanner and image processing techniques

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ABSTRACT

In this paper we present image processing methods and techniques for identifying wood abnormalities, cracks, notches, holes and other characteristics on wooden surfaces, in a simple and accurate way. The aforementioned problems have been widely discussed in scientific literature over the years. Nowadays, the need for mobile, automated and reliable methods is more evident than ever. The proposed methods and algorithms offer a new solution that can be used to estimate the precision of different wood machining techniques, to assist in the determination of mechanical properties of wood as well as to contribute to a more robust and simple quality control. Edge detection techniques, the first four central moments and the histogram of an image of wood that have been acquired using a typical scanner can provide useful information about characteristics of wooden surfaces. The experimental results demonstrate a novel and easy way of measuring the above characteristics of wood products by analyzing features on the wood surface using innovative image processing techniques.

Key words: Image processing, Wood abnormalities, Wood characteristics

1. INTRODUCTION

Vision is the most strong sense of the human body that gives a wealth of information about the world around us. Images are an important means of transmitting information, that almost all media today are based on. During the last decades the significant progress in sensoring technology has helped us capture high-resolution multimodal images that have resulted the development of methods for image and video processing and image-based reconstruction and synthesis. (Shashua, 1997 and Barmpoutis et al., 2010). Digital image analysis deals with the description and recognition of image content in order to substitute human vision.

The role of novel technologies in the industrial processing of wood is important and involves almost all sectors. In particular, it concerns the quality of raw material, production flow, inventory management, technological equipment, quality control of manufactured products, etc. (Dawei et al., 2010).

Several techniques have been proposed in the past for addressing the problem of detection of image characteristics. Texture is one of the important characteristics used in identifying objects or regions of interest in an image. Well known textural features for image classification are based on gray-tone spatial dependencies, and their application is illustrated in category-identification tasks described in (Haralick et al. 1973). In (Conners et al., 1983) an automated lumber processing system is described and an automatic inspection system to locate and identify surface defects on boards is proposed. Other studies concerning surface of wood images processing have been performed for knots detection in woods. In a different approach (Kyllonen and Pietikainen, 2000) a method which combines color features and texture features based on simple spatial operators for wood inspection is proposed while in (Gu et al., 2009) a tree-structure support vector machine (SVM) is proposed to classify four types of wood knots. Zhang et al. (2013) proposed defect detection based on a SOM (self-organizing map) neural network that requires fewer training samples. In (Zhang et al., 2015) principal component analysis (PCA) and compressed sensing are used to detect wood defects from wood plate images. Moreover, Hittawe et al. (2015) proposed the creation of a dictionary based on bag-of-words. The dictionary was obtained using LBP or SURF features and contrast enhancement, entropy maximization and image filtering was used to detect the potential defect regions using SVM classifier. More recently, Barmpoutis and Lefakis (2016) proposed a method for surface analysis and classifying three categories of woods using histograms, central moments and SVM classifier.

In this paper, to address the problem of detection of various characteristics on wooden surfaces we propose a novel algorithm which makes the following contributions:

- Detects various characteristics on wooden surfaces, using scanner and image processing techniques.
- Six different categories of wood samples are discriminated, namely, wood samples with cracks, wood samples containing annual growth rings, wood samples with relief, wood samples containing notches, wood samples containing holes and normal-clean wood samples which do not contain any of above characteristics.
- Statistical techniques are used and features are retrieved from grayscale images of woods and spatial texture analysis.
- Significant improvement in the classification results achieved through introduced dynamic score combination by mean value in multiclass, based on (Piras et al., 2013). It is used to obtain the final decision.

The rest of the paper is organized as follows: Section 2 describes in detail the different processing steps of the proposed approach. Experimental results are discussed in Section 3. Finally, conclusions are drawn in Section 4.

2. METHODOLOGY

The proposed method for detection of various characteristics on wooden surfaces, using scanner and image processing techniques scheme is shown in *Figure 1*. In the first step of the experiments, the surface of each wood sample is scanned. Data processing is then applied to each image. After that, to calculate statistical properties, histograms are computed both from grayscale images and images on which spatial analysis has been applied. Separately classifiers for two above elements are used to estimate the probabilities of woods belonging in a category of examined woods. Finally, dynamic score combination by mean value in multiclass is used to determine final decision about wood category. We contacted extensive tests and we analyzed the contribution of each feature.

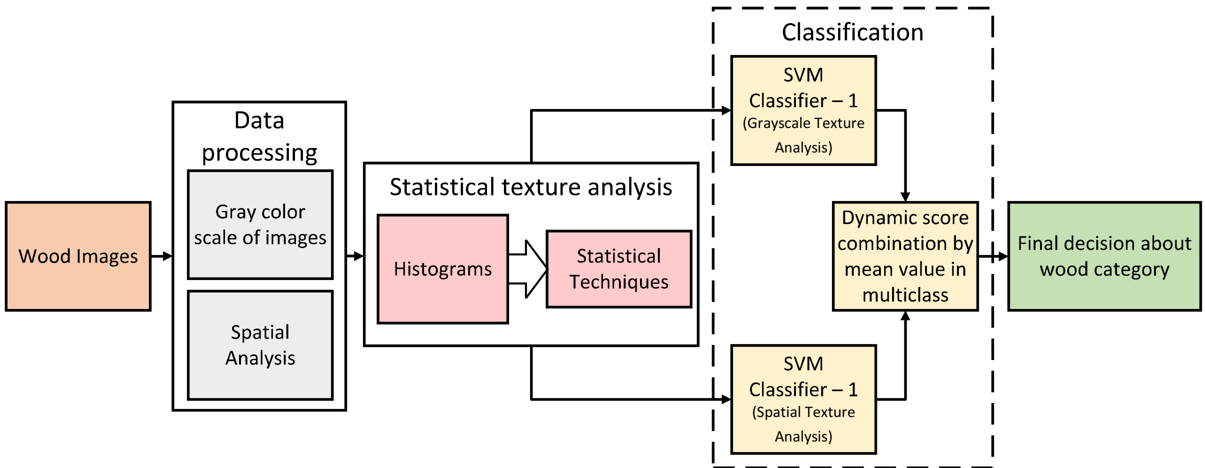
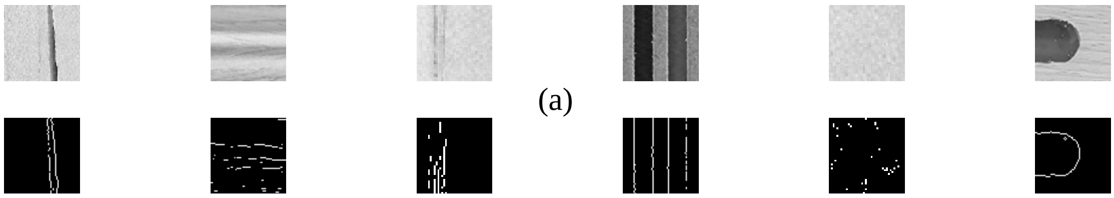


Figure 1. Overview of the proposed approach

2.1. Data processing

Wooden surfaces are scanned and images are converted to grayscale. A grayscale digital image is an image in which the value of each pixel is a single sample and carries intensity information. Apart from the usage of grayscale images, spatial analysis is applied in each image for detecting edges. The different methods for edge detection may be grouped into two categories: a) Gradient methods which find maximum and minimum values in the first derivative of images and b) Laplacian methods that search for zero crossings in the second derivative of images (Maini and Aggarwal, 2009). In the proposed approach we use a gradient method and specifically Sobel edge detector which is a powerful image processing technique that has considerable potential to quantify spatial variation on wood images. Spatial analysis returns edges at those points where the gradient of wood image is maximum.



(a)

(b)

Figure 2. Various wooden surfaces in a) grayscale images and b) images on which spatial analysis has been applied.

2.2. Statistical texture analysis

An important feature of an image is the texture. The technical description of texture can be grouped into three broad categories: statistical, spectral and structural. The statistical techniques primarily describe texture of regions in an image through higher-order moments of their grayscale histograms. The histogram of a digital image is a distribution of its discrete intensity levels. It is a graph showing the number of pixels in an image at each different intensity value found in that image. Statistical techniques measure contrast and indicate the existence of roughness. As seen in *Figure 1*, in the next step histograms of images are calculated. For each image, a vector of four features is computed using the statistical moments of the intensity histogram of images: a) mean, b) variance, c) skewness and d) kurtosis.

The mean of an image is simply the arithmetic average of the values of each image pixel, obtained by summing the values and dividing by the number of values. The mean (1) is a measure of the center of the image values distribution. The variance (2) of an image is the arithmetic average of the squared differences between the values and the mean. The variance is a measure of the spread of the distribution around the mean. The skewness (3) represents an imbalance and asymmetry from the mean of an image data distribution. Kurtosis (4) is a measure of whether image data is heavy-tailed or light-tailed relative to a normal distribution. Image values data sets with high kurtosis tend to have heavy tails on their values, or outliers. Image values data sets with low kurtosis tend to have light tails on their values, or lack of outliers.

If an image consists of N pixels and the intensity level of a pixel is g, then the $h(g)$ is the total number of image pixels with intensity level g. $H(g) = h(g)/N$ is the normalized histogram. The first four central moments are given by the equations:

Mean:

$$\mu = \sum_{g} gH(g) \tag{1}$$

Variance:

$$\sigma^2 = \sum_{g} (g-\mu)^2 H(g) \tag{2}$$

Skewness:

$$\mu_3 = \frac{1}{\sigma^3}\sum_{g}(g-\mu)^3 H(g) \tag{3}$$

Kurtosis:

$$\mu_4 = \frac{1}{\sigma^4}\sum_{g}(g-\mu)^4 H(g) - 3 \tag{4}$$

A vector which contains the above four features is computed for grayscale images and images that are based on spatial analysis respectively.

2.3. Classification

As a last step, the dynamic score combination by mean value in multiclass is used to obtain the final decision about the category that each wood belongs to. As we mentioned for each of the two elements (grayscale and spatial texture analysis) a SVM classifier is used for estimating probabilities for each image to belong to a classifying category. Using the above probabilities for each image six feature vectors (j=6, one for each category) are created. Each of them consists of the two probabilities p_j^i, $i = 1,2$ (*i=1* grayscale texture analysis, *i=2* spatial texture analysis). These vectors are fed as input to the dynamic score combination by mean value in the proposed multiclass problem:

$$a_j = \frac{1}{m}\left(\sum_{i=1}^{m} p_j^i\right) \tag{5}$$

where $m = 2$ is the number of proposed elements (grayscale and spatial texture analysis).

$$d_j = (1 - a_j)\min_i\{p_j^i\} + a_j \max_i\{p_j^i\} \tag{6}$$

Then each wood sample is classified by selecting the maximum score: $max(d^j)$.

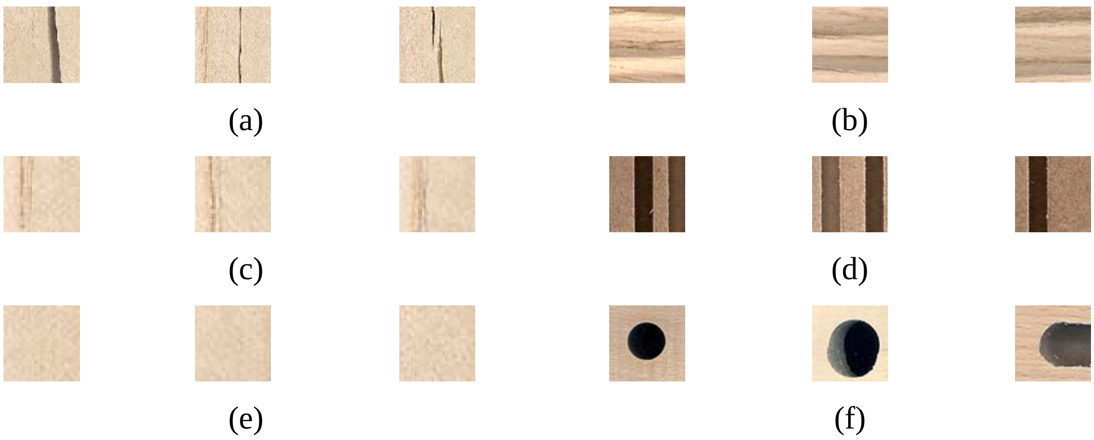


Figure 3. Images of a) wood samples containing cracks, b) wood samples with relief , c) wood samples containing annual growth rings, d) wood samples containing notches e) normal-clean wood samples which do not contain any of other characteristics and f) wood samples containing notches.

3. EXPERIMENTAL RESULTS

The assessment of the proposed methodology of surface analysis is detailed next. The goal of the assessment is three-fold. Firstly we evaluate our algorithm on the dataset (*Figure 3*), which consists of one hundred and forty four samples (twenty four images of samples for each category). The training and testing set has been formed by using twelve images of each category respectively. Secondly, in terms of the contribution of each feature in the classification process we elaborate a more detailed analysis. In each evaluation test, we follow the same training strategy for the classifying, i.e., the same training and testing set. Thirdly, the following validation tests concern the detection rate of each of the species separately. In the application domain of detection of various characteristics on wooden surfaces, we selected the following wood categories: a) wood samples with cracks b) wood samples containing annual growth rings c) wood samples with relief d) wood samples containing notches e) wood samples containing holes and f) normal-clean wood samples which do not contain any of above characteristics.

For the purposes of this research, samples from different wood species are used, like wood of tree of heaven (Ailanthus altissima, Mill.), a wood with ring porous structure, as well as samples from MDF, a wood product that surface is more uniform than natural woods. The resolution of wood images is 40x40 pixels.

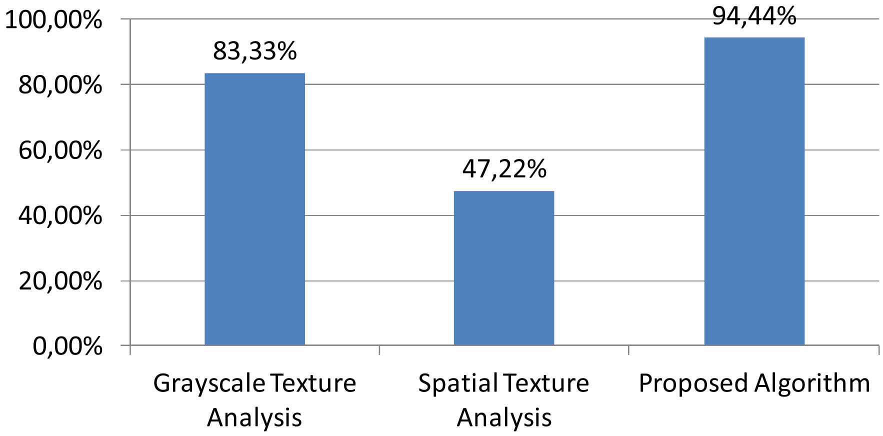


Figure 4. Results of proposed methodology

The proposed method achieves an average true detection rate of 94,44%. To further analyze the detection efficiency of the proposed algorithm, we provide a detailed study regarding the contribution of each feature in the classification process. We analyze each of the two main elements of the proposed method, i.e., grayscale texture analysis and spatial texture analysis. To have comparable results, we use the same training and test dataset using SVM classifier. As is clear grayscale texture analysis produces higher detection rate, 83,33%, than spatial texture analysis, 47,22% (*Figure 4*). The above analysis makes evident that each of the elements of the proposed algorithm plays a crucial role.

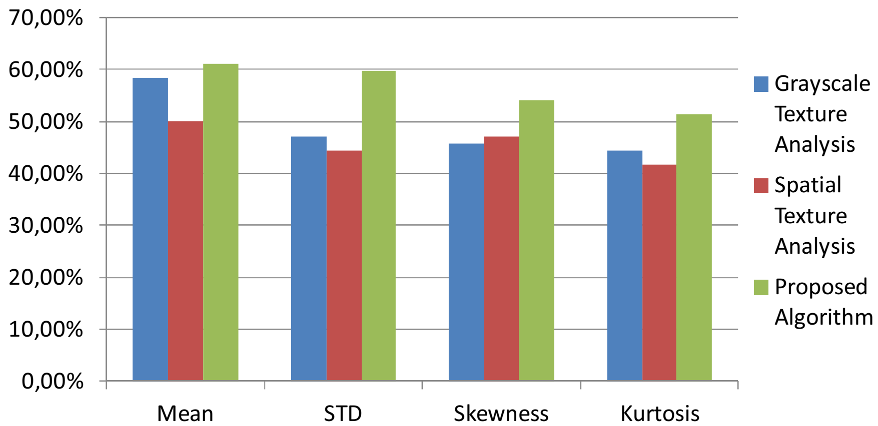


Figure 5. Contribution of the main four features of the proposed algorithm to the classification process

To have a more clear view, we analyze the contribution of each one of the four features of the proposed method for each category seperately. In each evaluation test we take into account one feature for the classification process. As it is clearly shown (*Figure 5*), the mean produces higher detection rate, 61,11%, than STD, 59,72%, while the detection rate for skewness is 54,17% and the detection rate for kurtosis is 51,39%.

The overall brightness of the wood is represented by the mean and the STD indicates the distribution of brightness values around the mean. Furthermore, the skewness indicates the asymmetry of brightness values around the mean and the kurtosis is a measure that reveals the existence of pulses.

The following validation tests concern the detection rate for each category of wood samples seperately: 91,67% for woods containing cracks, 100% for woods containing annual growth rings, 91,67% for wood samples with relief, 83,33% for wood samples containing notches, 100% for wood samples containing holes and 100% for normal wood samples which do not contain any of above characteristics. The contribution of each element for each category of wood samples is shown in *Figure 6*.

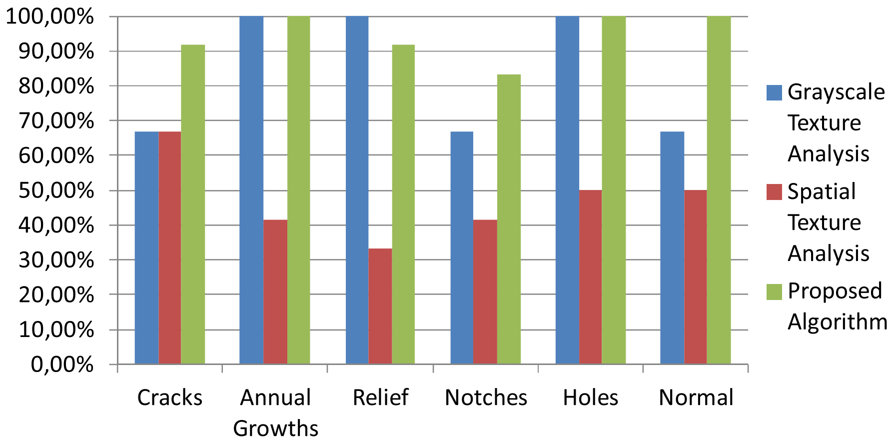


Figure 6. Experimental results for six categories of woods.

4. CONCLUSION

In this paper, we have proposed a new method using images that are retrieved from scanner. It has been demonstrated that the histogram of grayscale images as well as images that are based on spatial analysis, and the first four central moments could be used to analyze the surface of woods. The proposed method can be accommodated if any wood sample belongs in one of the following categories: wood samples with cracks, wood samples containing annual growth rings, wood samples with relief, wood samples containing notches, wood samples containing holes and normal-clean wood samples which do not contain any of above characteristics. Further research may be focused on different wood species, on retrieving images from mobile devices and on combining the proposed method with more image filters to improve the detection rates.

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