Classification of Wood Logs Based on Texture Features

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Abstract- This paper presents the variety of wood logs classification system using the texture features existing in the wood logs barks. Every variety of wood logs has its own uncommon pattern in its bark, which allowed the present system to classify it correctly. Automated wood logs classification system has not yet been well founded essentially due to insufficiency of research in this field and the problem in accessing the wood logs datasets. In our attempt, wood logs classification system has been performed based on pre-processing techniques, feature extraction and by interacting the features of those wood logs variety for their classification. The most well-known technique used for the texture classification is Gray-level Co-occurrence Matrices (GLCM). The features from the enhanced images are extracted using the GLCM is interacted, which terminates the classification between the different wood logs variety. The execution thus get display a high rate of classification accuracy verifying that the techniques used in applicable to be achieved for economic prospect.

Keywords- *Grey Level Co-Occurrence Matrix K-Nearest Neighbor classifier, Wood Classification.*

I. INTRODUCTION

There's plenty of it, it's relatively cheap (or even free), it's environmentally friendly, it looks great, it's warm and cozy, it's super-strong, it lasts hundreds or even thousands of years, and you can use it for everything from building bridges to making paper or heating your home. It's wood—and it's quite possibly the most useful and versatile material on the planet, with many thousands of different uses. The challenge of wood is its variability: the color, density, texture and even the smell of a wood can differ from tree to tree although all these aspects may equally help you to identify something. Ageing, stains, varnishes and usage can further alter the appearance. So whilst this box contains many wood samples, it is noticeable that the actual objects rarely match up exactly with them! An experienced eye, with a good knowledge of the properties of wood, should be able to make a 'best guess' at the genus of wood. However, it is extremely unlikely that you will be able to identify the exact species. These resources therefore concentrate on the most common genus. If you wish to look at the range of species, Terry Porter's book on Wood Identification & Use has been included, as this contains some good color illustrations. The best approach to wood is therefore to consider the function of the object, and what properties this may require.

The following pages on individual woods concentrate on significant properties and common uses. Combine this with a consideration of: 3. Identifying wood – easy places to start Color Looking at the samples in the box will show you that color can vary considerably, especially with the application of stains and varnishes. However, the tone should remain fairly consistent within a genus. A few woods have extremely distinctive color characteristics e.g. rosewood can be dark purple. Grain The grain is the visual effects produced by the rings, rays and pores on cut surfaces. It can be very distinct, or it can be scarcely visible at all. Smell Wood will smell the most when freshly cut. Items in collections are therefore unlikely to be particularly strong smelling, especially if varnished. However, interior surfaces may retain some odor.

Place of production Vernacular furniture and tureen is likely to have been locally made, at least until the late 19th century. It is worth knowing, therefore, which trees grow successfully in your region. This guide is separated into native and non-native species, so you can quickly see which woods are most likely to be found in the UK. For smarter items of furniture and high-value items, the exterior woods may well be imported, especially for fine veneers. However, the interior construction was still likely to be locally sourced. Examine the sides and backs of drawers, for example, to see if they are of a different wood. Other considerations Other aids to identification include the appearance of the rays, the hardness and weight of the wood.

The automated classification system is used to make volume information from the scale more meaningful and useful to traders in wood logs and managers of forest resources. The quality and potential end use of wood logs has significant influence on their value. In addition to monetary values, wood log classify can also determine whether wood logs are accounted for cut control purposes. Classification is a key component in marketing finished products such as lumber, plywood and shingles . The scalars' challenge is to assess the visible characteristics of each wood log, and, with strict reference to schedules of log classify, determine what can be recovered from it. As classification is in place to make scale data more meaningful it must serve many users including buyers, sellers and forest administrators. An automated classification must also be responsive to changes in utilization, forest practices and administration. While log classification have evolved and expanded in response to changing needs.

II. LITERATURE REVIEW

Over the years the forest products industry has recognized the importance of automation for yield improvement. While a few automated systems for defect detection have been introduced into the industry, most are limited in applications or have fallen short of expectations. Current automated optimizing cut-up systems in industry are based on single sensor technologies which are usually laser or camera based. The introduction of comprehensive and accurate automated defect detection will lead to improvements in lumber recovery and utilization of lower grades which could lead to drastic restructuring of the furniture and dimension industry. To reach the goal of reliable and comprehensive defect detection, a large amount of research has been conducted on various sensor types. The following is a review of the current research that has been accomplished to reach this goal. The majority of the research has been conducted on applying different types of sensing technologies to wood feature detection in order to test their abilities and limitations. Considerable work has been done over the last 15 years concerning the ability of various nondestructive evaluation methods to automatically detect features in wood (Szymani and McDonald, 1981; Portola and Ciccotelli, 1992). Methods that have been shown to be promising include optical, ultrasonic, microwave, nuclear magnetic resonance (NMR), and x-ray sensing techniques.

III. PROPOSED METHODOLOGY

In the proposed system the classification of wood logs based on its quality by first applying the preprocessing techniques. Extraction of texture features performed using GLCM and K-Nearest Neighbor is adopted for classifying the different qualities of wood logs. The proposed method is summarized on the diagram

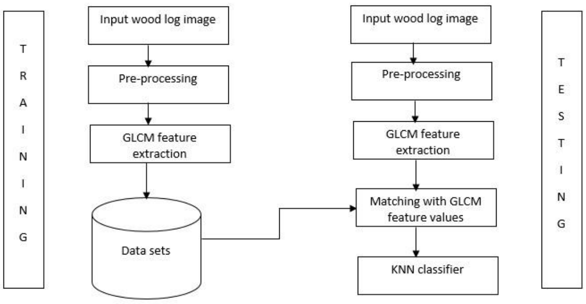


Fig.1: Proposed Model

Data Acquisition:

Data set consists of a total of 15 image samples of wood logs. This image set was further divided into three subsets (5 is neem, 5 is timber and the rest 5 are beete). Images are collected from the web of the image samples. The following are the few of the image samples in each category:

Neem wood log:

Beete wood log:

$$P(i,j) = \frac{P_d(i,j)}{\sum_{i,j=0}^{N-1} P_d(i,j)} \qquad (2)$$

IV. PRE PROCESSING

The next step in this application for the pre-processing steps of the image chosen for the analysis. This process includes resizing, gray scale conversion and by normalization of an wood log images.

V. FEATURE EXTRACTION

In this step we extract the desired features from the sample image for the analysis of two different classes of wood logs. Texture Feature Extraction is employed.

GLCM Feature Extractor:

Due to their stochastic nature, wood textures can be characterized by statistical means into first, second and higher-order statistics. Therefore, a texture analysis method was used to extract the distinct features of each wood. Texture analysis methods have been utilized in a variety of application domains such as remote sensing, surface inspection, medical imaging, and remote sensing (Jain et al., 2000). From our investigation of several texture analysis methods, the grey level co-occurrence matrix (GLCM) seems appropriate (Haralick 1973, 1979), though it has never been used in wood recognition application. In this approach, the textural features of an image I is based on the assumption that the texture information is contained in the overall or average spatial relationship which the grey tones in the image I have with one another. More specifically, this texture information is adequately specified by a set of grey tone spatial dependence matrices that are computed for various angular relationships and distances between neighboring resolution cell-pairs on the image. The features are derived from these grey tone spatial dependence matrices. The GLCM approach can be described as follows. Consider $\{I(x, y), 0 \le x \le N-1, 0 \le y \le N-1\}$ such that it denotes an $N \times N$ image with G grey levels. The $G \times G$ grey level co-occurrence matrix Pd for a displacement vector $d = (dx, dy)$ is defined as follows. The entry (i,j) of Pd is the number of occurrences of the pair of grey levels i and j which

are a distance d apart. Formally, it is given as in Equation (1) where:
$(r, s), (t, v) \in N \times N, (t, v) = (r + dx, s + dy)$, and |.| is the

cardinality of a set.
$Pd(i, j) = |\{((r, s), (t, v)) : I(r, s) = i, I(t,v) = j\}$

For each wood log, the co-occurrence matrices are calculated from four directions, which are horizontal, vertical, diagonal 45o and diagonal 135o. A new matrix is formed as the average of these matrices that is used for extracting the features. In this way, the extracted features will be rotation invariant at least for 45° steps of rotation. The final co-occurrence matrix is normalized using Equation (2) to transform GLCM matrix into a close approximation of the probability table.
Where Pd is GLCM matrices value of and N is range of i and j. The total features extracted using the GLCM approach from each wood sample orientation are given as follows:

1. Angular Second Moment

$$f_1 = \sum_i \sum_j \{P(i, j)\}^2 \qquad (3)$$

2. Contrast

$$f_2 = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=1}^{N} \sum_{j=1}^{N} P(i, j) \right\} \qquad (4)$$

3. Correlation

$$f_3 = \frac{\sum_i \sum_j (ij) P_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y} \qquad (5)$$

Where µx and µy are mean value and σx and σy are standard deviation.

4. Entropy

$$f_4 = -\sum_i \sum_j P_{ij} \log(P_{ij}) \qquad (6)$$

5. Inverse Difference Moment

$$f_5 = \sum_i \sum_j \frac{1}{1 + (i - j)^2} P_{ij} \qquad (7)$$

VI. CLASSIFICATION

Classification is done based on the different classes of wood logs. Wood logs is classified into three categories neem, timber and beete by using K-Nearest Neighbor (KNN). The classification tree is given in (Figure.2)

VII. EXPERIMENTAL RESULTS

Class 1 (Neem)

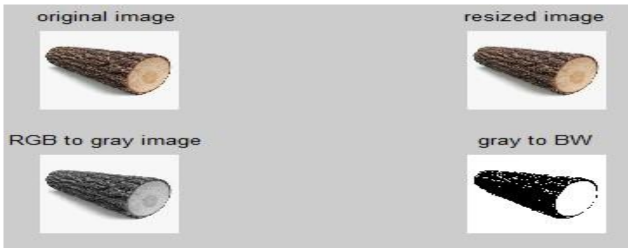


Fig.1: conversion of gray and binary image of neem wood log.

Class 2 (Timber)

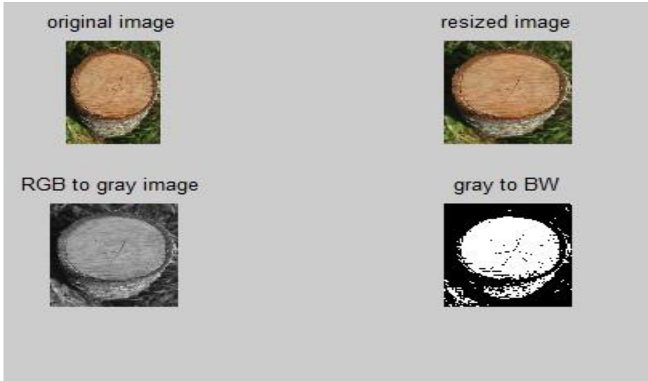


Fig.2: conversion of gray and binary image of timber wood log.

Class 3 (Beete)

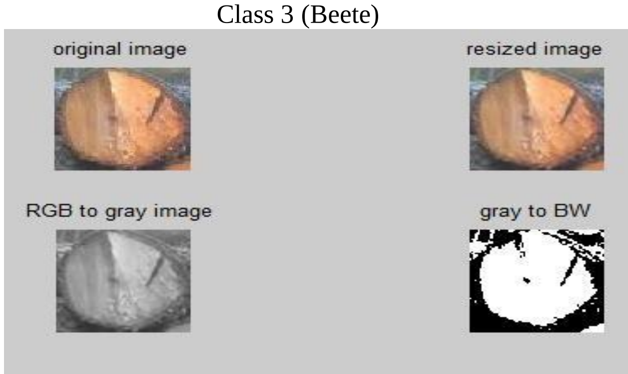
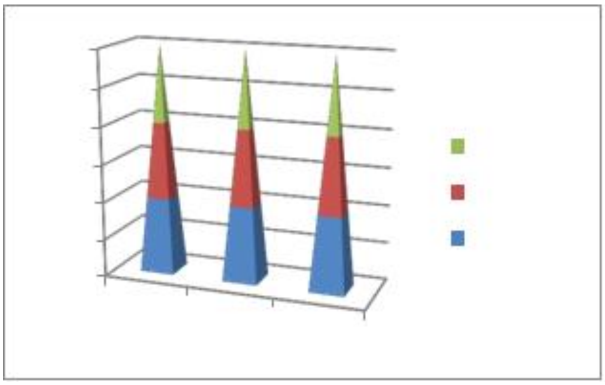


Fig.3: conversion of gray and binary image of beete wood log

Table 1:Accuracy rate for three different classes of wood logs.

class	precision	recall	f-
Neem	100	100	100
Timber	100	100	100
Beete	100	100	100



Graph 1:F-measure for three different classes of wood logs.

VIII. CONCLUSION

The wood logs classification is harmfully important for wood industries and sciences because it clarifies the anatomic features and properties of wood, which determine how the wood species is used. As a new research area, wood recognition remains particularly challenging in computer vision (CV) and pattern recognition (PR) fields. The automatic system for the classification of wood logs variety is based on artificial intelligence techniques has been proposed. The system was objectively designed to be cost- effective and as a means to replace wood inspectors due to difficulty in recruiting them as the job is rather laborious. The selection of features through the determination of the parameters that construct GLCM also very important because quite affects the accuracy and precision from the classification process, especially that use Roberts operator in pre-processing stage.

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