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Discrimination of bark from wood chips through texture analysis by image processing ☆

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ABSTRACT

Utilization of wood chips for bioenergy requires classification and segregation of the constituents of the chipped mass to help optimize energy conversion. Wood chips obtained from processes such as forest thinning can contain a considerable amount of material other than wood chips, such as bark. An image processing algorithm was developed to discriminate bark from wood chips. The algorithm involved object identification, image capture, single value decomposition to describe wood texture evident in grayscale image with a single numerical value, and application of logistic models involving the single values representative of wood texture to predict whether a chip is bark. The percentage of correct predictions using this system was about 98%.

1. Introduction

Use of waste wood as feedstock for the production of gaseous or liquid fuels shows promise as an economical and sustainable means of meeting fuel needs without diverting biomass resources from their current use in non-energy products. However, with lesser grade woody material, bark and foreign matter could become a problem, possibly increasing ash content. In particular, bark is a major contaminant in wood chips for pulping (Christie, 1987) and this is likewise the case for energy conversion processes. Therefore, separation of bark from the chipped wood would optimize pulping and energy conversion processes.

High rate and accurate examination of large volumes of material, such as wood chips, for inspection, classification, or measurement requires automated systems involving image processing. Automatic visual inspection or machine vision systems are nowadays used with good results in a wide range of applications (Piuri et al., 2005). Machine vision results in simple, rapid, efficient, consistent, economical, robust, recordable, and objective measurement and assessment of several products (Brosnan and Sun, 2002; Bucur, 2003; Simonton and Pease, 1993; Zheng et al., 2006a,b; Zion et al., 1999). In the field of wood science and technology, automated photoanalysis has become the universally accepted standard for wood chip sizing in the forestry and pulp sectors (Petterson et al., 1988; Thomson, 2006). Image processing has also found application in board quality and structure evaluation (Achiche et al., 2005; Bucur, 2003; Christy et al., 2005; Kurdthongmee, 2008; Piuri et al., 2005) and dirt counting (Fastenau et al., 1991; Ruuska et al., 2008). It is distinctly possible that optical image processing can be applied to the separation of bark from wood chips by developing an appropriate image acquisition and processing algorithm. However, this is premised on discovering suitable image parameters, and desirably a singular one, for accurate discrimination.

The most notable attribute of wood chips that is visually discernable is the grain pattern (Fig. 1). Grain is relatively uniform across the chip and can be considered a texture. In image processing, texture can be defined as the local variance in brightness from one small region to the next (Haralick et al., 1973; Zucker et al., 1975). Texture can be thought of as the roughness of the image. The roughness may be in a random pattern or with some uniformly predictable pattern. If large areas have a predictable pattern, they would be considered having the same texture.

Single value decomposition is the process of describing an image or object in an image with one value. An example is an arithmetic mean or a population variance. Single value decompositions have been used to describe textures in numerous applications (Dutta et al., 1995). One of the easiest forms of single value decomposition is using a convolution mask to determine an appropriate parameter. It was proposed that this manner of decomposition may be applied

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Fig. 1. Samples of wood and bark chips of oak showing the presence and absence of grain textures.

to determine discrimination parameters for the separation of bark from wood in a bulk. For high speed, high volume screening, better efficiency is achieved when simple algorithms are superimposed over an automated system. Therefore, the objective of the study was to discover a singular attribute of an image of a wood chip piece in order to determine if the object is wood or bark. The ultimate goal is to be able to examine each object in a bulk of chipped wood and be able to determine if it is wood or bark.

2. Material and methods

2.1. Algorithm development strategy

Development of the algorithm for wood-bark discrimination was the focal point of the research effort; thus, this was the basis for the experimental and developmental work planned and undertaken. Focusing on the texture difference between wood and bark, preliminary image acquisition of individual chips was undertaken to identify image attributes related to texture that could key the differentiation. This step was built on extensive prior work on object detection (detection of singulated chips of wood or bark) and image capture (Wooten, 1996). The identified image attributes were then quantitatively condensed into respective single statistical parameters representative of an entire object (a single chip of wood or bark). This operation was repeated for a large number of chips to develop a data set consisting of numerous entries of several statistical parameters tagged per chip that would be representative of wood or bark of a particular type of wood. The set of statistical parameters for a particular type of wood was then used in the development of logistic models (from logistic regression) that would serve to predict whether any examined chip is wood or bark. Thereafter, the image attributes of individual chips in the combined data set (all wood types) were then used to develop logistic models that would provide a decision on whether individual chips in a bulk of mixed types are wood or bark based on their image parameters. The prediction statistics were then analyzed to assess the accuracy of each logistic model and, by extension, the effectiveness of each discrimination parameter.

2.2. Test materials and equipment

Bulk samples of wood chips containing both wood and bark were procured. Three different types of wood were used. Oak (*Quercus* spp.) and pine (*Pinus* spp.) were used to represent hardwood and softwood, respectively. Elm (*Ulmus* spp.) was also used because it has little grain or texture, and represents the extreme for wood lacking visible grain (Fig. 1). Lots of wood chips and bark for each of the three wood types were separated for testing.

The wood/bark chip images acquired and analyzed for the study amounted to the numbers presented in Table 1. The samples pooled together comprised the combined set. Discrimination parameters were determined for each of these chips and then analyzed.

The image acquisition setup for this project consisted of a NTSC (national television standard committee) video camera (Model AG-190, Panasonic Corporation of North America, Secaucus, NJ, USA), a camera tripod, and various colored backgrounds made from poster board. The fluorescent green provided the highest intensity to the background, and the greatest contrast to the wood chips. Four 120 W incandescent indoor residential type spotlights and two light diffusers were used in various spatial configurations and orientations to determine optimal lighting. Digitization was accomplished by a 24-bit color frame grabber (CFG) installed in the work computer. The CFG had an NTSC output port for CRT monitor viewing of the image. The camera was aimed perpendicular to the plane of the sample comprised of 5–6 chips overlayed on a background large enough to fill the camera field of vision when the camera lens was zoomed to display an image 17.3 cm wide and 13.1 cm high on the flat display monitor having a resolution of 640×480 pixels.

The software library for image capture was ITEX CFG version 2.0 (Image Technology Inc., Bedford, Mass., USA). Borland C++ version 5.2 (Borland, Austin, Texas, USA) was used to compile the developed source program. The algorithms used for filtering and object detection were standard routines available in most image processing text books (Kanade, 1980; Pratt, 1991; Russ, 1992; Zucker et al., 1975). Box and median filters were used to remove noise and/or extreme variations in image details.

2.3. Optimum object detection

The order of image manipulation operations applied to grayscale images that provided the best overall results for object detection was the sequence below (Wooten, 1996). This was consistently followed in the study.

1. Two passes of the 5×5 octagonal median filter to remove noise and surface detail that would interfere with object detection.
2. Thresholding to determine the object boundaries.
3. Another pass through the median filter to remove any small noisy spots or pixels detected in the thresholding operation.
4. Two passes of the dilation operation to close any defects in the edges and to remove the outer edge and background of the object from being used in analysis.
5. Application of the area growing operation to identify the area of the objects.

Table 1
Sample numbers for each test set.

Type of wood	Number of samples	
	Bark	Wood
Oak	110	84
Pine	297	144
Elm	26	46
Combined	433	274