Detection of Trimmed and Occluded Branches on Harvested Tree Stems using Texture Analysis

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ABSTRACT

This paper describes a prototype computer vision system based on texture analysis that can automatically locate and identify certain classes of defects on freshly harvested tree stems (with bark present) by using digital camera imagery. This system includes two modules: (1) a feature extraction or "computing" module for estimating the oriented texture field from the raw image of the surface of a log; and (2) a scene analysis and detection module for analysing the oriented texture field. Basic principles of the system based on the gradient of the Gaussian filter have been given.

The sample digital images processed in this study are of sections of freshly harvested Radiata pine tree stems with bark still on them. The feasibility of the computer vision system has been very well demonstrated by initial experimental results.

This study has also resulted in a new taxonomy for texture description and identification in the field of forestry. Texture analysis technology has been found to be a potentially powerful approach to determine wood properties, timber and log quality.

The system developed in this study can be widely applied into forest industry activities and research.

Keywords: *Image processing, texture analysis, taxonomy, freshly harvested tree stem, external defects, bark, computer vision.*

INTRODUCTION

The commercial forest estate of New Zealand is currently 1.5 million ha (~5% of the land area), and is expanding at an average rate of about 70,000 ha/annum. Ninety percent of the plantation forest area is in one species, *Pinus radiata* D.Don, with an average growth rate in excess 20 m^3/ha/annum. This allows sawlog rotations of between 25 and 35 years. Harvested volumes are projected to double from the current level of 16 million m^3 within 15 years due to the high proportion of young plantations (NZ Forest Owners Association, 1996). The effective use of this large resource is very important for New Zealand's economy.

Many variables in forest management affect log quality which determines the value of the resource. The consequences of this are:

- Wood quality is variable within trees (different parts of each tree have different wood quality);
- Different parts in a tree may have very different uses;
- There are large differences in market value for high and low quality logs;
- Log defects are variable and difficult to predict;
- It is difficult to accurately and rapidly detect and measure the defects of freshly harvested tree stem with bark by manual methods.

Log making and grading are necessary to optimise the use of the resource and to maximise its value. Murphy and Cossens (1995) report that in New Zealand 5 to 15% of the forest owner's potential value is lost through manual log-making efforts. Murphy et al. (1996) provide an early progress report on the Forest Research Insitute's integrated and computerised value management system which is expected to capture much of this value loss for the forest industry. Their system will include the application of computer vision technologies for rapidly measuring stem geometry and detecting log defects automatically in the forest.

In addition, automated log inspection systems have the potential to increase mill productivity for the wood producer and to improve the quality of the material derived from logs. The value of the softwood timber cut from a log depends on the timber's quality, which in turn depends on the total clear area on a board's surface. Numerous studies (e.g., Occena et. al. 1989 and Steele et. al. 1989) suggest that at least 10 to 20% improvement in timber value can result from a well-chosen breakdown strategy (or saw

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pattern). Thus it seems reasonable to suppose that if one can locate and identify defects of a log prior to its breakdown into timber then one should obtain the highest possible value.

Currently, log inspection at the mills is mainly performed by human experts, but their performance is quite variable. Some researchers have tried to detect log defects using CT or X-ray scanners (Zhu 1996). Defects were determined afterwards using traditional image processing methods. No one has attempted to create a general-purpose computer vision system for detecting defects in freshly harvested tree stems in the forest. Traditional image processing technologies are not suitable for the images of log with the bark still present. Also these scanners can not be set up and do not work properly in the difficult and "dirty" environment at the log making site.

This study aimed at developing a new computer vision system based on bark texture analysis to detect knots in freshly harvested tree stems. The system consists of 3 components: (1) a data acquisition system (eg. digital camera), (2) a feature extraction module for. estimating a texture orientation field from raw images), and (3) a scene analysis and detection module for analysing the oriented texture field.

PROBLEM BACKGROUND

Scanning Technology

In recent years, much research on log making and grading has focused on log scanning technology. Inspection techniques for measuring the shape of a log have been tested and described in a number of published papers. The main techniques tested are optical (Araman et al. 1995, Lane and Murphy 1995 and Tian et al. 1995), X-ray (Wagner et al. 1990, Wells et al. 1991, Aune 1995, Cown and Tian 1995), microwave (Martin P. et al. 1995) and ultrasound technologies (Han 1994).

All current scanning technologies have their advantages and disadvantages (Tian et al. 1996). We believe it is necessary to develop a new technology which can automatically recognise defects and enable rapid and accurate measurement of log geometry and quality features.. Murphy et al. (1995, 1996) have described a value management system, whereby a network of electronic tools regularly feed information about trees, which have been optimally cut into logs, to a centralised computer. Digital camera technology is an effective and low cost means of capturing images and, therefore, multi image digital photogrammetry are useful for capturing tree stem data (Lane and Murphy 1995). This tool, which is still in the early stages of development as a computer vision system for freshly harvested tree stems will be able to automatically measure the geometric information (eg. diameter, sweep, ovality and length) along with log quality features such as knot size and position, scarring, splitting, and whorls.

Recent research efforts on improving this tool have focused on developing an effective way to determine the external quality features in freshly harvested tree stems under the variable and complex environmental conditions of the log making site.

For this study, a portable digital camera (Kodak DC-50) connected to a notebook PC has been used to capture log images.

Environmental Obstacles

The automated detection of quality features on a freshly harvested tree stem with the bark still present is much more difficult than simply capturing geometric information because it will be affected by many negative factors.

Variable and complex environmental conditions at the log making site are the main problem. The quality and utility of images captured by optical methods vary with the weather. On overcast days, insufficient lighting reduces recognisable visibility; on rainy days, the surface of the tree stem may be covered by mud, which produces fuzzy information interfering with log defect recognition. The shade of other tree stems may cause some confusing images. In addition, man-made "image noise", such as mechanical injuries or where bark has been knocked off, may cause some un-natural patterns in the image to be incorrectly identified as defects.

The determination of defect size and position on freshly harvested tree stems will still be a very complex problem in computer vision and pattern recognition even if the image is quite clear. This is mainly because the size and shape of log defects can not be categorised clearly like those of simple objects with regular shapes (such as a square, a circle etc.). The computer vision system should be able to recognise both freshly trimmed and occluded branches. Freshly trimmed branches show a branch stub and discontinuous bark cover. Trimmed branches do not directly indicate the position of the knot within the log, because the knot is not perpendicular to the pith as the angle between knot and the pith is normally greater than 20°. On pruned sections of a tree stem the branch stubs may be occluded. The sizes of knots in this case is itself a fuzzy concept because the knots do not directly show on the surface and may only be expressed through the bark texture.

It is very hard to detect the positions and sizes of trimmed or occluded knots using traditional methods in image processing (such as threshold methods based on grey level value, its color index and geometry information) because the image information may be very noisy due to environmental factors. The bark texture of a stem's surface does not change when environmental conditions change, so it may be an effective way to determine the position of knots on logs using texture analysis and flow visualisation analysis technologies.

TEXTURE OF LOG BARK

Defining Texture and its Taxonomy for Forest Applications

Webster's dictionary defines texture as "the visual or tactile surface characteristics and appearance of something". This calls for a distinction between the visual and tactile dimensions of texture. The texture of a reptile skin can be a good illustration of this point: apart from being smooth (the tactile dimension) it also has got cellular and specular markings on it that form a well defined pattern (the visual dimension). Interestingly, most researchers in computer vision do not make use of texture in their work.

In this paper, we have restricted ourselves to the visual dimension of texture as commonly done in computer vision, and adopted a more general view of texture in forestry applications considering it to be "the surface marking or 2D appearance of a surface" (Rao 1990).

We classify texture into several types by using texture description. Currently there are two main approaches to texture description: structural and statistical ones.

The structural approach tries to describe a repetitive texture in terms of the primitive elements and placement rules that describe geometrical relationships between these elements. We will refer to those textures that are amenable to a structural description as being strongly ordered textures. Strongly ordered textures, symbolised by **S**, are those which exhibit either a specific placement of some primitive element (like a piece of furniture or wooden wall, Figure 1 (a)) or are comprised of a distribution of a class of elements (such as a tree crown or tracheid length image, Figure 1 (b)).

The goal of the statistical approach, on the other hand, is to estimate parameters of some random processes, such as Marcov random fields, which could have generated the original texture. Disordered textures, symbolised by **D**, are those that show neither repetitiveness nor orientation and may be described on the basis of their roughness.

An important category of texture which can neither be modelled statistically nor structurally is that of weakly ordered texture or oriented texture. Such textures are characterised by a dominant local orientation at each point of the texture, which can vary arbitrarily. The importance of weakly ordered textures in determining surface orientation was described by Gibson (1950). Weakly ordered textures, symbolised by **W**, are those that exhibit some degree of orientation specificity at each point of the texture (such as knot in a piece of timber, Figure 1(c) and (d); bark surface texture without knot, Figure 1(e); and log surface texture with bark and knots Figure 1(f).

In forest applications, a texture image can be defined as any image that can be created by either a linear combination or functional composition or both, followed by an opaque overlap, or primitive texture. A primitive texture is either strongly ordered texture (**S**), weakly ordered texture (**W**), or disordered texture (**D**). These three classes of texture are collectively termed primitive texture.

The Characteristics of Surface Texture on Logs with Bark

In this research, we mainly deal with the visual texture of log bark that is comprised of flow-like patterns. The texture of the surface of a log with bark is a weakly ordered texture (**W**). The texture (Figure 1e and 1f) is characterised by local selectivity of orientation, which can vary arbitrarily over the en-

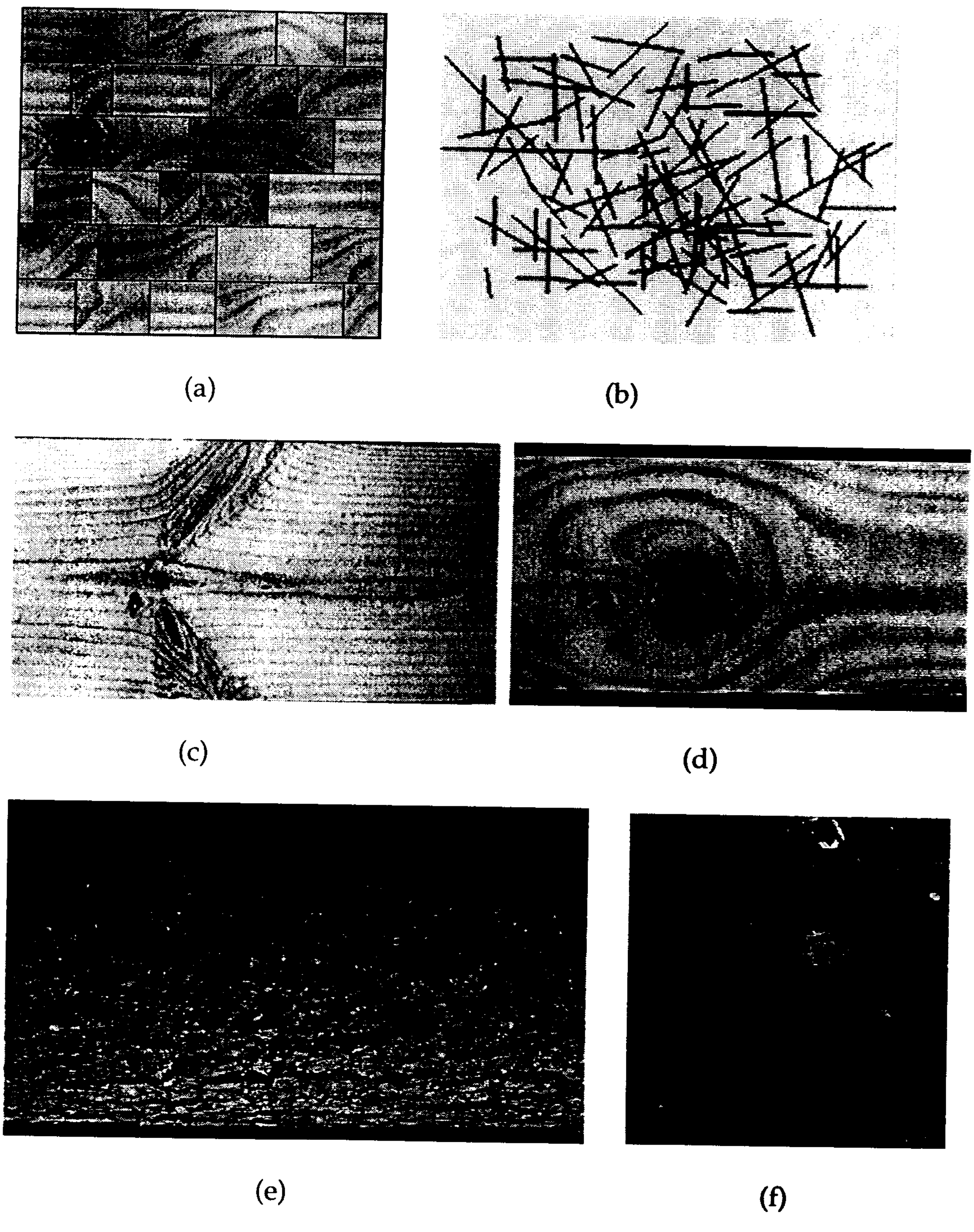


Figure 1. Illustrating the taxonomy for texture in forestry applications, (a) A wooden wall, (b) A tracheid length image, (c) and (d) knot in a piece of timber, (e) Surface of log with bark, and (f) Knots on surface of log with bark.

tire image. In other words, the texture is anisotropic, similar to other wood properties. But every point in the image is associated with a dominant local orientation, and a local measure of the coherence or degree of anisotropy of the flow pattern.

The orientation field of a texture image was defined by Rao, 1990, to be comprised of two components, the angle image and the coherence image. The angle image captures the dominant local orientation at each point in the terms of an angle (direction), and the coherent image represents the degree of anisotropy at each point in texture. The term orientation field is used because it is closely related to a velocity flow field, from fluid dynamics where at each point in space, a fluid element can have some velocity composed of a magnitude and direction.

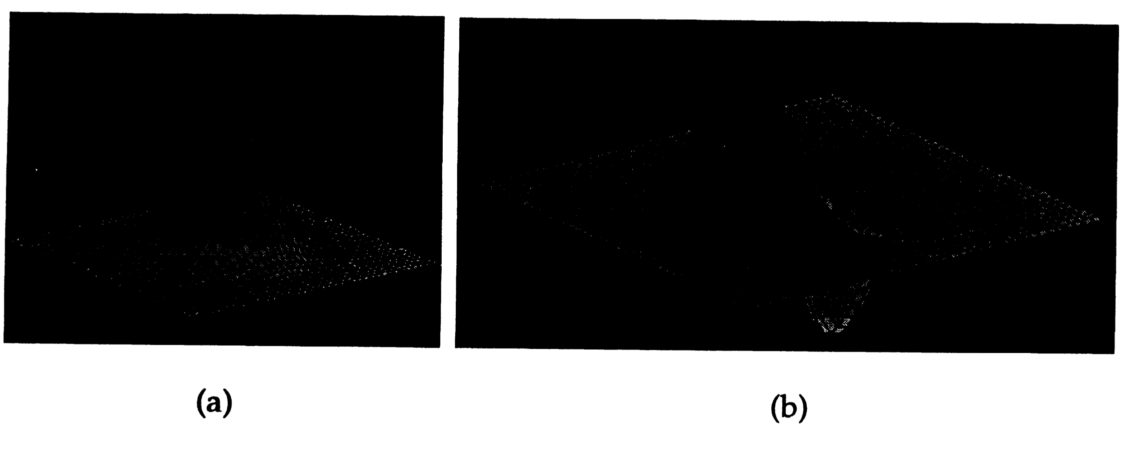
FUNDAMENTALS

The algorithm for estimating the orientation of a texture field presented in this paper is based on the gradient of a Gaussian filter. The approach is similar to the work of Kass and Witkin (1987) and Rao (1990). The Gaussian smoothing filter is a very good filter for removing noise drawn from a normal distribution (Jain, Kasturi and Schunck 1994). The 2D Gaussian smoothing operator G(x,y) (also called a Gaussian filter or simply a Gaussian) is given as

$$g(x,y) = e^{\frac{x^2+y^2}{2\sigma^2}} \qquad (1)$$

where x, y are the image co-ordinates and σ is the standard deviation of the associated probability distribution. σ is proportional to the size of neighbourhood on which the filter operates. Figure 2.(a) illustrates the three dimensional appearances of a Gaussian, which is shaped like a bell.

Figure 2.(b) is a plot of the magnitude of the Fourier transform of the first derivative of a Gaussian filter. In two dimensions, the maximum response is oriented along a line passing through the origin in frequency space, so that an oriented pattern does have a dominant frequency component. The response of a gradient of Gaussian filter can be tuned to this dominant component. The algorithm presented for estimating the orientation of a texture field is based on this fundamental property.



(a) (b)

Figure 2. (a) illustrates the three dimensional appearances of a Gaussian. (b) The Fourier transform of the first derivative of a Gaussian filter is tuned to detect oriented textures at a particular orientation and wavelength.

BASIC STRUCTURE OF THE COMPUTER VISION SYSTEM

The basic structure of the computer vision system includes two main modules: (1) a feature extraction or "computing" model; and (2) an analysis module.

Feature Extraction Module for Estimating Oriented Texture Field from the Raw Image on Log Bark Surface

The feature extraction module is made up of four steps. The mathematical basis for these steps will be presented in a later paper.

(i) Smoothing the Image with a Gaussian Filter

When an image is acquired by a digital camera, it often happens that the vision system for which it is intended is unable to use it directly because the image may have been corrupted by random variations in intensity, variations in illumination, or poor contrast, and must be dealt with in the early stages of vision processing. The Gaussian filter was selected as a smoothing filter in the system because (1) it has been shown to play an important role in edge detection for human vision (Marr and Hildreth 1980) and yield nearly optimal edge and line detection (Canny 1986); (2) it is a very good filter for removing "noise" drawn from a normal distribution. A smoothed image can be obtained by using the 2D Gaussian smoothing operator G(x,y).

An algorithm for computing the filter coefficients has been described by Schunck (1986,1987). Figure 4.(a) shows an original image of log bark with knots. Figure 4.(b) shows an image smoothed by using equation (1).

(ii) Computing the Gradient of the Smoothed Image by Partial Derivatives

Edges are significant local changes in the image and are important features for analysing oriented texture fields. Operators for describing edges are expressed using partial derivatives. A change of the image function can be described by a gradient that points in the direction of the largest growth of the image function. An edge is a vector variable that has two components: the magnitude and the direction. The edge magnitude matrix and the edge direction matrix are computed separately. Figure 4.(c) shows the magnitude image calculated from the smoothed image in Figure 4.(b)

(iii) Estimating the Dominant Local Orientation Angle

A method for estimating the dominant orientation angle θ in $\lambda \times \lambda$ neighbourhood of an image is given by Rao (1990). Figure 4.(d) shows the estimated flow direction overlayed on the gradient magnitude image shown in Figure 4.(c). To view the result clearly, Figure 4.(e) shows the estimated flow direction overlayed on a black background.

(iv) Computing the Flow Orientation Coherence of the Texture

The measure of coherence of a texture is related to the dispersion of its directional data. Mardia (1972) shows that both measures for orientation and coherence come from the same theory of statistics of directional data. The coherence measure can be calculated.by (a) projecting the gradient vector of each neighbourhood point of interest (i,j) in the direction of the estimated orientation angle at point (x,y) (Figure 3), (b) summing the absolute value of all such projections within the window of interest, and then (c) dividing by the sum of all gradient magnitudes.

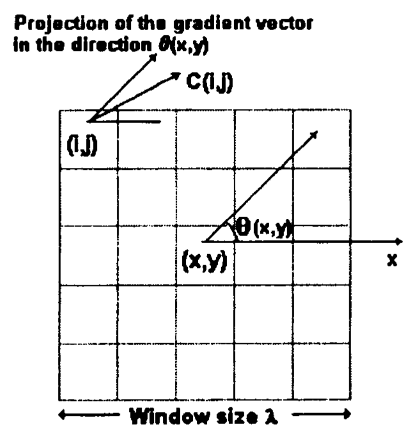


Figure 3. Illustration of the method used to compute the coherence of the texture flow field.

Analysis Module for Oriented Texture Field on Log Bark Surface

One of the central issues in computer vision is the problem of transformation from signal to symbol (Rao and Jian 1988), which has two components. The first is the choice of symbols to be derived. This is usually ignored or taken for granted. The second is the exact method used to transform the given image into this set of symbols. Researchers in computer vision have usually focussed on the second part of the problem.

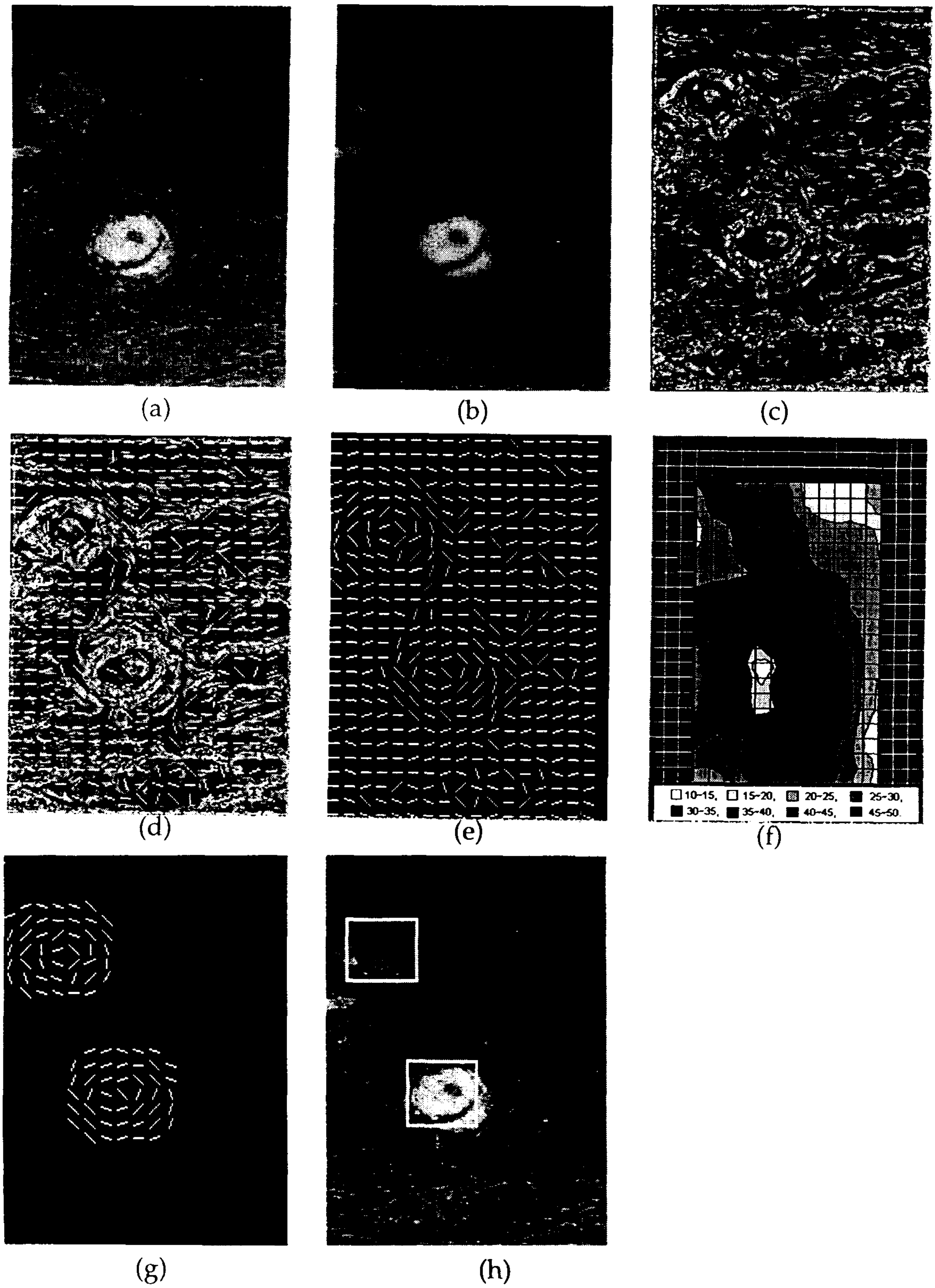


Figure 4. (a) An original image of log bark with knots. (b) The smoothed image with a Gaussian filter. (c) The gradient magnitude image in which each point value is a gradient magnitude value. (d) The estimated flow directions overlayed on the gradient magnitude image,. (e) The estimated flow directions overlayed on a black background, (f) The STDEV value map,. (g) The results of flow pattern recognition. (h) The detected positions of knots overlayed on the original image.

One approach for analysing a given orientation field is based on the geometric theory of differential equations (Lefschetz 1963, Arrowsmith and Place 1982, and Rao 1990). This theory involves the notion of a phase portrait, which represents the solution of a system of differential equations in a qualitative fashion. Details of the method can be found in the three papers referred to above.

In this paper, the oriented textures are analysed using a different method based on the statistics of directional data.

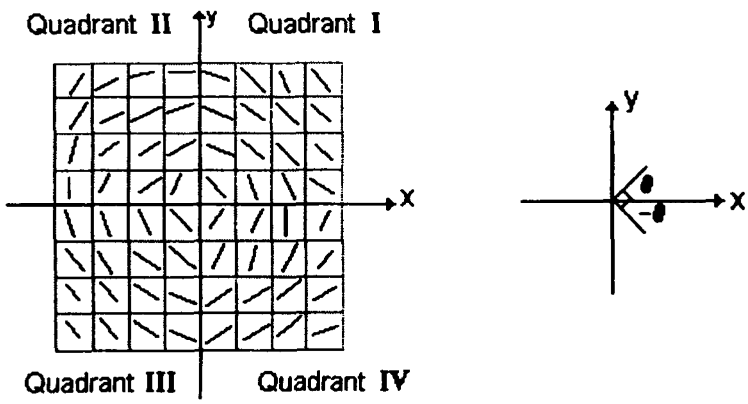


Figure 5. Illustrating a discrete orientation field of a knot texture put onto a 2D coordinate.

Consider two matrices,

$$\begin{bmatrix} \theta_{1.1} & \theta_{1.2} & .. & \theta_{1,\delta} \\ \theta_{2.1} & \theta_{2.2} & .. & \theta_{2,\delta} \\ .. & .. & .. & .. \\ \theta_{\delta,1} & \theta_{\delta,2} & .. & \theta_{\delta.\delta} \end{bmatrix} \text{ and } \begin{bmatrix} \kappa_{1.1} & \kappa_{1.2} & .. & \kappa_{1,\delta} \\ \kappa_{2.1} & \kappa_{2.2} & .. & \kappa_{2,\delta} \\ .. & .. & .. & .. \\ \kappa_{\delta,1} & \kappa_{\delta,2} & .. & \kappa_{\delta.\delta} \end{bmatrix} \quad (2)$$

Where is an orientation angle from angle image; is a coherence value from coherence image; i= 1,2,..,δ; j= 1,2,..,δ.

According to Schunck (1986), the range of the orientation angle θ in the angle image is from $-\pi/2$ to $\pi/2$. If θ is positive, the grain direction is to the left; if θ is negative, the grain direction is to the right. An orientation field of a typical knot texture is put onto a 2D coordinate with an origin at the centre of the knot texture in Figure 5. It is then easy to find that most values of θ are positive in the quadrant II and IV and most values are negative in the quadrant I and III.

Two hundred and eighty-six texture samples, including knot texture and non-knot texture (bark only) samples (window size δ=7) from angle images and coherence images were selected for statistical analysis and the development of the analysis module.

The statistical analyses included:

- Estimating the weighted standard deviation (STDEV) based on samples in the window with size = δ. and using the formula given in (3). The sorted value of STDEV is shown in Figure 6(a). We have found that the STDEV value of the knot area is larger than that of the bark area. For example, Figure 4(g). shows a map of STDEV value from the angle image and the coherence image whose original image is shown in Figure 4 (a).

$$\sqrt{\frac{\delta^2 \sum_{i=1}^{\delta} \sum_{j=1}^{\delta} \left(\theta_{i,j}\kappa_{i,j}\right)^2 - \left(\sum_{i=1}^{\delta} \sum_{j=1}^{\delta} \theta_{i,j}\kappa_{i,j}\right)^2}{\delta^2\left(\delta^2 - 1\right)}} \quad (3)$$

- Analysing the orientation angle histogram. The angle histogram of knot texture (Figure 6(b).) and the angle histogram of bark texture (Figure 6(c).) were calculated separately. We have found that there are two normal distributions around -45° and +45° for the knot angle; and a single normal distribution around 0° for the bark angle.

A fast algorithm, based on statistical analysis, was developed to detect the position of knots. We also found while developing the system that knot detection was improved if we linked grey level analysis with the analysis of orientation field in the log image.

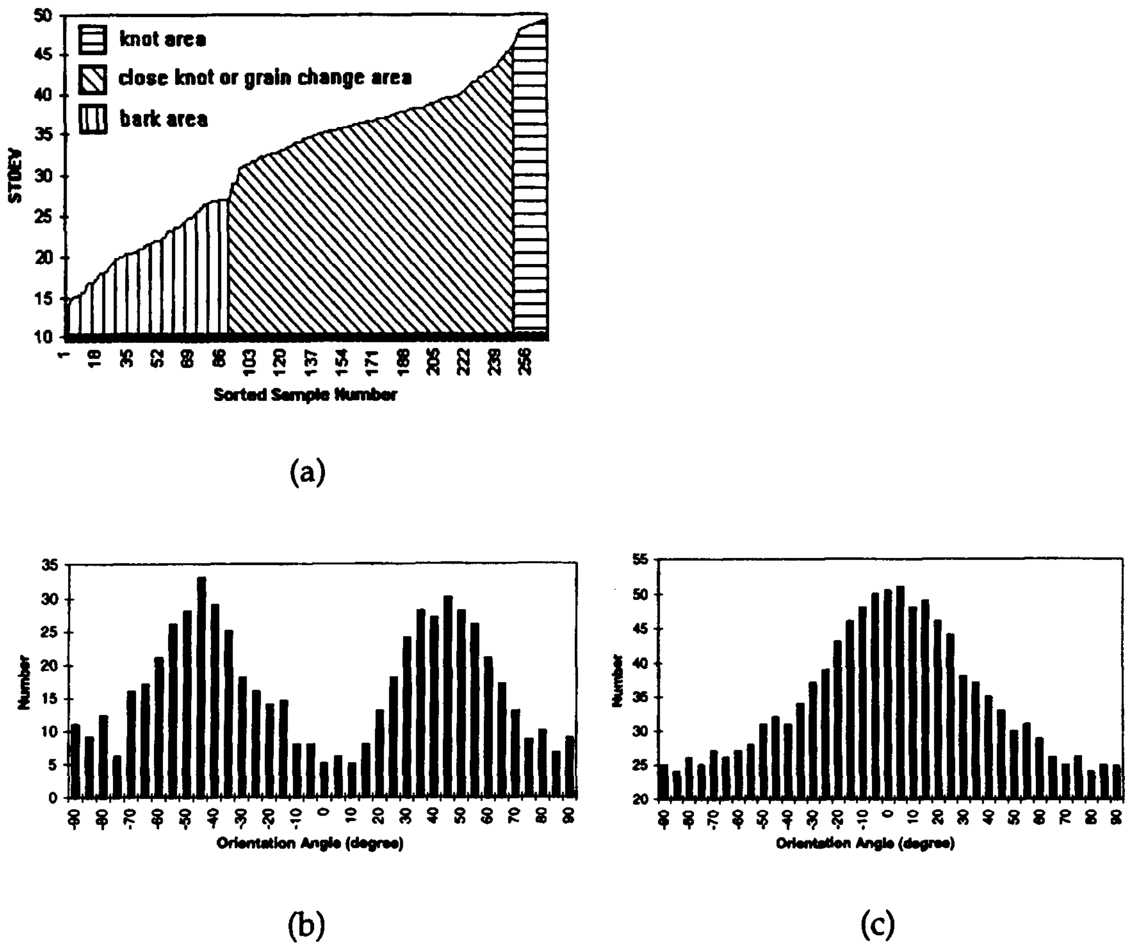


Figure 6. Illustration of the statistical analysis for oriented texture of log bark. (a) The sorted STDEV value based on samples in the window with size = *. (b) The angle histogram of knot oriented texture. (c) The angle histogram of bark oriented texture.

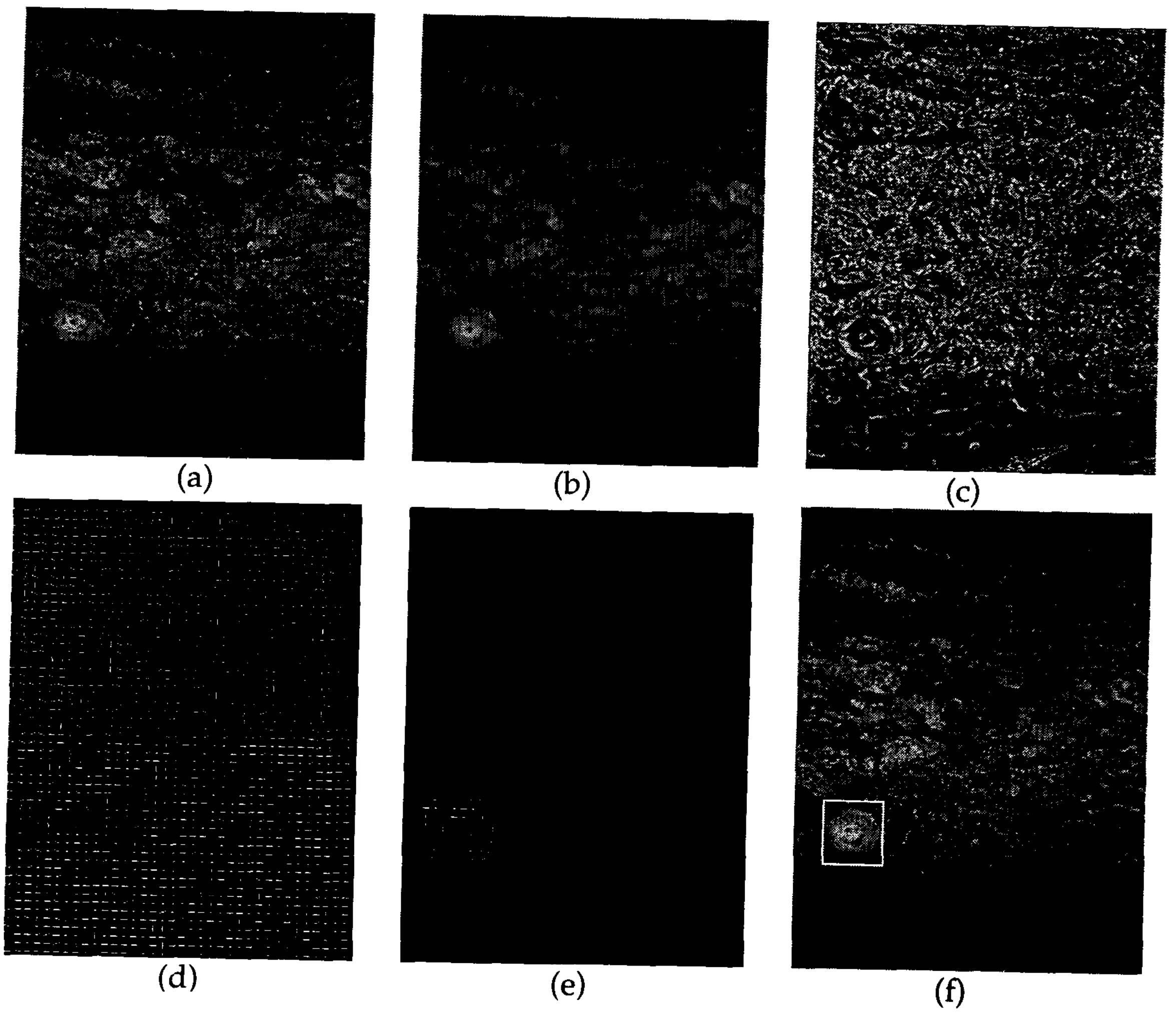


Figure 7. (a) An original image of a log with a knot. (b) The smoothed image with a Gaussian filter (c) The gradient magnitude image in which each point value is the gradient magnitude value. (d) The estimated flow direction overlayed on the gradient magnitude image, (e) The results of flow pattern recognition of a knot. (f) The detected position of a knot overlayed on the original image.

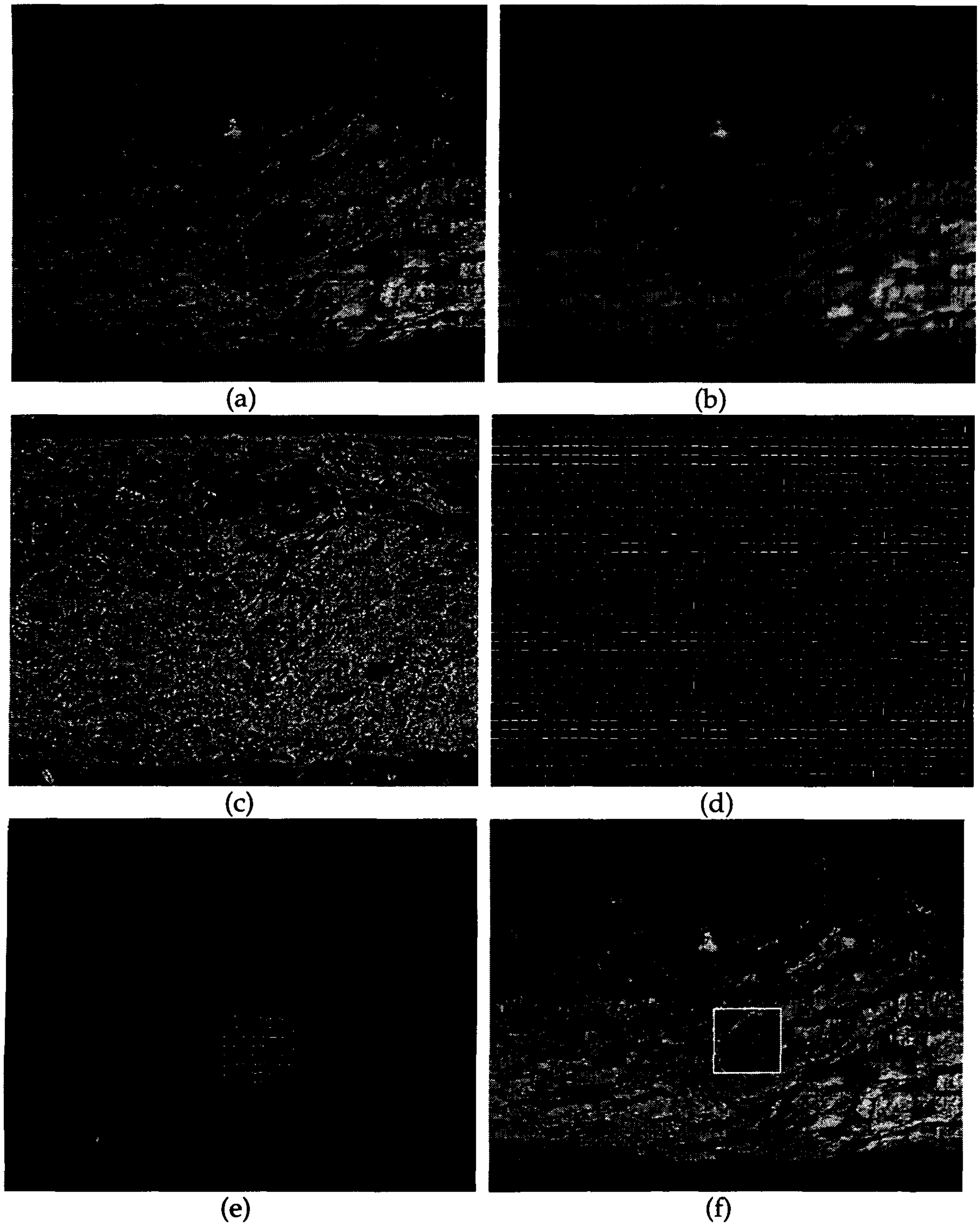


Figure 8. (a) An original image of a log with an occluded knot. (b) The smoothed image with a Gaussian filter. (c) The gradient magnitude image in which each point value is the gradient magnitude value. (d) The estimated flow direction overlayed on the gradient magnitude image, (e) The results of flow pattern recognition of the knot (f) The detected position of the occluded knot overlayed on the original image.

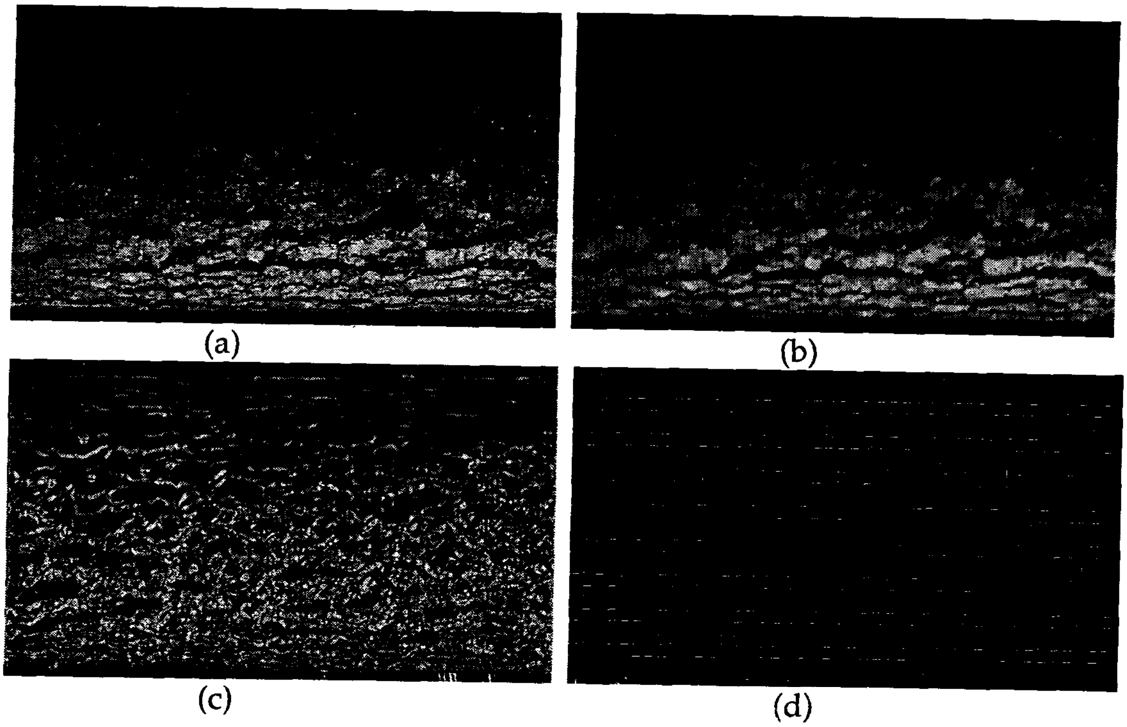


Figure 9. (a) An original image of a log with no knots. (b) The smoothed image with a Gaussian filter (c) The gradient magnitude image in which each point value is the gradient magnitude value. (d) The estimated flow direction overlayed on the gradient magnitude.

Figure 4.(g) shows the results of flow pattern recognition and Figure 4.(h) shows the detected positions of knots overlayed on the original image.

EXPERIMENTAL RESULTS

Experimental results indicate that the system can detect the presence or absence of various knots in freshly harvested Pinus radiata tree stems including small and medium size knots of occluded or trimmed branches.

Figure 4.(a)~(h) shows the complete process of defect (trimmed branches of medium size) detection using bark texture analysis. The image texture analysis software has been developed based on the same principle using the C++ programming language. The 286 image samples of freshly harvested tree stem were processed by this software. Those samples include logs with different branch size (large ,medium, small and without branches) and logs with different types of branches (trimmed branch stub, trimmed flush with stem and occluded).

Figure 7(a) ~ (f) show the results for a large size log with a small knot on it. It demonstrates that this system performs very well in detecting small size knots. We believe that the knot size detectable by this system will depend on the image resolution.

Figure 8(a) ~ (f) shows the results for a log with an occluded branch. Occluded branches can also be detected very well by the system. It indicated that this system can also be applied into detecting knots in timber.

Figure 9(a) ~ (d) shows the results for a log with no knots. There was no knot pattern in the bark texture, so the system could not detect any defect on the log surface.

CONCLUSIONS

Texture information is an important element of vision, and occurs in a variety of natural textures (bark texture, wood grain in timber) and man-made textures (furniture, wooden wall) in forest applications. The characterisation of texture is becoming increasingly important as a diagnostic tool in advanced manufacturing applications.

In this paper, we approached the problem of analysing texture from the viewpoint of signal-to-symbol transformation. It includes:

- Definition of a taxonomy for texture in forestry applications.
- Creation of an algorithm for extracting an orientation field from a raw image.
- Description of two ways of analysing an oriented texture field through phase portraits and statistics.
- Indication that the angle and coherence intrinsic images represent a necessary initial stage in the processing of oriented textures.

We have applied those theories to develop a computer vision system. Close to three hundred samples were processed by the system. The experimental results indicate that:

- a digital-camera-based computer vision system can be developed to locate and identify branches.
- the vision system can recognise occluded branches by using bark texture analysis.
- environmental changes should not affect the ability of the system to recognise knots.

In addition, we believe that the image analysis methods described here can extend to other applications (such as timber processing) and other data types (CT image, X-ray or laser image).

We also believe that the analysis method for the oriented texture field can be improved by using artificial neural networks. A new 2D classifier for directional data may be an effective way.

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