DETECTING 'YELLOW STAIN' IN WOOD USING SPECTRAL METHODS

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Keywords: Wood inspection.

Abstract: This paper deals with the detection of 'yellow stain' in wood samples using colour. We describe an investigation into the spectral properties of the stain and use the findings to design a detection system. We found that infected regions invariably differed from healthy regions in the 400nm to 450nm region of the spectrum. We developed a system based on an economical RGB camera and an optimised light source. The source consists of two narrow bands: one in the blue channel of the camera where the discriminative information is held, and one in the red channel that acts as a normalisation factor to remove the effect of the natural patterning of the wood. A simple classifier was used with the red and blue channels of the camera and produced results that agreed with our client's subjective judgement.

1 INTRODUCTION

This paper deals with the detection of 'yellow stain' in wood samples using colour, Figure 1. Yellow stain is a discolouration of the wood surface caused by a fungal infection. Although it does not affect the structural integrity of the timber, it does affect consumer perceptions of the material and its economic value. An inspection system must match the human visual system's colour sensitivity to the stain, yet be robust to the natural variation of healthy wood.

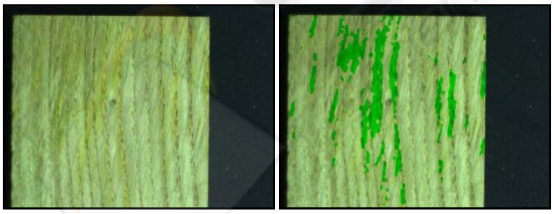

Figure 1: Example of yellow stained wood (left) the results of our classifier (right). For display we have lit the sample with fluorescent light which makes the yellow stain more apparent than under tungsten halogen light.

Timber is an important sector of the machine vision sector. Commercial systems are available and the topic is also the subject of academic research. Colour is an important aesthetic characteristic of timber but also a useful cue for identifying abnormalities and much of the research has concentrated on using colour, (Lampinen, Smolander and Korhonen, 1995) (Kauppinen and Silven, 1996) (Lebow, Brunner, Maristany and Butler, 1996). Spectroscopy has been applied, (Jones et al., 2005) and several authors have used multispectral and hyperspectral techniques, (Maristany et al., 1992) (Hagman, 1997) (Marszalec and Pietikaeninen, 1993) (Butler, Brunner and Funck, 2001). In this paper we will use hyperspectral imaging to identify the features that disclose yellow stain and use this information to optimise the spectrum of the illumination so that yellow stain can be detected using a conventional RGB camera.

In this paper we identify spectral features for detecting yellow stain and resolving it from the background wood texture. We use hyperspectral (HS) measurements, that is measurements that are both spatially and spectrally resolved, to identify spectral features that distinguish infected from clearwood. We then 'tune' the light source so that these features can be resolved by a conventional RGB Camera.

This paper describes 2 tasks: first we use the HS measurement system to measure spectra from both infected and clear regions of the samples. The spectra are analysed to identify wavelengths at which the two region types differ. These wavelengths are then used to design features that can

McGunnigle G. (2012).
DETECTING 'YELLOW STAIN' IN WOOD USING SPECTRAL METHODS.
In *Proceedings of the 1st International Conference on Pattern Recognition Applications and Methods*, pages 551-554
DOI: 10.5220/0003756205510554

be extracted from the measured data and used for classification. Second, we use a conventional RGB camera with spectrally optimised lighting to classify a series of samples.

We applied this approach to a number of samples supplied by our client. Afterwards the client was asked to examine the samples by hand and compare his judgement with our classification. In all cases the client agreed with the classification and was satisfied with the approach. This evaluation is, like that of the consumer, subjective. However, the fact that this approach gave satisfactory results suggests that the optimised lighting approach is superior to an earlier approach based on a high end colour linescan camera.

2 BACKGROUND

Yellow stain is a discolouration of cut hardwood affecting European oaks, chestnut and walnut species. The discolouration is the result of tannic acids being metabolised by the fungus *Paecilomyces variotii*. The initial infection and its progression are closely associated with the vascular structure of the wood. Fungal spores enter the structure of the wood in regions where the vascular structure has been breached, e.g. the wood has been cut across the grain. The infection then spreads most rapidly along the tracheids, especially through the less dense earlywood. Because the spread of the infection is largely determined by the microstructure of the wood, the visible results are correlated with the grain of the wood. Therefore although the stained regions may extend over long distances in the grain direction, they are often spatially localised in the perpendicular direction. Colour measurements must therefore be both spectrally accurate and spatially localised.

Hyperspectral imaging allows measurement of the colour spectrum at each pixel in an image. The result of a hyperspectral measurement is a three dimensional data set (or spectral cube) with two spatial dimensions (as with a normal image) and a third dimension corresponding to the colour spectrum. In fact the particular camera, sensor and lighting combination used in this report extends the colour spectrum into the NIR and has a working range from 380nm to 950nm. Our system is based on an imaging spectrograph which diffracts light along one of the axes of the sensor plane. Each frame from the camera has one spatial and one spectral axis. The spectrograph performs push-broom scanning, i.e. it is used as a line scan camera, with the spectral cube being built up slice by slice as each frame is captured. Hyperspectral imaging has been used for online inspection, however in this paper we will use it as an analytical tool to optimise a conventional inspection system.

3 HYPERSPECTRAL MEASUREMENT SETUP

3.1 Lighting

The spectral range of the imaging system is defined by the design of the imaging spectrograph, the response of the camera, and the spectrum of the incident illumination. In general we use tungsten halogen lamps because they are broadband, economical and are capable of supplying the large amount of light required by a hyperspectral system. They approximate a black body radiator and therefore suffer from a significant disadvantage for colour measurement: they are relatively weak at the blue end of the spectrum.

It is critical that our hyperspectral measurement system has sufficient signal in the blue. The X-Cite source (Lumen Dynamics, Canada.) is largely composed of a number of narrowband spectral peaks and would normally not be considered for spectral measurements Figure 2. However, by combining it with the tungsten halogen source and reducing it to 12% of its maximum value, we can extend the spectral range of the system further into the short wavelengths without reducing the system’s dynamic range.

3.2 HS Measurement Setup

The measurement uses a Jai CV M4 CL monochrome camera, 10 bits, 1380 x 1030 pixels, with a V10 (150µm slit) Imspector (Specim, Finland) and a 25mm lens (Electrophysics, USA). The sample is lit with two 500W tungsten halogen lamps run from a dc power supply, and a metal halide light source (Lumen Dynamics, Canada.). The samples were scanned using a linear stage (National Instruments, USA) with a longitudinal resolution of 300µm and a lateral resolution of 75µm. Between 300 and 500 frames were captured for each sample giving raw data sets of between 1 and 2Gb. To validate the system we imaged a series of colour standards (Labsphere, USA). Our measurements conform closely with the published reflectance curves.

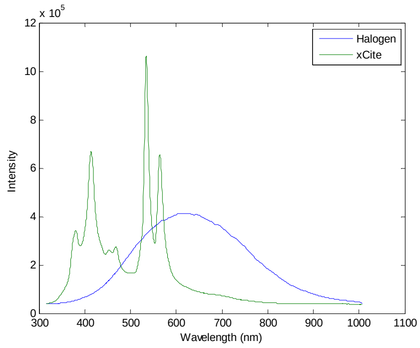

Figure 2: System response to white standard for tungsten halogen and xCite light sources.

4 SPECTRAL MEASUREMENTS

4.1 Method

We measure the spectra of small regions corresponding to both stained and clear wood. The raw data is corrected for dark noise, as well as the spatial and spectral inhomogenities of the light source using the white and dark standards. The spectrum is heavily oversampled (to a nominal resolution of 1nm), we downsample this to the resolution of the CIE standards (5nm). This significantly reduces the memory requirements of subsequent calculations. Next the RGB image is calculated from the HS cube and displayed—the user then crops the ROI from the image. The corresponding spatial region is then cropped from the HS cube and the cube is then normalised at each pixel by the sum of the spectral intensities at that pixel. An RGB image is then recalculated and displayed with the blue channel accentuated. The user then marks 4 small regions (5pix x 5pix) on the image. The average spectrum of each region is then plotted.

4.2 Results

Spectra for selected points on the test sample are shown below. All the spectra have an almost exactly linear relationship with wavelength, Figure 3. Most of the yellow stain spectra are distinguished by having lower energy in the 400-450nm range than the clearwood spectra.

Aside from this feature, the spectra are devoid of distinctive characteristics. This suggests that techniques such as differentiating the spectra are not worthwhile and features based on the intensity of the spectrum at defined wavelengths may be the most effective approach. This means that a multispectral rather than hyperspectral system is appropriate for this data set.

5 SHARPENED RGB

In the previous section it was shown that the 400nm-450nm region of the spectrum is critical for detecting yellow stain. We based our first feature on light reflected from the wood surface after it has been lit with a metal halide lamp filtered with a blue glass filter. This feature is measured by the blue channel of the RGB camera.

Wood is an inhomogeneous material and its reflectivity varies from latewood to earlywood. An inspection system must be able to detect yellow stain, but ignore the intensity variations caused by the normal structure of the wood. Our second feature is used to normalise the response of the first feature. Since we already use the blue channel of the camera, we must use either the red or green channels for this second feature. We opted for red to reduce crosstalk with the blue channel. To obtain this feature the sample is lit simultaneously by two sources: a tungsten halogen source, filtered with a red interference filter and a metal halide source filtered by a blue filter.

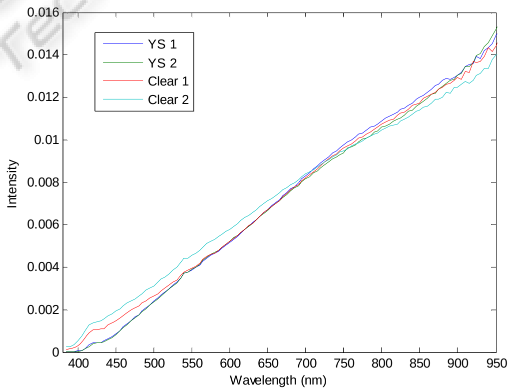

Figure 3: Sample spectra.

A conventional RGB camera is used to image the scene at a resolution of 640x480 pixels. The classification algorithm is remarkably simple: a feature is calculated from the red and green camera channels and then thresholded to give a classified image, Figure 4. The results are shown below in Figure 5. We believe that these results are promising — especially considering the simplicity of the classifier.

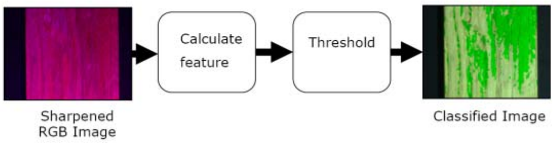

Figure 4: Sharpened RGB classifier.

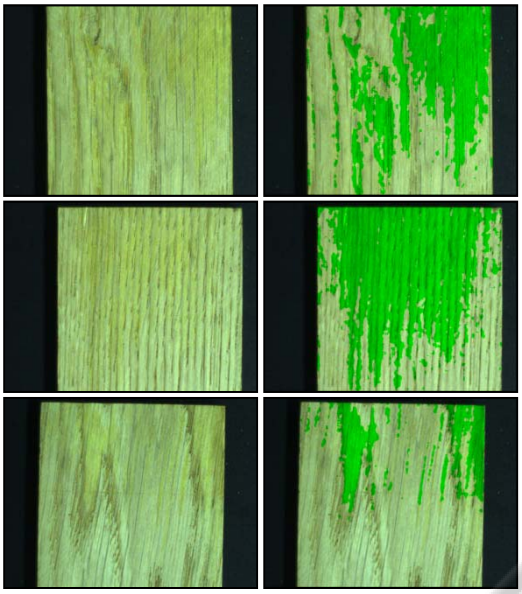

Figure 5: Test samples (left) and classification results (right).

6 CONCLUSIONS

This paper has shown that a colour based classification of yellow-stain must be based on the spectral band ranging from 400 to 450nm. We have developed a lighting system that gives intense illumination at these wavelengths — these wavelengths corresponds to the blue channel of the RGB camera. Wood is not a homogenous material, and the reflectivity varies from early wood to latewood. By using narrowband illumination corresponding the camera's red channel, we can normalise the blue channel and obtain a stable feature for detecting yellowstain. Using a simple threshold classifier this approach was shown the detect yellowstain effectively.

ACKNOWLEDGEMENTS

This project was supported within the COMET Programme by BMVIT, BMWFJ and the federal provinces of Carinthia and Styria.

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