IDENTIFICATION OF TRASH IN CANE USING MACHINE VISION

By

JR TULIP, WE MOORE

School of Information Technology, Charles Sturt University, Bathurst, Australia
jtulip@csu.edu.au

KEYWORDS: Trash, Billet Cane, Leaf, Tops, Texture, Texton, Image Classification.

Abstract

BILLET CANE, leaf, and tops form the overwhelming bulk of sugar mill feedstocks, but currently there is no accurate and reliable non-invasive method of directly estimating the amount of trash (combined leaf and tops) they contain, or distinguishing between the amounts of leaf and tops. This paper reports on a novel technique that can reliably and non-invasively distinguish between billet cane, leaf, and tops on the basis of high resolution colour imagery. The technique distinguishes between billet cane and both leaf and tops using detailed surface texture. The features distinguishing cane from leaf and tops are consistent across all cane varieties examined and do not require calibration for cane variety. Texture is not a good discriminator between leaf and tops. However, leaf and tops can be distinguished on the basis of hue since the differences in water content and degree of senescence which distinguish leaf and tops are associated with hue. Texture and hue based discriminators are then merged in a probabilistic framework to produce a combined classifier capable of achieving true positive identification rates between 80% and 90% and false positive identification rates below 10% for cane, leaf, and tops in unseen test images.

Introduction

Directly measuring trash levels in billet cane has been a difficult task for the sugar industry. The standard method of direct measurement has been physical sampling of mill input billet supplies and then separation and weighing of cane and trash components. This is a time consuming and expensive process, but more critically it has been found that the accuracy achieved using this method is insufficient to make meaningful distinctions in trash levels over the range found in actual industrial cane supplies. The key issue is the high degree of variability in trash levels at the small weight and volume scale of the samples that are practical to analyse.

Near infrared (NIR) fibre estimates have been used as an indirect measure of trash levels (Staunton *et al*., 1999; Bevin *et al*., 2002; Staunton *et al*., 2004). These measures have been used in determining cane payments at Mulgrave Mill (Pope *et al*., 2004) and have been successful in influencing and improving the quality of cane supplies. However, NIR fibre estimates do not distinguish between fibre from trash and fibre from billet cane, and the fibre

estimate must be calibrated for individual cane varieties in order to estimate the fibre contribution from trash. Distinguishing between the trash components of leaf and tops is important in relation to providing harvesters and growers with feedback and incentives for implementing harvesting best practice (Fuelling, 1999; Agnew, 2002; Agnew *et al*., 2002), since the causes of entrainment in feedstocks for leaf and tops differ, as do the remedial methods available. Distinguishing between leaf and tops may also be important in monitoring the efficiency of any mill-based cane cleaning processes (Dixon and Burbidge, 2000; Schembri *et al*., 2002).

Machine vision has been defined as the automated acquisition and analysis of images to make useful decisions about real world objects (Shapiro and Stockman, 2001). This paper describes an automated method using colour and texture information to analyse high resolution colour images in order to identify cane, leaf, and tops in sugar mill feedstocks.

Humans can easily distinguish billet cane from trash (leaf and tops combined) in high resolution black and white images, but find it impossible in low resolution colour imagery. This implies that humans use non-colour, detailed textural information in order to distinguish trash from cane. On close examination, the surfaces of leaves and tops show fine striations associated with leaf venation while the surface of cane stalk is frequently mottled with a waxy coating.

It is not possible to reliably distinguish between leaf and tops in the same high resolution, black and white images. This indicates that humans use colour information to distinguish between leaf and tops. Tops are associated with the actively growing apex of the cane plant. As the growing apex extends, top leaves dry out to become dry, brown side leaves. There is a continuum between green top leaf and dry, brown side leaf associated with photosynthetic activity, moisture content, and state of senescence. These changes in the physical and biological state of leaves are associated with changes in the leaf colour from bright yellow-green to dull brown.

The textural distinction between cane and both leaf and tops, and the colour distinction between tops and leaf suggest a simple scheme to identify cane, leaf, and tops in images; separate cane from leaf and tops on the basis of texture, and then separate tops from leaf on the basis of colour.

Textural analysis of images

Textures consist of patterns of differing hue, saturation and brightness and cannot be identified by single values of these primary image descriptors. More complex features than simple brightness or colour values are required, making texture analysis tedious and time consuming (Bernd, 2004).

Textures are built up of many repeated small elementary patterns. The concept of small elementary patterns that combine to create textures stems from Bela Julesz who showed that textural discrimination is based on a few simple local features, which he termed ‘textons’ (Julesz, 1962).

Julesz showed that textural discrimination was based purely on texton frequency rather than spatial organisation (Julesz, 1981; Julesz and Bergen, 1983). A texture is characterised by a texton histogram which describes the frequency with which different textons occur within a particular area (Cula and Dana, 2001; Varma and Zisserman, 2002). The appearance of a texture under different viewing and lighting conditions is captured by a set of texton histograms each of which characterises the appearance of the texture under a

particular set of conditions. These texton histograms are termed texture models for a particular texture.

Method

Five varieties of cane from the Maclean region of northern New South Wales and one variety from the Mackay region in Queensland were examined (Table 1). These varieties were chosen to test the performance of the colour-texture classifier over a range of cane varieties, particularly in situations where the visual range colour of cane and tops was not distinct.

Table 1—Cane varieties and colours.

Cane variety	Stalk colour	Locality
NB88-3347	Red	Maclean
Q155	Red	Maclean
Concord	Green	Maclean
Q203	Green	Maclean
Empire	Green	Maclean
Q124	Red	Mackay

All stalk material below the actively growing apical internode was classified as cane. Stalk material above the actively growing apical internode as well as all photosynthetically active green leaf was classified as tops, while all dry, brown leaf was classified as leaf.

Approximately 40 kg of whole fresh cane was harvested and then separated into cane, leaf and tops components. All components were cut to lengths of between 200–250 mm. Known weights of each component were mixed together in an 800 mm by 800 mm sample tray. This combination of sample size, and surface area gave sufficient depth within the sample tray to allow billets to assume a range of orientations.

The camera used in the investigation was a 5 mega-pixel Olympus C5050 digital camera. The image size was 2560 by 1920 pixels covering a field of view of 400 by 300 mm. This gave a spatial resolution for each pixel of approximately 0.15 x 0.15 mm.

The camera was mounted 800 mm above the surface of the sample. Lighting was designed to provide an even lighting field across the imaging area and to reduce shadowing.

Two images from each variety of cane were selected and then manually classified into cane, leaf, and tops. One image from each variety was used as a training image, and the other used as a test image.

The performances of texture only, hue only, combined texture and hue, and regionalised texture and hue based classifiers were evaluated using these images.

Image processing

Local contrast normalisation

In order to enhance textural features relative to object boundaries a pre-processing step designed to suppress high contrast boundaries and enhance low contrast features within objects was applied. An example of the effect of this local contrast normalisation is shown in Figure 1.

Note that cane (C) is relatively easy to distinguish from leaf (L), and tops (T) in the contrast normalised image, but that it is hard to distinguish between leaf and tops.

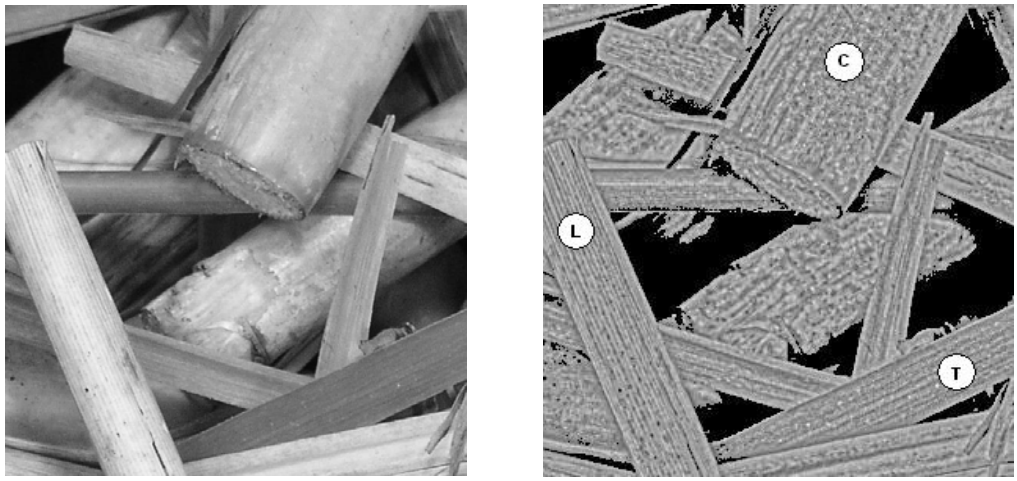


Fig. 1—Original and contrast normalised image, showing enhancement of texture in contrast normalised image, and differentiation between cane (C - speckled) and leaf (L – striated) and tops (T - striated).

Hue

In order to eliminate the effect of shadowing, each image was processed to extract an image containing only colour type or hue information. Figure 2 shows a black and white version of an example hue image for the same area as Figure 1. Note that tops are quite distinct while leaf and cane are similar in hue.

Fig. 2—Original image (left) and hue image (right), showing difference in hue between leaf (hue~ 0.1, dark) and tops (hue ~0.18, bright).

The frequency with which hues occurred in each category was calculated over all cane varieties and these frequencies converted to a probability measure. Figure 3 shows these probabilities for cane, leaf, and tops categories. The figure shows that leaf has a consistent yellow hue across all cane varieties examined. Tops show a larger spread of hue between yellow-green through yellow, and cane varies from green-yellow through red. The figure

shows that hue is an effective discriminator between leaf and tops, but is far less effective discriminating cane from either leaf or tops.

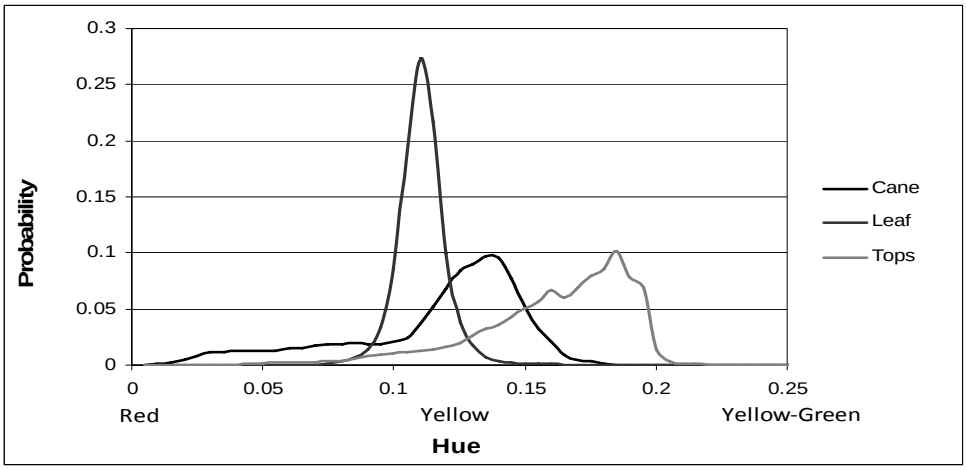


Fig. 3—Hue likelihoods for cane, leaf, and tops.

Mean-shift regions

Individual pixel's hue values are quite variable. In order to reduce 'speckle' in the final classifier and improve the reliability of the classification, category probabilities for individual pixels were aggregated over regions with consistent hue and brightness.

Regions were formed using the 'mean-shift' based clustering method of Comaniciu and Meer (2002). The mean-shift procedure was chosen because it tends to respect natural boundaries within the image.

Figure 4 illustrates the effect of applying the mean-shift based region forming process.

Fig. 4—Original image (left) and region image (right), showing relationship between natural particle boundaries and region boundaries.

Textons and texture models

The texton approach based on neighbouring pixel grey levels as set out by Varma and Zisserman (2003) was used to describe the surface textures of cane, leaf and tops.

Texton sets for cane, leaf, and tops were generated from contrast normalised images using three successively larger rings of pixels around a central pixel sampled at sixteen equal angular increments.

Figure 5 shows an example texton from each of the cane, leaf, and tops categories. The figure shows the pattern of brightness variation surrounding the central pixel that a texton encodes. The inner pixel ring is shown black, the middle ring medium grey, and the outer ring light grey.

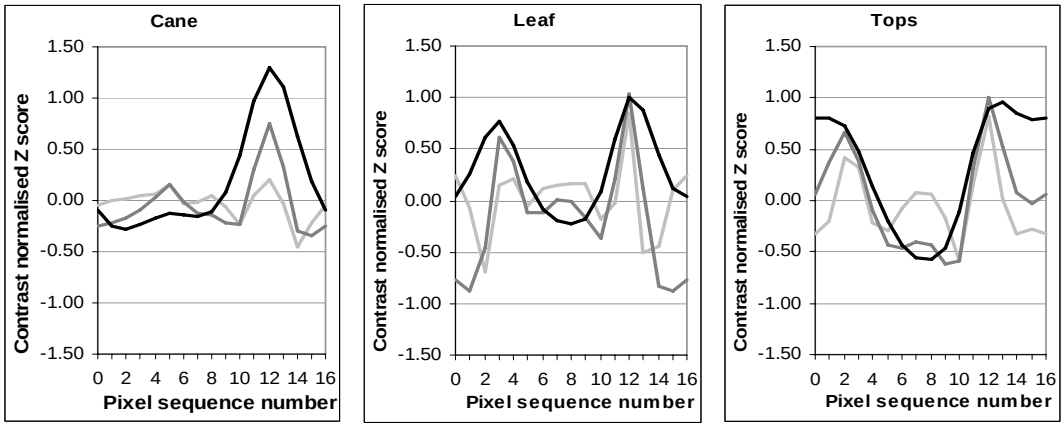


Fig. 5—Example cane, leaf, and tops textons.

Many leaf and tops textons are very similar and display a characteristic symmetrical 'two hump' appearance which indicates a linear striated texture. Cane textons more commonly show an asymmetrical appearance indicative of a brightness gradient.

Texture models were generated for cane, leaf, and tops using the manually classified training images. The frequency of each texture model in each category was calculated and then converted to a probability measure for the category given a particular model. These category probabilities are illustrated in Figure 6.

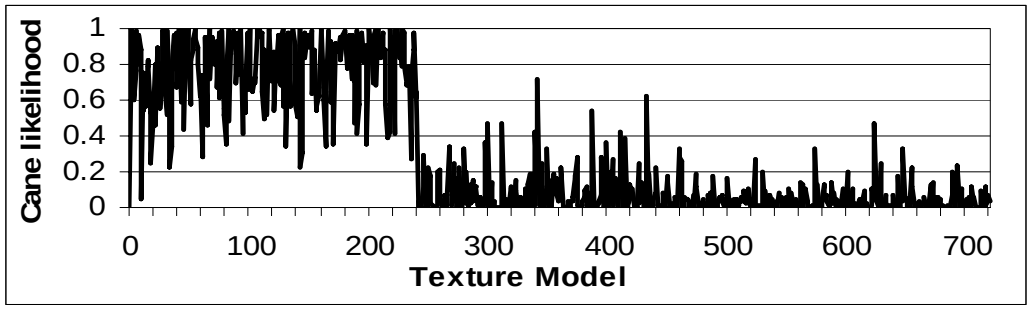
In this figure cane texture models make up the first 240 elements, leaf texture models the next 240, and tops texture models the last 240 elements.

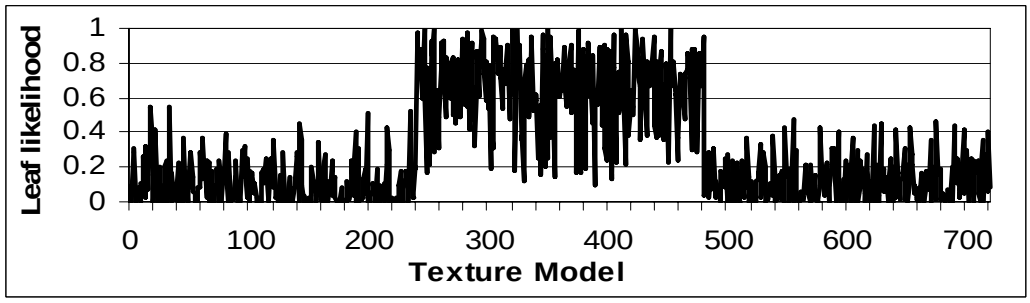
The figure shows that most pixels labelled with cane texture models are likely to be associated with cane.

Similarly, most pixels labelled with tops texture models are likely to be associated with tops. However, there is a relatively high probability that pixels labelled with a leaf texture model may actually be associated with tops.

It can also be seen that some cane and tops texture models have a relatively low probability of association with their respective categories.

Figure 6 indicates that the probabilistic classification approach adopted in this study is justified.





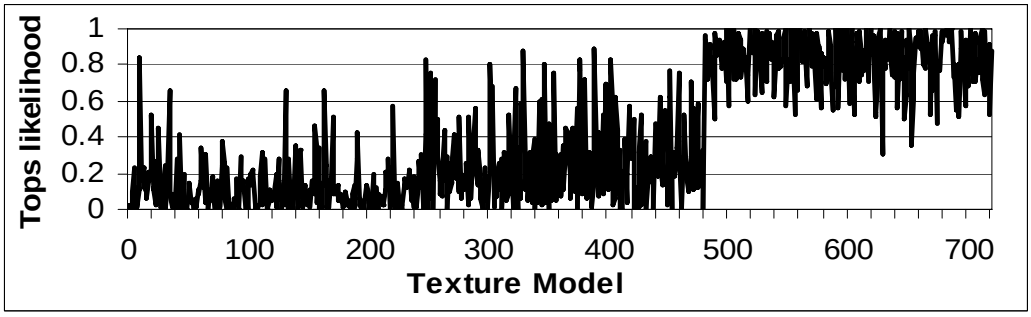


Fig. 6—Category probabilities for cane, leaf, and tops texture models.

Combined texture and hue, and regional probabilities

Texture and colour classifiers were combined by multiplying the probabilities generated by the texture and hue based classifiers together on a per category basis to give a joint probability for each category. After combined category probabilities were calculated on a per pixel basis, average category probabilities for mean-shift generated regions were calculated. The most likely category based on region probabilities was used in the final classifier.

Results and discussion

Figure 7 shows a training image that will be used to illustrate the results of the classification process. The image shows the extreme complexity of the imaged surface, with many overlapping and partially occluded particles of cane, leaf, and tops. The image also shows strong shadowing effects on some of the particles deeper within the pile.

Fig. 7—Training set image of mixed cane, leaf, and tops.

Figure 8 shows the results of texture based classification for the example image. In this image, as in all subsequent images, cane probability is shown as a flat stipple, tops probability as a right slanting stipple and leaf probability as a left slanting stipple. Unclassified areas of the image are shown black. Cross hatched areas represent classification uncertainty. Flat-right slanting cross hatching indicates uncertainty between cane and tops, Flat-left slanting cross hatching shows uncertainty between cane and leaf, and diagonal cross hatching shows uncertainty between leaf and tops.

Figure 8 shows good detection of cane, but also many areas of uncertainty along the boundaries of cane billets. Many pixels also show uncertainty discriminating leaf and tops.

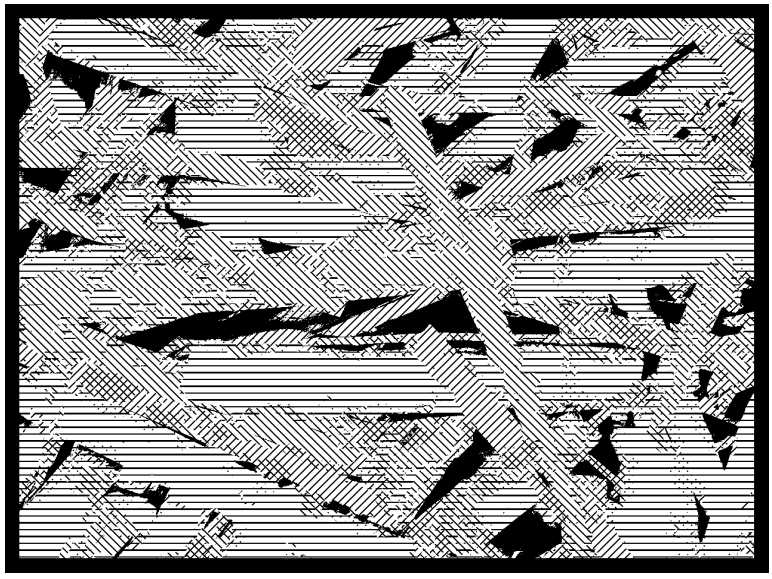


Fig. 8—Texture based cane, leaf, and tops classification.

Figure 9 shows a cane, leaf, and tops classification image based on the hue probabilities shown in Figure 3. The hue based classification image shows high certainty for several pieces of green leaf and little uncertainty between leaf and tops, but much of the image shows uncertainty between cane and tops or cane and leaf. There is also considerable misclassification of leaf as cane and vice versa. The hue based probability image retains much of the sharp boundary information lost in the texture classification process.

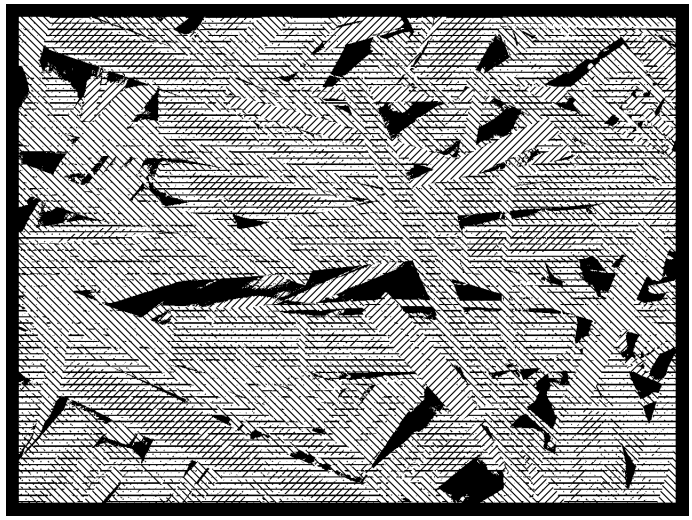


Fig. 9—Hue based cane, leaf, and tops classification.

Figure 10 shows the results of combining colour and texture classifiers in a probabilistic framework. This combined texture and hue based classification image shows greatly improved discrimination between all three categories. The certainty of classification is also much greater than in the hue based classification image as shown by the greatly reduced amount of cross hatching. Boundary information contained in the hue image has been retained, but there are many small misclassified areas within larger more consistent regions.

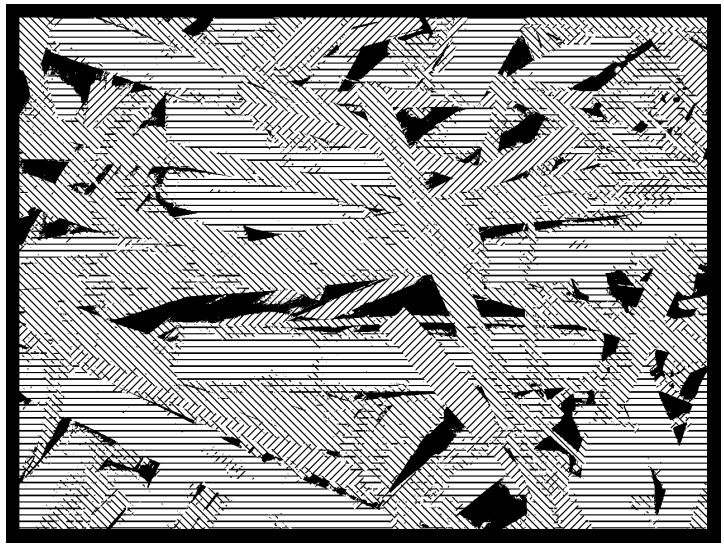


Fig. 10—Combined texture and hue based cane, leaf, and tops classification.

Figure 11 shows the effect of averaging category probabilities over regions generated by the mean-shift clustering process. The regionalisation process greatly reduces the 'speckle' of the pixel based classification and reduces classification uncertainty in many areas.

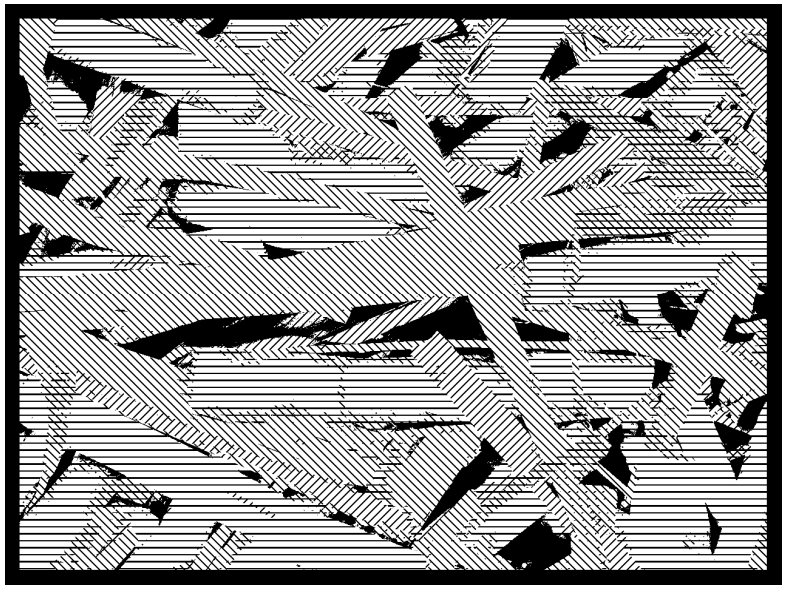


Fig. 11—Regionalised joint texture and hue based classification.

In the final classifier, pixels are classified as cane, leaf, or tops based on which category the regionalised probabilities indicate as most likely. Figure 12 shows the results for the example image. The manual classification results for the example image are shown in Figure 13 for comparison. There is a high degree of agreement between the final classifier and the manual classification results.

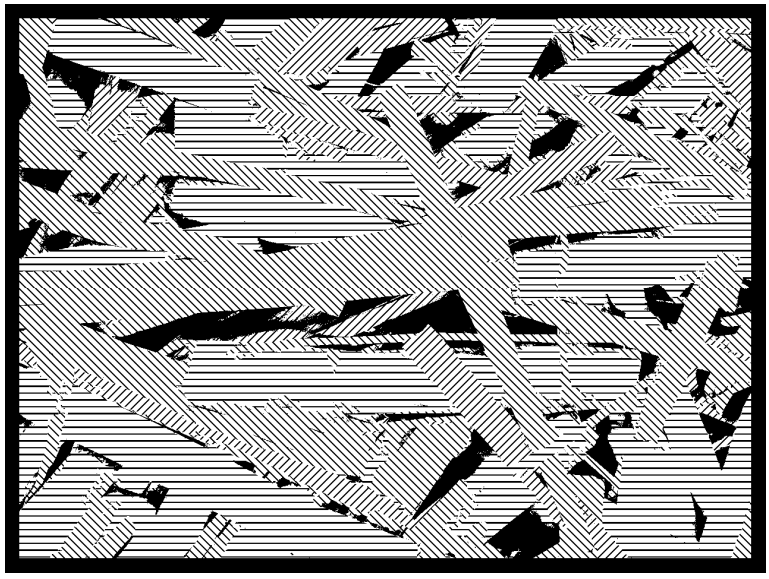


Fig. 12—Final regionalised texture and hue based classification.

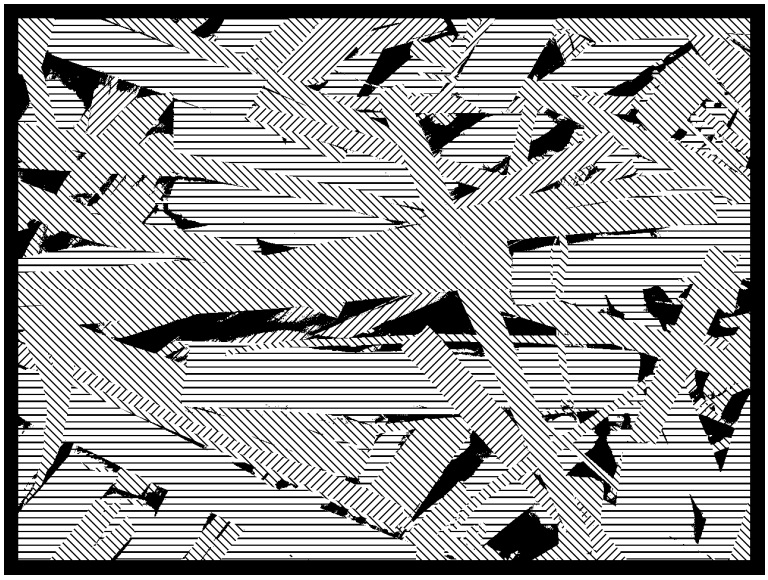


Fig. 13—Manual classification of cane, leaf, and tops.

Overall classification results for all training and test images are summarised in Figure 14 which shows plots of true positive rates versus false positive rates for classification schemes based on texture only, hue only, combined texture and hue, and regionalised combined texture and hue classifiers.

Figure 14 shows that the texture based classifier provides good discrimination of cane but poor discrimination of leaf and tops over all cane varieties examined. The hue based classifier provides good discrimination between leaf and tops, but poorer discrimination of cane over all cane varieties. Combining texture and colour provides a marked improvement in the accuracy and consistency of classification of cane, leaf, and tops across all cane varieties examined and there is a further improvement gained by using a regionalised classifier.

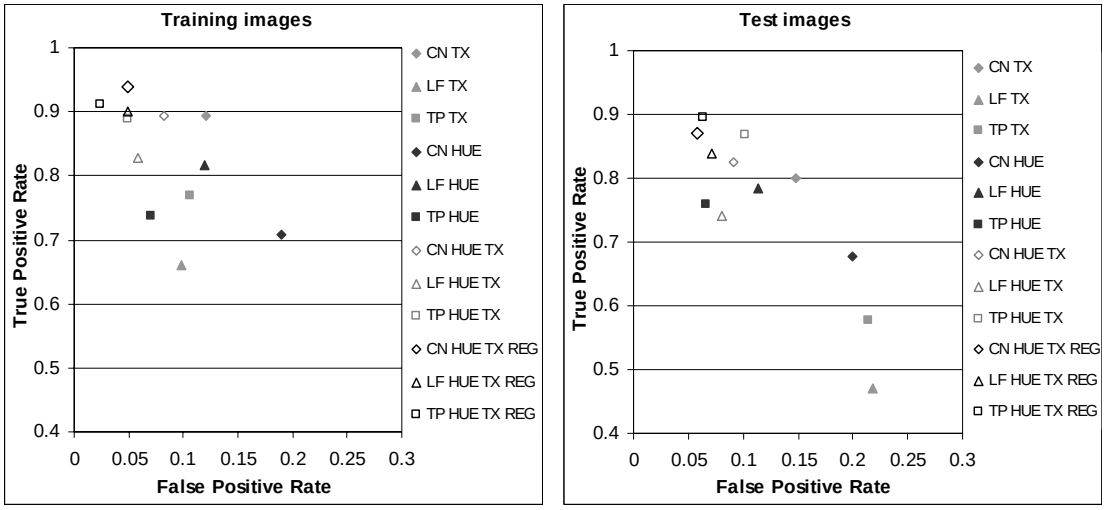


Fig. 14—True positive versus false classification rates for cane, leaf, and tops in training and test images.

The combined colour-texture image classification approach has several limitations and requirements. For the purpose of textural analysis, it is extremely important that sharply focussed high resolution images are obtained, given the fine scale of the features of interest. It is also important that specular highlights on cane or trash particles are avoided, as this effect washes out textural detail and obscures the true colour of the observed particles.

Some images in the current study were deficient in these regards which decreased the effectiveness of texton classification. Also, the amount of misclassification around cane nodes and the edges of cane billets indicates that more specific texture models covering more specific aspects of each category's textures could be desirable.

Summary and conclusions

Colour and texture can be used to identify cane, leaf and tops in high resolution colour images. The distinguishing textural features are consistent across all cane varieties examined, and discrimination between cane and non-cane using texture does not require calibration for cane variety. Textural discrimination is successful in distinguishing cane from trash but does not distinguish between the trash components of leaf and tops. Leaf and tops can be distinguished on the basis of colour, and this distinction is also consistent across all cane varieties examined. Combining both type of information makes a huge contribution to the accuracy of cane-leaf-tops discrimination.

The accuracy of the current colour-texture classifier approaches the accuracy required to quantify the types and amounts of trash present in sugar mill feedstocks. This would provide a non-invasive, direct method of estimating trash levels that the industry currently lacks. Further work is required both to improve the speed of the process, and to improve its accuracy in particular areas.

Acknowledgements

The authors thank Bruce Lamb of Sunshine Sugar, Maclean, New South Wales and Bob Aitkin of BSES, Harwood Island for their support with the trash investigation.

REFERENCES

Agnew JR (2002) A participatory approach towards improving industry sector profits through improved harvesting efficiency. SRDC Final Report SD02023. BSES, Brisbane.

Agnew JR, Sandell GR, Stainlay GT, Whiteing C (2002) Increased sugar industry profitability through harvesting best practice. *Proceedings of the Australian Society of Sugar Cane Technologists* **24**,184–189.

Bernd J (2004) 'Practical handbook on image processing for scientific and technical applications.' 2nd edn (CRC Press: London).

Bevin C, Staunton SP, Stobie R, Grimley SC, Kingston J (2002) On-line use of near infrared spectroscopy in a sugar analysis system (SAS). *Proceedings of the Australian Society of Sugar Cane Technologists* **24**, 404–410.

Comaniciu D, Meer P (2002) Mean shift: a robust approach to feature space analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **24**, 603–619.

Cula OG, Dana KJ (2001) Compact representation of bidirectional texture functions. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* **1**, 1041–1047.

Dixon TF, Burbidge D (2000) The future for cogeneration in the sugar industry. *Proceedings of the Australian Society of Sugar Cane Technologists* **22**, 38–45.

Fuelling T (1999) Harvesting quality sugarcane. Proceedings of the Australian Society of Sugar Cane Technologists **21**, 28–33.

Julesz B (1962) Visual pattern discrimination. *IEEE Transactions on Information Theory* **8**, 84–92.

Julesz B (1981) Textons, the elements of texture perception and their interactions. *Nature* **290**, 91–97.

Julesz B, Bergen JR (1983) Textons, the fundamental elements in preattentive vision and perception of textures. *Bell Systems Technical Journal* **62**, 1619–1645.

Pope G, McDowell R, Massey W, Staunton S (2004) The use of NIR spectroscopy in a cane quality incentive scheme. *Proceedings of the Australian Society of Sugar Cane Technologists* **26**, (CD-ROM), 8 p.

Schembri MG, Hobson PA, Paddock R (2002) The development of a prototype factory based trash separation plant. *Proceedings of the Australian Society of Sugar Cane Technologists* **24**, 12–18.

Shapiro LG, Stockman GC (2001) 'Computer Vision'. (Prentice Hall: Upper Saddle River, N.J.).

Staunton SP, Lethbridge PJ, Grimley SC, Streamer RW, Rogers J, Mackintosh DL (1999) Online cane analysis by near infra-red spectroscopy. *Proceedings of the Australian Society of Sugar Cane Technologists* **21**, 20–27.

Staunton SP, Mackintosh DL, Peatey G (2004) The application of network NIR calibration equations at the Maryborough sugar factory. *Proceedings of the Australian Society of Sugar Cane Technologists* **26**, (CD-ROM), 14 p.

Varma M, Zisserman A (2002) Classifying images of materials: achieving viewpoint and illumination independence. *Proceedings of the European Conference on Computer Vision*. **3**, 255–271 (Springer-Verlag).

Varma M, Zisserman A (2003) Texture classification: are filter banks necessary? *Proceedings of the 2003 IEEE Conference on Computer Vision and Pattern Recognition* **2**, 691–698.