An on-line monitoring system to measure the extraneous matter present in billet sugar cane

CSU001

Charles Sturt University, Sugar Research Institute

Dr W.E. Moore, School of Information Technology, Charles Sturt University,
Bathurst, 2795. Phone (02) 63384749 Fax (02) 63384649

This project was funded by the Sugar Research and Development Corporation

Executive Summary

Introduction

Extraneous matter (EM) in cane billets consists of two major types of material; dirt and trash. Dirt consists of primarily inorganic, rock derived material, while trash consists of primarily organic, non-productive sugar cane derived material such as leaves, tops, and root balls, Trash can also contain other non sugar cane derived organic matter such as weeds and other items included during the harvesting process.

Dirt and trash have long been important issues in the sugar industry. Dirt leads to increased physical wear on harvesting and processing equipment, in particular the milling train and bagasse fired boilers. Once regarded as completely useless and burnt off in the field before harvest, trash is now regarded as valuable biomass for production of environmentally friendly energy. However, trash also causes inefficiencies in the milling process, and there is now much interest in trash separation processes.

Monitoring is a necessary part of determining the efficiency of trash separation processes, and in determining dirt levels.

The project investigated the use of cheap VIS/VNIR spectrometers to measure dirt levels and image analysis to measure trash.

Dirt Estimation

The industry standard measure for dirt levels in cane supplies is ‘ash percent fibre’. Measuring ash is a time-consuming laboratory technique, which takes several days to generate a result, and can process only small numbers of samples at a time.

Over the years a variety of methods of measuring dirt levels in cane supplies have been tried. These include neutron activation, natural gamma ray detection, and X-ray fluorescence techniques. All these techniques require calibration for dirt parent material..

Recently, near infrared (NIR) spectra from prepared cane have been used to generate ash estimates. This is an attractive approach because NIR spectra can be used to estimate many other interesting properties of prepared cane, such as moisture levels, fibre, and Commercial Cane Sugar (CCS) concentration. There are some accuracy issues in current NIR dirt estimations.

A potential alternative to using NIR spectra for estimating dirt levels is the use of visual range (VIS) spectra. One of the primary descriptors of soil (or dirt) types is visual range colour. Visual range dirt spectra can be easily distinguished from cane spectra, and mixtures of the two can be analysed as a combination of the component spectra.

This study investigated the feasibility of using silicon diode based VIS/VNIR spectrometers to generate a dirt estimate and also to identify dirt types. VIS/VNIR spectroscopy is an attractive measurement technique because of the low cost and high speed of the detectors. The ability to automatically distinguish and calibrate for dirt type would also be a useful improvement to current spectrographic methods of estimating ash levels in prepared cane.

Trash Estimation

The sugar industry currently has no reliable idea of the amount of trash entering sugar mills along with billet cane. At present, the best method of measuring trash levels is to physically sample billet supplies and then separate and weigh the various trash categories. Physical separation is an extremely labour intensive, slow, and hence expensive process.

Determining the amount of trash in billet cane is a very different problem from determining the amount of dirt. Spectral characteristics of non-productive parts of sugar cane are relatively similar to productive parts. Therefore spectral determination of trash levels using prepared cane is much less likely to produce accurate estimates than spectral determination of dirt levels. However, trash is easily distinguished visually from cane at the billet stage.

This study investigated the feasibility of using image analytical techniques to make estimates of trash levels in billet cane. It could provide the basis of a rapid non-invasive on-line system to monitor trash levels in billet cane.

Outcomes

The project has shown that cheap silicon-diode based spectrometers operating on visual range and very-near infrared spectra can be used both for determining dirt types and estimating dirt levels in prepared cane. The methods developed in the project using VIS/VNIR provide an economical and accurate solution to the problem of dirt level estimation..

Image analysis cannot separate cane and trash on the basis of pixel colour alone, but with the use of region based spatial features, a classification accuracy of 75% was achieved. It was found that the computational cost of image analytical techniques is very high. Trash coverage levels are very high for relatively low amounts of trash. There is no detectable change in cane coverage proportions below around 80% cane weight fraction. Trash coverage proportions are highly variable for a given cane /trash weight fraction. This necessitates a high number of large images in order to produce a precise measurement.

A great deal of research still needs to be done to improve the accuracy and timeliness of the image analytical techniques used in the project. The project has provided a useful foundation for the development of image analytical techniques and provided insight into the problems that are encountered in non-invasive monitoring of trash levels.

1 Background

Extraneous matter (EM) consists of two major types of material. These are referred to as dirt and trash. Dirt consists of primarily inorganic, rock derived material, while trash consists of primarily organic, non-productive sugar cane derived material such as leaves, tops, and root balls, Trash can also contain other non sugar cane derived organic matter such as weeds, the odd cotton shirt or hanky, and some very unlucky small animals.

Dirt has long been an important issue in the sugar industry. Dirt leads to increased physical wear on harvesting and processing equipment, in particular the milling train and bagasse fired boilers. It also causes inefficiencies in the processing of extracted juice. Monitoring is a first step in developing incentive and penalty schemes aimed at reducing dirt levels in cane supplies and improving mill efficiency.

Trash has also long been an issue for the sugar industry. Once regarded as completely useless and burnt off in the field before harvest, it is now regarded as valuable biomass for production of environmentally friendly energy. While useful as a source of energy, trash also causes inefficiencies in the milling process, and there is now much interest in trash separation processes. Monitoring is a necessary part of determining the efficiency of such trash separation processes, and also in determining just how much trash is actually entering the milling train.

This investigation looks at monitoring these two classes of extraneous matter separately. This is based on the very different problems associated with determining these different classes of extraneous matter.

1.1 Dirt

The industry standard measure for dirt levels in cane supplies is ‘ash percent fibre’. This is a measure of the refractory residue left after incinerating the insoluble solid component of a sample of prepared cane. Measuring ash is a time-consuming laboratory technique, which takes several days to generate a result, and can process only small numbers of samples at a time. There is considerable industry interest in developing an on-line dirt measuring technique, to improve the timeliness, coverage and cost of the dirt measure.

Over the years a variety of methods of measuring dirt levels in cane supplies have been tried. These include neutron activation, natural gamma ray detection, and X-ray fluorescence techniques. All these techniques require calibration for dirt parent material. The natural gamma technique has proven most successful and a commercial instrument, the CaneScan 2000 is in production use in several mills.

Recently, near infrared (NIR) spectra from prepared cane have been used to generate ash estimates. This is an attractive approach because NIR spectra can be used to estimate many other interesting properties of prepared cane, such as moisture levels, fibre, and Commercial Cane Sugar (CCS) concentration. However, current NIR methods apply a ‘global’ calibration for ash estimates and there are some issues with the accuracy of the results in some situations.

A potential alternative to using NIR spectra for estimating ash levels is the use of visual range (VIS) spectra. There have been rapid advances in the technology of visual range spectrometers over the past few years. These spectrometers use silicon diodes as their detecting elements, which is essentially similar technology to that used in other silicon chips. They are sensitive to light in the visual and very near infrared range (400-1200nm) Relatively high quality visual range spectrometers are now available as PC peripherals for costs in the range of $1000.

One of the primary descriptors of soil (or dirt) types is visual range colour. Also, spectra from inorganic rock derived material differ markedly from living organic material. Hence, visual range spectra from dirt can be easily distinguished from cane spectra, and mixtures of the two can be analysed as a combination of the component spectra. Also, visual range colour differences might allow identification of dirt types and hence automatic calibration for parent material.

This study investigates the feasibility of using silicon diode based VIS/VNIR spectrometers to generate a dirt estimate and also to identify dirt types. VIS/VNIR spectroscopy is an attractive measurement technique because of the low cost and high speed of the detectors. The ability to automatically distinguish and calibrate for dirt type would also be a useful improvement to current spectrographic methods of estimating ash levels in prepared cane.

1.2 Trash

Trash levels in billet supplies are also an important issue. Although not associated with the physical wear problems caused by dirt, trash lowers the concentration of sugar (CCS) in cane supplies, and also causes transport and processing inefficiencies. Increasing interest in cogeneration of electricity at sugar mills has also raised the sugar industry’s interest in trash, particularly in its effect on the amount and thermal content of bagasse.

The sugar industry currently has no reliable idea of the amount of trash entering sugar mills along with billet cane. At present, the best method of measuring trash levels is to physically sample billet supplies and then separate and weigh the various trash categories. Commonly recognised categories include leaves, tops, root balls (or ‘stools’), and ‘other organic matter’, but there are no industry standards to facilitate identification or comparison of measurements. Physical separation is an extremely labour intensive, slow, and hence expensive process. There are anecdotes of mill hands making visual classifications of billet supplies into ‘low’, ‘medium’, and ‘high’ trash levels but the accuracy, reliability, and physical meaning of these classifications is unknown and prone to error.

The ‘wet chemical’ measure most closely related to trash is ‘fibre’. However, fibre includes all the insoluble residue in prepared cane, and hence a large contribution from billet cane. In fact, the effect of trash on the fibre measurement is unknown.

Determining the amount of trash in billet cane is a very different problem from determining the amount of dirt. Spectral characteristics of non-productive parts of sugar cane are relatively similar to productive parts – especially after the cane has been through a hammer mill. Therefore spectral determination of trash levels using prepared cane is much less likely to produce accurate estimates than spectral determination of dirt levels. However, humans can easily distinguish trash from cane visually at the billet stage.

It seems possible that an estimate of the levels of trash components can be made based on the visual appearance of the surface of billet supplies using image analytic techniques.

This study investigates the feasibility of using image analytical techniques to make estimates of trash levels in billet cane. If this proves feasible, it would provide the basis of a rapid non-invasive on-line system to monitor trash levels in billet cane.

2 Objectives

The objective of the study was to develop a fast cheap online monitoring system for extraneous matter in cane.

The central idea was to combine fast, cheap, VIS/VNIR spectrometry to determine dirt levels with fast, cheap, digital image processing to determine trash levels in order to produce a fast, cheap, integrated method for monitoring the total extraneous matter load in cane supplies.

A two-phase program of investigation was planned:

- Firstly, to investigate the use of fast, cheap silicon diode based VIS/VNIR spectrometers to measure dirt levels.
- Secondly, to investigate the use of image analysis to measure trash levels.

The first year of the study focussed on determining dirt levels, through the use of visual and near-infrared spectra of prepared cane. Research issues addressed were:

- Can fast, cheap, silicon diode detectors operating in the visual to very near infrared (VIS-VNIR) range of the spectrum be used to determine dirt levels in prepared cane?
- Can contaminating dirt types be distinguished on the basis of VIS-VNIR spectra?
- Does identifying contaminating dirt types improve the accuracy of dirt level determination?

This work became commercially sensitive, and too similar to other research work in the area. At the end of the year, the project was redirected into a strong focus on developing a non-invasive on-line trash monitoring system.

The objective of the second two years of the study has been to determine the feasibility of such a system. The research issues addressed have been:

- Is it possible to distinguish billet cane from trash in imagery? If so what is the best method?
- How accurately does a given cane/trash coverage ratio reflect a given cane/trash weight ratio?
- How do surface coverage proportions observed in an image relate to weight fractions of the cane and trash?
- Is it necessary to identify cane and trash in imagery to derive a measure for the relative weight fraction? If not, what methods might achieve this, and to what accuracy?
- Can the required image processing be done in sufficiently short a time to make image processing a viable technique for online trash monitoring?

The results of the investigation are presented in the following sections.

3 Methodology - Timelines

3.1 1999

The project started in 1999. A literature search was conducted and a set of batch tests were performed during the 1999 crushing season at Central Queensland University in Rockhampton (CQU), and the Sugar Research Institute in Mackay (SRI). The tests were intended to establish whether a silicon diode based spectrometer operating in the visual to near infrared range (VIS/VNIR) was capable of distinguishing dirt levels in prepared cane over the range of 0% to 10% dirt by weight and whether dirt types could be identified at these contamination levels. Results from these tests were presented in the first/second milestone, and as a poster paper at the Australian Society of Sugar Cane Technologists' 2000 conference in Bundaberg.

The results were considered sufficiently encouraging to warrant an online trial, and planning and preparation was undertaken to design and install a VIS/VNIR spectrometer at Racecourse Mill in Mackay.

3.2 2000

In April 2000 a review of the project was held in Brisbane. The review focused on the direction that the project was taking, and the emphasis on detecting and measuring dirt levels using spectroscopic techniques compared to the lack of development in image analytical techniques for monitoring trash levels. The review noted that while the results of the VIS/VNIR spectrometry experiments were useful, the project should concentrate on investigating and developing image analytical techniques. As a consequence of this review, the project refocused on image analysis of trash levels.

In the event, difficulties with fabrication and installation caused the abandonment of the planned online trial of a VIS/VNIR spectrometer during the 2000 crushing season. However, the imaging program based on an industrial visual/near-infrared four-colour camera donated to the project by Colour Vision Systems went ahead.

The project cooperated with Mackay Sugar in running a physical trash analysis program over the 2000 crushing season in order to provide calibration data for the imaging program. In return for access to the results of the sampling program and cooperation in triggering image capture, the project provided partial funding for a mill hand to perform physical trash analyses and to offset the costs of installing the project's camera and computing equipment. Mackay Sugar also made available NIR spectra from their new FOSS/NIRsystem spectrometer.

Installation of the four-colour camera rig over the billet conveyor was delayed by fabrication requirements, labour trouble and the exigencies of mill maintenance days, but went ahead in late August, 2000. This permitted a truncated batch imaging program to be undertaken while waiting for installation, which ultimately proved extremely beneficial. Following installation, problems with the automated image capture system and computer reliability hindered image acquisition, but eventually fourteen rakes were imaged, and supporting physical analyses and NIR spectra acquired.

Image processing was carried out and various analytical techniques developed and evaluated in the months following the crushing season. The results of the 2000 field seasons imaging program were reported on in Milestone 4 delivered in February 2001. Following this milestone, the project was extended for a year to allow a more complete investigation of the imaging technique.

3.3 2001

The 2001 field season was intended primarily to address a number of issues identified in the previous season. These issues were:

- Small image size for the online imagery.
- Differences in measurement technique between batch and online samples.
- Unknown size of errors in coverage proportion estimates.
- Variation in NIR brightness between images.

In the 2000 crushing season, online images were generally less than 50 by 30 pixels, due to limitations imposed by the automated image capture software. In the 2001 crushing season, image capture was triggered manually, which allowed images of 400 by 250 pixels to be captured.

In 2000, the project used physical analyses provided by Racecourse Mill as part of their trash analysis program. However, the analytical method used was not exactly that desired by this project. In particular, 'adhered leaf' was included in the 'cane' category. While this has negligible effect on the weight of the cane fraction, adhered leaf can be a significant proportion of the leaf fraction, particularly for relatively clean cane. In the 2001 crushing season, physical analyses were performed specifically for the project by the investigator and exactly the same methods and categories were used for both batch and online work.

Not enough batch imagery was captured in the 2000 crushing season to allow assessment of sample representivity or quantification of errors in coverage proportion estimates. These issues were addressed in 2001 by increasing the number of batch images. Also, the number and size of online images was increased.

There was considerable variation in average NIR brightness in images captured in the 2000 season. In 2001, a possible relationship between NIR image brightness and sample temperature was investigated by measuring cane temperatures with a remote infrared thermometer.

Images and physical analyses were again processed in the following months and the results of the 2001 field season reported in Milestone 5 delivered in March 2002.

4 Methodology - Technique

The project collaborated with the Non Invasive Assessment Group of the Central Queensland University (NIAG) and the firm Colour Vision Systems (CVS) to conduct the research program. These groups have extensive experience in NIR spectroscopy and image processing in online fruit quality assessment systems and provided valuable support and guidance throughout the program. In particular, Colour Vision Systems fabricated and donated an industrial visual and near infrared range four colour camera, lighting panel and associated control electronics for the use of the program.

4.1 Dirt

The basic experimental approach to dirt level determination used in this study was to acquire VIS/VNIR spectra from prepared cane samples from a single cane variety (Q124) at relatively constant moisture levels contaminated with known levels of a selection of dirt types.

Dirt samples were taken from ten different soils in the cane growing areas surrounding Mackay. Pale variants from two soil types were taken because of the perception that paler dirt types might present problems in estimating dirt levels. A summary of dirt descriptions and identifying codes of soil types (dirt) used in the project is given in Table 4.1.1.

Clean billets of Q124 were processed into prepared cane and split into sub-samples weighing 500 grams. Each dirt sample was disaggregated with a mortar and pestle. Portions from each type were then weighed out and added to the prepared cane samples to make up ten separate contamination series. The dirt levels used were 0.5, 1.0, 2.0, 5.0, and 10.0 percent dirt to total weight as well as a ‘clean’ control sample. The dirt and cane was mixed using a standard SRI mixing technique. Each sample was then subdivided to give a sample for spectroscopic analysis and a sample for ashing. Samples for spectroscopic analysis were placed in 15cm round containers and the surface pressed flat with a ten kilogram weight.

Ash samples were first dried at 110 degrees until dry weight stabilized, and then incinerated at 600 degrees for eight hours. Results are expressed as ash percent dry weight cane since no fibre measurement was performed. The ash percent dry weight figure given is not directly comparable to an ash percent fibre figure. Unfortunately, results for two series are missing due to error on the part of the investigator.

4.1.1 Comparison Observations

Full VIS/VNIR/NIR spectra for three dirt contamination series were collected using a bench mounted Foss/NIRsystem 6500 scanning NIR spectrophotometer in the Non Invasive Assessment Unit laboratory at Central Queensland University. This is a bench mounted laboratory instrument similar to the sugar industry standard instrument, the Foss/NIRsystem 5000 and utilizes the same detectors in the NIR range. Samples were pressed against an aperture in a light tight box and a NIRsystem reflectance measuring head mounted directly against the other side of the aperture. Four separate readings on each sample were taken, rotating the sample to present a different area to the probe with each reading. Dark current and white reference corrections were applied between samples. The white reference used was a slab of white Teflon plastic.

VIS/VNIR spectra for the same sample set were collected with an ASD field portable spectrophotometer designed for ground truthing satellite imagery. Samples were placed in a light-tight box with the spectrophotometer's optic sensor mounted 25cm vertically above the sample. The optic sensor was shrouded by a tubular fore-optic attachment to give a 3cm diameter field of view on the surface of the sample. The samples were illuminated by metal halide lights set at an angle of 45 degrees to the sample surface in order to reduce specular reflection. Four readings per sample were taken in a manner similar to the NIRsystem observations and white reference corrections made between each set of four readings. The white reference used was a flat surface of powdered barium sulphate.

The parallel observations were intended to assess the utility of the VIS/VNIR wavelength range (400-1100 nm) relative to the NIR wavelength range (1100-2500 nm) in developing prediction equations for dirt levels in prepared cane. They were also intended to assess whether the ASD instrument was capable of detecting differences in sample spectra throughout the region of interest.

Thanks to the support of Dr Kerry Walsh and the staff and members of NIAG at CQU, the comparison observations also provided valuable training in the techniques of acquiring accurate spectra and methods of analysing such spectra.

4.1.2 Independent Observations

Following the comparison observations, a second, independent set of measurements was collected using the ASD instrument alone. The independent observations examined dirt contamination series made up from the seven other dirt types collected. These observations were intended to assess the effect of dirt type on dirt contaminated prepared cane spectra, and the accuracy of prediction equations for dirt levels from a variety of dirt types. They were also intended to help assess whether dirt type could be identified using dirt contaminated prepared cane spectra.

For the comparison observations, repeat measurements are first assessed to gain an idea of observational precision. Then regressions for ash are developed for the NIRsystem instrument both with and without knowledge of dirt type using first the NIR (1100-2500 nm) range and then the VIS/VNIR range (400-1100 nm) of wavelengths. Similar regressions are then calculated for VIS/VNIR spectra from the ASD instrument and the results compared with the NIRsystem instrument.

For the independent observations, regressions were developed for VIS/VNIR spectra from the ASD instrument both with and without knowledge of dirt type and the results compared. Then, the spectra are subjected to discriminant analysis for dirt type. Regressions using the discriminant classification are developed and the results compared with the other regressions.

4.2 Trash

The technique of trash level estimation based on image analysis is completely novel in the sugar industry. The basic methodology was to acquire imagery of mixed cane and trash and then physically analyse the imaged sample to provide calibration data for trash level estimates derived from the imagery. Cane and trash components recognised included 'good' and 'bad' billets, billet fragments or 'chips', green leaf, dry brown leaf, 'adhered' leaf (i.e. leaf adhering to billet cane), tops, 'stools' or root balls, dirt, and 'other organic matter' such as weeds, dead cane, or animal body parts. The categories of cane and trash were chosen to give a degree of visual coherence to the categories. Hence the distinction between dry brown leaf, green leaf, and 'adhered' leaf.

The image analysis investigation was divided into two parts:

- an offline program intended to establish the basics of the technique. The ability to distinguish between cane and trash components, the consistency of cane/trash coverage proportions observed at a given trash level, and the relationship between coverage and weight fractions were investigated in the offline program.
- an online program, intended to investigate the practicalities of online installation and operation. The ability of the image analytical technique to generalize to a 'per rake' level was examined in the online program.

The camera used in the study was an industrial four-colour digital camera, which uses a two-lens system to capture three colour (RGB) visual range images and a monochromatic near-infra-red (N) image. The industrial camera uses pinhole lenses to capture images of 450 x 250 pixels. The pinhole lenses allow high-resolution imagery to be captured over a small area, or low-resolution imagery to be captured over a wider area. In this study, the camera was set at a distance of around 1400mm from the imaged surface and the images covered an area of 600 x 300 mm, giving a pixel resolution of around 4 square millimetres. The imaged surface was illuminated by a 1400 by 1200 mm panel of 'full spectrum' fluorescent tubes.

Figure 4.2.1 and Figure 4.2.2 show the camera rig and the associated control unit and lighting panel as used in the imaging program. In Figure 4.2.2 the camera rig is mounted on the frame used to suspend the unit above the cane conveyor in the online imaging program.

It was decided that image based discrimination and classification would concentrate on cane, leaf and tops due to the abundance of these cane/trash components relative to other categories such as stools, dirt and other organic matter.

4.2.1 Offline Imaging Program

The offline sampling and imaging procedure involved the following steps. First, 20kg samples were extracted from selected rakes. These were divided into 10kg sub-samples, which were analysed separately. Several images of each of the raw sub-samples were taken, with the sub-samples remixed between images. The sub-samples were then physically separated into cane and trash components, and the components weighed to gram accuracy. Leaf was stripped from billets in the separation process. Images of the separated components were then taken to form the basis of cane and trash component training sets. These were intended to establish whether it is possible to distinguish between cane and trash components. Multiple images of each unsorted sample were taken to investigate how well the surface coverage of cane and trash reflected the underlying weight fractions.

Following physical separation, 'trash series' were made up from a number of the offline samples by adding known quantities of leaf back into pure piles of cane billets. Multiple images at each trash level were taken with the samples remixed between images. The trash series were intended to assess the relationship between cane/trash coverage ratios and cane/trash weight ratios.

An additional trash series was also made up with cane and trash components spray painted distinctive colours to facilitate identification. This was intended to produce a 'best-case' scenario where leaf and cane could be unambiguously identified on the basis of pixel colours alone and accurate coverage estimates could be easily obtained while the effect of misclassification of cane/trash components was minimised.

The same sampling and physical separation techniques were used in both the 2000 and 2001 crushing seasons. In the 2001 crushing season, more images were taken of the unsorted samples, and more images were taken of each trash level in the various trash series. Also, in the 2001 crushing season, 'adhered leaf' was recognised as a sub-category of 'leaf', and 'green leaf' was recognised as a sub-category of 'tops'.

4.2.2 Online Imaging Program

Two online trials were also conducted during the 2000 and 2001 crushing seasons. The reasons for embarking on online trials so early in the development of the imaging technique are several: firstly, in the 2000 crushing season there was an opportunity to integrate with a trash sampling program conducted by Mackay Sugar and it was considered that the number and variety of samples examined would benefit the project. Secondly, there are many practical issues involved in online monitoring, and a trial is really the only way to discover and address these.

In the online trials, the camera was enclosed in a weatherproof housing and mounted above the input billet conveyor near the tippler at Racecourse Mill, Mackay. The image acquisition computer was installed in the sampling room of the control tower, and image acquisition triggered by a switch installed in the tipper viewing area of the control tower.

The online processing differs significantly from the offline processing in that physical samples and images are not explicitly linked. Also, because of the installation of the camera rig above the input feed conveyor, no separate images of sorted cane and trash components are available. Because images and physically analysed samples are necessarily distinct in the online trial, results are aggregated to the rake level

Rakes consisting of fifteen or more cane trucks were selected for sampling. Image capture commenced some ninety seconds after the first truck in the rake was tipped, allowing time for cane from the rake to reach the imaging rig. A fifteen truck rake would take approximately seven and a half minutes to be emptied onto the input conveyor by the tippler. Images were captured every 15 seconds as the selected rake passed beneath the camera rig resulting in around 30 images being captured per rake. In the 2000 crushing season, these images averaged only 30 x 30 pixels, but in the 2001 season images measured 300 x 150 pixels.

In the 2000 crushing season, up to 5 physical samples per rake were taken, each of around 20 kilograms. These were separated into good and bad billets, cane fragments, root balls, dead cane, dirt, and ‘leaves, grass and weeds’. These components were weighed to an accuracy of 10 grams. Adhered leaf was not removed from billets during component separation. In the 2000 crushing season, image capture was triggered by a mill hand when the first physical sample of the rake was taken, and then occurred automatically for the next 10 minutes. The first 90 seconds of imagery was discarded, and the next seven and a half minutes used, in order to ensure that the imagery was of the rake physically sampled.

In the 2001 crushing season, two physical samples were taken of the selected rake, each of around 20 kilograms, generally from the third/fourth and seventh/eighth trucks. These were separated into the same categories as used in the offline processing and weighed to gram accuracy. Adhered leaf was removed during separation of components. Images of 450 x 250 pixels were collected every 15 seconds by manually triggering image capture, while the sampled rake passed beneath the camera rig.

In the 2001 season, temperatures of sampled rakes were measured with a remote infrared thermometer. A set of 30 temperature measurements was made for each analysed rake by pointing the remote IR thermometer at slow moving cane in the base of the tippler area, shortly after the tippler had rotated.

5 Results – Dirt Analyses

5.1 Chemometric Spectrometry

Chemometric analysis of spectra relies on the fact that different substances absorb or reflect radiation selectively at different wavelengths. The strength of these reflectance/absorption (R/A) features in mixtures of substances gives an indication of the relative amounts of those substances.

Beers Law states that the concentration of an analyte in a dilute solution is proportional to the absorbance of light at a selected wavelength given constant measurement geometry. Absorbance is defined as the log of the ratio of the intensity of incident light to the intensity of transmitted light. Beers Law can be applied to light reflected from opaque solids where it may be interpreted as saying that the concentration of a contaminant is proportional to the log of the ratio of the intensity of light reflected from a pure substrate to the intensity of light reflected from a contaminated substrate.

Beers Law applies to the absorption of light at a particular wavelength, and involves the calculation of a ratio. It is inherently a univariate measure, and errors for the ratio are the product of the errors in the figures used to calculate the ratio. This study also approached the estimation of dirt levels in prepared cane from a purely statistical point of view. Essentially, it treats the measured spectra and dirt types as independent variables, dirt concentration as the dependent variable, and asks what the best multivariate regression model is for the observed data. For the multivariate treatment, a Beers model is neither necessary nor desirable because of the multiplication of errors, and regressions are formed for the raw spectra intensities or differences.

Reflectance and absorption figures are given relative to a white reference standard. When less light is detected for a particular wavelength than is detected for the white reference standard, then absorption is greater than unity, and when more light is detected, then absorption is less than unity. Reflectance is the inverse. When more light is detected for a particular wavelength than is detected for the white reference, then reflectance is greater than unity, when less light is detected, then reflectance is less than unity. The values for the NIRsystem data are ‘absorption’ figures while the values for the ASD data are ‘reflectance’ data.

Reflectance/absorption (R/A) features may be hard to identify in ‘raw’ or ‘intensity’ spectra. ‘Raw’ spectra also suffer from variability due to variations in lighting intensity, or differences in lighting-sample-detector geometry. This variability is especially pronounced in lighting-sample-detector geometries where the distances between the elements are very short, such as in the NIRsystem integrated lighting and detector sample probe. Small variations in sample distance produce relatively large effects in measured reflectance. Use of absolute intensity spectra is not favoured as a means of estimating relative strengths of reflectance or absorption.

For these reasons, ‘relative’ or ‘difference’ spectra are used. ‘Difference’ spectra express reflectance/absorption in terms of the difference in reflectance/absorption between adjacent detectors. Expressing spectra in this form removes the effect of absolute intensity from spectra, and allows comparison of spectra that may suffer from variability in absolute intensity due to differences in lighting/sample/detector geometry.

The wavelength response curve of a detector element is Gaussian, centred on its nominal wavelength, and the response bandwidth is wider than the nominal bandwidth. This 'smears' an instrument's response to a given R/A feature over a number of neighbouring detectors with the greatest response centred on the R/A feature's wavelength. 'Slope' or '1st difference' spectra show maxima or minima at the wavelength of R/A features, while 'curvature' or '2nd difference' spectra show zero crossings at the wavelength of R/A features and maxima and minima to either side. These features make identification and measurement of R/A features much easier in difference spectra

In '2nd difference' spectra, the distance between the zero crossing and the peaks on either side is one standard deviation of the detector's response Gaussian. This corresponds with the width of an R/A 'peak' at half its height In '1st difference' spectra, and is an indication of the response bandwidth of an instrument's detectors. Raw difference spectra from both instruments indicate that the response bandwidth of both instruments is approximately 30nm.

Difference spectra are highly susceptible to noise. For this reason raw spectra are smoothed before difference spectra are calculated. In this case, both the NIRsystem and the ASD spectra are smoothed with a Gaussian of 15nm standard deviation before difference spectra are calculated.

The NIRsystem spectrometer uses silicon diode based detectors in the 400-1100nm wavelength range, and gallium arsenide detectors in the 1100-2500 nm range. The two sets of detectors must be calibrated against a reference standard before measurements are made, and the detectors are sensitive to a variety of operating factors such as temperature, and length of time in operation. Errors in calibration between detector sets result in a sharp discontinuity in intensity and difference spectra at the 1100nm point. This discontinuity makes R/A features within 30nm of the crossover point unreliable in terms of estimating substance concentrations.

The ASD instrument does not measure in the 1100-2500 nm range at all, while the NIRsystem spectrometers commonly used in the sugar industry do not measure in the 400-1100 nm range. For these reasons the 400-1100 nm range and 1100-2500 nm range are treated separately. In fact, the main interest in this study centres on the relative performance of the 400-1100 nm range compared to the 1100-2500 nm range in detecting and measuring dirt levels in prepared cane, because the detectors used in the 400-1100 nm range are much cheaper than the detectors used in the 1100-2500 nm range.

There are many issues raised when comparing spectra concerning cross calibration between instruments which this study does not address. This study is concerned only with the issues of relative sensitivity and precision of the instruments used. It is still difficult to compare instruments for sensitivity and precision because the instruments express spectra in different units, have different numbers of detectors spanning the same range of wavelengths, and the measurements are expressed relative to differing white standards numbers.

5.2 Instrument Precision and Sensitivity

5.2.1 Precision

One way of expressing the precision of the instruments is as the sum over all detectors of the error for each detector, multiplied by the nominal bandwidth of the detectors, over the same range of wavelengths for each instrument. This is equivalent to the area between the mean sample spectra and the individual measurements. Another way of expressing precision is as the total error area divided by the number of detectors and the nominal bandwidth of the detectors. This is equivalent to the error per nanometer of wavelength and facilitates comparison between the 400-1100 nm range and the 1100-2500nm range. The first method gives an indication of the total error for the wavelength range, and the second method gives an indication of the average error per unit wavelength. First difference spectra were used for the area measurement, so the comparison is qualitative. Table 5.2.1.1 and Table 5.2.1.2 summarize these measures. The important points are:

- The ASD and NIRsystem instruments are comparably precise in the 400-1100 nanometer range.
- The 400-1100 nanometer range is more precise than the 1100-2500 nanometer range

5.2.2 Sensitivity

The sensitivity of the instruments can be expressed in similar terms to the precision of the instruments. In this case, it is the total difference between dirt contaminated prepared cane spectra and spectra from clean cane that is of interest, since this reflects the sensitivity of the instruments to changes in dirt contamination levels. Table 5.2.2.1 and Table 5.2.2.2 summarize these calculations. The important points are:

- The ASD and NIRsystem instruments are comparably sensitive in the 400-1100 nanometer range.
- The 400-1100 nanometer range is more sensitive to changes in dirt levels in prepared cane than the 1100-2500 nm range.
- The effect of a given level of dirt contamination on prepared cane spectra differs markedly according to dirt type.

5.3 Dirt Level Estimation

5.3.1 Spectra and Correlations with Dirt Levels

Illustrative, smoothed, intensity, 1st difference, and 2nd difference spectra from both the NIRsystem and ASD instruments for one dirt contamination series are given in Figures 5.3.1.1.1 through Figure 5.3.1.9.2. These figures also include plots of the correlation between band reflectance/absorption values and dirt levels.

First difference spectra from the NIRsystem instrument exhibit absorption features that show strong positive correlation with dirt levels at 470-480nm, 690-710 nm and

1000-1040 nm in the 400-1100 range and at 1240 nm in the 1100-2500 nm range. There are other absorption features that show lower degrees of positive correlation at longer wavelengths in the 1100-2500 nm range. NIRsystem first difference spectra also exhibit absorption features with strong negative correlation with dirt levels at 656 nm, and 930-980nm in the 400-1100nm range, and at 1140-1160nm, and 1280-1320nm in the 1100-2500nm range. Once again there are lesser features at longer wavelengths.

First difference spectra from the ASD instrument show reflectance features with strong negative correlation with dirt levels at 420-480nm, 615nm, 675-745nm and at 1000nm. There are reflectance features with strong positive correlation with dirt levels at 656nm and at 930-980nm.

Second difference spectra from both instruments show strong positive and negative correlations associated with these absorption and reflectance features. The distance between 2nd difference peaks is around 30nm for both instruments. NIRsystem difference spectra show marked increases in noise below 640 nm and above 1600nm while ASD spectra become very noisy below 500nm and above 960nm. Raw ASD spectra are noisier than raw NIRsystem spectra, but this is not apparent in smoothed spectra.

The range of values for first differences from both instruments is similar. Given the inverse relationship between reflectance and absorption, both instruments are detecting the same features with similar sensitivity.

Spectra and correlation charts indicate the following points.

- There are R/A peaks in the VIS/VNIR range that show equally strong correlation with dirt levels as those in the NIR range.
- The ASD instrument is similar in accuracy and sensitivity to the NIRsystem instrument in the 400-1100nm range.

Essentially, the comparison observations demonstrate that the ASD instrument is capable of measuring spectra with a similar degree of accuracy and precision to the NIRsystem instrument in the 400-1100nm range, and that the 400-1100nm range includes reflectance/absorption features that are similarly highly correlated with dirt levels as those found in the 1100-2500nm range.

5.3.2 Beers Model Regressions

In a dirt contaminated prepared cane spectrum, the pure substrate is clean cane. The Beers model used is the log of the ratio of the light reflected by clean cane to light reflected by dirt-contaminated cane. Figure 5.3.2.1 and Figure 5.3.2.2 show plots of the Beers model correlation coefficients for dirt concentrations for both the 400-1100nm and 1100-2500nm ranges. Correlations are shown for intensity, first difference and second difference spectra. These figures indicate that there are several candidate wavelengths for forming Beers model regressions both above and below the 1100nm crossover point. Table 5.3.2.1 summarizes the accuracy of regressions formed for several of these candidate wavelengths in both the comparison observations and the independent observations. This table shows figures for Beers models both without and with indicator variables for dirt type. The important points may be summarized:

- In every case, knowledge of dirt type improves the accuracy of the regression, in some cases by over 30%. Knowledge of dirt type makes most difference in the log and square-root regression modes.
- The standard Beers model (i.e. absorbance proportional to dirt level) is not the most accurate model possible. The best regressions are formed for the logarithm and square root of dirt levels with knowledge of dirt type.

5.3.3 Multivariate Regressions

A Beers model sacrifices a lot of the information contained in spectra in order to form a physically justifiable model. This is not strictly necessary. The data may be treated as a set of independent variables, with different 'treatments' (dirt types), a single dependent variable: dirt concentration, and multivariate linear regression techniques applied. There is also some indication from the preceding Beers model analysis that a standard Beers model may not be the best description of the effect of dirt on prepared cane spectra.

In order to apply classical multivariate statistical techniques, the number of variables in the data is reduced from the hundreds comprising the raw spectra to a number that can be constrained within the number of samples used in the analysis. Bands were aggregated into 'bins' by averaging band values within a 30nm range. This produced 21 variables in the 400-1100 nm range and 45 in the 1100-2500 range. First and second differences were then calculated for the aggregated variables. Multivariate linear regression using dirt levels as the dependent variable was applied to the dirt contamination series and the results for the comparison observations are summarized in Table 5.3.3.1.

The regressions were performed using raw dirt levels, the log of raw dirt levels and also the square root of raw dirt levels as the dependent variable. Regressions were calculated first without indicator variables for dirt type, then allowing indicator variables to enter the regression, and finally entering the indicator variables first and allowing band variables to enter as required.

The results can be summarized as follows:

- The most accurate regressions are for the logarithm of dirt levels with inclusion of dirt indicator variables on ASD 400-1100nm data using first difference spectra.
- The least accurate regressions were developed for raw dirt levels without inclusion of dirt indicator variables on NIRsystem 1100-2500nm data using intensity spectra.
- Similarly accurate regressions are obtained with 400-1100nm data as with 1100-2500nm data for the logarithm and square root of dirt levels. The 400-1100nm range generates less accurate regressions for raw dirt levels than the 1100-2500nm range.

- The ASD instrument generates marginally more accurate regressions in the 400-1100nm range than the NIRsystem instrument
- Indicator variables entered the analysis in preference to band variables log and square root regressions when free choice allowed. Inclusion of indicator variables significantly improved the accuracy of regressions for all types of spectra in both the 400-1100 nm range and the 1100-2500nm range.

A further 8 dirt contamination series were analysed with the ASD instrument alone. These observations were intended to establish the accuracy to which dirt levels could be estimated on the basis of VIS/VNIR spectra, and to investigate whether dirt types could be identified automatically from such spectra.

Table 5.3.3.2 summarizes the results for regressions constructed for the independent observations. The important points may be summarised as follows:

- The most accurate regressions are formed for the logarithm of dirt levels, with the inclusion of indicator variables for dirt.
- The least accurate regressions are for raw dirt levels without the inclusion of indicator variables.
- The regressions which do not include indicator variables for dirt, are markedly less accurate than those that do, and also are markedly less accurate than equivalent regressions formed for the earlier comparison observations.
- The regressions which do include indicator variables for dirt are comparable in accuracy to equivalent regressions formed in the earlier comparison observations
- Once again, indicator variables enter the analysis early when allowed to do so.

These observations indicate that knowledge of dirt type (or calibration for parent material) is the single biggest factor in improving the accuracy of dirt estimates based on spectral data. Regressions made without knowledge of dirt type produce systematic biases in estimated dirt levels according to dirt type.

Figure 5.3.3.1 shows the results for different dirt types of a regression for raw dirt level without the inclusion of dirt indicator variables. Figure 5.3.3.2 shows the results for different dirt types of a regression for the logarithm of dirt level without the inclusion of indicator variables for dirt type. Figure 5.3.3.3 shows the results for different dirt types of a regression for the logarithm of dirt level with the inclusion of indicator variables for dirt type. Figure 5.3.3.4 shows the errors observed in dirt level estimates for regressions of the logarithm of dirt level with the inclusion of indicator variables. It shows that the 95% confidence interval is around 1% for dirt contamination levels of 2%.

Regressions based on the logarithm of dirt levels with the inclusion of indicator variables show extremely good predictive quality, and most importantly, the magnitude of errors in the predicted log of dirt levels is relatively constant and uniformly distributed about the estimate across all dirt levels, and for all dirt types (See Figure 5.3.3.3). Regressions made for raw dirt levels show poor predictive qualities, errors increase with dirt levels, and errors are not uniformly distributed about the estimate (See Figure 5.3.3.1). In other words, log estimates are unbiased estimators of dirt levels, and the error distribution indicates that the log relationship model is appropriate.

5.3.4 Discriminant Analysis

It would be extremely useful if it were possible to automatically distinguish dirt type, given the improvement in estimation accuracy due to this knowledge. Spectra from the comparison and independent observations were subjected to discriminant analysis in order to test whether automatic identification is possible.

Spectra were separated randomly into two equal groups to provide prediction and validation datasets. Discriminant analysis was performed on intensity, first difference and second difference spectra. The procedure was repeated several times on different randomly formed prediction and validation datasets in order to identify the most useful variables for discrimination. The analysis was repeated for a small number of identified 'most useful' variables as a guard against over-fitting.

The results of the discriminant analyses are shown in Table 5.3.4.1. The results can be summarised:

1. In general, discriminant analysis is highly successful in identifying dirt types, both in the 400-1100 and 1100-2500nm range.
2. Neither range is markedly better than the other in discriminating dirt types. First and second difference spectra are more useful for discriminating dirt types than intensity spectra.
3. Discrimination based on both ranges combined is markedly more accurate than discrimination based on either range alone.
4. Discrimination is accurate down to 0.5% dirt levels.
5. More variables are required to discriminate a greater range of dirt types.

Based on these results, a regression based on dirt type predicted by discriminant analysis was developed and this is shown in Figure 5.3.4.1. This figure shows that dirt level estimates based on dirt type predicted by discriminant analysis are similar in accuracy to estimates made on the basis of known dirt type. Also, the estimates made are unbiased according to dirt type, and more accurate than those made without dirt type indicator variables.

6 Results – Trash Analyses

6.1 Image Analysis

There are two general approaches that may be useful in analysing images in terms of cane and trash proportions. These may be termed classificatory and non-classificatory techniques.

The classificatory approach seeks to identify elements in an image as one of the cane or trash component categories, and then form an estimate of their relative proportions based on the proportions of the area in the image identified as each category. The non-classificatory approach does not seek to identify individual image elements, but rather asks what features of the image reflect the varying proportions of cane and trash component categories. This study has approached the issue of estimating trash levels using the classificatory approach.

There are two main issues central to the classificatory approach. These are:

- can cane and trash component categories be identified in images, and to what degree of accuracy?
- how well do surface proportions of area reflect the underlying weight fractions of cane and trash components?
- which classificatory techniques produce the best results?

This study attempts to answer these questions. At this stage in the development of the technique, an attempt is made to distinguish between only cane, leaf and tops. This is because of the abundance of these components relative to other cane and trash categories.

6.2 Classification of Cane/Trash Components

6.2.1 Preliminary Findings

In the batch program of the 2000 crushing season, samples were separated into cane and trash components, and images taken of the separated components. It was discovered that within each sample, cane could be distinguished from leaf and tops on the basis of relatively higher reflectance in the near-infrared (N) band. Tops could be distinguished from cane and leaf by relatively higher reflectance in the green (G) band. This effect was apparent at all brightness levels within an image, and in each of the batch samples imaged. Table 6.2.1.1 shows values of band signatures for cane, leaf, and tops in one batch sample, and this information is shown graphically in Figure 6.2.1.1.

Based on these findings, images from a set of samples with known increasing levels of leaf were classified. The results of this procedure are shown in Figure 6.2.1.2 and in Table 6.2.1.2.

The preliminary analysis showed that cane, leaf, and tops could be distinguished, and that the surface proportions measured did relate to the underlying weight fractions as can be seen in Figure 6.2.1.3. However, the preliminary analysis was based on only a few batch samples and a single trash series and the results could not be generalized into a useful global classificatory rule. The preliminary analysis also highlighted several issues, which had to be addressed in subsequent investigations. These were:

- RGB and N image registration: In the preliminary analysis, poor registration between the RGB and N images resulted in ‘fringe’ effects occurring on the boundaries of billets. These contributed to high error rates in the classification.
- Lack of generality: Unexpected variations in average intensities for N and RGB images prevented the characteristic N/R and G/R ratios observed for cane and trash components in each sample from generalizing to a useful classificatory rule.
- Lack of spatial information: The band ratios of components overlap. This means that pixels cannot be unambiguously classified on the basis of pixel values alone. Information that could be of value in component classification such as the size, shape, and colour of surrounding regions was not considered in the preliminary classification.
- Large variation in coverage proportions: There was a high degree of variability in the coverage proportions estimated for a given trash level.

Addressing these issues led to development of a set of image preprocessing steps, which were applied in subsequent analysis. These steps are detailed below.

6.2.2 Image Pre-processing

6.2.2.1 Image Registration

The RGB and N images are vertically and horizontally offset, and the lenses in the separate cameras have slightly different optical parameters. Hence the RGB and N images must be registered with each other before band signatures can be determined.

A major problem for image registration is the extreme complexity and irregularity of the imaged surface. Conventional methods such as linear interpolation between identified points in both images or application of a global affine transformation fail to capture local misalignments due to the stereoscopic effect produced by the separation of the NIR and RGB camera lenses and the vertical irregularity of the surface.

To overcome this problem, a registration method based on cross correlation between the NIR image and a total RGB brightness image was developed. The registration offsets for each pixel are calculated using the best correlation between a small region centred on the pixel in the RGB image and a range of test regions in the NIR image. This method is computationally intensive but gives good registration results. The method effectively ‘rubber sheets’ the image on a pixel-by-pixel basis. There are some problems in areas without differentiating features and in areas with strongly periodic features.

6.2.2.2 Generality of Classification

There is substantial variation between rakes and individual batch samples in image average raw band intensities, particularly in the NIR channel. This independent variability in RGB and NIR image brightness prevented the differences in band signatures of cane and trash components observed in individual batch samples from generalizing to provide a useful classificatory tool.

The effect of this independent variability in average image intensity can be eliminated by the construction of 'normalized' images. A normalized image is formed by first subtracting the image average for each band from each pixel's band intensity figures. The results are then divided by the image standard deviation for each band. Normalization removes differences between images due to differences in average image brightness, while retaining pixel differences within each image.

The drawback to normalization is that pixel intensities are expressed as deviations about zero in units of a pixels 'normal score', which makes band intensity ratios awkward to calculate. This problem can be overcome by expressing normalized scores as 'standardized' intensity values centred on an arbitrary brightness value. The pixel's 'normal score' is then scaled to an arbitrary brightness interval. In this way, 'standardized' synthetic images with uniform brightness and contrast can be constructed, which may be usefully compared. In this study, the standardized images are centred on a brightness of 128 with a standard deviation of 10 intensity levels.

6.2.2.3 Spatial Information

The non-separability of components in terms of pixel RGBN intensities means that other classificatory features must be sought. For this reason, a set of features based on geometrical descriptors of a pixel's surrounding region was developed.

The most basic region forming method is the use of threshholding. However, while useful for discriminating background from foreground, thresholding cannot discriminate between components.

The next most basic approach is the use of edge detection. However, standard edge detection algorithms work on monochromatic images, and edge detection applied to monochromatic images of cane and trash fail to separate cane and trash components. Combining edges detected in each of the band images produces many small regions with undifferentiated geometries.

To overcome the problems of edge detection, a region-growing algorithm was developed which aggregates pixels on a 'most homogeneous region' basis. The algorithm compares neighbouring pixels or regions and computes their similarity as the difference in band intensity vectors between pixels or regions. It chooses the most similar pixels or regions, amalgamates them and then recalculates the similarity of the newly formed region with its surrounding pixels or regions.

An issue that became apparent during development of the region growing process is that regions of leaf and regions of cane were amalgamated before regions within a particular piece of cane were amalgamated. This indicates that there can be more variation in colour within a billet of cane than between the billet and surrounding trash components. As a consequence, the region growing method halts before regions resemble what a human would recognise as a complete piece of cane.

A stopping point was chosen which halts region growing before cane and leaf areas are confounded. Approximately 3-4000 regions are formed in a full size image and features of the final regions such as area, length, breadth, aspect ratio and boundary length are calculated and associated with each pixel. These spatial variables are then included in subsequent classification processing.

Spatial features generated from the region growing procedure include the regions size, aspect ratio, inner and outer boundary length (a measure of the curvature and complexity of the region boundary), and average region band intensities. These features were used as additional pixel descriptors in later classification steps.

6.2.3 Training Sets

Twelve samples were sorted into cane and trash components during the batch imaging program. Images of the sorted components were collected to provide the basis of training sets for identification of components. Band ratios for cane, leaf and tops are shown in Figure 6.2.3.1.

Average raw and standardized RGBN band intensities for the twelve training sets are given in Table 6.2.3.1 together with the N/R and G/R ratios which form the basis of distinguishing cane and trash categories. The average N/R and G/R band ratios of cane trash and tops training sets are presented graphically in Figure 6.2.3.2. Data for all training set elements is shown in Figure 6.2.3.3.

These figures show that while on average it is possible to distinguish between cane, leaf and tops, in detail there is considerable overlap in the band ratios used to distinguish cane and trash categories. This means that cane and leaf are not separable in the RGBN colour space used in this study and hence that cane and leaf cannot be classified on the basis of pixel band intensity ratios alone.

6.2.4 Discriminant Analysis

Individual pixel band intensities were combined with regional radiometric and spatial features for cane and trash component training sets from all batch samples and subjected to discriminant analysis. Discriminant analysis was performed using both sample based and ‘global’ prediction datasets. Three combinations of variables were analysed for each type of analysis:

- Individual pixel RGB intensities
- Individual pixel RGB and N intensities
- Individual pixel RGBN intensities with regional radiometric and spatial features

The results are summarized in Tables 6.2.4.1 and Table 6.2.4.2. The tables show that the inclusion of the N channel makes little difference to classification accuracy for individual sample based analyses but makes more difference in a global classifier.

The important point from the analyses may be summarized:

- In general, inclusion of region based radiometric and spatial features is associated with a major increase in classification accuracy in both individual and global classifiers.
- Global classifications based on pixel intensity values alone are much less accurate than analogous individual analyses. Global classifications including regional radiometric and spatial features are similarly accurate to their individual counterparts. This indicates the importance of regional radiometric and spatial features in global classifiers. Global classifiers achieve an accuracy of around 75%, although this is not consistent across all samples analysed.
- Classification accuracy is similar for cane, leaf, and tops. Cane tends to be misclassified as leaf or tops in equal proportions. Leaf is misclassified as cane or tops in equal proportions, while tops are three times more likely to be misclassified as cane than leaf.

6.2.5 Neural Nets and Fuzzy Logic

An attempt was made to classify training sets using neural nets and also fuzzy logic. The results were no better than produced by discriminant analysis, and these approaches were not continued with.

6.2.6 Cane – leaf coverage proportions and weight fractions

Cane and leaf differ hugely in their physical characteristics. Cane billets are generally compact cylinders, averaging around 20-25 centimetres in length and around 4-6 cm in diameter. Leaf varies widely in overall dimension, but is often long (> 30cm), and thin (< 1-2 cm), and may be extremely tangled and involute in appearance. Leaf has a much higher surface area to weight ratio than billet cane, and occupies a great deal more space than its actual mass and density would indicate. As a consequence of these differences, the representation of leaf and cane in images is not directly proportional to their weight fraction. In general, leaf is much more highly represented in imagery than its weight fraction might suggest.

Misclassification of cane and trash components affects the proportions of cane and trash estimated to be present in an image. The effect of misclassification is to reduce the range of proportions it is possible to observe. At the current best global classification rate of 75% accuracy, an image of pure cane will be reported as containing around 12% leaf, while an image of pure leaf will be reported as containing around 12% cane. Hence the coverage proportions observable will range between 12% to 88% cane to cane plus leaf, rather than between 0% and 100%.

An image is a sample of the coverage of cane and trash components presented at a given weight fraction and is subject to error. Table 6.2.6.1 summarizes the proportions of leaf and cane observed in the ‘spraypaint’ trash series. In this trash series, misclassification error was reduced to ‘best scenario’ levels by spray painting cane and trash components distinctive colours. The table shows that the coverage proportions observed for a given cane weight fraction are highly variable. For the images used, the standard deviation of coverage observed is around 14% for cane weight fractions between 50% and 95% and cane coverage proportions between 15% and 55%. In essence, this means that for the images used, it is impossible to distinguish between cane weight fractions in this range at the 95% confidence level.

Based on current results, it is estimated that in order to distinguish between cane weight fractions of 80% and 90% at the 95% confidence level, an image area at least six times the size of that currently used would be necessary. This means that either six times the current number of images are necessary, or that the size of the images must be six times larger for the same number of images. This estimate would apply even if classification accuracy can be improved, because it is a function of cane/trash coverage variability for a given weight fraction.

6.2.7 Trash Series

Three trash series were constructed as part of the batch analysis program. These series were made up by adding known quantities of leaf into pure sub-samples of cane. Most attention was focussed on the cane weight fraction range between 70% and 100% since this is the range most typical of mill billet supplies.

The results of the trash series analyses are summarised in Table 6.2.7.1 and Figure 6.2.7.1. The important points may be summarized:

- The relationship between cane and leaf coverage proportions and weight fractions is markedly non-linear.
- There is little difference in cane coverage proportions observed at cane weight fractions below 80%.
- Almost all variation in cane coverage proportion observed occurs at cane weight fractions between 80% and 100%.
- Variability in cane coverage proportion observed increases with cane weight fraction.

6.2.8 Online Physical Analyses and Imagery

Fourteen rakes were analysed in the online program during the 2000 crushing season and twenty-eight during the 2001 season. The results of the physical separations are summarised in Table 6.2.8.1 and Table 6.2.8.2. The important points may be summarised:

- Total cane weight fractions varied between 80% and 90% over all the online samples with an average of around 87%.
- Leaf weight fractions were generally lower than 10% for all the online samples with an average of around 4%. Leaf weight fractions were relatively stable throughout the samples analysed.
- Top weight fractions varied between 1% and 16% with an average of around 7%. Most of the variation in the weight fraction of millable cane versus trash levels could be accounted for by variation in the amount of tops present.

Coverage proportions estimates based on discriminant analyses using global prediction training sets have been made for both the 2000 and 2001 crushing season. Results from the physical separations and estimated coverage proportions for the 2000 crushing season are shown in Table 6.2.8.1 and the same data is shown graphically in Figure 6.2.8.1. Physical separation results for the 2001 crushing season are shown in Table 6.2.8.2 and the coverage proportion estimates in table 6.2.8.3. Figure 6.2.8.2 shows a plot of coverage proportion estimates versus cane weight fraction for the 2001 crushing season and Figure 6.2.8.3 shows the same data plotted against the offline trash series results

These tables and figures show that online analyses are broadly consistent with the trash series of the batch analyses. However, given the large variability in coverage proportions presented for a given cane weight fraction, it is not possible to make meaningful distinctions in trash level over the range of trash levels observed in the online program.

7 Outputs - Summary

This study has examined the two aspects of extraneous matter in cane from two very different perspectives. The work done in relation to dirt is an application of established techniques in NIR spectroscopy to the visual range. The work done in relation to trash is completely new. The conclusions reached are presented separately below.

7.1 Dirt

- The visual range is useful for the detection and measurement of dirt levels in prepared cane.
- Differing dirt types have differing effects on prepared cane spectra for the same level of dirt contamination. This produces systematic errors according to dirt type that increase with increasing dirt levels for estimates based on global calibrations.
- Calibration for dirt type removes the systematic and increasing errors and is the single largest factor in improving dirt level estimates.
- Discriminant analysis is capable of identifying dirt types with high accuracy across all dirt levels observed. Regressions using indicator variables for dirt type generated by discriminant analysis are nearly as accurate as those formed with prior knowledge of dirt type.

7.2 Trash

- Cane and trash categories are not completely separable in the RGBN colour space used. This means that no classifier based on pixel intensity values alone will be completely accurate.
- Region based spatial and radiometric features greatly improve classification accuracy. In this study, region features improved global classification accuracy from around 60% using RGBN pixel intensities to around 75%. Unfortunately, generation of such features has a significant processing cost.
- Surface coverage proportion of cane, leaf and tops are highly variable for given weight fractions of cane and trash components. The number of images used in this study is sufficient to establish a mean estimate. However, in order to decrease the error in the estimate to levels that allow meaningful distinctions of trash levels for industrially realistic cane and trash fractions, image areas at least ten times the size of those used would be required.
- The relationship of cane and trash coverage proportions is non-linear. A small amount of leaf generates a large coverage figure, and a very high fraction of cane is required before this coverage level is significantly affected. There is very little difference in the coverage proportion of cane observed at cane weight fractions less than 80%, and almost all the variation in coverage proportions occurs at cane weight fractions above this level. This corresponds to the range of cane weight fractions actually observed in the online sampling programs conducted.

- Significant improvements are required in terms of number and size of images, speed of image acquisition, and processing time to make the image analytic technique viable as an online trash monitoring system – but it appears that with these improvements, such a system is possible.

9 Expected Outcomes

Dirt

- Expect automatic discrimination of dirt types using VIS/VNIR/NIR spectra to become standard practice
- Expect calibration for dirt parent material to become standard practice in spectrographic methods of dirt level estimation.
- Expect VIS/VNIR range detectors will be incorporated into installed and future NIR spectrometers used by the industry

Costs of these measures will not be significantly above present levels.

Benefits to the sugar industry will be significantly improved accuracy in spectrographic dirt level determinations.

Trash

- Expect the image analytical method of trash level monitoring to be further developed and eventually put into production use.

Cost of development is likely to be moderately high due to the pioneering nature of the research and development. Cost of final implementation is also likely to be moderately high due to the compute intensive nature of image processing.

Benefits to the sugar industry will be continuous, online, non-invasive, monitoring of trash levels. Other benefits will be feedback to cane growers on the efficiency of harvesting, and possibly input to cane payment systems. Finally, continuous trash level monitoring will provide valuable feedback on the efficiency of trash separation processes associated with cogeneration of green energy.

10 Future Research Needs

Considerable further research in image analysis and machine vision needs to be carried out in order to make the image analytical technique more accurate.

11 Recommendations

A follow up project aimed at commercializing the image analytic method should be funded.

12 List of Publications

Two publications have resulted from the research to date. A further two are in preparation for publication in 2003.

Tulip, J., Joyce, K., and Moore, W.E. (2000) ‘Dirt in Cane – Results of Preliminary Batch Tests’, Proc. Aust. Soc. of Sugar Cane Technologists, 22nd Conference, Bundaberg, p 526.

Tulip, J. (2001) ‘Monitoring Dirt: What’s the Best Way?’ Australian Sugarcane (Milling Focus) June-July 2001, pp14-15

In preparation:

Tulip, J., Moore, W.E., and Wilkins, K.J. ‘Dirt Level Estimation in Prepared Cane using VIS/VNIR spectra’

Tulip, J., and Moore, W.E. ‘Trash Level Estimation in Billet Cane using Machine Vision’