AMPC
AUSTRALIAN MEAT PROCESSOR CORPORATION

Carcase inspection with Rubens sensor

Proof of concept of the Rubens sensor for the end-of-line carcase inspection – Stage 2

Contents

1.0 Executive Summary

The aim of this Proof of Concept (PoC) project was to evaluate the capability of the Rubens spectral scanner to detect contaminants in red meat. The Rubens scanner, developed by Rubens Technologies to assess fruit quality and maturity, is based on a combination of absorbance and fluorescence spectroscopy, from the UV to the near-infrared spectral range.

The utilisation of optical fluorescence has been proposed as a tool to evaluate meat quality, authenticate beef, and detect faecal contamination in carcases. This previous research, and the availability of the Rubens scanner, motivated this project, with the aim of verifying that a handheld spectral system can be used to detect contaminants, and of building a roadmap of extending this technology to line scanners.

This project has been carried out with the assistance of Cedar Meats Australia, which provided trimmed samples from lamb and mutton carcases. The samples had a variety of contaminants, including Faeces, Urine, Grass Seeds, Ingesta and Wool. Clean samples were also scanned to provide a baseline. The samples were sourced in two occasions from Cedar Meats facilities, and scanned at Rubens Technologies' premised on the same day of collection.

The data was reduced by identifying wavelength bands in the fluorescence and absorbance spectra, that contains features that are specific to each contaminant or group of contaminants. In this way, the reduced data can be used directly for rapid contaminant identification. In addition, and perhaps more importantly, identified bands in the spectra could be used to design optical filters for a future line scanner based on a combination of spectral sensing and machine vision.

The results outline the ability of the Rubens scanner to detect the vast majority of contaminants, in the range of samples that was measured. Detection of ingesta, grass seed, and wool appears to be possible from the spectra alone, after identification of the relevant bands. Specific fluorescence bands for urine and faeces have also been identified, but are not sufficiently separated from other features to enable full identification from spectra alone. The spectral data shows candidate bands that suggest a good identification is possible, and can be used in conjunction with a vision system for fully automated identification of contaminants in a line scanner.

The conclusions above suggests a practical way to approach the development of a line scanner. Three of the key requirements of a line scanner system are: 1) Being more cost-effective than a hyperspectral imaging system. 2) Being able to achieve higher sensitivity (i.e. able to detect small quantities of contaminant) than a hyperspectral system and 3) Generating a manageable amount of data, both for processing and for auditing purposes.

The concept of such a line scanner system was developed in the second part of this project, outlining its main technical characteristics, estimated costs, and modes of utilisation. The concept is meant to be a starting point for the development of a prototype, subject of a draft Stage 3 application. While the details of the prototype will require the critical input of the industry, a few of the technical characteristics that we have outlines in this report will ensure cost-effectiveness and flexibility of deployment, minimising costs associated with installation and personnel training.

In conclusion, the technical work described in this report has produced important information regarding the type of detection and the wavelength bands that are likely to produce a good identification of contaminants. This has produced a baseline of data which informs the applicability of this technology to line scanners. The latter will be the subject of a forthcoming draft application for a Stage 3 submission.

2.0 Introduction

Rubens Technologies have developed a multi-spectral hand-held scanner and line scanner for the horticulture industry currently being used to assess fruit quality (pre-harvest) and fruit grading (post-harvest). The device is based on a miniaturised spectral sensor capable of detecting light spectrum in three modalities:
1) Fluorescence
2) VIS Reflectance
3) NIR Reflectance
The purpose of this research project was to pilot the Rubens scanner, evaluate its ability to detect contaminants in red meat, and provide a plan for extending this technology to line scanners, assessing its technical feasibility and estimated costs. The scope of the project was limited to the use of the existing scanner, for a PoC work.

Optical fluorescence has been proposed as a tool to evaluate meat quality (Islam *et al.*, 2019), authenticate beef (Aït-Kaddour *et al.*, 2017) and detect faecal contamination in carcases (Gorji *et al.*, 2022, Veritide system), among other applications. A potential advantage of optical fluorescence, as opposed to near-infrared spectroscopy, is that fluorescence is not affected by moisture. Water is always the most prominent feature in near-infrared spectra (see, e.g. Chapter 16 and 17 of Burns & Ciurczak, 2008) which may hinder the differentiation of different substances with similar moisture content. Prominent fluorescence features of red meat, and of contaminants that may be presents, justify this study for contaminant identification. In addition, since the Rubens sensor can detect fluorescence and absorbance at the same time, this technology t can provide a flexible tool for the identification of different types of contaminants in all types of red meat.

3.0 Project Objectives

The project objectives as specified in the signed Agreement are:

   1. Demonstrate to AMPC staff the working functionality of the concept(s) through pilot test of our current hand-held scanner on carcases to identify what contaminants can be detected and at what level.

   2. Demonstrate the applicability of pilot results (obtained with a hand-held device) to a line scanner detection system (on paper and through simulations/animations)

   3. Develop indicative targeted $RRP

   4. Draft a Stage 3 application submission, which includes an indicative indication of Stage 4+ and commercialisation plan. The draft will specifically address the R&D required to translate the concept to line scanners and the path towards future concept automation

   5. Provide literature that substantiates that the proposed platform is likely to succeed.

4.0 Methodology

4.1 Samples

Lamb and mutton meat samples were sourced from Cedar Meats Australia (Global Meat Exports Pty Ltd) on 20th September and 6th October 2022 and measured on the same day of collection. The available contaminants on these samples were: 1) Faeces, Urine, Grass Seeds, Ingesta and Wool. Clean samples were also scanned to provide a

baseline. The samples were inserted into individual bags, labelled and kept refrigerated until the measurements. Two examples of the samples, as obtained from Cedar Meats is shown in Figure 1.
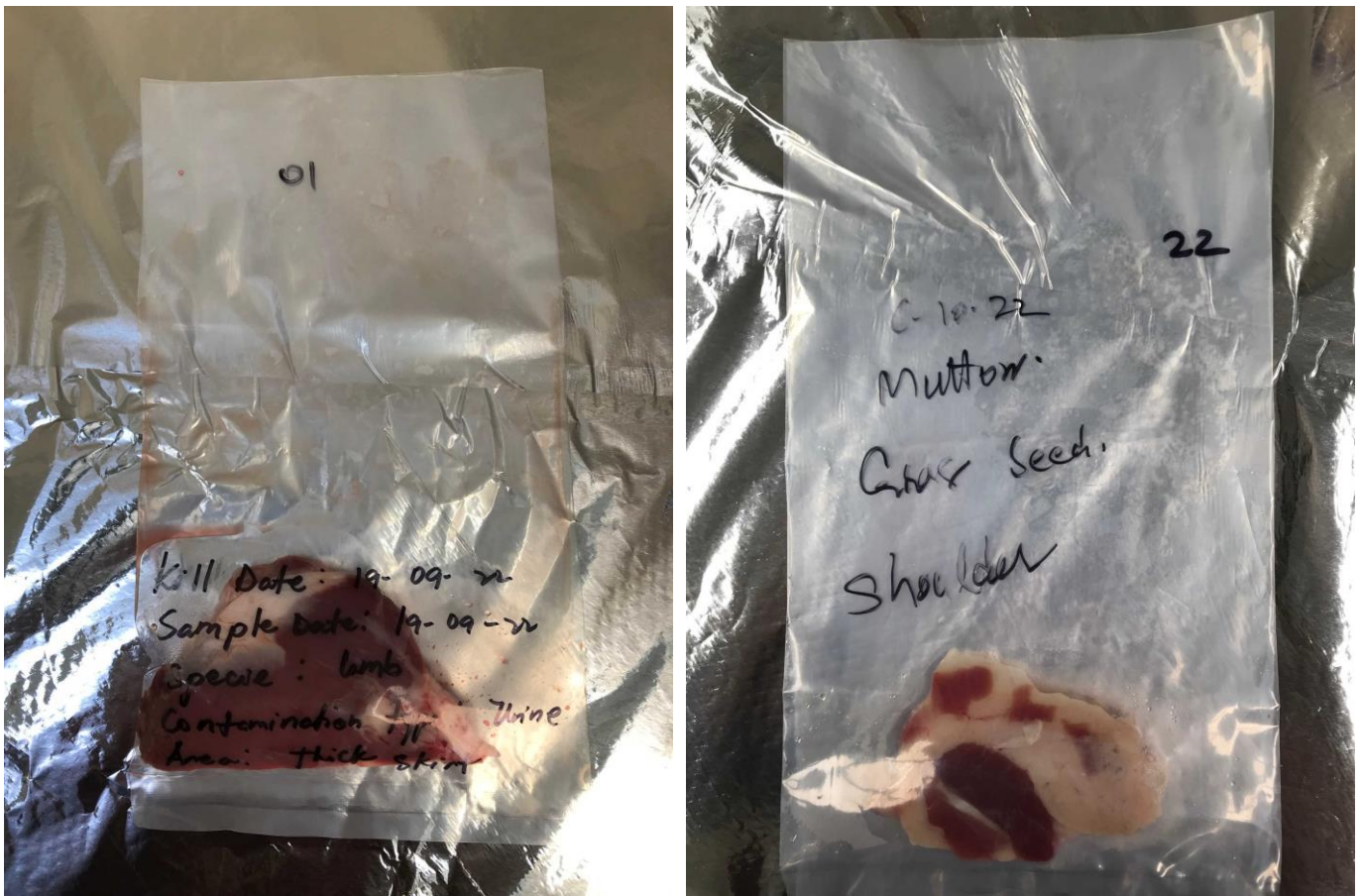

Figure 1. Examples of meat samples used in this project. Left: lamb sample sourced on 20th September. Right: Mutton sample sourced on 6th October.

4.2 Rubens scanner and data acquisition

The samples were scanned with the Rubens Technologies handheld sensor. The scanner is capable of detecting optical fluorescence, visible light reflectance and near-infrared reflectance with a single spectrometer. For fluorescence measurements an excitation LED with near-monochromatic emission at 365 nm is used; for visible reflectance, the light source is a white LED with broadband emission in the range 400-700 nm; and for near-infrared reflectance, the light source is an LED with broadband emission in the range of approximately 650-1050 nm. During a scan, each light source operated in turn, with sample emissions captured in the wavelength range of approximately 400-900 nm. The data is background corrected by subtraction with a scan captured in the absence of LED lights.

The Rubens scanner is originally designed to scan pre-harvest fruit. Its design include a "fruit shroud", that is an opaque, silicone-based cover, designed to avoid the detection of sunlight when measuring in the field (see left pane of Figure 2). The purpose of this project was to explore the feasibility of the technology to contaminant detection in meat in a cost-effective way. For this reason, we minimised changes to the scanner, essentially limited to removing the fruit shroud. As a consequence, all measurements were taken in a dark environment, to minimise ambient light

detection. A photo of a typical scan configuration is shown in the right pane of Figure 2 (as noted, the photo is for the purpose of illustration only. The actual scans were acquired in a dark environment).

The scanner was adjusted so that each sample was located approximately in the same plane of measurement. Each sample was scanned multiple time around the area of interest, with a minimum of 5 scans, and the individual scans were averaged.

Figure 2. Left: Picture of the entire Rubens scanner, including the fruit shroud (dark grey) and its docking station. Right: Rubens scanning of a meat sample. The shroud was removed to allow for a close-up scan. Note that this photo was taken for the purpose of illustration only. The actual scans were taken in a dark environment, as explained in the text.

4.3 Data analysis

An overview of the data collected is shown in Figure 3. On the left-hand side we show the optical absorbance spectra in the visible and near-infrared region. On the right-hand side the corresponding fluorescence spectra. The data is colour-coded for the type of contaminant that was measured, including two clean sample in the fat and lean region respectively.

Starting with a qualitative analysis, we noted that:

◆ Most contaminants display unique or characteristic spectral features that can be used for identification.

◆ The strength of the characteristic spectral features depends on the quantity of the contaminant being scanned, and the type of cut/region of the underlying sample. The fat regions of the sample, due to the lighter colour, have a much stronger reflectance and fluorescence compared to the lean region. This, in turns, has an effect on the strength of the spectral features of the contaminants in each region.
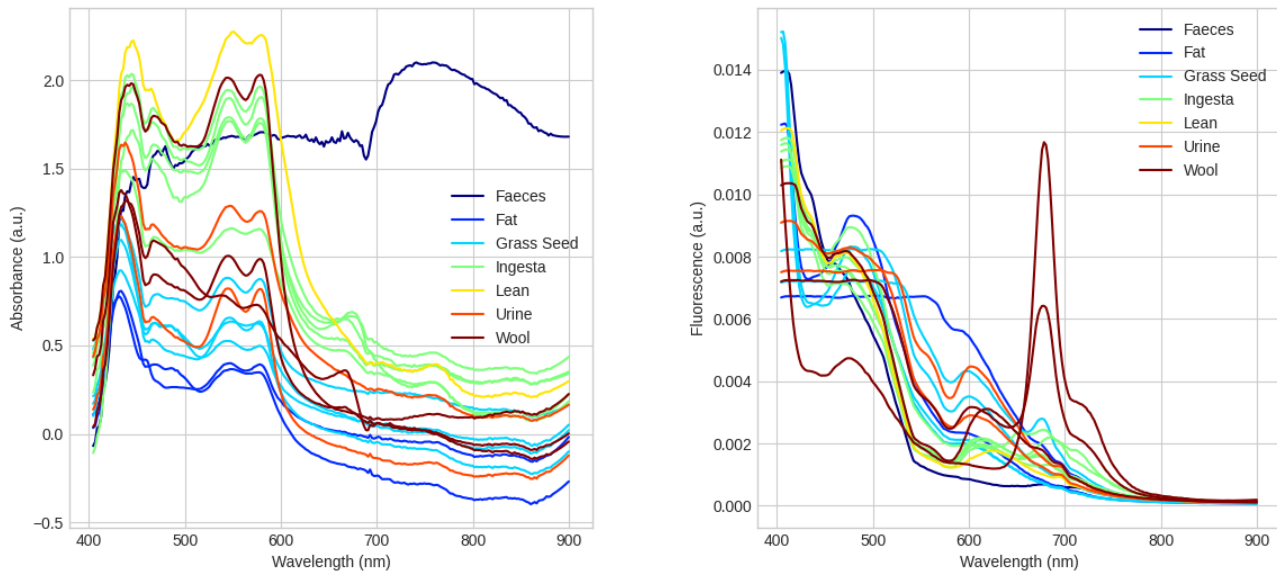

Figure 3. Left: Absorbance spectra in the visible and near-infrared region. Right: Corresponding optical fluorescence spectra.

For the purpose of this preliminary project, where we aim at a qualitative identification of contaminants, the different strength of the spectral feature is not a serious issue. We anticipate however, that this must be accounted for in a fully automated system (Stage 3 proposal).

For the purpose of identification, we selected the spectral bands that were considered more representative of the type of contaminant. Depending on the type of contaminant, these bands could be selected in the absorbance spectra, fluorescence spectra, or both. The purpose of this band selection is two-fold: 1) It simplify the analysis and enables a rapid visual identification of the type of contaminant in a scatter plot (see below for details). 2) It mimics band-pass filters that could be physically added to a vision system in a future development of this prototype.

5.0 Project Outcomes

The key project outcomes are as follows:

◆ Meat and meat contaminants samples have distinctive spectral features in absorbance and optical fluorescence.

◆ These distinctive features can be used for contaminant identification in the lamb and mutton samples that were scanned with the Rubens sensor.

◆ Rapid identification of contaminant can be achieved by defining appropriate contaminant indexes, which quantify the amount of fluorescence (or absorbance) in the relevant wavelength band for each contaminant.

◆ Many contaminant features significant chlorophyll fluorescence, which can be readily detected by the Rubens sensor.

◆ The contaminant indexes, calculated in post-processing on the spectral data, provide full discrimination of ingesta, wool and some grass seed contamination using spectral data alone. The discrimination of urine and faeces using contaminant indexes on spectral data is only partial and it will require imaging in addition to spectroscopy.

◆ The definition of contaminant indexes can be translated into a practical way of developing a line scanner, based on the selective acquisition of specific wavelength bands using optical filters and conventional cameras.

◆ The concept of a line scanner, which take advantage of the key learnings of this project has been proposed and a roadmap for further development has been outlined.

6.0 Discussion

6.1 Experimental results

The data analysis below has been divided into the different contaminant type, providing a visual assessment and a discussion of the ability of the system to detect that specific contaminant type, and further improvement that are envisaged in a future development. A common trait that was observed in all samples is the ability of our system to detect residual chlorophyll in contaminants. In addition to other identifiers, chlorophyll fluorescence and absorbance is one of the main identifier that enables contaminant identification

Ingesta

Most ingesta could be identified by chlorophyll fluorescence around the 650-750 nm band, alongside chlorophyll absorption in the absorbance spectra (centred around 680 nm). The amount of fluorescence and absorption, suitably normalised to the baseline, were combined in tow indicators that we called "Ingest Index 1" and "Ingesta Index 2" respectively. A scatter plot of these two indicator shows that the ingesta samples are clearly separated from the rest, including clean fat and lean samples.
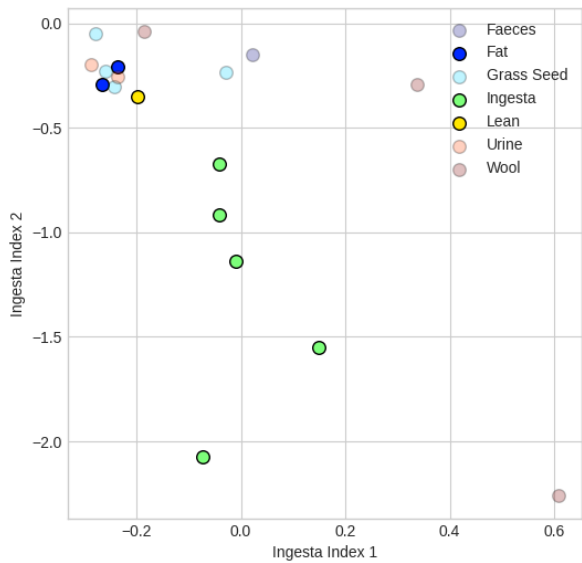
Figure 4. Scatter plot of the Ingesta Indexes as defined in the text. The ingesta samples are marked in light green and are clearly separated from the other samples using the Ingesta Indexes. For clarity, all data points other than ingesta, clean lean and clean fat data points are shown as semi-transparent.

Grass Seed

We noted that some (not all) grass seeds produce chlorophyll fluorescence, likely due to the type of seed. In all samples we had, the grass seed were embedded in fat tissue and depending on their size/density, their identification was made difficult by the high reflectance and fluorescence of fat tissue. Nevertheless, all samples displayed increased absorbance around the 430 nm band (blue). This absorbance band, along with the chlorophyll fluorescence band were normalised into Grass Seed Index 1 and 2 for a scatter plot, as shown in Figure 5.
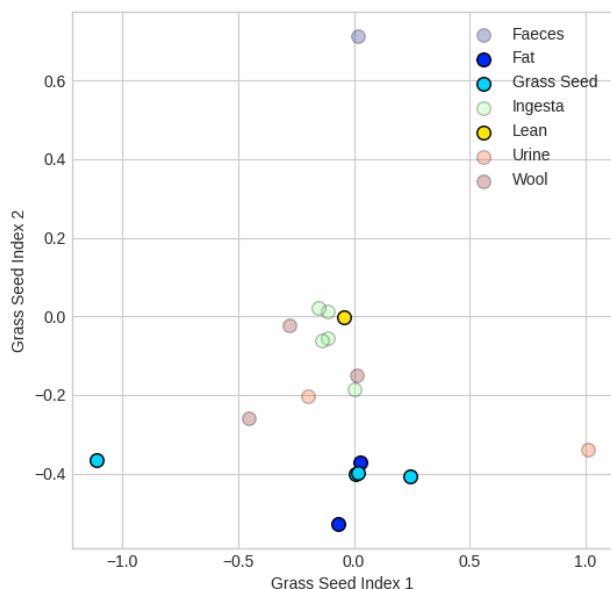

Figure 5. Scatter plot of the Grass Seed Indexes as defined in the text. The seed samples are marked in light blue and are clearly separated from the other samples except for the fat tissue. For clarity, all data points other than grass seed, clean lean and clean fat data points are shown as semi-transparent.

Scatter plot using Grass Seed Index 1 and 2 enables the separation between the Grass Seed samples and the rest, with the exception of clean fat tissue. Since, as noted, all grass seeds were found in fat tissue, the effect of the surrounding tissue affects the ability to discriminate this type of contaminant. When chlorophyll fluorescence is

present there is good discrimination. In other cases, the detection will have to be aided by machine vision in the bands we identified.

Wool

Most, but not all, wool samples produced very strong fluorescence under UV illumination. This seems again to be ascribed to chlorophyll, likely residual grass on the wool. Wool indexes based on chlorophyll fluorescence and absorbance, as in the scatter plot of Figure 6, are able to discriminate wool compared to other contaminants. In fact, the fluorescence is strong enough to be visible by eye (see Figure 7), which suggests that visual identification by machine vision could be a valid technology, using a suitable wavelength filtering.
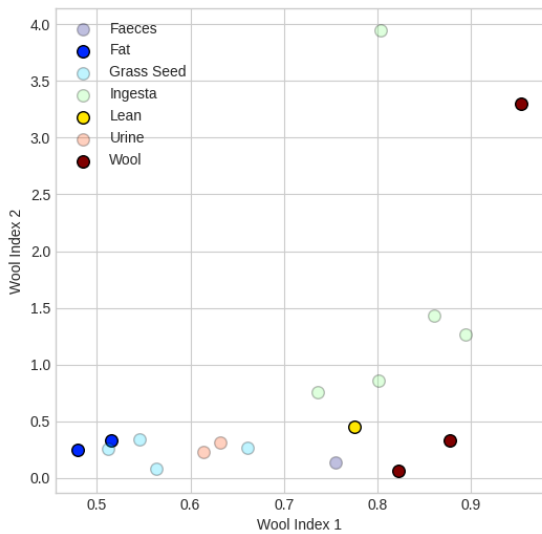

Figure 6. Wool samples (dark red) fall on the right-hand side of the scatter plot of Wool Indexes, mainly identified by chlorophyll fluorescence. Ingesta samples are in a similar location, but can be unambiguously identified using the Ingesta Indexes and visual assessment.

Figure 7. Left: Strong red fluorescence of wool samples under UV illumination (a UV filter was placed on the camera for this photo). Right: Same sample under normal illumination. The sample is from a mutton.

Urine

Urine identification was more complicated, due to the small quantities of urine contaminant that was found on the samples we scanned. We identified a small shift in one of the fluorescence peak, compared to most other samples from which we defined Urine Indexes plotted in Figure 8. These indexes appear to isolate the Urine samples in the top-middle of the scatter plot. However, since only two samples were measured, we cannot draw definite conclusion on this approach.
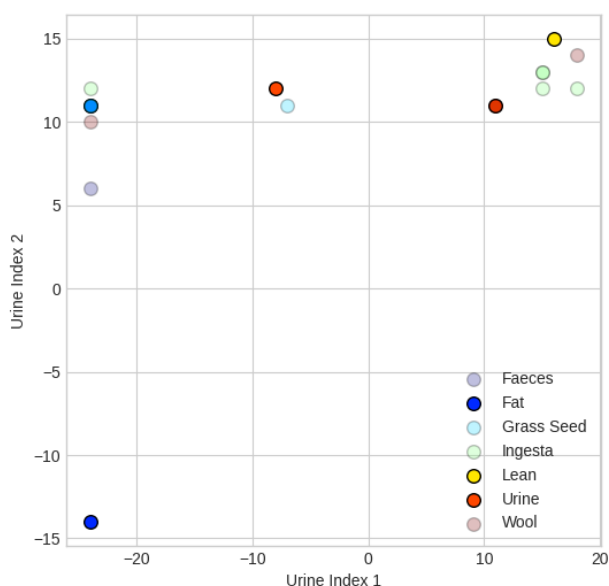

Figure 8. Scatter plot of the Urine Indexes as defined in the text. The seed samples are marked in light blue and are clearly separated from the other samples except for the fat tissue. For clarity, all data points other than urine, clean lean and clean fat data points are shown as semi-transparent.

Faeces

We were able to scan only one sample containing pellet-like faeces contamination in lamb meat. Therefore the data from the faeces is qualitatively very different from the other samples, whereby the signal from the surrounding tissue is essentially absent. The faeces samples are clearly visible and characterised by a stronger absorbance on most visible and near-infrared bands (see left pane of Figure 3). We did not detect chlorophyll fluorescence on this sample, and we expect that a combination of machine vision and fluorescence can be the best approach to identify faeces contamination.

6.2   Applicability of the pilot results to a line scanner

The main results of the technical component of the pilot work are:

- The combination of optical fluorescence and absorbance (or reflectance) provide a rich information to detect a number of contaminant, at least in the lamb and mutton samples that were scanned.

- In some cases, the contaminant identification can be done using the spectral information alone. In other cases, it was recognised that visual information is required to achieve accurate identification.

- The identification of the different contaminant was achieved by identifying relevant spectral bands that are characteristic of each contaminant. Based on these spectral bands, whether in fluorescence, absorbance, or both, we identified a number of "Contaminant Indexes", for instance "Wool Index" or "Grass Seed Index", etc. For instance, the Wool Index is calculated from the fluorescent emission in the 650-750 nm spectral range normalised to a baseline.

- The spectral bands, and the relative indexes, are calculated in post-processing, by selecting a window in the acquired spectra.

The conclusions above suggests a practical way to approach the development of a line scanner. Two of the key requirements of a line scanner system are: 1) Being more cost-effective than a hyperspectral imaging system. 2) Being able to achieve higher resolution (i.e. able to detect small quantities of contaminant) than a hyperspectral system and 3) Generating a manageable amount of data, both for processing and for auditing purposes.

The three objective above can be achieved by an array of conventional, low-cost RGB cameras. Each camera will be equipped with an optical filter designed to cover one specific spectral band. The system will feature an array of LEDs illuminators, specifically chosen to emit at specific wavelengths. The combination of illumination and imaging detection, when suitably timed, will provide an effective multi-spectral system, specifically designed for contaminant detection, at a fraction of the cost of a conventional multi-purpose hyperspectral system.

For instance a combination of 6 different LED types and 6 RGB cameras with different bandpasses will produce an effective 6x6=36 channel spectral imaging system with a combination of absorbance and fluorescence detection. Each acquisition will therefore produce 36 independent images of a carcase. These images can then be combined into the contaminant indexes we have identified in stage 2. Note that this latter process is commonly employed to generate indexes of importance for agriculture from satellite imagery (see for instance the Tona & Bua, 2018).

Figure 9 shows the concept of a line scanner based on the results of this project. The scanner can be mounted on a moveable stage on a vertical rack to scan a carcase from top to bottom. It can also be mounted in a fixed configuration to image meat parts in a line. In both cases, the requirements on the imaging system and, most importantly, on the software stack are less strict enabling high operation speed. Typical motion speed can exceed 1m/sec.
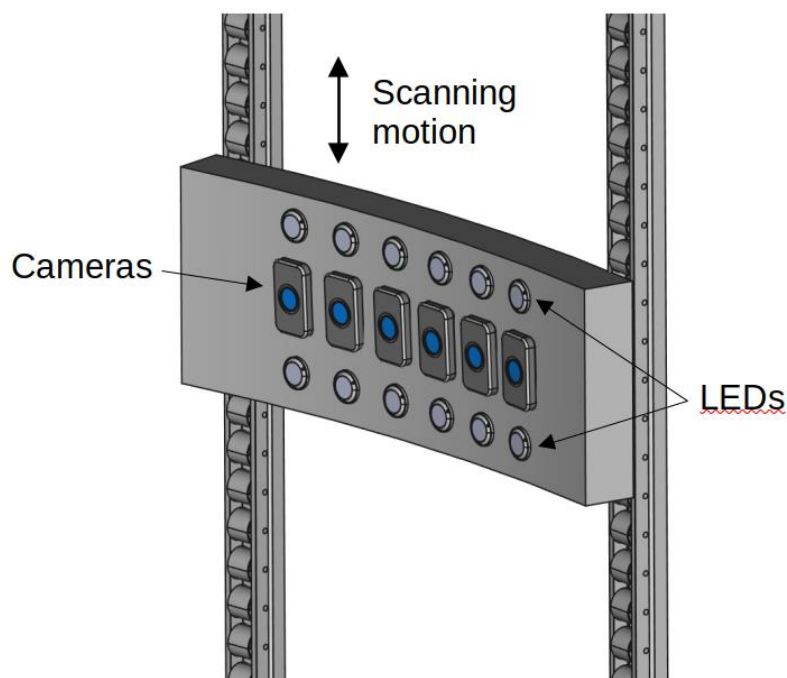

Figure 9. Line scanner concept.

6.3 Indicative target $RRP, Stage 4+ and commercialisation plan

The prototype described above is to be considered a concept only. We anticipate that the actual prototype will be developed in close consultation with processors, to make sure the approach is fit for purpose and provides the functionalities required to alleviate labour costs and maximise return on investment.

What we have described is the technical functionality of the prototype that will achieve the objectives of 1) Cost-effectiveness, 2) High-speed and sensitivity, and 3) manageable size of the data produced. On this basis, a basic unit comprising of 6 cameras, LED source lights, onboard computer (with machine vision included), monitor, dashboard, mounting rack mounted on castors, motion stage, and battery could retail for approximately $15,000 (excluding installation) at the current costs. Note that the battery is required for standalone operations, where the machine is moved by an operator. Fixed systems could deliver savings compared to the battery version.

The approach delineated here also ensures system modularity. Multiple units can be deployed and their results pooled together for further analytics and reporting, providing additional benefit to the processing operation. Another advantage of the modularity is the ability to upgrade the system, for instance adding different machine vision modules (i.e. lamb vs beef), specific optical filters and remote operation support.

The system is designed to require minimal operator input, thus minimising the costs required to train new operators. The concept design will also ensure that updates and troubleshootings can be carried out online, thus minimising the costs and turnaround time required for any of these operations.

In light of recent industry trends, the modular system is also amenable of "Hardware-as-a-Service" commercial model, where the system, including access to machine vision, is leased on a subscription basis.

The cost structure would be different in this second case, which however will reduce the CAPEX investment of the plant. As mentioned, the form factor and functionality of the system will have to be developed together with processors, so that all required functionalities are included, but nothing more, to keep the costs at a minimum. We plan to carry out a consultation with the processors at the beginning of a Stage 3 project. This consultation will define the directions of the development, but also the commercial strategy.

7.0 Conclusions / Recommendations

The data acquisition and analysis discussed in this report, outlines the ability of the Rubens scanner to detect the vast majority of contaminants, in the range of samples that was measured. The Rubens scanner has been specifically designed to detect fluorescence of plant pigments and it is therefore well tuned to detect chlorophyll fluorescence, which appears to be present in most contaminants.

The approach we followed, was to identify specific wavelength bands in the fluorescence and absorbance spectra, that could be used for contaminant identification. This approach enables a rapid visual identification of the data. In addition, and perhaps more importantly, identified bands in the spectra could be used to design optical filters for a future line scanner based on a combination of spectral sensing and machine vision.

Detection of ingesta, grass seed, and wool appears to be possible from the spectra alone, after identification of the relevant bands. Detection of urine and faeces will likely require an imaging system. The spectral data shows candidate bands that suggest a good identification is possible, and could be used in conjunction with a vision system for fully automated identification of contaminants in a line (the Rubens sensor is designed for spot measurement and it does not have an imaging system).

The conclusions above suggests a practical way to approach the development of a line scanner, in order to meet key requirements of cost-effectiveness, sensitivity and easy implementation. The concept of such a line scanner system was developed in the second part of this project, outlining its main technical characteristics, estimated costs, and modes of utilisation. The concept is meant to be a starting point for the development of a prototype, subject of a draft Stage 3 application.

In conclusion, the technical work described in this report has produced important information regarding the type of detection and the wavelength bands that are likely to produce a good identification of contaminants. This has produced a baseline of data which informs the applicability of this technology to line scanners. The latter will be the subject of a forthcoming draft application for a Stage 3 submission.

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Veritide system: https://www.veritide.com/