Illumination compensation in ground based hyperspectral imaging

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Abstract

Hyperspectral imaging has emerged as an important tool for analysing vegetation data in agricultural applications. Recently, low altitude and ground based hyperspectral imaging solutions have come to the fore, providing very high resolution data for mapping and studying large areas of crops in detail. However, these platforms introduce a unique set of challenges that need to be overcome to ensure consistent, accurate and timely acquisition of data. One particular problem is dealing with changes in environmental illumination while operating with natural light under cloud cover, which can have considerable effects on spectral shape. In the past this has been commonly achieved by imaging known reference targets at the time of data acquisition, direct measurement of irradiance, or atmospheric modelling. While capturing a reference panel continuously or very frequently allows accurate compensation for illumination changes, this is often not practical with ground based platforms, and impossible in aerial applications. This paper examines the use of an autonomous unmanned ground vehicle (UGV) to gather high resolution hyperspectral imaging data of crops under natural illumination. A process of illumination compensation is performed to extract the inherent reflectance properties of the crops, despite variable illumination. This work adapts a previously developed subspace model approach to reflectance and illumination recovery. Though tested on a ground vehicle in this paper, it is applicable to low altitude unmanned aerial hyperspectral imagery also. The method uses occasional observations of reference panel training data from within the same or other datasets, which enables a practical field protocol that minimises in-field manual labour. This paper tests the new approach, comparing it against traditional methods. Several illumination compensation protocols for high volume ground based data collection are presented based on the results. The findings in this paper are applicable not only to robotics or agricultural applications, but most very low altitude or ground based hyperspectral sensors operating with natural light.

Keywords: hyperspectral, atmospheric correction, illumination compensation, reflectance retrieval, ground based, robotics

1. Introduction

An elevated awareness of environmental issues, food security and sustainability, coupled with an ever-present desire to reduce costs and waste, maximise quality and increase produc-
tivity has highlighted precision agriculture (PA) as an important tool for optimising farming practices (Tey and Brindal, 2012). Mapping and analysing the reflected light spectrum of vegetation has emerged as an important method for various PA objectives (Lee et al., 2010). Multispectral imaging, which can capture image data in several wavelength bands, has been used in various mapping applications (Zhang and Kovacs, 2012; Mulla, 2013), such as the estimation of soil properties (Gomez et al., 2008), weed management (López-Granados et al., 2016), pest management (Du et al., 2008), and crop classification (Panigrahy and Sharma, 1997).

Hyperspectral imaging, which is able to sense spectra of objects in hundreds of narrow bands, provides even more detailed information. This allows for precise measurement of plant health indicators (Thenkabail et al., 2002; Behmann et al., 2014), as well as classification of individual plant species based on spectra alone (Okamoto et al., 2014). There is a substantial body of research covering hyperspectral imaging in the remote sensing community, where both satellite and aerial imaging have been used to map vegetation for various research and farming applications, for example for mapping cotton field variability (Yang et al., 2004), vegetation cover estimation (Zhang et al., 2013), biomass estimation (Marshall and Thenkabail, 2015), vegetation/crop classification (Oldeland et al., 2010; Xue et al., 2017), disease mapping (MacDonald et al., 2016) and nutrient/chlorophyll concentrations (Sims et al., 2013; Rao et al., 2008; Moharana and Dutta, 2016; Pullanagari et al., 2016).

More recently, hyperspectral imaging solutions operating at lower altitudes have begun to appear on both unmanned aerial vehicles (UAVs) (Uto et al., 2013; Honkavaara et al., 2013, 2016; Aasen et al., 2015) and mobile ground vehicles (Deery et al., 2014; Klose et al., 2010; Underwood et al., 2017), which are increasingly being used to provide high spatial resolution data. Mobile ground platforms for agricultural applications have ranged from simple hand pushed frames to manually driven motorised tractors or buggies to autonomous systems (Zhang et al., 2012; Deery et al., 2014). Recent examples of autonomous platforms include Ladybird (Underwood et al., 2017), Bonirob (Ruckelshausen et al., 2009), and the tracked Armadillo (Nielsen et al., 2012). Larger manually driven “buggies”, such as BreedVision (Busemeyer et al., 2013) and PhenoMobile (Deery et al., 2014), can carry more weight and supply more power, and therefore tend to include a greater array of sensors, including 3D time-of-flight, light curtains, and thermal imaging.

Retrieving reflectance, which is a property of the imaged surface only (Chandra and Healey, 2008; Ahlberg, 2010), by compensating for environmental illumination is a particular consideration for hyperspectral sensors. Because higher altitude and satellite imagery generally require relatively clear skies, lighting is more consistent, being only dependent on the time of the day and atmospheric composition. Low altitude and ground based platforms can operate under cloud cover, allowing data acquisition whenever there is sufficient light, but this increases the amount of dynamic lighting variation, due to fluctuating cloud cover density. Additionally, because these configurations image smaller regions of the scene at a time, total scan durations are longer, increasing likelihood that not only the intensity but also the spectrum of light on the ground changes. This makes it difficult to obtain reflectance accurately, but it is often impractical to wait for opportune lighting conditions.

These difficulties highlight the need for autonomous platforms, which ensure that data acquisition is both consistent and fast, while minimising disruption to crops. Factors such as the trajectory of the platform, including its orientation and velocity can be tightly controlled,
allowing data to be obtained in a regular manner, which is suitable to feed into automated
processing frameworks. Autonomous systems allow very high resolution data to be obtained
practically over large areas of a farm, breaking the trade-off between resolution and coverage.

In this paper, we examine the use of an unmanned ground vehicle (UGV) to gather
high resolution hyperspectral data of crops, which are post processed to compensate for
illumination changes in order to retrieve reflectance.

The contributions of this paper are:

• The development of several different field protocols for gathering the necessary training
data for the illumination compensation method by Drew and Finlayson (2007). These
present different trade-offs between the accuracy of illumination compensation and the
logistical complexity of the field work.

• Testing the applicability of using historical reference data to correct for illumination
in future datasets.

• An analysis of the sensitivity to illumination compensation of several metrics/indices
that are commonly used in agricultural applications.

• Evaluating the suitability of a previously developed logarithm subspace method for
illumination and reflectance extraction (Drew and Finlayson, 2007) for use on a large,
high spatial and spectral resolution agriculture based field dataset.

By using the approach detailed in Drew and Finlayson (2007), the following important
advantages can be realized:

• No reference target readings need to be tied to imaged pixels.

• Significantly reduced number of reference target readings.

• Feasibility to recover reflectance and illumination from previously acquired training
data, where no reference panel readings are available.

• No need to obtain or estimate atmospheric parameters.

In Section 2, we briefly review the literature on illumination compensation. Particular
focus is given to the subspace model method by Drew and Finlayson (2007), which approx-
imates both illumination and reflectance spectra based on sets of training data. We posit
this method as a basis for more convenient and practical novel field protocols that facilitate
compensation for lighting. In sections 3 and 4, experiments are documented that use high
spatial (3 mm by 9 mm) and spectral (2 nm) resolution hyperspectral data cubes, covering
2.75 hectares of a plant phenomics trial. The experiments highlight the magnitudes of re-
fectance error that can occur when illumination compensation is ignored, and demonstrate
the effectiveness of several illumination compensation approaches. Based on these results we
provide some clear guidelines for obtaining reflectance in hyperspectral data from ground
based field robotics systems (Section 5).
2. Surface reflectance retrieval methods

In this section, we summarise the most common methods used for atmospheric correction and illumination compensation in order to retrieve surface reflectance. For brevity, we use “reflectance” and “surface reflectance” synonymously, as opposed to “at-sensor reflectance” or “top of atmosphere (TOA) reflectance” (Teillet, 2015).

2.1. Empirical methods

There are several early scene-based approaches to reflectance retrieval from the 1980s (Gao et al., 2009), including the Internal Average Reflectance (IAR) (Kruse, 1988) and flat field (Roberts et al., 1986) correction approaches. The former divides a hyperspectral image by the average spectrum for the whole scene, while the latter assumes that there is an area with spectrally neutral reflectances (little variation with wavelength) in the scene, which can be averaged and used to retrieve reflectance. While these methods are convenient, because no in field reference measurements are required, they often do not provide accurate results (Gao et al., 2009).

Using a reference panel that is measured in the same lighting conditions (i.e. in the same scene or the same image as the surface of interest) is a common way to determine reflectance of a surface (Yao and Lewis, 2010; Uto et al., 2013). Ideally this target should be a Lambertian scatterer with uniform reflectance in the spectral range of the sensor, such as Spectralon by Labsphere, which exhibits a very flat reflectance curve at a wide wavelength interval from about 300 to 2400 nm (Geladi, 2007). Once the radiance of the reference target has been measured, the reflectance of a surface in the same lighting conditions can be obtained by dividing its radiance spectrum by the reference’s and multiplying by the target’s known reflectance (see Section 3.4). This method is effective in situations where the sensor is close to the object being measured, such as laboratory, factory, low altitude aerial and ground based applications, as long as lighting does not change from the conditions measured at the reference panel. Interpolation has been used in the past to take into account gradual lighting changes (Suomalainen et al., 2014). This is useful over shorter durations, where lighting conditions change approximately linearly. However, this method is less suitable where abrupt or non-linear changes occur throughout the data collection period.

In higher altitude aerial (above approx. 100 m) and satellite applications, any light that is scattered back to the sensor along its line of view (path radiance) cannot be ignored (Mobley, 2016). More rigorous methods, such as the empirical straight line method take this into account. This requires at least two readings of known calibration targets that have different reflectances at all wavelengths (Conel et al., 1987; Karpouzli and Malthus, 2003). A best fit line model can then be obtained to derive a function for each band. As with the simple reference panel method, this approach is susceptible to changes in lighting that deviate from what was measured at the reference targets.

As an alternative, reference targets can be substituted with a sensor that continuously measures downwelling illumination directly (Noble et al., 2002; Honkavaara et al., 2013; Deery et al., 2014; Hakala et al., 2013). The downside is that they are usually mounted to the platform and may therefore not exactly represent the lighting incident upon the objects being imaged. For example, illumination at higher altitude aerial platforms will be different to the light on the ground, as the length of propagation through the atmosphere is different,
or because of the geometry between clouds, sun, imaging platform and imaged surface. In ground based imaging platforms this may be less of an issue, depending on the geometry of the platform, while in aerial platforms the problem can be partially overcome by using a ground reflectance panel reading that is adjusted based on the continuous downwelling sensor data (Kuusk and Kuusk, 2010). In addition, there is an increased cost and complexity of having an appropriately calibrated downwelling sensor, which may be restrictive for some applications. Some manufacturers of higher cost sensors use fibre-optics to pipe downwelling light into a portion of the pixel space of the sensor to avoid the need for multi-sensor calibration (e.g. Jan et al. (2008)), however, this is often not available in cheaper sensors.

Another reflectance retrieval method takes advantage of overlapping tie points between consecutive images. These can be used to determine radiometric model parameters via least squares optimisation (Honkavaara et al., 2013; Hakala et al., 2013), and may also make use of radiative transfer codes (Prosa et al., 2013). The prerequisite is that a proportion of the imagery overlaps for every change in lighting. This makes it more suitable for data from full frame (snapshot) multi- or hyperspectral cameras, such as Fabry-Perot interferometer-based units (Geelen et al., 2014; Saari et al., 2009), which are starting to find increased interest in unmanned aerial vehicle (UAV) applications. Theoretically, the method should be extensible to line scanning cameras if there is spatial overlap at times that span the full range of illumination.

2.2. Radiative transfer codes

In remote sensing applications, atmospheric modelling from first principles (atmospheric radiative transfer codes) (Staenz et al., 2002) is a widely used method to derive an estimate of reflectance. Radiative transfer codes take as input atmospheric parameters, such as column water vapour and aerosol content to model the propagation of electromagnetic radiation as it is affected by scattering, absorption and emission on its path to the surface and then to the sensor. Several codes have been developed, including ATREM (Gao et al., 1993), MODTRAN (Berk et al., 1999) and 6S (Vermote et al., 1997).

Atmospheric transfer codes are known to be computationally intensive (Guanter et al., 2009), and therefore some efforts have been made to produce more efficient algorithms, such as Simple Model for Atmospheric Radiative Transfer (SMART) (Seidel et al., 2010). Alternatively, look up tables are commonly computed, that allow more efficient retrieval of reflectance using a number of input parameters (e.g. wavelength, pixel position, atmospheric water vapour content, aerosol optical depth, and terrain elevation) and interpolation (Staenz and Williams, 1997). An obvious advantage of using radiative transfer codes is that no reference targets are required. On the other hand, obtaining atmospheric parameters is not simple (Karpouzli and Malthus, 2003), and therefore “standard atmospheres” are often used, introducing inaccuracies (Mather and Koch, 2011). Some solutions, such as FLAASH (Adler-Golden et al., 1998), HATCH (Qu et al., 2001), and ACORN (Green, 2001), are able to estimate some atmospheric parameters, including column water vapour. However, commonly these require data in wavelength ranges that are well beyond the capabilities of cheaper hyperspectral sensors commonly used on mobile ground and UAV platforms (which usually operate below 1000 nm). In addition, reliable parameter estimation often requires favourable conditions. For example, FLAASH does not deal well with heavy haze or water vapour content (Matthew et al., 2002). Belluardo et al. (2016) performed an analysis on
the SDISORT radiative transfer model (Dahlback and Stamnes, 1991), that quantified the estimated spectrum’s uncertainty based on uncertainty of the input parameters. To improve accuracy, Thompson et al. (2016) have recently examined combining radiative transfer models with empirical reference measurements via Bayesian inference.

2.3. Subspace model recovery of illumination and reflectance

Approximating the constituent components of an at-sensor radiance spectrum (illumination, reflectance, path scattered radiance etc.) as linear combinations of distinct basis spectra is an alternative approach, that was originally introduced by Ho et al. (1990) in order to achieve colour constancy. Most commonly, basis vectors are estimated from existing training data of illuminants and reflectances (and sometimes path scattered radiance) using a Singular Value Decomposition (SVD) (Chandra and Healey, 2005; Drew and Finlayson, 2007). For each given input signal, these algorithms attempt to find an optimal combination of basis function coefficients, either using an iterative method or analytically. Being able to use a finite set of training data to compensate for illumination in a dataset opens up an opportunity for applications in ground based and low altitude platforms.

The standard use of reference targets ideally requires each pixel to be tied to a corresponding target measurement. With the subspace model method, however, reflectance and illumination spectra can be estimated without this requirement, as long as suitable training reflectance and illumination data are available. This permits simple field protocols where only a few representative reflectance targets need to be measured along with representative surface pixels. Furthermore, if a diverse enough database of prior training spectra is available, it is feasible that no reference measurements need to be made during future campaigns.

Drew and Finlayson (2007) propose an analytic solution using logarithms and includes an additional regression step to refine the results. The authors demonstrated that their method is over 100 times faster than non-analytical iterative approaches with 10 base spectra for both illumination and reflectance, while being at least as accurate. There is an obvious practical benefit in being able to rapidly compute results in both post-processing and real-time applications, such as weed detection and control (Wendel and Underwood, 2016; Underwood et al., 2015).

One downside of this method is that absolute intensity of illumination and reflectance are not recoverable (Drew and Finlayson, 2007). This is a consequence of the inherent ambiguity in intensity of the two results. However, for many applications, such as indices and classification, this is not a disadvantage, as in these cases only relative intensities (i.e. spectral shape) within a given reflectance spectrum are of importance.

3. Materials and methods

This section outlines the equipment, materials and methods used to acquire data and carry out experiments. A hyperspectral line scan camera and reference target mounted to an unmanned ground vehicle (UGV) were used to scan thousands of different plots of cereal and legume crops for a phenotyping trial. After acquisition, hyperspectral data were first thinned and treated for saturation (except for maps). Then radiance was calculated using dark current and integrating sphere measurements. The data were then ready to be tested
using the various lighting compensation methods. Experimental results were compared to reference results from a target that was in view at all times during data acquisition.

3.1. The autonomous ladybird system

The Ladybird robot (Fig. 1) was designed and built in 2014 at the Australian Centre for Field Robotics (ACFR) at The University of Sydney as a flexible tool to support research and development of robotics applications for the commercial vegetable production industry (Underwood et al., 2017). The Ladybird is mechanically adjustable for width, height of the central sensing tower, and height and angle of the solar covers, allowing adaptation for different farm configurations and crop heights. Forward and rear facing lidar and a spherical camera support obstacle avoidance and crop row detection, while real time kinematic (RTK)/global positioning system (GPS)/interial navigation system (INS) allows for map-based farm traversal. Crop sensing is provided by hyperspectral line-scanning, stereo vision (with strobe), thermal infra-red vision and the same lidars used for obstacle avoidance.

![Figure 1: The ladybird and mounted sensor configuration.](image)

(a) Scanning a field
(b) Sensor configuration

The Ladybird achieves autonomous traversal of crop rows and headland, by navigating over a pre-constructed farm-map. The map specifies the geometry of rows and headland access areas and how they are connected. Using the RTK/GPS/INS, a control system guides the Ladybird along these composite path segments with centimetre precision while maintaining constant speed and orientation. This is particularly important for spectroscopy, where a surface’s reflectance may change depending on the sun’s and observing instrument’s relative angles.

3.2. Data acquisition

Hyperspectral data were acquired with a Resonon Pika II visible to near-infrared (VNIR) line scanning camera that was mounted to the Ladybird robot, pointing towards the ground at approximately 34° below horizontal, such that the visible line intersects the row of crops perpendicularly approximately 2.9 m in front of the Ladybird (see Fig. 1(b)). The camera
produces hyperspectral line-images of 648 spatial pixels with 244 spectral channels in each pixel (spectral resolution of 2 nm from 390.9 to 887.4 nm) at a rate of 133 frames per second and native bit depth of 12 (saved as 16 bit binary files). A Schneider Cinegon 8 mm objective lens was used at an aperture setting of approximately f/2.5, and manually focused with a checker board at the expected crop heights. The lens provides a 33° field of view translating to a 3.0 mm/pixel spatial resolution per line scan, across the row, imaging just wider than a single crop row. There is a linear trade-off between vehicle speed and hyperspectral resolution along the row. At the top speed of 1.2 m/s, which allows approximately 0.72 ha/h and was used in this study, a resolution of 9.0 mm/pixel was achieved. This is well matched to the camera-lens combination’s instantaneous field of view (IFOV) of 1.9 mrad, translating to a ground resolution of 11.8 mm.

For all scans examined in this study, a reference panel (QPcard 102, MFR #GQP102) was mounted permanently at the edge of the field of view of the camera (see Fig. 2). Spectral smile and keystone can be of particular concern when the panel is mounted at the image border, but calibration documentation from Resonon indicates that for this camera these effects have been optically minimised to less than half a spectral pixel peak to peak, therefore not requiring further correction. This was corroborated via personal correspondence with Resonon (R Swanson 2016, personal communication, 25 August). Dark current measurements were recorded regularly (approx. every 2-4 h), by completely blocking all light to the sensor, while averaging the data over approximately 10 s.

![Figure 2](image-url)

Figure 2: Permanently mounted calibration target (a) mounted to the platform and (b) as seen in a high resolution close up example of hyperspectral data in true colour. The calibration target can be seen at the bottom of (b) and appears saturated due to the gain applied for aesthetic purposes. The undulating appearance is a result of swinging and vibration of the target mount as Ladybird moves.

The data were acquired from a number of different phenotype trials operated by South Australian Research and Development Institute (SARDI). Throughout the campaign a large number of datasets (continuous logs) were collected, spread over three sites (Mallala, Pinery and Turretfield), which are located within a radius of 41 km in South Australia. For a complete description of all data gathered for phenotyping, and details regarding the automation of the platform, the reader is referred to Underwood et al. (2017). The sets used in this paper for experimentation and testing were selected based on how much lighting variation

8
due to cloud movement they exhibit. The individual datasets are summarised in Table 1 with some of their properties.

### Table 1: Dataset Summary

<table>
<thead>
<tr>
<th>Dataset Name</th>
<th>Date</th>
<th>Length</th>
<th>Auto/Manual</th>
<th>Plant Types</th>
<th>Environmental Conditions</th>
<th>% Sat.</th>
<th>% Sat. Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>DDPA-1</td>
<td>19/08/2015</td>
<td>17 min 11 s</td>
<td>Auto</td>
<td>Pulses</td>
<td>Cloudy, low light with some variation due to cloud movement.</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>DDPA-2</td>
<td>19/08/2015</td>
<td>21 min 37 s</td>
<td>Auto</td>
<td>Pulses</td>
<td>Cloudy, low light with some variation due to cloud movement.</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>CDA-0</td>
<td>19/08/2015</td>
<td>52 min 55 s</td>
<td>Auto</td>
<td>Cereal</td>
<td>Cloudy, moderate brightness with some variation due to cloud movement.</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>NMAD-1</td>
<td>20/08/2015</td>
<td>56 min 11 s</td>
<td>Auto</td>
<td>Various</td>
<td>Cloudy, clearing near the end of the set. Low light at beginning of log to bright near the end.</td>
<td>0.0%</td>
<td>0.1%</td>
</tr>
<tr>
<td>ML-0</td>
<td>18/08/2015</td>
<td>28 min 25 s</td>
<td>Manual</td>
<td>Lentils</td>
<td>Bright with a number of clouds causing heavy variation in lighting conditions throughout the log.</td>
<td>0.3%</td>
<td>27.8%</td>
</tr>
<tr>
<td>SUL-0</td>
<td>18/08/2015</td>
<td>36 min 30 s</td>
<td>Manual</td>
<td>Lentils</td>
<td>Bright with a number of clouds causing heavy variation in lighting conditions throughout the log.</td>
<td>0.2%</td>
<td>20.9%</td>
</tr>
<tr>
<td>DBVL-0</td>
<td>18/08/2015</td>
<td>45 min 5 s</td>
<td>Manual</td>
<td>Lentils</td>
<td>Bright with a number of clouds causing heavy variation in lighting conditions throughout the log.</td>
<td>0.1%</td>
<td>16.9%</td>
</tr>
</tbody>
</table>

1 Percentage of total pixels that are saturated (excluding line scan pixels 500-648, which mostly correspond to the reference target).
2 Percentage of line scans where the calibration target is saturated and therefore excluded from calculation of metrics.

3.3. Thinning and saturation removal

An average dataset of 40 min duration contained approximately 100 GB of raw 16 bit data, which expands to 200 GB when radiometrically corrected due to the use of a 32 bit floating point representation. Experiments were performed on data that were thinned line scan wise by a factor of 100, to allow faster processing of experimental iterations (while still retaining sufficient spatio-temporal coverage). High resolution snapshots such as Fig. 2(b) and voxelised maps such as those in Fig. 9 were produced using the full unthinned dataset.

There are also several instances in the data where pixels saturated (see Table 1). Scan lines where any bands in the reference target spectra were equal to the maximum value of the range of the sensor were excluded from any calculations or statistics due to saturation, the processing of which is outside the scope of this paper. It should be noted that this was done to allow calibration with a continuously visible target. As most of the non-target pixels were not saturated, compensation methods that do not require continuous target readings, such as the subspace based method tested in this paper, can still be used.

3.4. At-sensor radiance calculation

Raw hyperspectral imaging data from the Pika II camera come in digital counts. To account for the effects of non-uniform lens transmittance and sensor quantum efficiency, both spatially and spectrally, these should first be converted to sample at-sensor radiance ($L_{\text{Sample}}$), as follows (Suomalainen et al., 2014),
Sample(\lambda) = \frac{DN_{Sample}(\lambda) - DN_{SampleDarkCurrent}(\lambda)}{DN_{FlatField}(\lambda) - DN_{FFDarkCurrent}(\lambda)} L_{FlatField}(\lambda),

where \(DN_{Sample}\) and \(DN_{SampleDarkCurrent}\) are raw digital number measurements of the sample and nearest dark current respectively. \(DN_{FlatField}\) and \(DN_{FFDarkCurrent}\) are flat field digital number measurements and corresponding dark current. Flat field images were acquired by averaging approximately 10 s of data in an integrating sphere, where the light level was set to about 95% of saturation. The corresponding dark current was measured in the same environmental conditions. The integrating sphere’s detector also provides internal radiance measurements at each wavelength, represented by \(L_{FlatField}(\lambda)\). It should be noted here that the camera’s parameters, including integration time, offset, gain and lens aperture must be the same for sample, dark current, and flat field measurements.

3.5. Reflectance quantities

In most natural light situations, including satellite, aerial and ground based sensing, incoming electromagnetic flux is hemispherical and reflected flux is conical, where the solid angle depends on the instantaneous field of view (IFOV), which is known as the hemispherical conical reflectance factor (HCRF) (Schaepman-Strub et al., 2006). However, where reflected solid angles are very small, as is the case with many imaging sensors, including the one used in this paper, the HCRF closely approximates the hemispherical directional reflectance factor (HDRF) (infinitesimally small reflected cone solid angle) (Schaepman-Strub et al., 2006). All reflectance quantity results in this paper refer to the HCRF or HDRF for the geometric configuration (zenith and azimuth angles) at that point in time. The target reflectance panels are assumed to be Lambertian, and consequently their laboratory reflectance measurements were used to directly calculate the illumination portion of the at-sensor radiance spectrum.

3.6. Reflectance and illumination calculation using reference panel

Benchmark (ground truth) sample reflectance \((R_{Sample})\) measurements were obtained per line scan with the permanently mounted reference panel with the following equation,

\[ R_{Sample}(\lambda) = \frac{L_{Sample}(\lambda)}{L_{Ref}(\lambda)} R_{Ref}(\lambda), \]

where \(R_{Ref}\) and \(L_{Ref}\) are reference panel reflectance and radiance values. This assumes that path radiance is negligible due to the sensor’s close proximity to the ground. We implemented an algorithm that automatically extracted ten pixels from the centre of the “mid grey” step of the QPcard 102 reference panel (which varied spatially due to swing and vibration), and averaged them to obtain \(L_{ref}\) for each line scan. Calibration target reflectance \((R_{Ref})\) was measured prior to data collection using an ASD FieldSpec 3 spectrometer with controlled halogen illumination.

From Eq. 2, one can deduce that the incident illumination can be estimated using

\[ L_{Illum}(\lambda) = \frac{L_{Ref}(\lambda)}{R_{Ref}(\lambda)}, \]
As mentioned in Section 3.5, since we are actually measuring HCRF \((\approx \text{HDRF})\), \(L_{\text{Illum}}\) represents the amount of light that would be reflected by a perfectly Lambertian and reflective surface in the direction of the camera, given the hemispherical illumination at the time. It therefore does not represent the full hemispherical electromagnetic flux incident upon the reference panel surface. Computing illumination for every single line scan individually is referred to as REF, and is considered to be the ground truth benchmark against which all other methods are compared.

In addition, other simplistic illumination compensation approaches were simulated using partial reference target data. For the most basic approach, the illumination spectrum was fixed for a whole dataset, based on the first line scan reference (referred to as CONST for brevity). This emulates a field protocol where only one initial reference measurement is taken. Linear interpolation was included as an intermediate method that fits between the above two methods in terms of expected accuracy. Calibration target samples were extracted at different fixed intervals, and the spectra were interpolated with (Suomalainen et al., 2014)

\[
L_{\text{Ref}}(\lambda) = \frac{t - t_{\text{Ref}_1}}{t_{\text{Ref}_2} - t_{\text{Ref}_1}} L_{\text{Ref}_1}(\lambda) + \frac{t_{\text{Ref}_2} - t}{t_{\text{Ref}_2} - t_{\text{Ref}_1}} L_{\text{Ref}_2}(\lambda),
\]

where \(t_{\text{Ref}_1}, t_{\text{Ref}_2}\) and \(t\) are timestamps for the first, second and interpolated measurements, and \(L_{\text{Ref}_1}, L_{\text{Ref}_2}\) and \(L_{\text{Ref}}\) are radiance spectra vectors for the first, second and interpolated measurements. Saturated target samples were simply removed, with the exception of the first and last samples, which were moved to the first or last unsaturated instance respectively. For comparison, several target extraction intervals were simulated from the continuously visible reference, emulating a field protocol where a reference target might be periodically placed on the ground rather than being permanently mounted to the vehicle. Interpolation methods are referred to as INT-\(n\), where \(n\) is the interval between target readings. A special case, INT-BE refers to interpolating between the first and last (non-saturated) line scan only. The interpolation intervals simulate manual placement of reference targets on the ground at regular intervals. Shorter intervals result in more manual labour for the operators.

### 3.7. Log subspace illumination and reflectance recovery

While several subspace illumination and reflectance recovery variations have been proposed, the method described as “REGLOGSEP” by Drew and Finlayson (2007) was implemented, due to its computational advantages, as described in Section 2.3. For brevity, in this paper it is referred to as LOGSEP. For this section we also adopt that paper’s naming convention as follows, which denotes absolute non-logarithmic quantities with hats.

\[
\hat{C}(\lambda) = L_{\text{Sample}}(\lambda) \\
\hat{E}(\lambda) = L_{\text{Illum}}(\lambda) \\
\hat{S}(\lambda) = R_{\text{Sample}}(\lambda)
\]

\[
C(\lambda) = \log(L_{\text{Sample}}(\lambda)) \\
E(\lambda) = \log(L_{\text{Illum}}(\lambda)) \\
S(\lambda) = \log(R_{\text{Sample}}(\lambda))
\]

Ignoring the effect of upward atmospheric transmittance and path scattered radiance, which is reasonable for very low altitude applications, the at-sensor sample radiance \(\hat{C}(\lambda)\) can be modelled as
\hat{C}(\lambda) = \hat{E}(\lambda)\hat{S}(\lambda) \quad (6)

The foundation of the subspace model is that both \( \hat{E} \) and \( \hat{S} \) can be approximated by a much smaller number of basis vectors than the dimensionality of the spectra. Therefore we have

\[
\hat{E}(\lambda) = \sum_{i=1}^{m} \hat{\epsilon}_i \hat{E}_i(\lambda),
\]

\[
\hat{S}(\lambda) = \sum_{j=1}^{n} \hat{\sigma}_j \hat{S}_j(\lambda),
\]

where \( m \) and \( n \) are the number of illumination and reflectance basis functions respectively, \( \hat{E}_i \) and \( \hat{S}_j \) are the individual basis functions for illumination and reflectance respectively, and \( \hat{\epsilon}_i \) and \( \hat{\sigma}_j \) are the corresponding coefficients.

Drew and Finlayson (2007) take the logarithm of \( \hat{C} \). Dropping the hats for logarithmic quantities, this turns the at-sensor radiance into a sum of reflectance and illumination, changing Eq. 6 into

\[
C(\lambda) = \sum_{i=1}^{m} \epsilon_i E_i(\lambda) + \sum_{j=1}^{n} \sigma_j S_j(\lambda),
\]

The optimum coefficients \( \epsilon_i \) and \( \sigma_i \) can be found by solving the following equation,

\[
A \alpha = h \quad (10)
\]

\[
A = \begin{bmatrix} M & N \\ N^T & P \end{bmatrix}, \quad \alpha = \begin{bmatrix} \epsilon \\ \sigma \end{bmatrix}, \quad h = \begin{bmatrix} f \\ g \end{bmatrix}
\]

where,

\[
M = E^T E, \quad N = E^T S, \quad O = N^T, \quad P = S^T S, \quad f = E^T L, \quad g = S^T L
\]

Eq. 10 can be solved in the standard way by performing the matrix product of the inverse of \( A \) on the left of both sides to obtain \( \alpha \) and thus \( \epsilon \) and \( \sigma \). See Drew and Finlayson (2007) for details on the derivation of Eq. 10.

\( E \) and \( S \) are \( s \times m \) and \( s \times n \) matrices containing the respective basis vectors in their columns, where \( s \) is the number of bands. Correspondingly, \( \epsilon \) and \( \sigma \) are the coefficient vectors for illumination and reflectance basis functions.

Drew and Finlayson (2007) further refine the method by including an additional regression step, which serves to take the initial separation result and guide it using a known set of at-sensor radiances, which is the set of all training illuminant and reflectance combinations. A regularisation step is also added by penalising large norm solutions during the regression. The regression and regularisation are achieved with the following equations:
\[
W = \frac{1}{(m+n)} \sum \text{diag}(\tilde{\alpha} \tilde{\alpha}^T) \mathbf{I}_{(m+n)},
\]

(13)

\[
Q = \tilde{\epsilon} \tilde{\alpha}^T (\tilde{\alpha} \tilde{\alpha}^T - \lambda W)^{-1},
\]

(14)

\[
R = \tilde{\sigma} \tilde{\alpha}^T (\tilde{\alpha} \tilde{\alpha}^T - \lambda W)^{-1},
\]

(15)

where \( \mathbf{I}_{(m+n)} \) is the \((m+n) \times (m+n)\) identity matrix and \( \lambda \) is a tuning parameter. \( \tilde{\epsilon}, \tilde{\sigma} \) and \( \tilde{\alpha} \) are the sets of \( m \times N \) illuminant, \( n \times N \) reflectance, and \((m+n) \times N\) combined coefficients respectively for all \( N \) illuminant and reflectance combinations.

The resulting regression matrices can be applied to any coefficient estimate \( \alpha \) with,

\[
\alpha_{\text{new}} = \mathbf{T} \alpha,
\]

(16)

Note that \( \mathbf{T} \) differs from equation 15 of Drew and Finlayson (2007), due to an apparent typographical error. Two methods of training data selection were used: from line scans that are evenly spaced in time, and line scans that were manually selected at times where the greatest lighting variation occurred. The first simulates placing a calibration target on the ground at regular intervals (as with the INT-\( n \) methods). This will be referred to as LOGSEP-\( n \), where \( n \) is the interval between readings. The second method simulates a policy where training data are collected manually when qualitative lighting changes are observed by operators in the field, spanning as much variation as possible, while minimising the number of training samples (only 5-8 line scans per dataset). This method will be referred to as LOGSEP-M. Full line scans were used as input training data, where reference panel pixels were used to obtain both illumination and reflectance training spectra. Basis functions were obtained separately for illumination and reflectance spectra, using Singular Value Decomposition (SVD) on the logarithm of the training spectra. To ensure tractability, the number of illumination and reflectance spectra was thinned to a maximum of 1000 each (i.e. \( N_{\text{max}} = 10^6 \)) for determination of the regression matrices only. Scan lines where the reference target was saturated were removed from the training data.

Reflectance using the LOGSEP methods can be recovered in two ways: directly from the reflectance base spectra coefficients or by dividing the at-sensor radiance by the recovered illumination spectrum. In our experiments we consider both groups of results. We differentiate the two groups of methods as LOGSEP and LOGSEP-IND (see Table 2).

When taking the logarithm of spectral values, very low, negative or zero values must be dealt with. For all processing in this paper, any input spectra were set to an appropriate floor value prior to processing with LOGSEP.

3.8. Georeferencing, voxelisation and mapping

One important advantage of acquiring hyperspectral data with a mobile ground based platform is the ability to create very high resolution orthorectified maps (Abd-Elrahman et al., 2016). In this paper, this enables us to visually demonstrate the result of compensating...
Table 2: Summary of Reflectance and Illumination Calculation Methods

<table>
<thead>
<tr>
<th>Short Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>REF</td>
<td>Illumination spectrum derived from target in view at each linescan. Benchmark reference method used to compare all other methods against (for example when calculating spectral angle)</td>
</tr>
<tr>
<td>CONST</td>
<td>Illumination spectrum derived from first target observation and assumed to be constant for entire duration.</td>
</tr>
<tr>
<td>INT-BE</td>
<td>Linear interpolation between illumination spectra at the start and end of the datasets.</td>
</tr>
<tr>
<td>INT-n</td>
<td>Linear interpolation of illumination spectra at ( n ) second intervals.</td>
</tr>
<tr>
<td>LOGSEP-( n )</td>
<td>Direct subspace based separation with training spectra at ( n ) second intervals.</td>
</tr>
<tr>
<td>LOGSEP-M</td>
<td>Direct subspace based separation with a few hand selected training spectra.</td>
</tr>
<tr>
<td>LOGSEP-IND-( n )</td>
<td>Like LOGSEP-( n ) but using recovered illumination to indirectly obtain reflectance. Only applies to reflectance recovery.</td>
</tr>
<tr>
<td>LOGSEP-IND-M</td>
<td>Like LOGSEP-M but using recovered illumination to indirectly obtain reflectance. Only applies to reflectance recovery.</td>
</tr>
</tbody>
</table>

for lighting changes. Georeferencing allows the placement of hyperspectral pixels in real world 3D coordinates in order to generate orthorectified maps. Each pixel is represented as an infinite ray in Cartesian space using the standard pinhole camera model. The rays are georeferenced using the vehicle’s location and pose estimates from a Novatel SPAN RTK/GPS/INS. The intersection of the rays and local horizontal ground planes define the location of each point in world coordinates, where the local planes are defined by the wheel contact points at each moment in time. This assumption is reasonable where the ground does not slope significantly across the span of the sensor/ground footprint, which was the case for all trials in the this study. It does not take into account plant height, but the accuracy was sufficient for visual interpretation of results. The maps were generated by grouping the resulting 3D points into a regular 3 cm grid (column voxelisation), where the mean was calculated on true colour values (at appropriate red, green and blue wavelengths) and NDVI (see Section 3.9).

3.9. Normalised difference vegetation index

In some of the experiments, the Normalised Difference Vegetation Index (NDVI), calculated with Eq. 17, is used as an example to demonstrate a practical output measure that is very commonly used in precision agriculture (PA) and remote sensing in general.

\[
NDVI = \frac{NIR - Red}{NIR + Red}
\]  

Its applications include quantifying leaf area index (LAI), percent vegetation cover, intercepted photosynthetically active radiation (IPAR), and green biomass (Zhao et al., 2007). The NDVI was originally designed to be used with broadband sensors, such as multispectral cameras, whereas its application with narrow band spectroscopy and hyperspectral imaging requires specific red and NIR bands to be selected. In addition, to reduce noise, it is often necessary to average (bin) adjacent bands to maximise the signal to noise ratio (SNR) of the input values, which requires an additional parameter, averaging width.

All NDVI values in this paper were obtained using red and NIR values at wavelengths 670 nm and 800 nm respectively, which is one of the most common combinations in the literature (Slonecker, 2012; Wu et al., 2008). An averaging width of 10nm was found experimentally
to provide adequate amelioration of noise. In practice different parameters may be chosen depending on the desired outcome.

4. Results

In this section experimental results of the reflectance retrieval methods (Table 2) are outlined in detail. We demonstrate the significant effect lighting variation can have, and we assess the effectiveness of the various compensation methods. The overall accuracy of each method was measured using its spectral angle (SA) with REF for recovered spectra within each of the tested datasets. These are also plotted over time to demonstrate the stability of each method. Maps are presented to illustrate the results and show the improvement of illumination compensation when using ratios and indices. The possibility of compensating for lighting variation in one dataset using data from another or several others is also evaluated using the LOGSEP recovery method.

4.1. Effect of lighting variation on hyperspectral data

The light incident upon the ground is a combination of direct sunlight and light scattered through the atmosphere (skylight) and from other objects. Skylight is blue shifted compared to direct sunlight, because the atmosphere scatters the light more at lower wavelengths than at higher wavelengths. When the amount of direct sunlight is reduced, for instance by cloud cover, the total illumination incident upon the ground is also blue shifted. This can be seen in Fig. 3(a), where the high cloud cover illumination spectrum falls off more steeply from 500 to 700 nm, compared to the low cloud cover spectrum. The two spectra were taken from the same dataset (ML-0), highlighting the additional difficulty experienced when operating under changing cloud cover conditions.

Fig. 3(b) demonstrates the effect on a recovered reflectance spectrum if illumination is not determined accurately. The same sample reflectance spectrum was multiplied by the two illumination radiance spectra to simulate at-sensor sample radiance spectra. The two radiance spectra were then divided by one illumination spectrum, simulating using one constant illumination measurement for all data (i.e. CONST compensation, see Table 2), which does not account for lighting changes. A clear discrepancy can be seen in almost all wavelengths, which affects the outcome of any further analysis, such as the calculation of Normalised Difference Vegetation Index (NDVI) (see Section 3.9). The NDVI variation over time due to changes in lighting can be observed in Fig. 4 for the spectrum in Fig. 3(b) for every point in time throughout the ML-0 dataset (again compensated with CONST). NDVI values peak at about 0.63 and dip below 0.57, changing by over 9% within only minutes. Closer examination of the illumination spectra in Fig. 3(a) suggests that an even greater effect may be seen in indices, classification and other analysis that rely more heavily on the wavelengths approximately below 500 nm, between 600 and 700 nm, and between 740 and 800 nm. Subtle effects in plant spectra can easily be overshadowed by environmental lighting variation, which highlights the necessity for accurate lighting compensation.

4.2. Choice of basis functions and regularisation parameter

The LOGSEP method is parameterised by three variables that must be selected appropriately for the data. Fig. 5(a), (b) and (c) illustrate the effect of varying the number of
Figure 3: Sample (a) illumination and (b) reflectance spectra demonstrating the significant differences between a low and high cloud cover scenario. A representative plant sample reflectance spectrum was multiplied by the illumination spectra in (a), and retrieved using one constant reference (CONST) to yield the reflectance spectra in (b). All spectra were taken from the same dataset (ML-0, see Table 1) at the times indicated in Fig. 4. The spectral vectors were normalised to unity length to allow a direct shape comparison (in reality, the high cloud cover spectrum is significantly lower in magnitude). Note: The plots use different y-axes as they are individually normalised spectra, and therefore a direct comparison between plots is not meaningful.

Figure 4: NDVI values plotted over time for a representative plant sample reflectance spectrum, multiplied by illumination spectra in a high lighting variation dataset (ML-0, see Table 1), and retrieved using one constant reference (CONST). The two red vertical lines indicate the times of the spectra in Fig. 3. The vertical grey regions indicate locations where the reference target was saturated and which were therefore excluded from training, interpolation and calculation of any statistics.
Figure 5: Basis function and regularisation parameter test results. In (a), results obtained with varying numbers of reflectance basis functions are plotted against spectral angle (as measured against REF). Each curve represents a different number of illumination basis functions. The effect of the number of illumination basis functions on accuracy is shown in (b), plotted for a fixed number of reflectance basis functions of 12. In (c), computational time is graphed for a varying number of reflectance basis functions (illumination basis functions fixed at three). In (d), the effect of varying the regularisation constant with respect to accuracy is shown (note the logarithmic x axis).
illumination and reflectance basis functions on the LOGSEP illumination estimate accuracy, shown as average spectral angle from REF, and computation time. To generate the results, 235 scan lines (152280 pixels) were taken from evenly spaced locations in the ML-0 dataset. Error levels out after approximately 12 reflectance and three illumination basis functions, while computation time increases with the number of basis functions. This presents a trade-off, and the relatively small increase in accuracy gained by increasing the number of basis functions further was not considered worth the corresponding computational cost. Consequently, all subsequent experiments were done based on three illumination and 12 reflectance basis functions.

Fig. 5(d) shows the effect of the regularisation parameter $\lambda$ on accuracy. Overall the effect is minimal, but after about $\lambda = 10^{-6}$ the error increases more noticeably, and thus all subsequent experiments were performed with this value of $\lambda$.

4.3. Recovery accuracy

In order to evaluate the accuracy of retrieved reflectances, the SA of the resulting reflectance spectra for each calibration method were calculated against the continuous reference panel result REF (see Section 3.6) as an error measure. All line scans were calibrated using the methods outlined in Table 2. Average SA error results are shown in Table 3. In rare cases, where INT-$n$ reference readings coincide with corrupted calibration target readings (see Fig. 8), SA results within the affected time intervals were omitted from averaging for all methods in Table 3 to facilitate a fair comparison. Similarly, affected line scans were removed from LOGSEP-$n$ training data.

Table 3: Spectral Angles to REF ($\times10^{-2}$ radians)

<table>
<thead>
<tr>
<th>DATASET</th>
<th>CONST</th>
<th>INT-BE</th>
<th>INT-180s</th>
<th>INT-30s</th>
<th>LOGSEP-30</th>
<th>LOGSEP-M</th>
<th>LOGSEP-IND-30</th>
<th>LOGSEP-IND-M</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMAD-1</td>
<td>6.55</td>
<td>7.73</td>
<td>3.92</td>
<td>3.71</td>
<td>8.25</td>
<td>8.39</td>
<td>4.54</td>
<td>4.79</td>
</tr>
<tr>
<td>DDPA-2</td>
<td>4.09</td>
<td>3.90</td>
<td>3.72</td>
<td>3.63</td>
<td>8.72</td>
<td>8.69</td>
<td>3.65</td>
<td>3.88</td>
</tr>
<tr>
<td>CDA-0</td>
<td>4.98</td>
<td>3.32</td>
<td>2.57</td>
<td>2.47</td>
<td>6.20</td>
<td>6.32</td>
<td>2.98</td>
<td>3.18</td>
</tr>
<tr>
<td>DDPA-1</td>
<td>3.12</td>
<td>3.23</td>
<td>2.86</td>
<td>2.73</td>
<td>7.12</td>
<td>7.12</td>
<td>2.78</td>
<td>3.03</td>
</tr>
<tr>
<td>ML-0</td>
<td>2.80</td>
<td>2.71</td>
<td>2.29</td>
<td>1.46</td>
<td>4.50</td>
<td>4.59</td>
<td>2.08</td>
<td>2.29</td>
</tr>
<tr>
<td>DBVL-0</td>
<td>3.00</td>
<td>4.07</td>
<td>2.23</td>
<td>1.63</td>
<td>5.51</td>
<td>5.61</td>
<td>2.37</td>
<td>2.53</td>
</tr>
<tr>
<td>SUL-0</td>
<td>3.22</td>
<td>2.77</td>
<td>1.99</td>
<td>1.57</td>
<td>5.67</td>
<td>5.35</td>
<td>2.47</td>
<td>2.63</td>
</tr>
<tr>
<td>AVERAGE</td>
<td>3.97</td>
<td>3.96</td>
<td>2.80</td>
<td>2.46</td>
<td>6.56</td>
<td>6.58</td>
<td>2.98</td>
<td>3.19</td>
</tr>
</tbody>
</table>

The two interpolation methods, perform best on average, though the LOGSEP-IND methods produce comparable results. LOGSEP-M and LOGSEP-IND-M perform similarly to LOGSEP-30 and LOGSEP-IND-30 respectively.

An example of a typical radiance spectrum and its recovered illumination and reflectance are shown in Fig. 6, along with spectral angle values in the legend. Both LOGSEP-30 and LOGSEP-M qualitatively appear to closely model the reference illumination and reflectance. LOGSEP is compared to LOGSEP-IND in Fig. 6(d). Both are similar to each other, yet directly obtaining reflectance as a combination of base spectra (LOGSEP) inherently tends to smooth results, while LOGSEP-IND retains more high frequency detail. Fig. 7 illustrates an example reflectance spectrum that was poorly recovered using LOGSEP. In contrast, LOGSEP-IND appears to provide better recovery performance here.
To demonstrate the evolution of the errors over time, illumination spectral angle values were averaged per line scan and plotted over time in Fig. 8 for four representative example datasets, two with heavy and two with light illumination variation. The interpolated method’s SA drops to zero every 30 s, at which time the illumination spectrum is exactly equal to the continuous method (REF). It also maintains the lowest spectral angle for the majority of the duration. In most cases, the two LOGSEP methods produce an error that remains close to INT-30 and well below CONST, particularly in Fig. 8(c), whereas in Fig. 8(a) the LOGSEP methods fluctuate more significantly.

Figure 6: Reflectance (c and d) and illumination (b) extraction example from a typical at-sensor radiance sample (a). In (d), note the inherent smoothing that occurs when extracting spectra directly with LOGSEP. The noise present in the original reflectance spectrum most likely unfairly inflates LOGSEP reflectance spectral angles. Therefore, illumination and LOGSEP-IND reflectance results are a better gauge of recovery accuracy. Spectral angles from REF in radians are shown in brackets. Note: The plots use different y-axes as they are individually normalised spectra, and therefore a direct comparison between plots is not meaningful.

Fig. 9(a) shows an uncompensated example of a true colour hyperspectral map of ML-0. Clear lighting differences are visible in several places as clouds moved through the scene on the day of acquisition. In Fig. 9(b), continuous calibration (REF) compensated NDVI values are plotted for the same field, clearly showing differences in vegetation densities, but no obvious illumination effects, as expected. Fig. 9(c) and 9(d) compare REF NDVI
values with CONST and LOGSEP-M results respectively by taking the square difference and
mapping it. The CONST result is clearly much more susceptible to lighting variation when
compared to the LOGSEP-M square differences, which are barely visible at the same scale.

4.4. Ratio stability
For analysis and mapping, it is very common to calculate vegetation indices, such as
NDVI, from hyperspectral imaging data. Compensation for illumination should aim to
ensure accuracy when computing these indices, which are generally ratios of reflectance
values at one wavelength to another. To illustrate how the various calibration methods
perform, ratios were calculated for all combinations of wavelengths. A generic normalised
ratio of reflectances at two wavelengths is expressed as

\[ r(\lambda_1, \lambda_2) = \frac{R(\lambda_2) - R(\lambda_1)}{R(\lambda_2) + R(\lambda_1)}, \]

where \( R(\lambda) \) is the reflectance value at wavelength \( \lambda \). For appropriate selections of \( \lambda_1 \) and
\( \lambda_2 \) this equation covers a number of vegetation metrics from the literature, including NDVI,
normalised pigment chlorophyll index (NPCI), and photochemical reflectance index (PRI)
(Slonecker, 2012).

The root mean square error (RMSE) for each ratio was calculated for CONST, INT-30
and LOGSEP-IND-30, with respect to REF. The data are the same used in Section 4.3, and
results are shown as a matrix in Fig. 10.

As expected, CONST exhibits greater RMSE values for a large proportion of wavelength
combinations. As demonstrated previously, interpolating every 30 s generally corrects for
illumination changes well, while LOGSEP-IND-30 performed much better than CONST, as
expected, but slightly worse than interpolation. The greatest deviation can be seen in ratios
that include wavelengths at the blue extremes (<470 nm), which can be attributed to a
greater amount of noise, though the effect is not as bad at the near infra-red (NIR) end of
the spectrum (>800 nm). Importantly, however, the ratio region that commonly corresponds
to NDVI has been improved markedly by both LOGSEP and INT.
Figure 8: Scan line average spectral angle values calculated for illumination extraction results fromCONST, INT-30, LOGSEP-30, and LOGSEP-M against the reference REF. In (a) and (b), environmental lighting was bright and sunny with frequent moving clouds resulting in sudden significant changes. In (c) and (d), however, cloud cover was heavy and variation was limited. The vertical grey regions indicate locations where the reference target was saturated and which were therefore excluded from training, interpolation and calculation of any statistics. The large spikes are caused almost exclusively by the following: excessive swaying of the calibration target, pushing it outside of the field of view of the camera, or confusion of the extraction algorithm with separate calibration targets that were placed directly on the ground (but not used in this paper). All of these affect each of the methods equally, except in rare cases where an INT-n reference coincides with one of the spikes, in which case they were excluded, as indicated on the plot as vertical red regions. Spikes were also removed from LOGSEP-n training data.
Figure 9: Orthorectified hyperspectral maps for ML-0. An uncorrected true colour hyperspectral map is shown in (a). Absolute lighting differences due to moving clouds can be seen in several places, as lighter and darker regions along the rows. An NDVI map is shown in (b), based on continuous calibration compensated data (REF). (c) illustrates the square difference between the NDVI results of CONST and REF compensated NDVI, while (d) gives the difference between LOGSEP and REF compensated NDVI. Both (c) and (d) are scaled to 0-0.0051. Difference values were scaled by the same amount in both images. Because CONST does not correct for variations in illumination that occur in the scan, errors occur at the times during the scan when clouds moved past the sun. Given the progressive scan motion of the vehicle, this causes a strong spatial correlation of the errors, which can cause ambiguity. In the LOGSEP compensated image, these differences are much smaller, as quantified in Table 3.
4.5. LOGSEP cross dataset testing

An interesting application of subspace based illumination and reflectance extraction is using a prior known set of training spectra to build a subspace model that can be used on any data where a reference target is not available. Previous sections in this paper have focused on both training and testing on separate data from within the same dataset. This relates to a field protocol where training illumination and reflectance spectra are obtained during the acquisition of each dataset, and compensation is performed as a post-processing step. This section investigates the results from training on illumination and reflectance spectra from one dataset and testing on a different one, which would mean no reference target is needed once training is complete.

Tables 4 and 5 summarise the illumination extraction results with LOGSEP-30 and LOGSEP-M respectively, when trained and tested on all possible dataset combinations. In most cases, best or close to best performance is achieved when training and test spectra came from the same dataset (diagonal). It can also be observed that datasets that came from similar conditions result in better performance. For example, DBVL-0, ML-0 and SUL-0 combinations (high variation, sunny) perform well, as do DDPA-2, DDPA-1 and CDA-0 combinations (low variation, cloudy). Conversely, training on a low variation, cloudy dataset and testing on a high variation, sunny one generally produces lower accuracy.

To explore this further, Fig. 11 compares the highest and lowest magnitude LOGSEP-30 illumination training spectra from representative sunny and cloudy datasets (ML-0 and CDA-0). Both cloudy spectra are blue shifted with respect to the sunny ones (higher relative magnitude between 400 and 500 nm, and lower relative magnitude between 600 and 700 nm). As a result, LOGSEP, and in particular the regression step, can be expected to perform poorly when attempting to reproduce the original illumination (and by extension reflectance) spectrum.

To address this, we combined the training data sets from one higher overall illumination and one lower overall illumination dataset, for the purpose of training on a more diverse range
Table 4: LOGSEP-30 Cross Dataset Illumination Extraction Spectral Angles ($\times 10^{-2}$ radians)

<table>
<thead>
<tr>
<th>Source of Training Data</th>
<th>NMAD-1</th>
<th>DDPA-2</th>
<th>CDA-0</th>
<th>DDPA-1</th>
<th>ML-0</th>
<th>DBVL-0</th>
<th>SUL-0</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMAD-1</td>
<td>4.47</td>
<td>6.79</td>
<td>5.91</td>
<td>5.51</td>
<td>6.72</td>
<td>8.80</td>
<td>9.67</td>
</tr>
<tr>
<td>DDPA-2</td>
<td>5.72</td>
<td>3.31</td>
<td>4.09</td>
<td>4.07</td>
<td>6.37</td>
<td>6.77</td>
<td>7.88</td>
</tr>
<tr>
<td>CDA-0</td>
<td>5.15</td>
<td>4.52</td>
<td>3.08</td>
<td>4.50</td>
<td>4.98</td>
<td>5.14</td>
<td>5.91</td>
</tr>
<tr>
<td>DDPA-1</td>
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<td>ML-0</td>
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<td>3.92</td>
<td>2.85</td>
<td>2.92</td>
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<tr>
<td>DBVL-0</td>
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<td>3.92</td>
<td>2.85</td>
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<td>SUL-0</td>
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<td>3.14</td>
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<td>5.66</td>
<td>4.80</td>
<td>5.26</td>
<td>5.78</td>
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</tbody>
</table>

Table 5: LOGSEP-M Cross Dataset Illumination Extraction Spectral Angles ($\times 10^{-2}$ radians)

<table>
<thead>
<tr>
<th>Source of Training Data</th>
<th>NMAD-1</th>
<th>DDPA-2</th>
<th>CDA-0</th>
<th>DDPA-1</th>
<th>ML-0</th>
<th>DBVL-0</th>
<th>SUL-0</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMAD-1</td>
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<td>7.25</td>
<td>6.06</td>
<td>5.42</td>
<td>6.64</td>
<td>8.77</td>
<td>9.65</td>
</tr>
<tr>
<td>DDPA-2</td>
<td>5.58</td>
<td>3.43</td>
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<td>4.46</td>
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<td>7.04</td>
<td>4.24</td>
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<td>5.68</td>
<td>4.93</td>
<td>5.43</td>
<td>5.89</td>
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</table>

Figure 11: Comparison of illumination spectra in high and low variation datasets.
of data. As there are a large number of possible combinations, only three were selected on
the following criteria:

- Range: DBVL-0 and DDPA-2 cover a large combined minimum to maximum range of
illumination magnitude.
- Overlap: SUL-0 and CDA-0 have large combined illumination magnitude overlap.
- Best individual training sets (lowest average SA) combined: ML-0 and CDA-0 each
produced the best average SA in their respective high variation and low variation
groups.

The results are shown in Table 6. Compared to Tables 4 and 5, average scores have
clearly improved. In most cases, individual accuracies have improved to approximately
the better of the two datasets in the training combinations. For instance, consider ML-0-
CDA-0-LOGSEP-30 SA results: Test dataset DDPA-2 has a score of $4.13 \times 10^{-2}$ rad, which
correlates well with the CDA-0 LOGSEP-30 training set score of $4.09 \times 10^{-2}$ rad, and test
dataset DBVL-0 has an SA of $4.10 \times 10^{-2}$ rad, which also closely matches ML-0’s LOGSEP-30
training set score of $3.92 \times 10^{-2}$ rad.

Table 6: Combination Cross Dataset Illumination Extraction Spectral Angles ($\times 10^{-2}$ radians)

<table>
<thead>
<tr>
<th>Source of Training Data</th>
<th>Large Range</th>
<th>Best Ind. Perf.</th>
<th>Large Overlap</th>
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<tr>
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<td>5.86</td>
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<td>CDA-0</td>
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<td>4.67</td>
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<td>LOGSEP-M</td>
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<td>4.10</td>
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<td>4.11</td>
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</table>

5. Discussion

The results in Section 4 demonstrate that the LOGSEP methods are able to extract
illumination spectra with an accuracy similar to short time interval interpolation methods.
LOGSEP and LOGSEP-M provide very similar performance overall, suggesting that for
LOGSEP to extract illumination and reflectance spectra accurately, it is not as important to
have a large quantity of training data, but a comprehensive sampling of different illumination
conditions.

It is important to note that all REF, CONST and INT illumination spectra are inherently
smoothed, as reference panel readings were averaged over ten pixels. This in turn results in
high frequency noise being transferred to reflectance when dividing into the radiance spec-
trum. On the other hand, reflectances obtained directly from LOGSEP (as a combination
of reflectance base functions) exhibit a smoothing effect themselves. This can artificially
inflate their spectral angle scores as computed against REF, resulting in the inferior results of LOGSEP-30 and LOGSEP-M seen in Table 3. On the other hand, LOGSEP illumination results are also smoothed by the limited number of basis functions, and so LOGSEP-IND (calculated by dividing illumination into radiance) provides a fairer quantitative comparison of reflectance results to REF, CONST and INT.

Additionally, there is also the possibility that if certain reflectance spectra are not well represented in the training data (e.g. uncommon non-vegetation spectra), LOGSEP will provide a poor reflectance estimate directly (as a combination of basis functions). Because illumination spectra are modelled in a lower dimensional subspace (three in this case), its spectrum is more strictly constrained, resulting in much better reflectance recovery with LOGSEP-IND, as shown in Fig. 7. For this reason, it is generally preferable to use LOGSEP-IND over LOGSEP.

The results also demonstrate that it is possible to compensate for illumination changes in any datasets, where a reference target is not available, if a sufficient range of historical illumination training spectra is present. By combining training data from datasets with differing lighting conditions, LOGSEP was universally applicable to all datasets, in contrast to other methods that require in field reference measurements (e.g. Uto et al. (2013), Suomalainen et al. (2014), and Karpouzli and Malthus (2003)).

Based on the results, we are able to provide guidance on which compensation method and matching field protocol to use and when. If accuracy of data is of critical importance and it is practically feasible to permanently mount a calibration target to the platform, continuously imaging a calibration target panel in every line scan will lead to the best results (REF), as no other method was able to perfectly reconstruct the data. However, mounting the target correctly can be tedious and restrictive, or impracticable (e.g. for aerial applications). For example, high crop growth made it very difficult to mount the target while maintaining an optimal sensing geometry in our case, as the covers of the Ladybird needed to be adjusted. We also found that this approach increased the footprint of the vehicle, raised potential safety concerns and was prone to damage. In some cases, the target had to be completely removed to allow for taller crops. In general, it would be a challenge to universally cater for all possible crop heights with a single configuration. Another consideration is the loss of pixels where the target is in view. On some fields, uneven ground caused excessive swing, sometimes even moving the target out of view (as can be seen by the spikes in Fig. 8).

Furthermore, as shown in Table 1, there are a number of occasions where the reference target was completely saturated (although the majority of vegetation/soil data were not saturated). This can be avoided in the field by adjusting the exposure, lens aperture and/or reflectance of the target itself, however, there is a trade-off, as signal to noise ratio (SNR) is reduced as the aperture or target reflectance is decreased in low light conditions. Alternatively a downwelling illumination sensor may be considered (e.g. Deery et al. (2014) and Kuusk and Kuusk (2010)), which introduces increased cost and complexity as previously discussed.

A next best alternative is to image reference panels in close succession (INT-x) and interpolate (as in Suomalainen et al. (2014)). This is also tedious and time consuming, as targets need to be manually placed on the ground in line with the intervals (which could correspond to the end of rows, for example). If shorter intervals cannot be maintained, accuracy will deteriorate as sudden changes in illumination are not captured.

On the other hand, field protocols based on the subspace model reflectance extraction
method (LOGSEP) can provide a convenient alternative that avoids many of the aforementioned shortcomings. If no historical reference data are available, we have shown that LOGSEP can perform well when only a few separate (≥6) reference panel (and therefore both illumination and reflectance) samples are acquired from each field that is being scanned (LOGSEP-M). This would require operators to monitor conditions (visually or with a light meter, for instance) and image reference targets when lighting has changed significantly. It is important to capture as much lighting variation as possible. We have shown that by combining training samples from datasets with differing lighting conditions, illumination compensation is possible for a wider range of environmental illumination.

If historical illumination and reflectance spectra spanning a wide range of lighting conditions is available, no further in-field training samples are necessary. It would therefore be possible to compile a training set of illumination and reflectance spectra based on previously acquired data. No additional calibration panel measurements would be required, which carries several advantages. The complexity of the system is reduced, because no mounted panels or additional downwelling sensors are required. Completely autonomous operation is made possible, because there is no need to manually place reference panels on the ground, increasing convenience for operators, which is an important factor both for research and commercial applications. In addition, with the exception of a continuously imaged panel, all other reference panel methods require the extraction of reference measurements as a post processing step. A pre-trained system based on prior training spectra enables processing of pixels as they are acquired, allowing real time reflectance retrieval. An additional benefit is that compensation can be performed retrospectively on datasets where a reference target was not available. In contrast to approaches that utilise radiative transfer codes (e.g. Berk et al. (1999) and Qu et al. (2001)), specific atmospheric parameters and their variation with time do not need to be known or estimated explicitly when using LOGSEP.

6. Conclusions

This work examined the use of an unmanned ground vehicle (UGV) for acquiring large quantities of high resolution hyperspectral data of agricultural crops, and compensating for natural illumination variation, in order to retrieve surface reflectance. A previously introduced fast logarithm subspace method for reflectance and illumination extraction was employed and tested against more traditional approaches using reference target panels. We demonstrated that the new approach competes well with frequently (every 30 s) interpolated illumination spectra, while requiring far fewer reference readings. In light of this, we compared and recommended a number of in field policies to obtain appropriate data for the various correction methods. Our experiments show that calibration can be achieved with only six calibration target readings per continuous scan of 60 min. Furthermore, we show that it is possible to train a dataset entirely on historical data, which could allow compensation for lighting changes without any further in field reference data. Future work will validate this idea with a wider array of data in order to understand how a training set would be optimally compiled.
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