Spectral band selection and testing of edge-subtraction leaf segmentation

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INTRODUCTION

While the spectral features of plants have been studied in the context of automated plant identification, they have very little heritage within manual plant identification systems. Even colour is used sparingly, generally reserved for flowers or seeds. Shape features stand in contrast; the shapes of leaves, seeds, and to a lesser degree entire plants, are common elements of traditional plant taxonomies. Despite these established methods for identification, incorporating these shape features into automated systems has proven difficult. One reason for this is the challenge of separating individual green leaves out of an image containing other similar green leaves. Segmentation of leaves in the image is a necessary precursor to the use of leaf shape in automated identification. There are a number of solutions that take advantage of the spectral signature of green plant tissues when individual leaves are set entirely against a non-plant background. The difficulty arises when individual leaves overlap and occlude one another. Differences between individual leaves can be subtle, making the boundaries between them difficult to define and creating a significant challenge for subsequent shape analysis.

In this study, an approach to leaf segmentation was investigated that took advantage of the NIR wavebands for separating leaves from one another and explored the utility of classical edge detectors for defining leaf-leaf boundaries.

Segmentation for shape identification may refer to separating an entire plant from the background for plant-scale shape features or separating individual leaves from the rest of the plant. Separating the entire plant may be done using a number of spectral and colour based approaches. Where possible, the use of NIR information improves the plant/background segmentation due to the large reflectance differences in this region. NIR information was used by Guyer et al. (1986) via a NIR sensitive camera, and Guyer et al. (1993) using a camera and visible wavelength blocking filter. As digital RGB cameras have become readily available (and NIR bands have not), segmentation approaches using colour indices have been more common. A modified excess green measure (2g-r-b) using the normalized chromacity values, has been used to good effect to segment plants (Woebecke et al. 1995; Tang et al. 2003). A study by Philipp and Rath (2002) on using colour space transformations for plant discrimination found that the third component of the i1i2i3 colour space, and of their modified i1i2i3_new colour space were better than other colour space transforms investigated. On closer examination, the i3 component of the i1i2i3 space was essentially equivalent to the modified excess green measure, with the i3_new component being only slightly different.

Until plants reach a point where individual plants are starting to overlap each other, the entire plant approach may be appropriate. However, as scene complexity increases and individual leaves are required, these approaches are hindered by the similarity of leaf colour. Some work has been done on this
problem. Lee and Slaughter (2004) developed a watershed-style algorithm for defining boundaries between multiple-leaf blobs that had been segmented from a colour image. This approach attained up to 57% separation performance on tomato seedlings, with this measure defined as the number of properly segmented leaves divided by the sum of leaves that were fragmented, not separated, and separated. It was, however, computationally demanding.

Deformable templates have also been investigated for leaf segmentation (Manh et al. 2001). Green foxtail (Setaria viridis (L.) Beauv.) and background were segmented using colour information. Starting points for template fitting were defined as leaf tips, which were found using a global search by a small window, followed by regional assessment when the small window was covering plant pixels exclusively. An ellipse was rotated around the tip, and the position that yielded the highest number of plant pixels covered by the ellipse was taken as the template starting point. The template was iteratively deformed outward until a stopping criterion was met. This approach was somewhat dependent on leaves having definable tips, the appropriate definition of the template skeleton, and was not able to account for shared leaf edges within the term driving the deformation, making it somewhat susceptible to occlusion. As such, it does not appear to be a globally applicable solution.

An edge-following algorithm was developed by Franz et al. (1995) for use with broadband NIR plant images. After determining gradient slope and magnitude using a set of 3x3 Sobel kernels, edges were traced using a series of algorithms that were similar to those of the Canny edge detector (Trucco and Verri 1998) to produce a single-pixel wide edge definition using upper and lower edge thresholds. A considerable amount of additional logic for excluding petioles and stems and for linking edges was included beyond the classical Canny detector. Leaf extraction rates for the four species studied ranged from 71.4% for giant foxtail (Setaria faberii Herm.) to 95.8% for ivyleaf morning glory (Ipomoea hederacea Jacq.). The algorithms developed required significant user input for deciding where to start traces and locating areas of interest, but demonstrated the potential of using NIR information, in which there can be considerable variation between leaves and edge-based segmentation for leaf separation.

One of the challenges in using edge-based approaches to segmentation of leaves is the large degree of variation of edge strengths within the regions of interest. The edge strengths between leaf and soil are very large, while leaf-to-leaf edge strengths are lower. Leaf veins and texture also add edge components to the image. Images need to have high edge strength contrast between overlapping leaves relative to other internal edges, which is not typical in RGB images. A possible simplification of the edge-based approach could be made if a spectral band or bands can be used in which leaf edges are strong relative to the edges resulting from other internal structures, even in areas of occlusion (leaf-leaf boundary). In this case, the edge-strength image could be thresholded at this level and simply subtracted from the vegetation image mask. By subtracting the leaf edges, the leaf interiors would be separated from one another, leaving an image of blobs which could be further analyzed for shape.

OBJECTIVES

Given the degree of variation observed between leaves in the NIR bands of the hyperspectral imagery available, it was hypothesised that a band would exist with sufficient contrast between leaves to make edge-subtraction segmentation feasible. Since edges occurring at the boundary between green vegetation and the background are both very strong and easily obtained from the vegetation mask, only the interior edges were of interest for band selection. Interior edges could be due to leaf-leaf boundaries (leaf overlap), veins, or blemishes on a leaf. The first objective was to identify a waveband at which leaf-leaf boundaries were differentiable from other interior edges for four species. While using multiple bands may be beneficial, the problem of how to combine the information from multiple bands was beyond the scope of this exploratory study. This band would then be used to test the edge-subtraction segmentation approach using the edge-strength image from a Sobel edge enhancer and from a Canny edge detector, the algorithm of which has some commonalities to the algorithm used by Franz et al. (1995).

METHODS

Spectral images were collected of trays containing several specimens of four plant species using the University of Saskatchewan imaging spectrophotometer (Noble et al. 2003; Noble 2006). For each tray, the data cube contained data in 115 spectral bands between 400 and 1000 nm at 5 nm bandwidths and intervals. Each pixel represented an area in the image of approximately 1×1 mm. The four species selected were redroot pigweed (Amaranthus retroflexus L., AMARE), common purslane (Portulaca oleracea L., POROL), soybean (Glycine max sp., SOYBE), and stinkweed (aka field pennycress, Thlaspi arvense L., THLAR). These species represented a range of leaf properties (venation, thickness, size) and plant growth patterns. One maturity level for each species was chosen, and the entire-tray image was used for each. Pixel intensity values ranged between zero and 1024, and were calibrated to reflectance with full-scale being equal to 100% reflectance.

The vegetation mask image was created for segmenting plant material from the background, taking advantage of the change in reflectance between the red and NIR portions of the spectrum. The vegetation mask was in represented as a binary image, and calculated according to Eq. 1.

\[
V_{\text{mask}}(x) = \begin{cases} 
R_{760}(x) > 3 & \text{AND} \left( R_{667}(x) > 30\% \right) 
\end{cases}
\]

where:

- \(x\) = location vector for the images, and
- \(R_{760}\) and \(R_{667}\) = image bands at 760 and 667 nm, respectively.

Edge-strength images were generated for each datacube by first smoothing each band with a 5 x 5 Gaussian kernel to suppress noise, followed by a pair of 3 x 3 Sobel kernels. The edge-strength image was the sum of outputs from the horizontal and vertical Sobel convolutions (ENVI Sobel operator, Research Systems Inc., Boulder, CO). As only the interior leaf edges were of interest for band selection, the exterior (plant-background) edges were removed by masking the edge-strength images with a two-iteration erosion version of their vegetation.
masks. An example of these operations and a resulting interior edge-strength image are shown in Fig. 1.

For each species, sample points were selected at interior boundaries. Three general leaf-leaf overlap edges categories were used: overlap involving newly emerged leaves and older leaves (New-Old), overlap of leaves high in the canopy over leaves deep in the canopy (Upper-Lower), and overlap of peer leaves (Peer-Peer). Peer leaves were leaves of similar maturity, reflectance, and height within the canopy. While edges placed in the Peer-Peer category were exclusive from the other two categories, it was technically possible for an edge belong to both New-Old and Upper-Lower categories. However, this was relatively rare in practice. Newly emerged leaves tended to be closer to the centre of the plants, and the leaves deep in the canopy were either covered by middle leaves or extended toward the periphery of the plants. All plants were planted at the same time, so new leaves did not occur deep in the canopy.

Edge categories that did not represent leaf boundaries were veins, general leaf tissue, and overlap bleedthrough. Bleed-through occurred in some instances where the outline of an occluded leaf was visible through the covering leaf. Not all of these non-leaf edge categories were present in all species.

The number of edge points selected ranged between 25 and 45 per category, depending on availability, and were selected by a single evaluator. Selections were made sparsely across images containing upwards of 18 individual plants of a single species. This was done to avoid biasing the analysis toward one particular edge. Ultimately, these classes were not rigorously defined; the intent was to generally separate the major combinations of leaf reflectance differences resulting from leaf position and age to provide some isolation of these effects on edge strength at a given wavelength. In the final analysis, only the ability of the selected waveband to separate along all leaf edge types combined (i.e. segment leaves), not along particular edge types, was formally evaluated.

Basic descriptive statistics of edge strength were calculated for each edge class in all wavebands, and the Fisher criterion calculated for all interior leaf edge versus non-leaf edge combinations:

\[
Fisher = \frac{(\bar{X}_i - \bar{X}_j)^2}{s_i^2 + s_j^2}
\]

where:

\[\bar{X}_i = \text{mean of class } i, \text{ and}\]

\[s_i^2 = \text{variance of class } i.\]

Class means and the minimum Fisher criterion at each waveband were plotted (Fig. 2). Candidate bands were selected based on the Fisher criterion plots and observation of animations of the edge-strength bands. The performances of the selected wavebands were compared by plotting the edge strengths along transects of the images, and a band selected based on these comparisons.

Edge-based segmentation was tested for the Canny and Sobel edge detectors using the selected band. The Canny edge detector was implemented in IDL (Research Systems Inc., Boulder, CO), while the Sobel detector was a built-in function of IDL. Tests were conducted on a window around the previously defined transects. The image was masked by the vegetation mask and the edge detectors were applied. Threshold values were set using the edge transects and testing. The vegetation mask was then masked by the inverse of the thresholded edge images (edges = 0, everything else = 1). These results went through a single iteration of the NI-IMAQ
Fig. 2. Interior Sobel-edge class means (primary axis) and the minimum pairwise Fisher criterion for leaf versus non-leaf edge (secondary axis) for AMARE, POROL, SOYBE, and THLAR.
Separation operator (National Instruments, Austin, TX) to remove small isthmuses joining neighbouring blobs. This is a proprietary operator, but is based on “erosions, labelling, and conditional dilations” (National Instruments 2005). This was followed by a particle filter to remove all blobs smaller than 30 pixels. A hole-filling operation was done to fill interior holes in the leaf blobs left by wholly interior vein edges that were not eliminated during edge strength thresholding. Lastly, the segmented leaf image was opened (erosion followed by dilation) to smooth the leaf blob boundaries. Results of the Canny and Sobel based segmentation schemes were compared by counting the number of leaves fully or partially visible in the original image. The number of correctly segmented leaves, unsegmented leaves, and over-separated leaves were counted in each of the segmented images. Comparisons were made based on the rates of segmentation, un-segmentation, and removal.

RESULTS and DISCUSSION
Mean edge strengths and Fisher criterion values for the four sample species are shown in Fig. 2. The pattern of edge strengths corresponded closely to the typical patterns of leaf reflectance and degree of difference between leaves. All species showed separability in the red edge region based on the Fisher criterion, with all but SOYBE reaching a global maximum there. The red edge location is sensitive to variations in chlorophyll content, which is influenced in turn by leaf maturity and light exposure. The global maximum for SOYBE was at 745 nm, which is at the upper end of the red edge region. Local maxima were located around 552 nm for all species. Low Fisher criterion values were found for AMARE and to a lesser extent THLAR. These species both showed significant bleedthrough effects in the NIR bands, with the edge of occluded leaves being clearly visible through the covering leaves in several cases. For the purposes of this study, these were interpreted as false edges. In the case of the new-old and bleedthrough classes for AMARE, mean edge strengths were nearly identical from 800 to 1000 nm, and were greater than the peer-peer edge strengths from 735 to 1000 nm.

Wavebands centred at 714, 719, and 745 nm were selected for further analysis on the basis of being the locations of global maximum Fisher criterion value for one or more of the sample species. The band centred on 552 nm was included as a means of comparing NIR performance with what might be possible with visible information only. An additional band, centred at 823 nm was also included. This band appeared to have good interior leaf edge enhancement and non-leaf-edge suppression characteristics when the bands of the SOYBE sample were viewed as an animation.

A transect line was drawn across each sample species datacube. This line was positioned with the intent of crossing as many of the different edge classes as possible. The edge strengths along the transect lines were plotted for each of five candidate bands and arranged below a corresponding false-colour composite image of the transect line and surrounding area. Vertical lines were drawn through the plots at points where the transect line intersected an edge. Solid lines were placed at leaf boundaries and dashed lines were placed at veins or other undesired edges. In some cases, edges appeared along leaf-background boundaries, even after these had been removed or reduced. These edges were ignored. In general, leaf boundary edge strengths increased with wavelength. Background-noise edge strength also increased in some instances. Edge strengths and the response of edges caused by veins with respect to wavelength varied with species.

Leaf-boundary edges of AMARE (Fig. 3) were the most difficult to clearly separate from non-leaf boundary edges. While the strength of leaf-boundary edges tended to increase with wavelength, non-boundary edges caused by veins and bleedthrough often did as well. Edge strengths were also generally lower than some of the other species. Based on these observations, 714 and 719 nm were identified as the best candidate bands for edge-based segmentation of AMARE. The edge strength of bleedthrough and vein features increased substantially in the bands with longer wavelengths.

Analysis of the POROL edge transect was inhibited somewhat by the small leaf size and corresponding high number of leaf boundaries. Bleedthrough edges were not evident with POROL, possibly due to leaves being thicker and better diffusers of light. Veins were not visible. Edge strengths increased with wavelength until 745 nm, decreasing or remaining approximately the same at 823 nm. Wavebands centred at 719 and 745 nm were selected as the best candidates for separating POROL leaf boundaries.

The edges of the SOYBE transect were generally the strongest and most clearly defined of the four species. Unlike AMARE, vein edges were most pronounced at shorter wavelengths, diminishing to near zero at 745 and 823 nm. However, the one instance of a bleedthrough edge in the transect increased in strength at these same wavelengths. The wavebands at 719 and 745 nm were selected as potential bands based on the SOYBE sample.

Bleedthrough effects were very evident in the THLAR sample, thought not well represented in the transect. The bleedthrough edge became relatively pronounced at 745 and 823 nm, while being unperceivable in the visible and faint in the other NIR bands. Edges due to veins were insignificant in the transect. In an attempt to minimize the bleedthrough effect and maximize leaf boundary edge strength, the band centred at 719 nm was selected as the best candidate band based on the THLAR sample.

While not optimum for all of the samples, the band at 719 nm was selected overall for testing the edge-subtraction leaf segmentation approach.

Edge-based segmentation testing
Edge threshold images were determined for each of the four transect-window images. An overall edge strength threshold was set at 225 for the Sobel-based edges. This level was selected to exclude most false edges at 719 nm as reflected in the transect images. The Canny edge strength was calculated as the root sum of squares of the horizontal and vertical gradients. Based on test histograms of these edge strengths, the high Canny threshold was set at 30, and the low threshold set at five, with hysteresis search neighbourhood of width five. These images were input into a LabVIEW routine with the corresponding vegetation mask images and the Canny and Sobel-based segmentation
images produced. A sample of the transect image, Canny-
segmented image, and Sobel-segmented images are
shown for THLAR in Fig. 4. Several examples of the
differences in segmentation are numbered in the Canny and
Sobel-based segmentation images.

Leaves in the transect-window images were manually
numbered, and the corresponding blobs in the segmentation
images labelled. Segmented blobs that corresponded to a single
leaf were counted as correctly segmented; shape correspondence
was not a major factor in this labelling. Cases of multiple leaves
corresponding to a single blob were counted as un-segmented;
each actual leaf within the bounds of these blobs was counted in
this total. A set of blobs that corresponded to a single leaf was
counted as a split leaf. The number of leaves eliminated for each
case was calculated as the difference between the number of
leaves identified in the transect window and the sum of
segmented, un-segmented, and split leaves. Rates of correctly
segmented, un-segmented, and eliminated leaves were
calculated by dividing these quantities by the number of leaves
in the corresponding transect window. Counts and rates are
shown by species and edge-detection scheme in Table 1. Mean
rates are shown across species. The Sobel-based segmentation had a higher segmentation rate and a lower un-segmented rate for all four samples. Split numbers and elimination rates were slightly higher for the Sobel-based segmentation. The higher elimination rate is beneficial for further stages of processing, as the leaves that are eliminated are small leaves or occluded leaf segments that add clutter to the segmented leaf image. Generally, the fineness of the edge extracted by the Canny edge detector is one of its main benefits. For image segmentation in this context, however, the relatively wide edges extracted by the Sobel edge enhancer proved better able to segment the leaf blobs.

With a mean segmented fraction of 64%, the performance of the Sobel segmentation scheme is lower than that reported by Franz et al. (1995). However, the test images used in this study contained multiple plants in dense stands as opposed to single seedlings. The algorithm used by Franz et al. (1995) also had considerable logic in addition to that contained in the standard Canny algorithm, allowing it to both search for weaker edges that were not parallel to main edges above the high threshold, and for estimating occluded edges. This more advanced algorithm comes at a higher computational cost than the Sobel-based edge subtraction approach.

The primary drawback of the approach taken to both band and threshold selection was the qualitative nature of the selection process. This was acceptable given the exploratory nature of this particular study; however more attention will need to be paid to this issue going forward. The band selected at 719 nm was a compromise among the species used. More bands could have been used; however this would have raised additional questions around how the data from each should be combined. Threshold selection was fixed for all species, and while based on the data available (edge transects) was ultimately an informed judgement call. These particular data were calibrated to reflectance and illuminated with a uniform light source. As such, it is expected that

Table 1. Segmentation results.

<table>
<thead>
<tr>
<th>Number of leaves</th>
<th>Fraction properly segmented</th>
<th>Fraction unsegmented</th>
<th>Fraction eliminated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cannys Sobel</td>
<td>Cannys Sobel</td>
<td>Cannys Sobel</td>
</tr>
<tr>
<td>AMARE</td>
<td>49</td>
<td>0.45</td>
<td>0.71</td>
</tr>
<tr>
<td>POROL</td>
<td>113</td>
<td>0.23</td>
<td>0.56</td>
</tr>
<tr>
<td>SOYBE</td>
<td>66</td>
<td>0.45</td>
<td>0.55</td>
</tr>
<tr>
<td>THLAR</td>
<td>71</td>
<td>0.35</td>
<td>0.72</td>
</tr>
<tr>
<td>Mean</td>
<td>0.37</td>
<td>0.64</td>
<td>0.58</td>
</tr>
</tbody>
</table>
other data collected using the same instrument would have comparable results using the same thresholds. Having tested the edge-subtraction approach to segmentation, there would be value in stepping back and investigating mechanisms for combining data from multiple wavelengths and appropriate threshold selection techniques.

The impact of image resolution is also of interest. Recent work using a similar edge subtraction approach, but using a band at 766 nm and higher spatial resolution, had significantly poorer results (Kennedy and Noble 2007). This was attributed, in part, to better definition of non-leaf edge features as a result of the higher resolution. However, having higher resolution may be necessary to properly preserve the shape smaller leaves have after the edges are removed. This suggests that either a better separation of non-leaf edges from leaf edges is required, or that there may be some benefit in using a multi-resolution analysis approach.

CONCLUSIONS

A leaf segmentation approach was tested that used a combination of a vegetation mask and an edge strength image that was calculated for a band that provided contrast for leaf-leaf boundaries. Based on tests with four species, the band centred at 719 nm was selected. Comparisons were made between edges found using a Sobel edge detector and a Canny edge detector. Masking the vegetation binary image with the inverse Sobel edge threshold image resulted in an average correct leaf segmentation rate of 64%. This approach effectively and simply segmented the upper, un-occluded leaves of the image from those underneath. It was not able to reconstruct the occluded leaves, or to specifically eliminate partial leaves from consideration. As such, any shape identification that is run subsequently to this segmentation step must have a mechanism for ignoring partial leaf sections.

A shortcoming of the Sobel segmentation is that it removes a significant portion of the leaf area. This can alter the shape of smaller blobs in particular. It is also highly dependent on the ability of the band selected to provide leaf-leaf edge contrast while minimizing edges from veins and blemishes. It was observed that no single band was optimal for all species, and that veins of different species did not always change in the same way with wavelength. Further study on methods for quantifying the selection of appropriate bands for this type of operation is warranted, as is study on methods for combining the edge information from multiple bands.

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