Spectral Sensing of Different Citrus Varieties for Precision Agriculture

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Abstract. Researchers have used different forms of non-destructive computer vision sensing on citrus for years; however, no system has been developed to identify maturing green citrus fruit while they are still on tree. This project is a preliminary study as to the validity of distinguishing green citrus fruit varieties from leaves using only their spectral characteristics.

A spectrophotometer was used to measure diffuse reflectance of green leaves and three citrus fruit varieties (Orlando Tangelo, Hamlin, and Valencia) in the 200 nm to 2500 nm range. The growing pattern and maturing process of the fruit samples were studied for optimal classification. In addition, moisture contents were calculated and compared with sample spectral characteristics to better understand the role moisture has in determining the fruits' spectral characteristics.

The best wavelengths for green fruit identification were determined using discriminability. These feature spaces used in discriminant analysis to distinguish between fruit and leaf were proven highly accurate. Using two-thirds of the total data as training data and one-third as validation data, a $R^2$ as high as 1.0 was found possible. Calculations using all samples found the optimal wavelengths for leaf/fruit separation were 881, 781, and 1383 nm. These results prove that highly accurate identification of green citrus fruits from leaves is possible while using diffuse reflectance spectral bands.

Keywords. citrus, classification, discriminability, precision agriculture, reflectance, spectral sensing

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Introduction

Florida produces more than 74% of the total citrus grown in the United States. With an "on-tree" value of citrus estimated to be $1.13 billion in 2005 (Florida Agricultural Statistics Services, 2005), the citrus market is extremely important to Florida’s economy. Due to the “input-intensive” nature of citrus production and the Florida’s volatile trend of cost per unit area, precision agriculture is a vital technique to manage the cost of production (Sevier and Lee, 2003). In addition to minimizing costs, precision agriculture offers citrus growers better managed groves, a protected environment, and increasing overall crop yield and profits. Proper implementation of a precision agricultural system requires knowledge of in-field variability; in this case, citrus yield variability.

Fruit identification using machine vision systems is not a new concept. Original concepts date back nearly forty years (Schertz and Brown, 1968). These vision systems have been used for the identification of everything from apples to weed types. Researchers working on citrus harvesting systems have been using different forms of traditional machine vision for years with mixed results and a wide variation of algorithms (Jimenez et al., 2000). Current work in this field of study includes (Chinchuluun and Lee, 2006) and (MacArthur, 2006) However, almost every vision system has used the visible light spectrum as the only means to decipher fruit from the surrounding leaf canopy. A current gap in research is the early seasonal identification of citrus fruit. By solving this problem, precision agricultural techniques can be used earlier in the growing season compounding their benefits.

Annamalai and Lee (2004) proposed a method to decipher green citrus fruits from leaves by their spectral differences in the near infrared (NIR) region. The use of NIR information has been studied in the maturing stages of citrus by Merzlyak et al. (1999) to characterize pigments conversion from chlorophyll to carotenoid. Beyond this, no research has attempted to determine the best means of green citrus fruit identification. This research seeks to fill that gap by qualitatively identifying the critical wavelength bands for separation of green citrus fruit and leaf. In addition, the reflectance spectra of the sample classes will be discussed to narrow down the range of useful wavelengths.

Materials and Methods

Fruit and Leaf Samples

Over the last citrus growing season (June 2005 - January 2006) 540 samples (270 leaves, 100 Hamlin fruit, 100 Tangelo fruit, and 70 Valencia fruit) were taken from the University of Florida’s citrus research grove. One fruit and one leaf located next to each other were picked per tree.

Table 1. Sample acquisition dates and varieties (T-Tangelo, H-Hamlin, and V-Valencia).
Ten of these fruit/leaf samples were obtained bi-weekly from three citrus varieties (Orlando Tangelo, Hamlin, and Valencia). Table 1 shows the dates and citrus variety obtained. Each collection of 10 leaves and 10 fruit constituted a sample set and was measured its diffuse reflectance by a spectrophotometer (Cary 500, Varian, Inc) on the same day as harvesting. The samples were not cleaned as natural on tree and in grove characteristics were desired. There were a total of 27 sample sets collected: 10 Tangelo, 10 Hamlin, and 7 Valencia.

**Diffuse Reflectance**

The spectrophotometer measured the diffuse reflectance percent of the samples from 200 to 2500 nm in one nm wavelength increments. Each day the spectrophotometer was used, the lamps were allowed to warm up for one hour prior to use. This stabilized the lamp light sources used in the reflectance measurements. A “baseline” for 100% diffuse reflectance was measured using a 50 mm diameter polytetrafluoroethylene (PTFE) disk.

**Citrus Moisture Content Calculations**

There were 190 citrus samples weighted to the nearest 100th of a gram by a digital scale (Adventurer, Ohaus, Inc) on the same day as being picked. All citrus diameters were measured using a sliding caliper to the nearest 100th of a millimeter. Samples were labeled and stored in Ziploc bags at 6ºC. The weighed citrus samples were dried in an oven for 72 hours at a consistent 60ºC. They were sliced in half (perpendicular to the juice sacs) and dried for an additional 24 hours. Slicing was required to rid all moisture for the fruits’ juice sacs inside. The dry weight was then measured using the same digital scale as before. The samples’ wet basis moisture content was calculated. Sample moisture contents were compared to their spectral characteristics. Most emphasis was placed on the water absorption bands (1450 and 1940 nm).

**Separation Based on Reflectance**

**Discriminability**

Two types of classification were desired from our data. Most important was a distinction between leaves and any variety of citrus. This recognition would allow citrus growers to use statistical data to identify all immature green fruit regardless of variety. This information is critical as it offers transferable functionality not only to local oranges but to limes, grapefruits and more. The second classification studied was the separation of fruit into the various varieties; in this case Tangelo, Valencia, and Hamlin. There are some spectral changes over the course of the six month growing season, due to chemical and physical alterations within the fruits’ peel. However, for the purpose of this paper a Gaussian distribution was assumed over the reflectance of all fruit varieties and leaves. Two histograms of fruit and leaf probability density function’s (pdf) for the wavelengths of 955 nm and 881nm are shown in Figures 1a and 1b, respectively.

These wavelengths were selected as they show a good comparison of the good and bad discriminability. Figure 1a shows a high amount of overlap between the two pdfs, while Figure 1b has a better separation. These pdfs are not ideal Gaussian distributions; however, no other standard distribution function would fit the data more precisely. The primary issue with the data was the wide range of standard deviations across the wavelengths. To solve this, discriminability was used to normalize the distance between means by a function of the variance.
Figure 1. Example histograms of fruit and leaf probability density functions.

The discriminability of two pdfs with the same standard distribution is defined by (Duda, 1968) as:

\[ d' = \frac{|\mu_2 - \mu_1|}{\sigma} \]  \hspace{1cm} (1)

Where

\[ d' = \text{discriminability} \]
\[ \sigma = \text{standard deviation} \]
\[ \mu_1, \mu_2 = \text{means of class 1 and 2}. \]

In general a higher discriminability is desired as it means a greater separation between classes. In this case, the standard deviations could be different between the two classes at the same wavelength, thus the standard formula could not be used. Figure 1b displays an example of two pdfs with different standard deviations from the sample data used. For this reason the following alteration to equation (1) should be made:

\[ d' = \frac{|\mu_1 - \mu_2|}{(\sigma_1 + \sigma_2)/2} \]  \hspace{1cm} (2)

Averaging the two classes’ standard deviations and replacing this for the standard deviation of equation (1) allows the discriminability to scale with magnitude changes in the different pdf’s standard deviation. Extending this method to a case with three pdfs, (citrus varieties) the distance between means was averaged:

\[ d' = \frac{\left( |\mu_1 - \mu_2| + |\mu_1 - \mu_3| + |\mu_2 - \mu_3| \right)/3}{(\sigma_1 + \sigma_2 + \sigma_3)/3} = \frac{|\mu_1 - \mu_2| + |\mu_1 - \mu_3| + |\mu_2 - \mu_3|}{\sigma_1 + \sigma_2 + \sigma_3} \]  \hspace{1cm} (3)

If we know \( \mu_1 \leq \mu_2 \leq \mu_3 \), then (3) simplifies to:

\[ d' = \frac{2|\mu_1 - \mu_3|}{\sigma_1 + \sigma_2 + \sigma_3} \]  \hspace{1cm} (4)
This function does not give a full understanding of discriminability between two pdfs, but an average of the discriminability among all three pdf combinations (pdf₁ to pdf₂, pdf₁ to pdf₃, and pdf₁ to pdf₃). This was acceptable in the simple three citrus variety case of this paper.

Discriminability is the simplest way to determine which wavelengths are optimal; however, this can not be the only consideration. Reflectance characteristics at one wavelength share common properties with those wavelengths near it. To maximize the quality of the feature extractions, the wavelength with the largest calculated \( d' \) was initially chosen as a feature. A second feature was required to be outside a threshold of 100 nm, allowing two distinct features to be chosen.

In the case of fruit vs. leaf, two methods (method 1 and method 2) were investigated. Method 1 included the use of the two highest \( d' \) calculations that met the threshold mentioned above. Meaning the two selected wavelengths were allowed anywhere on the spectra. Method 2 required one wavelength feature having a fruits’ reflectance greater than the leaves’ while the second wavelength feature having the fruits’ reflectance less than the leaves’.

**Principal Component Analysis**

Dimensionality reduction is a major issue with any recognition system using more than one variable. The most well known and commonly used dimension reduction technique is principal components analysis. This method searches for the direction in the data that contains the greatest separation between classes with regard to variance. By projecting the multi-dimensional data points onto the calculated direction(s), a smaller number of dimensions maybe used for classification. Fisher linear discriminant analysis (FLDA) was used to calculate the direction, \( \mathbf{w} \), for projection. Duda et al. (1988) defines \( \mathbf{w} \) as the “linear function yielding the maximum ratio of between-class scatter to within-class scatter”. An additional byproduct of this analysis is the reduction of “noisy” directions (Welling, 2006). In this paper, only a one-dimensional projection direction vector was calculated for reduction of the data from a two dimensional array space (i.e. two features). The result was a one-dimensional feature space with two qualitatively better classes of separation.

**Results and Discussion**

**Reflectance Trends of Citrus Fruit vs. Leaf**

Identification and separation of green citrus fruit from green citrus leaves is the corner stone of this paper. As such, a discussion about the basic characteristics of fruit and leaf reflectance pattern is presented. Figure 2 below is the average reflectance spectra of 270 citrus samples against the 270 leaf samples. From both reflectance spectra two traits should be observed. The large increase of reflectance between 690 and 720 nm is referred to as the red edge. This is a result of plants having higher absorption rates in the visible light region due to photosynthetic pigments. Absorption rates of the red edge region by chlorophyll pigments are lower resulting in higher reflectance (Ding, 2005). The second trait seen in both curves are the water absorption bands at 1450 and 1940 nm. These valleys in magnitude of reflectance are a result of water within the samples.

Categorizing differences between the fruit and leaves, a large magnitude of change in reflectance between 720 and 1120 nm is observed. A simple experiment and literature prove this to be a result of the thickness of the citrus fruit compared to the thinness of the leaves. This was verified by stacking multiple leaves and testing the reflectance as the leaf count increased. The results showed an increase in leaves lead to increased diffuse reflectance, most
significantly between 720nm and 1400nm. There were no significant increases in the reflectance outside this range. The results are supported by Fraser et al. (2002) which showed light penetration depths in apples was larger in the 700 to 900 nm range than 1400 to 1600 nm. They claimed this to be a result of the absorption profile of water.

The second important spectral difference between fruit and leaf was the “cross over” occurring at near 1150 nm. All fruit varieties showed lower reflectance then leaf at wavelengths above this fruit/leaf “cross over”. The reflectance differences between fruit and leaf past the “cross over” are due to different chemical components in them (Merzlyak et al., 1999).

![Figure 2. Green citrus fruit and leaf average spectral reflectance.](image)

**Reflectance Trends of Citrus Fruit Varieties**

All three of the tested citrus varieties held similar spectral characteristics, Figure 3 below.

![Figure 3. Citrus varieties average spectral reflectance.](image)
These patterns included high correlations throughout the UV-Vis to NIR range. The slight difference in the average visible light range (400 to 750 nm) was a result of the dates the fruits were maturing in the experiment and the color brightness differences of the mature fruits. A difference in the chlorophyll to carotiod conversion was the leading cause of this color brightness. The most important separation was seen in the reflectance magnitude differences between varieties. Hamlin had the highest, followed by the Valencia and finally the Tangelo showing the lowest reflectance over the whole spectral range.

The leaf varieties’ average reflectance showed a maximum of about 3 nm separation (data not shown). These separations are insignificant when compared with standard deviations on the order of 3.5 nm. For this reason, leaf variety classification was not analyzed.

**Spectral Growth Patterns of Maturing Citrus Fruit**

To verify that the chemical and biological changes occurring inside the maturing green citrus fruit would not significantly harm our identification methods, a brief survey of the spectral growth pattern was conducted. Previous research has been conducted on the maturing process of citrus. Most of this work focused on identifying wavelengths with growth changes to the reflectance (Merzlyak et al., 1999). Here we are trying to avoid such poor sampling ranges to prevent maturing to harm the accuracy of our system. The goal is to have wavelengths that will identify green citrus from green leaves; however, a system that works for mature fruit would be ideal. A solution that can identify both early season and end of season citrus fruit could be implemented in harvesting systems.

![Graph showing reflectance changes over the growing season (Hamlin).](image)

The greatest changes to the citrus fruits reflectance wavelengths are dramatically illustrated in Figure 4. Early season for Hamlin sets harvested on 12 July 2005 and 20 September 2005 are compared with later set on 2 November 2005 and the last set 12 December 2006. By mid December, 2005 the Hamlin samples were turned into an orange color. If one wants to design a machine vision system that identifies green or orange citrus from green leaves, the 500 to 750 nm range needs to be avoided due to large spectral changes.
Water band and Moisture Content

The sample sets moisture content and water band’s (1450 and 1940 nm) reflectance averages were compared on scatter plots, displayed in Figures 5a and 5b. The graphs do not show the expected negative slope, where a decrease in moisture content leads to an increase in reflectance. The lower moisture content of the Valencia sets are an example of the flat reflectance change against moisture content change. However, there are two important features to be observed in these graphs. First, the citrus varieties held the same reflectance magnitude order seen at all other wavelengths. The conclusion is that more than just a fruit’s moisture content will determine reflectance at the water bands. The second observation is the tight clustering of moisture content ratios, as samples showed a tendency to remain between 0.840 and 0.865 for all fruit varieties. This moisture content stayed consistent throughout the citrus growing season, as the last two Valencia samples sets (3 and 11 January 2006) have moisture contents below 0.830.

Training and Validation

Prior to using the pattern recognition techniques discussed in the paper, a performance evaluation was conducted using two-thirds of the samples as training data and one-third as validation data. The 180 fruit and 180 leaf training samples and were selected at random. Using only the 360 fruit and leaf training samples, the wavelengths for separation were selected. These feature wavelengths were used to create a scatter plot of fruit and leaves. Fisher linear discriminant analysis was used to find the best projection vector. The remaining 90 fruit and 90 leaf validation samples were identified after being projected onto the one-dimensional vector space. Only fruit vs. leaf was verified using these techniques, as the main purpose of this study was the correct identification of fruit vs. leaf. The two methods (method 1 and method 2) of fruit and leaf feature wavelength selection were used.

The discriminability results of the training data show the fact that separation between pdfs is greatest at 863 nm. The second best wavelength, that meets the 100 nm distance threshold, was found at 763 nm. The best wavelength for separation above 1150 nm was located at 1389 nm. Feature 1 for both methods has a very high rate of discriminability at 7.84. This implies the distance between means of the two pdfs is almost eight times the average standard deviation of
those same pdfs. The second features show lower separation but are still relatively high for classification purposes. These results display excellent separation properties.

Table 2. Discriminability results of the training data.

<table>
<thead>
<tr>
<th></th>
<th>feature 1 wavelength (nm)</th>
<th>feature 1 discriminability, $d'$</th>
<th>feature 2 wavelength (nm)</th>
<th>feature 2 discriminability, $d'$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fruit &amp; Leaves (method 1)</td>
<td>863</td>
<td>7.84</td>
<td>763</td>
<td>6.72</td>
</tr>
<tr>
<td>Fruit &amp; Leaves (method 2)</td>
<td>863</td>
<td>7.84</td>
<td>1389</td>
<td>4.87</td>
</tr>
</tbody>
</table>

Scatter plots of the validation data of methods 1 and 2 are shown in Figures 6a and 6b. The validation data was projected onto a line passing through the complete training data's centroid with a slope equal to the calculated projection vector. Figures 7a and 7b are histograms of the fruit and leaf validation data after being projected into one-dimensional space. The histograms unmistakably show the separation of two distinct pdfs. Using the centroid of the training data as the line of separation, all but one fruit was incorrectly identified using method 1, yielding $R^2 = 0.994$. Using method 2, all of the validation data was correctly identified, producing $R^2 = 1.000$.

Figure 6. Scatter plot and histogram showing Fisher linear discriminant of method 1.

Figure 7. Scatter plot and histogram showing Fisher linear discriminant of method 2.
**Discriminability**

The result of the discriminability search using all the samples is shown in Table 2. It was noticed that method 1 of the fruit to leaf separation showed the greatest discriminability; however, the scatter plot of method 2 had better separation, by visual inspection, in the two dimensional space (Figures 8 and 9). This visual inspection corresponds with the performance evaluation of methods 1 and 2 above. Poor discriminability in wavelengths with high mean separations, such as 1650 nm, is most likely an artifact of the multi-model nature inherent in the total fruit pdf. This is reasonable when the slight separation of fruit varieties are considered, Figure 1a serves as an example. The feature wavelengths selected for variety classification display a diverse spread about the spectra. The wide range suggests a great amount of inconsistency with citrus variety standard deviations. This could be a result of too few samples of each variety (100 Tangelo, 100 Hamlin, and 70 Valencia) or the slight changes in reflectance during the growing season.

Table 2. Best features (wavelengths) by discriminability using all 540 samples.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Feature 1 wavelength (nm)</th>
<th>Feature 1 discriminability, $d'$</th>
<th>Feature 2 wavelength (nm)</th>
<th>Feature 2 discriminability, $d'$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fruit &amp; Leaves (method 1)</td>
<td>881</td>
<td>7.44</td>
<td>781</td>
<td>6.64</td>
</tr>
<tr>
<td>Fruit &amp; Leaves (method 2)</td>
<td>881</td>
<td>7.44</td>
<td>1383</td>
<td>4.92</td>
</tr>
<tr>
<td>Tangelo &amp; Hamlin</td>
<td>1712</td>
<td>5.52</td>
<td>1392</td>
<td>5.44</td>
</tr>
<tr>
<td>Tangelo &amp; Valencia</td>
<td>1417</td>
<td>2.96</td>
<td>1882</td>
<td>2.83</td>
</tr>
<tr>
<td>Hamlin &amp; Valencia</td>
<td>1711</td>
<td>3.20</td>
<td>1813</td>
<td>2.89</td>
</tr>
<tr>
<td>Tangelo, Hamlin &amp; Valencia</td>
<td>1713</td>
<td>3.70</td>
<td>1381</td>
<td>3.61</td>
</tr>
</tbody>
</table>

Figures 8, 9, 10, 11, and 12, in the next section, show scatter plots created by the features of Table 1. Visual inspection shows the simplest expected separation of the two class types in Figure 7. The fruit variety plots, most significantly Figure 10 show the difficulty inherent in features that hold minor dependencies on each other. This has created class clusters of ‘cigar’ shapes with greatest variances in the same direction. This plot type can create difficulty with class separations by means of PCA, due to the dependences of one feature on the next.

**Fisher Linear Discriminant Results**

The lines on Figures 8, 9, 10, 11, and 12, are the projection lines calculated by Fishers linear discriminant analysis. While several of the calculated projection lines, $w$, are intuitively correct (Figures 9 and 10), others are not so easy to explain (Figure 8). However, the slight parallel nature of the two ‘cigar’ clusters is the cause of this strange looking projection line. The means of the projected data will not be a great distance apart; however, the “between-class scatter to within-class scatter” is the best. A look back at Figure 5a is an example of the same tendency for the projection line to be perpendicular to ‘cigar’ shaped clusters.

The definitions of the projection vectors for the two class systems shown on the next page mathematically in Table 3.
Table 3. Projection vector by Fisher linear discriminant analysis

<table>
<thead>
<tr>
<th></th>
<th>Feature 1 (x-axis)</th>
<th>Feature 2 (y-axis)</th>
<th>projection vector, ( \mathbf{w} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fruit &amp; Leaves (method 1)</td>
<td>881 nm</td>
<td>781 nm</td>
<td>( \mathbf{w} = (-0.1309, 0.0439) )</td>
</tr>
<tr>
<td>Fruit &amp; Leaves (method 2)</td>
<td>881 nm</td>
<td>1383 nm</td>
<td>( \mathbf{w} = (-0.0612, 0.0380) )</td>
</tr>
<tr>
<td>Tangelo &amp; Hamlin</td>
<td>1712 nm</td>
<td>1882 nm</td>
<td>( \mathbf{w} = (-0.5119, -0.1092) )</td>
</tr>
<tr>
<td>Tangelo &amp; Valencia</td>
<td>1417 nm</td>
<td>1813 nm</td>
<td>( \mathbf{w} = (-0.9040, 0.7114) )</td>
</tr>
<tr>
<td>Hamlin &amp; Valencia</td>
<td>1711 nm</td>
<td>1381 nm</td>
<td>( \mathbf{w} = (-0.1751, -0.0312) )</td>
</tr>
</tbody>
</table>

Figure 8. Fruit vs. leaf (method 1) with Fisher projection line.

Figure 9. Fruit vs. leaf (method 2) with Fisher projection line.

Figure 10. Tangelo & Hamlin with Fisher projection line.

Figure 11. Tangelo & Valencia with Fisher projection line.
A scatter plot including all fruit varieties is seen in Figure 13. The x-axis and y-axis are feature wavelengths of 1713 and 1381 nm respectively. These two feature space were taken from Table 3. A more complete scatter plot including all data samples of every class is in Figure 14. The x-axis is feature wavelength of 881 nm (highest discriminant for fruit vs. leaf) while the y-axis is the feature wavelength of 1713 (highest discriminant for fruit varieties).

Conclusion

A sample of green citrus varieties and citrus leaves were obtained and measured for diffuse reflectance over the UV-VIS and NIR range, 200 to 2500nm. From the average reflectance graphs, it appeared that certain spectral bands separated between fruit/leaf and citrus variety, but these were not necessarily the best wavelength bands to use as the features due to high standard deviations. Wavelength features for both fruit/leaf and citrus variety scatter plotting were chosen by discriminability calculations. These features were then used to calculate the ideal projection line by Fisher linear discriminant analysis. Using two-thirds of data as training and one-third data as validation showed an $R^2$ of 1.0 was possible using these pattern
recognition techniques. As expected, separating green leaves from green citrus fruit proved to be easier than distinguishing among different citrus varieties.

The best method of green citrus fruit to leaf separation would be the scatter plots of feature wavelengths 881 nm (x-axis) and 1383 nm (y-axis) projected onto the one dimensional feature space defined by the direction (-0.0612, 0.0380). A vision system, using band pass filters to segment feature wavelengths, will incur large amounts of noise from both the system filters and light inconsistencies in nature. To combat these issues more than two feature wavelengths maybe used and will be investigated in future work.

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References


