BLUEBERRY MATURITY STAGE DETECTION BASED ON SPECTRAL-SPATIAL DETECTION OF HYPERSPECTRAL IMAGE USING SELECTED BANDS

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ABSTRACT

Hyperspectral imaging can help blueberry growers by detecting berries of various maturity stages, so that they can deploy harvesting labors more efficiently. Spectral-spatial detection from hyperspectral images using selected bands is applied to the blueberry maturity stage detection. Nested clustering technique and morphological operations are used as two approaches to spatially process the hyperspectral images. Spatial analysis is integrated with spectral analysis using spectral angle mapper. The detection schemes achieve high accuracies, and provide blueberry detection maps with more homogeneous regions and less noise compared to the results using only spectral detection. The detection methods will be used to develop a maturity and yield mapping system for blueberry harvesting.

Index Terms— Blueberry, spectral-spatial detection, clustering, morphological operation

1. INTRODUCTION

Blueberry farms that supply fresh markets require that the berries be mainly handpicked. Blueberries mature gradually within a single fruit bunch. Therefore, the harvesting is very labor intensive. Early yield estimation is beneficial, since it helps farmers to arrange the harvesting labor efficiently based on the estimated yield variation in the field and decrease harvest cost. Much literature describes about applying pixel-scale hyperspectral image processing in agricultural applications, such as food safety inspection, food quality control, nutrition stress detection, crop characterization, meat inspection, etc. However, hyperspectral images have relatively high spatial resolution, which agricultural applications did not adopt. To achieve better results, spectral-spatial detection/classification becomes more and more popular since spatial information is also available in hyperspectral images. Benediktsson et al. (2003) proposed the morphological profile originated from the granulometry principle. The profile contained opening and closing profiles, which were reconstructed by a series of morphological operators. The spectral features and morphological profile performed well in terms of classification accuracies, and relatively fewer features were needed. Van der Meer et al. (2005) proposed a spatial-spectral contextual image analysis named the template matching algorithm. The algorithm was used to characterize hydrothermal alteration in epithermal gold deposits. Li et al. (2012) applied supervised spectral-spatial hyperspectral image segmentation. They integrated the spectral and spatial information in the Bayesian framework by subspace multinomial logistic regression and Markov random fields. Their approach showed accurate characterization for both simulated and real hyperspectral data sets. Tarabalka et al. (2009) proposed the spectral-spatial classification method based on two partitional clustering techniques: ISODATA and Gaussian mixture resolving algorithm. The proposed methods improved classification accuracies and provided decision maps with more homogeneous regions.

The objective of this study was to carry out spectral-spatial detection methods to improve the detection of blueberry maturity stages toward the development of an early yield mapping system. Two spectral-spatial detection schemes were applied, one was to combine the segmentation of nested clustering results with spectral detection results, and the other was to carry out morphological operations after spectral detection.

2. MATERIALS AND METHODS

Hyperspectral images were acquired in a blueberry research and demonstration farm at the University of Georgia cooperative extension in Alma, GA, United States (31.53438°, -82.51019°, WGS84) in July, 2012. The camera system contained a digital CCD camera (MV-D1312, Photonfocus AG, Lachen SZ, Switzerland), a camera body (a line scanning spectrometer V10E, Specim, Oulu, Finland), a lens (CNG 1.8/4.8-1302, Schneider Optics, North Hollywood, CA, USA), a camera body (a line scanning spectrometer V10E, Specim, Oulu, Finland), a lens (CNG 1.8/4.8-1302, Schneider Optics, North Hollywood, CA, USA), an image grabber (NI-PCIe 6430, National Instruments Inc. Austin, TX, USA), a DAQ card (NI-6036E, National Instruments Inc. Austin, TX, USA), an encoder (Omron-E6B2, OMRON cooperation, Kyoto, Japan), a tilting head (PT785S, ServoCity, Winfield, KS, USA), and a laptop (DELL Latitude E6500) with an image acquisition and control program written in LabVIEW (National Instruments Corporation, Austin, TX, USA). There were three fruit classes according to its maturity
stage: mature, intermediate and young fruit. The background included branch, soil, sky and man-made objects such as polyvinyl chloride pipes, ribbons, etc. The six selected bands from Yang et al. (2013) were utilized in this study instead of the original bands. The selected bands were: 543.1 – 572.6 nm, 627.4 – 658.8 nm, 663.6 – 695.2 nm, 725.4 – 757.4 nm, 773.5 – 805.6 nm and 838 – 870.5 nm. The methods in this study were for multispectral image processing with the specific wavebands in the future development of an infield blueberry yield estimation system.

As a preprocessing step, the dark background, man-made objects, soil and sky of the images could be removed by the spectral difference within the NIR range. These objects have relatively low value in the NIR range comparing to the well-illuminated vegetation. Therefore, the sixth band 838 – 870.5 nm was used as a gray image for performing Otsu’s method. Otsu’s method was used to automatically perform image threshold based on the histogram of the gray image.

Spectral-spatial Processing Based on Nested Clustering Techniques

This spectral-spatial processing based on partitional clustering techniques is adopted from Tarabalka et al. (2009) with several changes. There are two major steps in the clustering technique: similarity measure and grouping. In the first step, distance measures include Euclidean distance, Mahalanobis distance, cityblock and cosine. Euclidean distance was shown to be the most suitable for the blueberry detection task after trial and error. The second stage is to group the pixels with the greatest spectral similarity into the same clusters. This study explored a nested clustering algorithm using agglomerative clustering from linkage (Griffiths et al., 1978). The algorithm started with singleton clusters and successively linked clusters to generate a hierarchy of nested clusters. It arranged the clusters and sub-clusters in a tree-structured fashion. After clustering, every pixel had a unique label, which was assigned based on spectral information. However, the image plane was to be segmented with the same label within a fruit object. According to Tarabalka et al. (2009), connected-component-labeling algorithm was used to label the connected components from the same cluster.

Pixel scale spectral detection was parallel to the segmentation because it did not use any of the segmentation results. Since the blueberry hyperspectral images were taken from the outdoor condition containing a large amount of uneven illumination, SAM was applied for the detection of the pixels. Spectral angle mapper (SAM) is insensitive to illumination because it only uses the feature vector direction rather than magnitude. Due to the different spectral variations in each class, the spectral angle thresholds varied for different classes. The result of SAM is an image with each pixel labeled to its best matching class.

After these steps, two decision images were generated: one from segmentation based on nested clustering strategy and the other from pixel scale detection using SAM. The next step was to combine the two decision images by a majority vote. For every segmentation region, all the pixels were labeled to a most frequent class within that region. After this step, a new decision map was generated with the segments assigned according to the spectral detection result. A post-regularization step for removing noise in the decision map was carried out. The final decision map after the post-regularization would result in more homogeneous regions.

Spectral-spatial Processing Using Morphological Operations

The main procedure includes fruit detection in the spectral domain, morphological operation in the spatial domain, and post-processing. First, SAM was applied to the image. Spectral angles between the pixels and the library were calculated. Since SAM was calculated in the pixel scale with only the spectral information, there were many incorrectly detected pixels that scattered all over the image. In addition, pixels on the fruit edge might be missed because of strong shadow. To eliminate the scattered pixels and noises in the image, spatial information process such as removing salt-and-pepper noise and morphological opening and closing could be used. Morphological opening helped to remove small objects in the foreground, and closing helped to remove small objects from the background. It is logical to close the fruit area so that the fruit pixels in the shadow could be considered as correctly detected pixels if they are missed after SAM. Discs with size 1 to 4 were used in this study by trial-and-error in morphological operations depending on fruit maturity stages.

After morphological operations, some pixels were labeled as two or more classes. This happens where fruits of different maturity stages are connected with each other. Larger detected areas for connected fruits caused the pixels to overlap. Therefore, majority vote of the pixel’s eight neighbors were carried out as post-processing to eliminate the overlapping. The pixel was labeled to the most frequent class within the 8-neighborhoods window. A final decision map was generated after this step.

3. RESULTS AND DISCUSSIONS

Detection Result Based on Nested Clustering Techniques

Nested clustering of the images was performed using agglomerative clusters from complete linkage. The pixels were grouped with the nearest Euclidean distance with a cutoff value 1.15 by trial and error. The algorithm split the images into hundreds of clusters. The segmentation map after union-find contained more segments than the number of clusters from the previous step. The reason is that many clusters have pixels that are not connected. Therefore, a single cluster can be assigned into several neighboring segments. There are still many small segments with only one or two pixels. However, over-segmentation is not a concern because it is probable to classify the neighboring
pixels into more homogeneous areas in later steps (Tarabalka et al., 2009).

There were a large amount of pixels that were far away from their reasonable class assignments after SAM detection because this algorithm did not consider spatial correlation among pixels. Example results of SAM are shown in Figure 3 B) with different colors: purple representing mature fruit, red representing intermediate fruit and light green representing young fruit. The optimal thresholds for mature fruit, intermediate fruit and young fruit were 0.15, 0.2 and 0.05, respectively. The different thresholds were because of the different variations of the fruit classes. There are scattered pixels for all the three maturity stages, most of which are false positives. The true positive and false positive detection rates of the SAM detection step are shown in Table 1. The highest true positive rate is 75% for young fruit, and the lowest is 52.4% for intermediate fruit. The possible reason was that the intermediate fruit pixels were easier to be classified into the wrong classes because intermediate was the middle stage of the three fruit classes. The false positive rates for all three fruit classes are very high mainly because of the scattered pixels all over the image. Young fruit class obtained the highest false positive rate because the branches in the image had similar spectra with young fruits.

Table 1. True positive and false positive rates after each step of the spectral-spatial detection based on nested clustering technique.

<table>
<thead>
<tr>
<th>Class</th>
<th>SAM</th>
<th>SAM+Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TP(%)</td>
<td>FP(%)</td>
</tr>
<tr>
<td>Mature fruit</td>
<td>68.7</td>
<td>30.9</td>
</tr>
<tr>
<td>Intermediate fruit</td>
<td>52.4</td>
<td>43.8</td>
</tr>
<tr>
<td>Young fruit</td>
<td>75.0</td>
<td>175.0</td>
</tr>
</tbody>
</table>

After the spectral detection, the results were combined with the segmentation decision by majority voting. Post regularization was performed on the spectral-spatial based decision map using remove-salt-and-pepper with 8-neighborhood, because smaller objects such as young fruits would need to be saved. The example final results were shown in Figure 1 C) with the same color presentation as in Figure 1 B). This step helped to obtain higher intermediate detection accuracy because the segmentation step took majority vote. The regions that seem to be loose in Figure 1 B) become more homogeneous in Figure 1 C). True positive rate of mature fruit decreased, however, the false positive rates for all three fruit classes significantly decreased after the spectral-spatial operation, as shown in Table 1. This is mainly because the false detections and noise pixels were removed by the post regularization step.

Detection Result Using Morphological Operations

SAM detection was carried out with the same thresholds in the first spectral-spatial method because they were optimized with several training images under all possible illumination conditions. Since some dark background pixels that were not removed by the Otsu step had very similar spectra with mature fruit, the mature fruit map after SAM had more scattered pixels than other classes. Morphological close, open, and remove-salt-and-pepper were applied to the mature fruit map. Morphological close and remove-salt-and-pepper were applied to the intermediate fruit map. Young fruit was easier to miss because it has much smaller size than the mature fruit and intermediate fruit. Therefore, two morphological closes were applied. The example mature fruit map, intermediate fruit map and young fruit map before and after the morphological operations of the same hyperspectral image are shown in Figure 2. The white areas are the detected pixels and all the other areas are shown black. Table 6-2 shows the detection results after each step of using this spectral-spatial detection method. After removing background and SAM, the true positive and false positive rates are almost the same with the result of the spectral-spatial method based on nested clustering technique. However, the results after morphological

Figure 1. Overview of spectral-spatial detection results of a blueberry hyperspectral image based on nested clustering techniques. Purple color = mature fruit, red color = intermediate fruit, green color = young fruit. A) RGB representation of the hyperspectral image, B) SAM detection result, C) SAM combined with segmentation.
operations are much better than the first spectral-spatial detection method. True positive rate of mature fruit is more than 78%, and false positive rate is 13%. Performance of detecting intermediate fruit class increased over 30% from the first step, while false positive decreased to lower than 10%. The main contribution of the morphological operations was to increase the pixel amount on the edge of fruits, where there were heavy shadows.

All in all, spectral-spatial detection using morphological operations performed much better than based on nested clustering technique. This shows that the in-field condition of the blueberry plants was impacted seriously by the heavy shadow. Although SAM is not supposed to be impacted by shadow, when shadow is too strong, it is difficult to classify the pixels under shadow into the correct classes. A possible solution is to consider more classes, such as mature fruit in shadow, intermediate fruit in shadow, and young fruit in shadow. Another problem was caused by the biased opinion of the expert knowledge for labeling the pixels. The variation of decisions was a major concern among experts when labeling some specific pixels on the edge and in the shadow.

Table 2. True positive and false positive rates after each step the spectral-spatial detection using morphological operations.

<table>
<thead>
<tr>
<th>Class</th>
<th>SAM TP(%)</th>
<th>SAM FP(%)</th>
<th>SAM+Morphological TP(%)</th>
<th>SAM+Morphological FP(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mature fruit</td>
<td>67.7</td>
<td>25.4</td>
<td>78.3</td>
<td>13.2</td>
</tr>
<tr>
<td>Intermediate fruit</td>
<td>52.4</td>
<td>41.9</td>
<td>83.8</td>
<td>9.5</td>
</tr>
<tr>
<td>Young fruit</td>
<td>75.0</td>
<td>183.3</td>
<td>75.0</td>
<td>25.0</td>
</tr>
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</table>

4. CONCLUSION

Two spectral-spatial detection schemes were carried out, and they both improved the detection of blueberry maturity stages using only spectral information. The first method was to combine segmentation of nested clustering results with spectral detection results, and the second method was to combine the spectral detection results with morphological operations. Remove-salt-and-pepper was also used for noise removal caused by the spectral detection step. The spectral-spatial detection schemes were proved to perform much better than spectral detection. Spectral-spatial detection using morphological operations outperformed the detection based on nested clustering by achieving more than 75% true positive rates for all three fruit classes. The major problem that hinders the performance of the detection schemes are the strong shadows under field conditions and the biased expert opinions for pixels on the edge and in the shadow.

5. REFERENCES


