THE INTERNATIONAL SOCIETY OF PRECISION AGRICULTURE PRESENTS THE
13th INTERNATIONAL CONFERENCE ON
PRECISION AGRICULTURE
July 31-August 4, 2016 • St. Louis, Missouri USA

A precise fruit inspection system for Huanglongbing and other common citrus defects using GPU and deep learning technologies

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A paper from the Proceedings of the
13th International Conference on Precision Agriculture
July 31 – August 4, 2016
St. Louis, Missouri, USA

Abstract. *World climate change and extreme weather conditions can generate uncertainties in crop production by increasing plant diseases and having significant impacts on crop yield loss. To enable precision agriculture technology in Florida's citrus industry, a machine vision system was developed to identify common citrus production problems such as Huanglongbing (HLB), rust mite and wind scar. Objectives of this article were 1) to develop a simultaneous image acquisition system using multiple cameras on a customized conveyor that rotates citrus fruit in order to allow the imaging hardware to acquire the entire fruit surfaces, 2) to develop a machine vision algorithm with a deep learning technique utilizing a convolutional neural network to accurately inspect the visual characteristics of fruit surface and distinguish HLB-infected citrus from fruit with other common defects, and 3) to simulate real-time video processing utilizing a GPU for faster image processing. A real-time video processing with the state-of-the-art deep learning algorithm was developed and tested using uncompressed RGB video streams recorded from the developed hardware. Accuracy of various defect detection by deep convolutional neural network was 100, 89.7, 94.7, and 88.9 percent for healthy, HLB, rust mite and wind scar classes, respectively. The system can be used in citrus packing houses or developed on a portable conveyor that identifies severity of the diseases in particular locations and enables site-specific crop management in the field.*

Keywords. *Convolutional neural network, deep learning, machine vision, non-destructive inspection, post-harvest evaluation, precision agriculture, rust mite, video processing, wind scar.*

Introduction

Due to the rapid growth of world population to an estimated 9.2 billion by 2050, and 11 billion by 2100 (United Nations, Department of Economic and Social Affairs [DESA], 2015), it is expected that the current pace of crop yield increases will not fulfill the growing food demand (United Nations, Food and Agriculture Organization [FAO], 2009). Furthermore, world climate change and extreme weather conditions can generate uncertainties in crop production by increasing plant diseases that can substantially reduce crop yields (Pautasso et al., 2012).

Precision agriculture technologies have been considered key solutions to current agricultural challenges by adopting advanced sensing technologies, analyzing in-field spatial variability of various cropping factors, and allowing site-specific field management. For example, in Florida, a combination of unfavorable weather and introduction of a disease called Huanglongbing (HLB or citrus greening) has resulted in a 34.4% citrus production decrease (USDA, 2014; Choi et al., 2015). The HLB infected fruit are harvested along with healthy or less symptomatic fruit and these can impair the overall quality of harvested fruit. In order to manage citrus groves efficiently and maintain or increase citrus yields, growers need to first identify the HLB-infected trees in the grove and determine severity of infection. For instance, citrus growers in Florida adopt a tree eradication program to remove infected trees, or a foliage nutrient application program, applying more fertilizer to the infected trees to maintain tree health (Salifu et al., 2013).

For site-specific management of HLB in the field, the development of an advanced and automated HLB-detection system is essential. Machine vision systems to detect to citrus diseases have been developed. For HLB, a detection system was developed by Pourreza et al. (2014) by measuring accumulation of starch in citrus leaves using a narrow band imaging system with polarizing filters. Textural features, including local binary pattern, and gray-level co-occurrence features were extracted and used to classify the leaves as healthy or HLB-infected samples. They reported 100% accuracy for HLB detection in Valencia oranges without Zinc-deficiency, 73.3% accuracy for HLB-infected sample with Zinc-deficiency, which revealed similar symptoms as HLB when imaging with polarizing filters.

López-García et al. (2010) developed an application for fruit surface defect detection in oranges using multivariate image analysis (MIA) strategy on RGB images. In their method, the MIA strategy was combined with principal component analysis (PCA) to extract an eigenspace model from defect-free surface. Scores from test images using the eigenspace model were used to compute defective maps. In their algorithm, samples were classified into two categories: sound skin, and damaged skin, but types of defects were not specified. Therefore, various symptoms were included in damaged skin, such as stem-end injury, green mold, rind-oil spots, wind scar, and sooty mold. The method showed a 94.2% accuracy but also showed dependency on orientation of textures. In their study, they reported that the processing time for a single view of one fruit was between 600 to 900 ms which was not fast enough to be used in real-time processing.

In this article, a machine vision system combining a graphical processing unit (GPU) and a deep learning technique was developed. A GPU supports parallel computing and accelerates processing speed in image processing applications. Deep learning is often referred as algorithms with deep architectures especially using multiple layers of convolutional neural network (CNN or ConvNet) for signal and information processing, compared to the shallow one or two layers of traditional neural network. The deep learning techniques are called an end-to-end learning system due to its automatic feature extraction capability and has become more popular in recent years due to remarkable results in challenging image recognition applications (Deng and Yu, 2014; Chatfield et al., 2014). In this study, real-time GPU-accelerated video processing was simulated with uncompressed RGB video streams recorded using the developed hardware to identify fruit infection with HLB or injury from wind scar, or rust mites, which are common in Florida. The specific objectives of this study were: 1) to develop a simultaneous image acquisition system using multiple cameras on a customized conveyor that rotates citrus fruit in order to allow the imaging hardware to acquire the entire fruit surfaces, 2) to develop a machine vision algorithm with a deep learning technique utilizing a convolutional neural network to accurately inspect the visual characteristics of fruit surface and distinguish HLB-infected citrus from fruit with other common defects, and 3) to simulate real-time video processing utilizing a GPU for faster image processing. Using the developed system, combined with high performance and customized hardware and a state-of-the-art deep learning algorithm, it is anticipated that citrus growers and packers can better identify HLB-infected fruit for better management of the disease in the field and prevention of inferior quality fruit from being marketed.

Materials and Methods

Machine Vision Hardware

The image acquisition hardware (Figure 1) was developed on a 6-feet long conveyor system (three lane labeler, Durand-Wayland Inc., LaGrange, GA). The traveling speed of the conveyor was fixed at 60.3 cm/sec. The conveyor had rotating wheels, which fully rotated individual fruit every 21.4 cm traveling distance. In order to acquire the entire fruit surface without missing areas, four USB 3.0 cameras (DFK 23UV024, 640 by 480 pixels, The Imaging Source, LLC, Charlotte, NC) were installed 5.35 cm apart (21.4 cm/4 cameras) which corresponded to ¼ revolution of the fruit. A total of 10 halogen light bulbs (five on each side, Satco S3166, 100 Watt, 1650 Lumens, Satco lighting, Brentwood, NY) were installed to secure enough illumination for fast image acquisition of the moving objects. In order to avoid saturated areas on the fruit surface, white colored diffusing fabric (Nylon Silk Diffusion Fabric White, ALZO Digital, Bethel, CT) was attached in front of the light bulbs. Also, circular polarizing filters were installed under the camera lens to obtain evenly distributed illumination throughout each image (25 mm Circular Polarizing Filter, Tiffen, Hauppauge, NY).

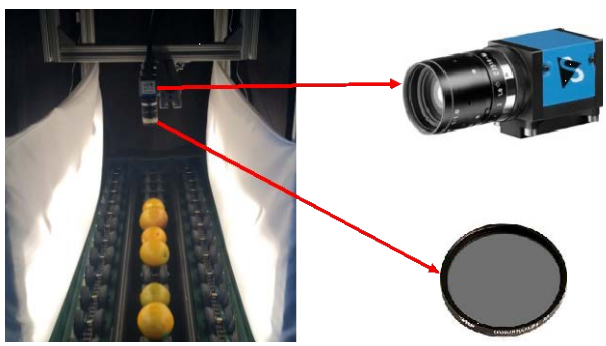

Fig 1. Composition of image acquisition system: six feet conveyor belt with rotating wheels, 10 halogen light bulbs, diffusing fabric, and four USB 3.0 cameras with circular polarizing filters.

Video Acquistion of Fruit

Customized video acquisition software was written in C++ using a software development kit (SDK) provided by the camera manufacturer (IC imaging control SDK, The Imaging Source, LLC, Charlotte, NC) and Visual Studio 2010 (Microsoft, Redmond, WA). Continuous image streams from the four cameras were recorded simultaneously in an uncompressed RGB video format and used for simulating real-time video processing. The resolution and frame rate of the videos were 640 by 480 pixels, and 30 frames/sec, respectively. Oranges were divided into training and validation sets, and fed manually by poured on the conveyor belt. The training and validation videos recorded separately, but in the same video acquisition conditions. Oranges were categorized in four classes: healthy, HLB, rust mite, and wind scar. In the training set, a total of 100 oranges for each class was recorded by four cameras. For the validation set, 18, 29, 19, and 18 oranges for healthy, HLB, rust mite, and wind scar were recorded, respectively.

Real-time Video Processing Algorithm

GPU-enabled techniques were used for faster video processing. The algorithm was developed and tested using Matlab parallel computing toolbox with GeForce GT 720M (1GB memory, 96 cores, NVIDIA, Santa Clara, CA). In the video processing, every frame was checked if a scene contained any part of an orange. In order to detect fruit, a threshold in red channel from RGB color space was determined from the training videos and applied to remove background pixels since the background of the videos was relatively dark compared to the oranges. After thresholding, the centroid of the orange object was calculated and its locations tracked in subsequent images (fig 2). When an orange firstly appeared in the scene, the centroid tracking system turned on. When the centroid passed the center line (yellow line in fig 2), the average diameter of the orange was calculated and square shaped image around the detected orange was immediately extracted with a size of 90-pixel bigger width and height than the estimated orange diameter (red box in fig 2). After the orange image extraction, the tracking system was turned off, and a new tracking process was started if a new fruit appeared in the lower part of the image.

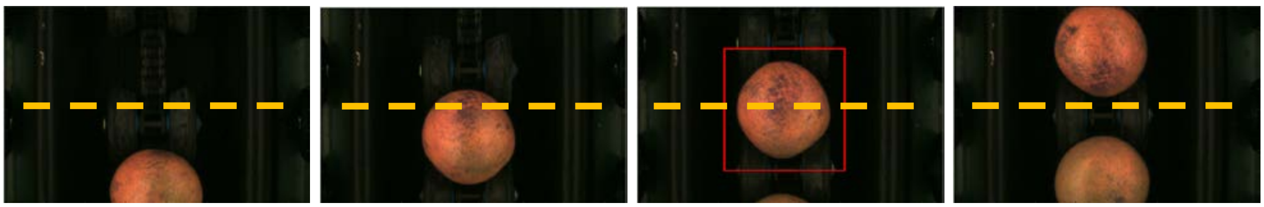

Fig 2. Illustration of orange tracking system in video processing. A tracking system was turned on when firstly orange appeared in the lower part of the image. When the centroid of the orange passed the center line of the image (yellow dotted line), the square shaped image around the orange object was extracted for further processing.

Classification of Orange Disease Using Deep Convolutional Neural Network

In deep learning techniques, feature extraction and ranking are not required, since the CNN consists of multiple layers that extract non-linear features automatically. For instance, the CNN starts extracting edge features using simple Gaussian-like filters in small regions in an image in the first layer, and combines those features to create bigger features to recognize objects in upper layers. In this study, the Fast Convolutional Neural Network (CNN-F, Chatfield et al., 2014) architecture was adopted for classification of diseases and trained using Matlab and MatConvNet deep learning library. The CNN-F model was developed to classify color images, the first layer filters included color blob detectors as well as edge detectors (fig. 3). The CNN-F model consisted of 8 layers, including 5 convolutional layers, and 3 fully connected layers with max-pooling and rectification linear unit (RELU) layers.

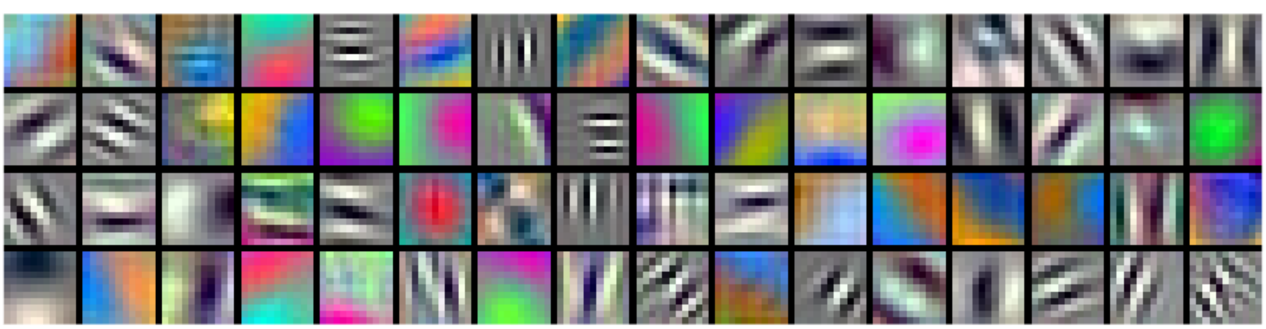

Fig 3. Feature extractor in the first layers of CNN-F model. This filters can detect edges and colors in small areas of an image.

Before training the CNN-F, a structure of the model was slightly modified: dimensions of the last fully connected layer and soft-max layer were modified from1000 to four, since the number of orange classes were four (healthy, HLB, rust mite, and wind scar) in this study. Also, the size of input image was defined to be 224 by 224 pixels, so the extracted images were rescaled (fig 4).

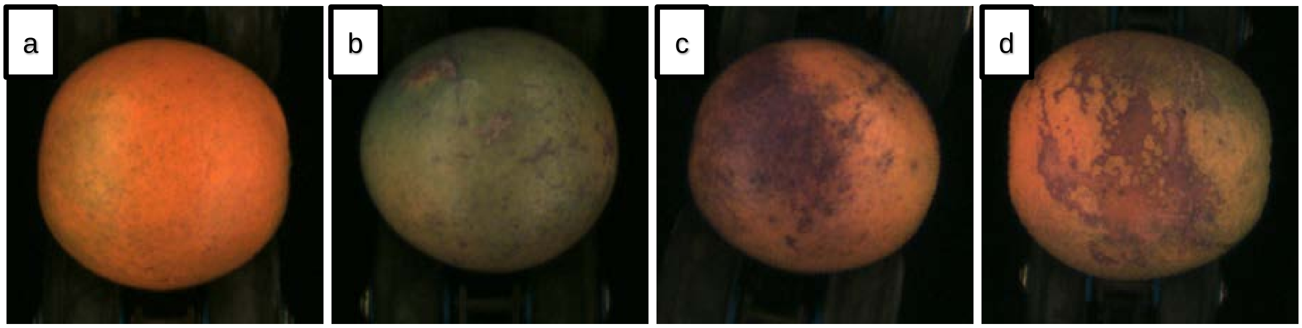

Fig 4. Examples of rescaled images in each class. (a) healthy orange, (b) HLB infected orange, (c) rust mite, and (d) wind scar.

Results and Discussion

Training process was terminated after 37 epoch (numbers of forward and backward passes through all training examples) since accuracy in the validation set was not improved with more than 37 epoch. Example images of the final classification results are shown in fig 5. After the classification, each image was labeled with the class that had the highest score from the CNN-F classifier.

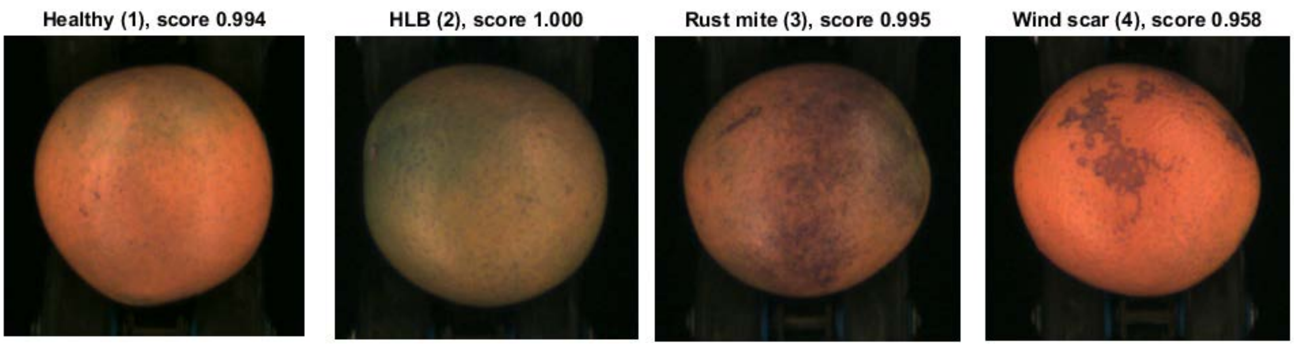

Fig 5. Examples of classification of each class with score from the classifier. (a) healthy orange, (b) HLB infected orange, (c) rust mite, and (d) wind scar.

Final class of each fruit was determined based on majority voting system of all 4 images, since four cameras recorded simultaneous videos of different surface of an orange. In the event of a tie, a defect type with a higher score was chosen to be the final class. The result from the majority voting is shown in table 1. In the table, healthy fruit showed 100 percent accuracy, since it showed very simple texture compared to other diseases. The rust mite showed higher accuracy than the HLB and the wind scar because the size, colors and textures of the defected areas were consistent throughout the samples. Even though the accuracy of the HLB detection was slightly lower than the healthy and rust mite, the detection rate of the HLB was still good due to the unique visual characteristic found in the HLB infected fruit such as a lopsided appearance, smaller sizes than healthy fruit, and greener colors due to the poor coloring. However, the wind scar showed the lower accuracy since the size of the defected areas tended to be smaller, with more random shape which created more complexity than the other disease classes.

Table 1. Confusion map of the final result using majority voting among four images. Each column is shown actual class of orange sample, and each row shows the estimated class by the majority voting. In this table, the numbers of oranges in each category are shown along with the percentage of accuracy in parenthesis.

	Healthy	HLB	Rust mite	Wind scar
Healthy	18 (100)	1 (3.4)	0 (0)	0 (0)
HLB	0 (0)	26 (89.7)	0 (0)	1 (5.6)
Rust mite	0 (0)	0 (0)	18 (94.7)	1 (5.6)
Wind scar	0 (0)	2 (6.9)	1 (5.3)	16 (88.9)

The total image processing time was 44.7 ms/image with GPU enabled image processing in Matlab which corresponded to 178.8 ms/orange (4 images per orange). Image acquisition time per one RGB image frame was about 1.5 ms. With this speed, approximately 5.4 oranges/second can be executed which was significantly faster compared to the study by López-García et al. (2010, 600 to 900 ms/image). A GPU with higher specifications such as bigger memory sizes and more number of cores, or simultaneous use of multiple GPUs can be implemented in order to increase the efficiency of the developed system. Also, the proposed algorithm can be developed using C/C++ to improve the processing speed of the system.

Conclusion

Fruit with diseases or blemishes are harvested along with healthy or less symptomatic fruit which can compromise the quality of harvested citrus. In this study, a machine vision system combined with a graphical processing unit (GPU) and a deep learning technique was developed and a real-time video processing was simulated to identify HLB-infected citrus fruit from those with wind scar or mites injury, which are common citrus defects in Florida. Accuracy of disease detection by deep convolutional neural network was 100, 89.7, 94.7, and 88.9 percent for healthy, HLB, rust mite and wind scar, respectively. The proposed system can be mounted on a portable conveyer system and used in citrus groves, or integrated into optical grading systems currently found in packinghouses. The portable conveyor system can identify diseased fruit in specific field locations to aid in site-specific crop management. In addition, the system can remove diseased fruit to maintain quality of the harvested fruit.

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