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Detection of Fruit Skin Defects Using Machine Vision System

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***Abstract*—External appearance is one of the most significant attributes for fruits when consumers decide to choose or reject them, thus packinghouses need to adopt appropriate systems that are capable of detecting the skin defects for fruits before packing them into batches and reaching the end consumers. For this purpose, this paper proposes a new method to detect fruit skin defects by using machine vision system, which is proved to be more accurate, more robust to color noise and has more modest calculation cost. The color histogram is extracted in the local image patch as image feature, while the Linear SVM (Support vector machine) is used for model learning. In a case of orange inspection, this system realizes a recall rate of 96.7% and a false detection rate of 1.7%.**

Keywords-fruit skin defect detection; machine vision system; support vector machine

I. INTRODUCTION

China is one of the largest fruit producing countries in the world. Since the quality of fresh food varies greatly, efficient technologies are needed for assessment of fruits quality in order to cope with the increasing market expansion and segmentation. Since consumers use fruits appearance to make first evaluation of the quality of fresh food, the presence of skin defects seems to be one of the most influential factors in the quality and price of fresh food. For this reason, packinghouses demand appropriate systems that are capable of detecting fruit skin defects. The importance of detecting defects and their connection with the quality can be seen by a number of research publications dealing with machine vision systems or image processing techniques for detecting the defects of diverse types of fresh fruits such as apples (Leemans & Destain, 2004; Li, Wang, & Gu, 2002), olives (Diaz et al., 2004), and other agro-food commodities including raw meat (Du and Sun 2009) and fish (Quevedo et al. 2008; Quevedo and Aguilera 2010).

This paper proposes a new method to detect fruit skin defects, which is more robust to color noise, more accurate, and has modest calculation cost.

II. BASICS OF MACHINE VISION SYSTEM

Following its origin in the 1960s, machine vision has experienced its growth with applications expanding in varied fields. The technology aims at duplicating the effect of human vision by electronically perceiving and understanding an image, with advantages including generation of precise descriptive data, being quick and objective, reducing tedious human involvement, and being consistent and efficient, etc. Other advantages include being non-destructive, undisturbing, robust, and allowing permanent record, convenient for further analysis later (Brosnan & Sun, 2004).

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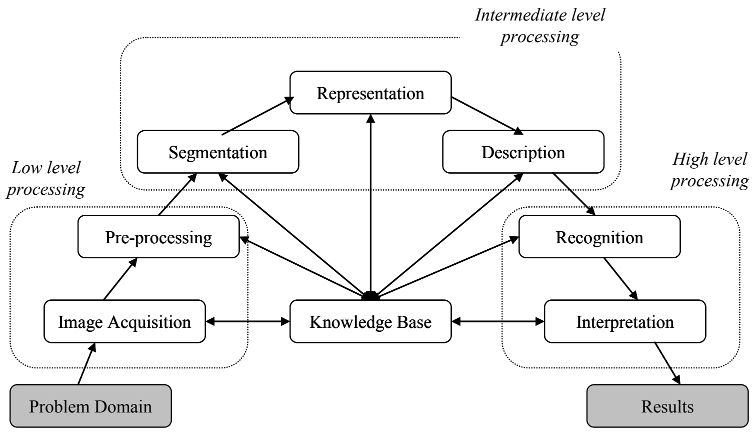

Figure 1. Image Processing Process (Sun, 2000)

Image processing and analysis are recognized as the core of machine vision. Image processing involves a series of steps, which can be broadly divided into three levels: low level processing, intermediate level processing and high level processing (Sun, 2000), as presented in Figure 1.

III. APPLICATIONS

In this paper, we apply the machine vision system to a fruit skin defects detection mechanism, and orange is taken as an example of this technology.

A. Device design

Oranges travel at a high speed under the camera in inspection conveyors in packinghouses, where the fruits are sorted and packed into batches, as demonstrated in Figure 2. In order to acquire images with sufficient quality, cameras freeze the movement by using high-speed electronic shutters that are combined with adequate illumination, and as the shutter speed increases, the intensity of lighting also increase to avoid underexposure. By this device, the fruit can be inspected by means of a machine learning method considering the difference between fruit's normal skin and defective skin.

During image acquisition, the conveyor to the field of view transports oranges samples individually. The convey speed is selected by trial-and-error to avoid distortion on image size and spatial resolution and to fit the predetermined exposure time. There are two cameras on the two sides above the conveyor, to capture the comprehensive image of the samples.

The device design is shown in Figure 2. A panoramic light source is used in order to get clear images and also avoid the shadow of fruits in the image.

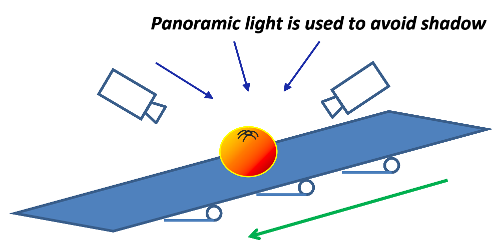

Figure 2. The Design of Image Capturing.

B. The image feature

Color is a good feature describing the difference between good and bad orange skins. In this paper, we adopt the RGB color space, which has 3 channels totally: Red, Green and Blue. Considering that the pixel colors vary in a very large range even in the normal orange skin, we propose to sample image patches in the image randomly, and then calculate the color histogram of the image patches. We set 16 bins for each channel in RGB color space, so the final feature dimension number is 16 * 16 *16 = 4096, which is a very large number, not only time-consuming for calculation but also noise-sensitive for classification.

In order to reduce the dimension number of the feature histogram, we use Fisher Linear Discriminant Analysis (Fisher-LDA) method, which projects the data onto the directions in which the data of different classes are separated optimally. The original dimension number is N=4096 and the reduced one is M=64, while the dimension reduction can be operated by:

$$z_i = W^T \bullet x_i \qquad (1)$$

where the W is a N×M matrix, and to get it, Fisher-LDA maximizes the following objective :

$$J(w) = w^T S_B w / w^T S_W w \qquad (2)$$

where S_B is the "Between classes scatter matrix" while S_W is the "within classes scatter matrix". As the solution of equation (2), the m basis vectors (column vectors) of W are the eigenvectors of ($S_W^{-1} S_B$) corresponding to the m largest eigen-values (Liu, 2005).

C. Classifier: Support Vector Machine

Now that we have a two-class task, we can select a very powerful machine learning method: Support Vector Machine (SVM), to acquire the color classifier (Wang et al., 2013). An SVM model is a representation of the examples as points in space, all of which are mapped so that the examples of the separate categories can be divided by a clear gap as wide as possible. New examples are then mapped into that same space and are classified to a certain category based on which side of the gap they fall on (Wikipedia, SVM).

D. Detection procedure

The learning procedure produces an SVM color classifier. In detection procedure, with a constant step, we slide a window in the images from left to right and from top to bottom. For each window image, we extract the color histogram with dimension reduced as the input to the color classifier and get the label (+1 or -1) of the current window. With the window sliding done, we merge the neighboring windows which have the same "-1" label to get a bad skin area in the image (as shown in Figure 3, with merged area marked as a red rectangle).

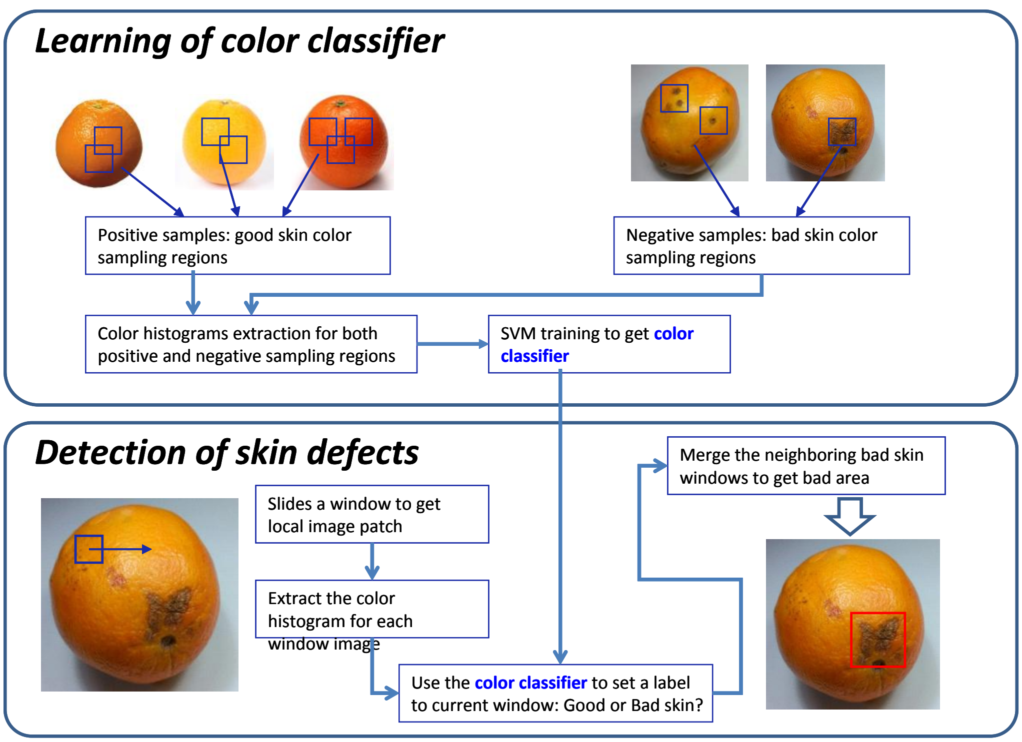

Figure 3. Flow-Chart of Apple Skin Defect

E. Algorithm evaluation

650 images are used for SVM model training, of which 300 images corresponds to bad skin case. We get another 50 bad skin images for evaluation, in which there are 61 defects. Our SVM color classifier can detect 59 defects, and the other 2 defects are missed because they are not obvious. The recall rate is: 59 / 61 = 96.7%. At the same time, there is one false defect detected, which means the false detection rate is: 1 / (59+1) = 1.7%.

IV. CONCLUSIONS

In this paper, we develop a new method to inspect fruit skin defects, which is more accurate, more robust to color noise, and has reduced calculation cost. Packinghouses can adopt this system to distinguish damaged fruits from good ones before packing them into batched, therefore the quality of the products can be guaranteed in this stage. The features of the algorithm in this paper are: (1) the color histogram extracted in the local image patch makes the algorithm more robust to color noise in the orange skin; (2)the Fisher-LDA used for the vector dimension reduction decreases the time cost and makes the algorithm more accurate; (3)the Linear SVM is used for machine learning, which provides higher accuracy and more modest calculation cost.

However, while detecting the external defects of fresh fruits, it would cause trouble if producers do not distinguish between different types of defects. It is essential that the presence of leaves, dirt or any other extraneous material be identified and not confused with true skin defects. In future research, a more complex system should be studied for sorting fruits according to the external defects they present, taking both speed and accuracy into account. Beyond the detection of defects, producers can separate rotten or seriously damaged fruits which must be rejected, from other fruits containing slight damages that only affects their appearance and can be marketed as second quality.

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