NIR/MIR Dual-Sensor Vision System for Apple Defect and Stem-end/Calyx On-Line Recognition

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Abstract
One of the difficult problems in automated machine vision apple sorting is the distinction between true defects and the stem-end/calyx. To solve this problem, a dual imaging approach using near infrared (NIR) and mid-infrared (MIR) was developed for combined sensing. Based on this method, the MIR is sensitive to the stem-end/calyx, whereas the NIR is sensitive to both stem-end/calyx and defects. Through image processing of combined images, the distinction is achieved. Experiments show the robustness of the method for on-line defect sorting of apples.

INTRODUCTION
Apple defect sorting is an essential post-harvest process to the quality packing in the fruit industry. Because the traditional visual inspection is labor intensive and prone to human error and variability, automated machine vision systems for automatic online defect inspection are needed to speed up the inspection process. Over the years, a persistent problem in apple defect sorting systems is how to distinguish the stem-end/calyx from true defects (Miller and Delwiche, 1991, Yang, 1993, Throop J.A., et al, 1995, Tao et al 1996, 1998, 1999, Wen and Tao, 1998a,b, 2000). In a single camera NIR image sensing approach, the stem-end/calyx of an apple is usually confused with true defects and is often mistakenly sorted. In order to solve this problem, a dual-camera NIR/MIR imaging method was developed. In this paper, a near-infrared (NIR) and mid-infrared (MIR) dual-camera imaging approach for on-line apple stem-end/calyx detection is presented. Based on this method, the MIR camera can identify only the stem-end/calyx parts of the fruit, while the NIR camera can identify both the stem-end/calyx parts and the true defects on the apple. A fast algorithm is presented to process the NIR and MIR images and then to achieve reliable defect detection for on-line apple sorting.

The objective of this research was to develop the NIR and MIR dual-wavelength method and image-processing algorithms for apple defect and stem-end/calyx on-line discrimination. The algorithms, including dual image registration, image normalization, inverse image transformation, and dual image combination, were established to eliminate the effect of apple stem-ends and calyxes from the true defect. These algorithms were expanded from the prior dual wavelength method (Wen and Tao, 1998a,b, 2000) along with the dual image registration and synthesis strategies for improved detectability and accuracy of online defect identification.

MATERIALS AND METHODS

System Configuration
The machine vision system for apple defect inspection consists of a dual-spectrum infrared sensing system and a computer controlled image-grabbing system, which is schematically shown in Fig. 1. The near-infrared sensor is a Hitachi KP-MI CCD camera attached with a Corion’s 700nm interference long-pass filter. The middle infrared sensor

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is an Indigo uncooled thermal camera with a spectrum range from 7.5 to 13.5 microns. The two infrared sensors are synchronized to obtain the image at the same pace. A lighting chamber was designed to provide uniform illumination for the infrared sensors. A rolling conveyor belt was constructed to carry fruit on six lanes. Both near infrared images (NIR image) and middle infrared images (MIR image) are captured, processed, and analyzed by a host computer equipped with an image processing board.

**NIR and MIR Dual-Image Processing**

**NIR Image Normalization**

In the near-infrared spectrum from 700 to 1000nm, a dark-colored fruit has a lower light reflectance than a bright-colored fruit. Different brightness levels cause detection errors, especially for bright-colored defective apples and dark-colored good apples. To avoid these errors, a normalization operation is applied to the original NIR image (ONI). The details of the method can be found in Wen and Tao (1998). The normalized NIR image (NNI) can be obtained from ONI by eliminating the effect of the brightness variations in ONI:

\[
NNI(x, y) = c_0 \frac{ONI(x, y)}{I_{max}(x, y)}
\]

where \(I_{max}(x, y) = \max(ONI(x, y))\) for all \(x, y\), and \(c_0\) is a constant equal to 255 in this application; \(I_{max}\) is generated by a recursive calculation represented by the following formulation:

\[
I_{max}(x, y)_k = \max\{I_{max}(x-x', y-y'), B(x', y')(x-x', y-y') \in D_1; (x, y) \in D_B \}
\]

\[
I_{max}(x, y)_0 = ONI(x, y); k = 1, 2, 3...
\]

where \(B\) is an all-one 3x3 mask matrix; \(D_1\) and \(D_B\) are domains of \(I_{max}\) and \(B\), respectively.

**Adaptive Spherical Transform for an NIR Image**

Apples are considered to have substantial spherical shapes. The curved apple surface causes inconsistent reflection of light. As a result, in an NIR image, the intensity distribution on apples is not uniform. It appears that the pixels around the boundary of an apple have a much lower intensity than the pixels at the center. On the other hand, the defective portion has a lower intensity. The intensity levels of the two kinds of pixels are comparative.

An effective method, known as *adaptive spherical transform*, is used to resolve the issue. The detailed description of this method can be found in Tao (1996). The idea of this method is to transform the edges of spherical objects to an intensity level near the intensity of the center, and thus, to generate a plane object image with uniform intensity without losing defect information on the objects. The basic principle can be represented as shown in Fig. 2. There are three images involved in the transformation process: a normalized near-infrared image or NNI, an inversed image (INI), and a synthesized image. The inversed image is a mirror image of NNI with the same shape and image size but without any defects. INI is generated by:

\[
INI(x, y) = c_0 \{1 - kR_N(s; (x, y))\}; (x, y) \subset NOI(x, y), s \subset S_d
\]

where \(s\) represents the size of apple, \(S_d\) is a subset of the variable range values of pixels from 0 to a maximum diameter pixel value of the objects. \(k\) is the position adjustment factor ranged from 0 to 1. \(R_N(s; (x, y))\) is the reflection correction function based on the brightness normalized images of spherical objects. The light reflectance on
the curved surface differs from point to point. The correction functions are, in fact, a group of transformation curves varied by the different sizes of the objects. The transformation curves of two different sized objects are shown in Fig. 3. The transformed near-infrared image \( TNI \) is obtained by combining \( NNI \) and \( INI \) together:

\[
TNI(x, y) = NNI(x, y) + INI(x, y), (x, y) \subset s_i
\]

where \( s_i \) represents the pixels within the range of interest in \( NNI \).

**MIR Image Stem-end/Calyx Extraction**

The mid-infrared sensor is sensitive to the temperature differences on the objects within its field of view. Low temperature objects present less intensity in the mid-infrared image than high temperature objects. Because of the concave shape and difference in emissivity on apple stem-ends and calyxes, the temperature in these areas are lower than the other parts of the apple surface after being refrigerated. As a result, stem-ends or calyxes appear differently from the other part of the apple by presenting a low intensity level in the MIR image. On the contrary, defects show the same intensity levels as the non-defective parts on the apples.

To extract the stem-ends and calyxes from the original MIR apple images, the background is removed and only the object of interest is considered. A threshold is used for the original MIR image \( OMI \) to obtain the blobbed mid-infrared image \( BMI \) as:

\[
BMI(x, y) = \begin{cases} 
OMI(x, y) & OMI(x, y) < T_1 \\
0 & \text{others}
\end{cases}
\]

where \( T_1 \) is the globe threshold value.

**Pixel Registration**

Two-dimensional image-coordinate transformation is needed to map objects in the original MIR image \( OMI \) to those in the original NIR image \( ONI \). The transformation is a global image processing since it is applied to the entire image. Let pixel \((x,y)\) in the \( OMI \) be corresponding to pixel \((u,v)\) in \( ONI \), then

\[
\begin{bmatrix} x \\ y \end{bmatrix} = \Phi \cdot \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} a & b & x_0 \\ c & d & y_0 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix}
\]

where, \( \Phi \) is the 3x2 transformation matrix. Elements a, b, c, d in \( \Phi \) are the factors related to the possible scaling and rotation of the two coordinate system. The elements \( x_0 \) and \( y_0 \) represent the displacements in x- and y- axes respectively. Matrix \( \Phi \) can be solved by picking at least six points in the middle infrared image plane and obtaining at least six sets of \( x,y,u,v \) values for Eq. (6).

The different focus lengths of the two sensors in the system cause the resolution differences between the original near-infrared and middle infrared images. The same objects appear different sizes in the middle infrared and the near-infrared images. In our system, the image size of an object in a middle infrared image is smaller than that in a near-infrared image. A bilinear interpolation method is used to rescale the middle infrared image. As shown in Fig. 4, the scaling factors in the x and y directions are \( d_x \) and \( d_y \), respectively. Bilinear interpolation takes the weighted average of a 2x2 pixel neighborhood as the assigned value to evaluate the interpolated pixel. Weights are determined by measuring the distance from the interpolated pixel to its nearest four surrounding pixels. The value of the interpolated pixel \( P \) in Fig. 4 can be evaluated as,
\[ p_{12} = d_1 p_1 + (1 - d_1) p_2 \\
\]

\[ p_{34} = d_3 p_3 + (1 - d_3) p_4 \\
\]

\[ p = d_y p_{12} + (1 - d_y) p_{34} = d_y d_1 p_1 + (1 - d_y) d_1 p_2 + d_y (1 - d_1) p_3 + (1 - d_y) (1 - d_1) p_4 \]  

(7)

where, \( p_1, p_2, p_3 \) and \( p_4 \) represent the pixel values from a 2x2 pixel neighborhood of the interpolated pixel \( P \). \( p \) is the value of \( P \). \( p_{12} \) and \( p_{34} \) are the intermediate pixels values used to derive the value of \( p \).

### Dual Image Synthesis and Blob Labeling

Both near and mid infrared images after pixel registration are labeled into blobs. The blobbed near infrared image (BNI) and blobbed mid-infrared image are compared to remove stem-ends and calyces from true defects in the result. The combination of BNI and BMI is used to decide which blob extracted in the BNI represents the stem-end or calyx. In the result of the final combined image (CI), the blobs that represent the stem-ends or calyces are eliminated, and only the blobs of true defects remain. CI is generated by a recursive calculation as shown below:

\[
CI_0(x, y) = 0, \quad \text{sign} = 0; \\
CI_k(x, y) = \begin{cases} 
0, & \text{sign} = 1 \quad \text{if } BNI(x, y) = k \text{ and } BMI(x, y) \neq 0 \\
\text{BNI}(x, y), & \text{others} 
\end{cases} \\
CI_{k+1}(x, y) = \begin{cases} 
0, & \text{sign} = 0 \quad \text{if } CI_k(x, y) = k \text{ and } \text{sign} = 1 \\
CI_k(x, y), & \text{others} 
\end{cases}
\]  

(8)

where, \( k = 1\ldots N \), represents the N number of blobs in BNI, \( \text{sign} \) is a flag variable.

### RESULTS AND DISCUSSION

Samples of both good and defective ‘Red delicious’ apples were used to verify the effectiveness of the on-line processing algorithms. A total of 155 apples (19 good apples and 136 defective apples) were selected for the test. Samples were refrigerated at about 4°C of CA storage temperature before being tested. The samples were randomly placed on the rolling conveyor.

A series of intermediate images and the final result image are presented in Fig. 5. Fig. 5(a) shows the original NIR image from the NIR sensor. The one located on the lower right is a non-bruised apple, which was used as the control. The other three apples have at least one defect each (the apple in the upper-left has two defects). Note that except for the apple on the upper left, the other three apples have stem-ends shown in the original near-infrared image. See the caption for the explanations.

The statistical results on the performance of the algorithms show the feasibility of the dual-sensing methodology, as shown in Fig. 6. The classification accuracy of 100% was obtained for good apples on the test. A 91.8% defective apple classification rate was achieved. The test results show that the method of image registration and dual-image combination reduced the possible misclassification rate of the stem-end and calyx to 6% and 8%, respectively. The recognition rates on both good apples and defective apples show the feasibility of the dual-sensor method.

The misclassification usually happened in two situations. One is when the stem-end or calyx appeared near the edge of the observed apple surface. The other is when small defects appeared very near the stem-ends or calyces. The first situation could be improved by adjusting the threshold values in the imaging algorithms, while the second situation could be improved by performing the morphological operations.
Another factor that might affect the inspection results is the temperature distribution on the surface of the test samples. The thermal camera is sensitive to temperature changes above 0.1°C. It is impossible to implement absolutely uniform temperature distribution during the processes of the online test. Some apple samples have un-uniform temperature distribution on the surface. As a result, in the MIR images, un-uniform changes of gray levels were observed. Fortunately, the un-uniform distribution of gray levels in the MIR image are not significant, and the proper selection of the global threshold of the MIR algorithm by user would minimize their influences.

CONCLUSION

The on-line dual-sensor NIR/MIR imaging method has been proposed and presented in this paper. The sensing effects of the dual spectrum were examined and over 92% classification accuracy was achieved for online apple defect recognition, while maintaining that all the good fruit had not been rejected. Using the 700-750 nm wavelength sensor, both defects and stem-ends on the apple were detected. The thermal sensor with 7.5-12.5 microns spectrum was demonstrated to be effective in identification of the stem-ends and calyxes on the apples. The methodology and algorithms can be considered for inspections of other fruits or similar objects.

Literature Cited

**Figures**

Fig. 1. Schematic representation of the system

Fig. 2. Schematic representation for the principle of spherical transformation method.

Fig. 3. Spherical transform curves for two different sized objects.
Fig. 4. Schematic representation of binary interpolation

Fig. 5. An example result of dual NIR/MIR sensing algorithm. (a) original NIR image, (b) background removed MIR image, (c) normalized NIR image, (d) resized MIR image, (e) adaptive transformed NIR image, (f) blob extracted MIR image, (g) blob extracted NIR image, (h) dual image combination result image. The boundary lines on the apples in (f), (g) and (h) were artificially added for visualization purpose.

Fig. 6. Test results of recognition rates for the online dual NIR/MIR imaging algorithm on test samples with bruises and insect holes.