Apple Internal Quality Classification Using X-ray and SVM

Liangliang YANG***, Fuzeng YANG*, Noboru NOGUCHI**

*College of Mechanical and Electronic Engineering, Northwest A&F University, Taicheng Road #3, Yangliang, Shaanxi, 712100, China; (e-mail: yfz0701@163.com).
**Graduate School of Agriculture, Hokkaido University, Kita-9, Nishi-9, Kita-ku, Sapporo, 060-8589, Japan; (e-mail: yang@bpe.agr.hokudai.ac.jp, noguchi@bpe.agr.hokudai.ac.jp)

Abstract: Classify the apple’s internal quality is important for apple’s quality. Mould core apple is not eatable and can reduce the juice quality if used for making juice. The core tissue’s color is brown and the density of mould core apple is lower than a normal apple. This paper describes the detection of apple’s one internal quality (mould core disease) on the physical basis -- density. X-ray technology can provide us internal image of an object that reflects the object’s density. This paper presents the method of processing the X-ray image and creating the feature vector for using support vector machine (SVM) method to classify the apple’s internal quality. The experiment results show that the classification method could detect the mould core apple at the accuracy of 91.03%, and detect un-mould core apple at the accuracy of around 95.95%.

Keywords: Apple, Internal quality, X-ray, Image processing, SVM.

1. INTRODUCTION

In order to detect fruit’s internal quality, some special sensors or equipments, such as Ultraviolet (UV), Near-Infrared Spectroscopy (NIR), Multi spectroscopy, Magnetic resonance imaging (MRI), have been utilized to change the invisible internal information to the visible information, such as spectrum information, image. After getting the information that can reflect fruits internal quality, the analyser or classifier is designed to analyse the information to detect the fruit internal quality. Ayaz and Bertoft (2001) has detected the sugar contents of oleaster fruits using Gas Chromatography (GC) and Mass Spectrometry (MS), and detected the Phenolic acids using a destructive method. In order to non-destructively detect the sugar of fruits, the NIR was also utilized (Rodriguez-Saona et al., 2001, Carlomagno et al., 2004), in the classification Rodriguez-Saona et al. using Partial least-squares regression and Carlomagno et al. (2004) using minimum distance classifier.

In the field of brown heart or water core quality fruits detection, Clark et al. (1998) has done a research on the detection of water core of ‘Fuji’ apple using MRI. (Zerbini et al., 2002) developed a non-destructive detection method of brown heart in pears using Time-resolved reflectance spectroscopy, but the classifier was not designed. Similarly, Clark et al. (2003) have utilized NIR to detect the apple’s brown heart in ‘Braeburn’ apple. Regression-based Ratio, MLR and PLS calibration models were applied for classifying the apple. Lammerytyn et al. (2003) have tried to use X-ray CT imaging and MRI to design a detection system of core breakdown disorder in ‘Conference’ pears, and found that MRI is better than X-ray in this detection method. Yang et al. (2009) have tried to use X-ray in the apple’s mould core detection. Moreover, recent years more researches about detection brown heart using NIR (McGlone et al., 2005, Fu et al., 2007), or hyper spectral (Ariana et al., 2006, Siciliano et al., 2008) have been done. However, only a few researches about designing intelligent classifier have been done. Recently, SVM was adopted in the sorting of Chinese jujube using ChIF, the best classification accuracy is 93.33% (Zheng et al. 2010). And SVM was used in the classification of foreign fibre in cotton lint, which produced an accuracy of 93.57% result (Li et al. 2010).

The objective of this paper is using Support Vector Machine (SVM), which is a novel binary classifier and can training a classifier with small training sets (Cortes and Vapnik, 1995, Gunn 1997), classify the apple internal quality.

This paper is organized as follows. Section 2.1 introduces the experiment equipments. Section 2.2 gives how to get the image database. Section 2.3 shows the image processing procedure. Section 2.4 shows the SVM based mould core detection. Section 3 gives the experiment result and section 4 gives the conclusion of this paper.

2. MATERIALS AND METHODS

2.1 Instruments of detection system

Fig. 1 illustrates mould core apple detection system equipments, which constructed by a low-level radiation X-ray radiator (1), a black and white CCD camera (4) and an image processing computer (5), which is used for capture and
process the apple X-ray image. In Fig. 1, (2) indicates the position of apple sample, (3) is the X-ray imaging monitor, from which the camera get the image. Table 1 gives the detail specifications of this detection system.

### 2.2 X-ray images database

The X-ray images were obtained when the apple was put at the up-down direction, as shown in Fig. 1. We got 100 apple’s image database. In addition, the image database was extended by the way that images are rotated five times at a random degree from 0 to 180 degree to simulate that the apple was not placed at the up-down pose when detecting. This step aimed to improve the flexibility of detecting apple without considering the apple’s pose in the detection system. In the procedure of performing SVM, 300 images are selected randomly as training sets; and the other 300 images are as testing sets.

![Fig. 1. The apple X-ray image detection system.](image)

Table 1. Specifications of the detection system

<table>
<thead>
<tr>
<th>Items</th>
<th>Model</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>X-ray radiator</td>
<td>BJI-1U</td>
<td>Field of Vision: 50mm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>View objects thickness: 200mm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>X-ray leakage: 1.29*10^{-5}C/Kg·H</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Power: AC 110-250V 50Hz/DC 12V</td>
</tr>
<tr>
<td>CCD camera</td>
<td>HTS ECB-1793</td>
<td>Image sensor: 1/3”SONY Super HAD CCD</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Effective Pixels: PAL,752(H)x582(V); NTSC,768(H)x494(V)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SNR: &gt;48dB</td>
</tr>
<tr>
<td></td>
<td></td>
<td>White Balance: Automatic</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Shutter: Open/close selectable</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Power: DC12V/120mA</td>
</tr>
<tr>
<td>Image Processing</td>
<td>Itellistation</td>
<td>CPU: Intel(R) Xeon(R) 2.33GHz</td>
</tr>
<tr>
<td>computer</td>
<td>Z Pro MT: 9228</td>
<td>Memory: 4GB</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hard disk: 320G</td>
</tr>
</tbody>
</table>

### 2.3 Mould core area feature extraction

The X-ray images were processed by the following procedure:

1) The wiener filter was utilized for de-noising image. It estimates the local mean and variance around each pixel,

\[
\mu = \frac{1}{NM} \sum_{n_1, n_2} a(n_1, n_2),
\]

\[
\sigma^2 = \frac{1}{NM} \sum_{n_1, n_2} a^2(n_1, n_2) - \mu^2,
\]

where \( \eta \) is the N-by-M local neighbourhood of each pixel in the image A. Wiener filter estimates the denoised image pixel value,

\[
b(n_1, n_2) = \mu + \frac{\sigma^2 - \nu^2}{\sigma^2} (a(n_1, n_2) - \mu),
\]

where \( \nu^2 \) is the noise variance.

In this paper, \( N, M \) is 5, and the noise variance is estimated by calculate the mean of \( \sigma^2 \) of the full image.

2) The histogram equation method is introduced for X-ray image enhancement to make the background and foreground easier to be segmented. The histogram equalization result is,

\[
c_k = T(b_k) = \sum_{j=1}^{k} p_r(b_j),
\]

\[
= \frac{\sum_{j=1}^{k} n_j}{n},
\]

for \( k=1,2,\cdots,L \), where \( c_k \) is the intensity value of the processed image corresponding to \( b_k \) of the input image.

3) Apple area was segmented out before extract mould core feature. A threshold decided by Otsu algorithm is utilized to transform the image from intensity image to binary image (Fig. 2.d). In this binary image, the X-ray machine border is the black area when the white area is the apple area. There are some black and white points and areas in the apple and X-ray machine border area respectively. In order to remove these points or/and areas, the erode algorithm of mathematical morphology was performed. The erosion of \( C \) by \( D \), denoted \( C \ominus D \), is defined as,

\[
C \ominus D = \{ z \mid (D)_{z} \cap \hat{C} \neq \emptyset \},
\]

where \( D \) is the structure elements and \( C \) is the image will be eroded, \( \hat{C} \) is the result of NOT \( C \).

In the experiment, \( D \) is a disk shape structure whose radius is eight pixels.

Fig. 2.f is the segmented image from Fig. 2.c by extract the area corresponding to the white area in Fig. 2.e.

4) After getting the enhanced apple’s area image (Fig. 2.f), the feature of mould core is need to be expressed in a logical way that can be easily used for constructing classification feature vectors. The Laplacian of Gaussian (LoG) edge detection algorithm was utilized to detect the edge of the mould core. The image was reduced dimension by extracting...
approximation coefficients using Lifting Wavelet Transform (Sweldens, 1995, Sweldens, 1996). The wavelet base function used in the experiment is the simple Haar wavelet. The approximation coefficients of wavelet transform is corresponding to the main characteristic of the image. Fig. 2.g shows the edge detection result, from which we can see that a white circle on the outside circle and some very short line and small points which are edge from the apple’s outside circle and the un-continuous noise points respectively. These line or points could influence the classification results in the following section. We have to de-noise the image Fig. 2.g to improve the classification accuracy. Image label method was utilized to label the connected lines in eight directions of Fig. 2.g, and generated a new image by removing the longest labelled line, which corresponding to the apple’s outside circle, and the shortest and second shortest lines, which corresponding to the noise short line or points in Fig. 2.g. The result is shown in Fig. 2.h. From this image, we can see that most of the noise points and the longest outside circle was removed.

![Image processing results of a mould core apple](image1)

Fig. 2. Image processing results of a mould core apple.

![Image processing results of an un-mould core apple](image2)

Fig. 3. Image processing results of an un-mould core apple.

pattern recognition problem. SVM can generate an optimal separating hyperplane that can separate the data and maximise the distance between it and the nearest data point of each class. In this paper, the apple need to be separated into two groups, mould core apple and un-mould core apple, which is a typical classification problem in the design of classifier or learning machine.

In the application of SVM classification, at first, the feature space should be constructed. Fig. 4 shows the first feature construct method:

![Feature construct method 1 of the apple X-ray image](image3)

Fig. 4. Feature construct method 1 of the apple X-ray image.
Firstly, in the apple core edge image (Fig. 2.h, Fig. 3.b) start from X-axis direction at a step of 45° generate a series of sector areas. Then count the pixels whose pixel value is one at each area, name the result as feature vector \( P \) that have eight dimensions. The centre pixel is attributed to \( p(1) \) for which was not considered at above. The second feature construct method is shown as Fig. 5, from the centre pixel counting the pixels that pixel value is one from the internal circle to the outside circle. And labelled as,

\[
q(i) = \sum_{n} p_i(n) ,
\]

where \( p_i(n) \) is the pixel value \( n \) is pixel coordinate at the nth circle. The centre pixel is also attributed to \( q(1) \) as the same reason of \( p(1) \).

\[
Q = [q(1), q(2), \cdots, q(n)]^T ,
\]

where \( p_i(n) \) is pixel value \( n \) is pixel coordinate at the nth circle. The centre pixel is also attributed to \( q(1) \) as the same reason of \( p(1) \).

Fig. 5. Feature construct method 2 of the apple X-ray image.

Consider that if an image is a little big, the dimension of the vector \( Q \) will be very high. It will improve the complexity in the applying of using SVM. Therefore, low dimension vector \( Q' \), which is a compressed vector from \( Q \) by sum a given number of continuous \( q \) together, is used in the SVM to construct feature space with \( P \). Finally, the feature space vector is,

\[
X = [P, Q']^T .
\]

In this paper, the dimension of \( Q' \) is 10.

In this way, the classification problem could be said as how separating the vector belonging to two separate classes \( Y \),

\[
D = \{ x(1), y(l), \cdots, x(l), y(l) \} , \quad y \in \{-1, 1\} .
\]

Where \( x(l) \) is the element of \( F \); \( l \) is the length of the training sets; \( y \) represents the quality of apple, -1 is mould core apple and 1 is un-mould core apple.

The aim at now is to design a classifier which inputs \( X \) when outputs \( Y \). Under the frame of SVM, more detail of this can be read in (Cortes and Vapnik, 1995, Gunn 1997), written in vector form the problem is,

\[
\min_{x} \frac{1}{2} \sigma^T H \sigma + c^T \sigma ,
\]

where

\[
H = Z K Z^T , c^T = (-1, \cdots, -1) ,
\]

with constraints

\[
\sigma^T Y = 0, \sigma_i \geq 0, i = 1, \cdots, l ,
\]

where

\[
Z = \begin{bmatrix}
    y_1 x_1 \\
    \vdots \\
    y_f x_f
\end{bmatrix} , \quad Y = \begin{bmatrix}
    y_1 \\
    \vdots \\
    y_f
\end{bmatrix} .
\]

\( Y \) is the vector that represents the quality of apple, the elements value of \( Y \) are -1 and 1, which represent mould core apple and un-mould core apple respectively.

The classifier is,

\[
f(x) = \text{sgn} \left( \sum_{i \in SV} \sigma_i K(x_i, x) \right) ,
\]

where \( SV \) are the support vectors from the training step.

In above \( X, Y \) can be gotten form training sets, if \( K \) is fixed than \( \sigma \) can be calculated. After getting \( \sigma \), the classify result \( Y \) of testing sets \( X \) can be calculated by using (10). Here \( K \) is the kernel function of SVM. In this paper liner, polynomial kernel functions were utilized for classification.

3. EXPERIMENT RESULTS AND DISCUSSION

We did the experiment using the feature vectors that are calculated using (7). We used linear and polynomial two kinds of kernel function in SVM. The results are shown in table 2.

\[
| \text{Detect result} | \begin{array}{c|c|c|c}
\hline
\text{Apple Class} & \text{Mould core} & \text{Un-mould core} & \text{All} \\
\hline
\text{Amount} & 78 & 222 & 300 \\
\hline
\text{Linear Kernel function of SVM} & \begin{array}{c}
\text{Right detected} \\
\text{Accuracy}
\end{array} & \begin{array}{c}
71 \\
91.03\%
\end{array} & \begin{array}{c}
213 \\
95.95\%
\end{array} & \begin{array}{c}
284 \\
94.67\%
\end{array} \\
\hline
\text{Polynomial Kernel function of SVM} & \begin{array}{c}
\text{Right detected} \\
\text{Accuracy}
\end{array} & \begin{array}{c}
57 \\
73.08\%
\end{array} & \begin{array}{c}
203 \\
91.4\%
\end{array} & \begin{array}{c}
260 \\
86.67\%
\end{array} \\
\hline
\end{array}
\]

How to decide the right or wrong detection: After using this paper’s method to detect the apple, we cut all the apples to see their inside quality and comparing the computer detected result with the real apple quality, then we got the results shown in table 2.
From table 2, we can see that the result is better when using linear kernel function. This can be explained that the classification problem of mould core apple attribute to a simple linear classification problem. The classifier might over fit with the training sets when training using polynomial kernel function, which lead to the lower fitness of the classifier. Therefore, the classification error is higher than using linear kernel function.

At the same time, for comparing we use a threshold method as a classifier to detect mould core apple. As shown in Fig. 6, the feature is created by calculate the sum of eight elements of vector \( P \) on every image, the x-axis is the sample index from 100-200, y-axis is the feature of the corresponding apple, from this figure we decided a threshold 50 to classify the mould core apple. If the feature value is higher than the threshold the apple will be graded to mould core apple, in contrast, lower than the threshold will be graded to un-mould core apple. In this sets, only very few apples are classified wrongly. However, when classify all the samples the correct detect of mould core apple is 62 out of 72 with the accuracy of accuracy 79.47%. The results of using threshold indicate that this method can be not easily promoted to more samples.

Moreover, the authors would like to give thanks to China Scholarship Council (2009630021) for the scholarship providing.

REFERENCES


SWELDENS, W. 1995. Lifting scheme: a new philosophy in biorthogonal wavelet constructions. San Diego, CA,
USA: Society of Photo-Optical Instrumentation Engineers, Bellingham, WA, USA.


