
http://researchrepository.murdoch.edu.au/18291/

Copyright © 1999 IEEE

Personal use of this material is permitted. However, permission to reprint/republish this material for advertising or promotional purposes or for creating new collective works for resale or redistribution to servers or lists, or to reuse any copyrighted component of this work in other works must be obtained from the IEEE.
Machine Grading and Blemish Detection in Apples

G. RENNICK, Y. ATTIKIOUZEL and A. ZAKNICH

Centre for Intelligent Information Processing Systems (CIIPS),
Department of Electrical and Electronic Engineering,
The University of Western Australia,
Nedlands, WA 6907, AUSTRALIA
yianni@ee.uwa.edu.au, tonko@ee.uwa.edu.au

Abstract: - Five classifiers including the K-means, Fuzzy c-means, K-nearest neighbour, Multi-Layer Perceptron Neural Network and Probabilistic Neural Network classifiers are compared for application to colour grade classification and detection of bruising of Granny Smith apples. A number of suitable discriminate features are determined heuristically for the categorisation of four classes including: high grade fruit, high grade fruit with bruising or blemishes, off-grade fruit, and off-grade fruit with bruising or blemishes. Robust features based on intensity statistics are extracted from enhanced monochrome images produced by special transformation from original RGB images. The best of the five classifiers using the optimal feature set, is shown to outperform human graders viewing the same images.


1 Introduction

Quality inspection of fruit up until the 1990s was performed manually. Manual inspection is labour intensive, slow and can be inconsistent due to fatigue and due to the relatively large staff turnover caused by boredom. This problem of inconsistency is compounded by the fact that there are inadequate standard definitions of quality. However, manual grading does have the benefit of having a complex quality knowledge base. Human graders are capable of making complex inferences related to season and geographical location. They can also easily adjust to environmental conditions such as lighting. Nevertheless, the speed and cost effectiveness of machine inspection systems, coupled with their ability to make consistent classifications within design boundaries, makes them attractive alternatives to human inspection.

Experimental work on machine grading of apples was done under laboratory conditions [1,2,3]. In 1985 an automatic bruise detection system was proposed by Taylor et al [4]. Systems were mostly based on grey scale or monochrome images. Colour based systems have more recently been used in grading [5], however, they have been mostly applied to assessing fruit quality rather than bruise detection. A variety of image analysis techniques have been used to solve apple grading problems. Information in the images can be extracted globally using algorithms such as the fast Fourier transform. Alternatively, localised methods such as edge detection can be used to isolate bruised tissue on the apple surface.

This paper describes a vision system composed of a colour image processing algorithm coupled with a classifier designed to perform both grading and blemish detection of Granny Smith apples. The algorithm first extracts the apple area from the image background and then a feature vector is created from the colour image of the apple surface before passing it to the classifier. The design uses localised techniques in the preprocessing stage combined with a global feature extraction algorithm. A number of classifiers including the K-means [6], Fuzzy c-means [7], K-nearest neighbour (KNN) [6], Multi-Layer Perceptron (MLP) neural network [8] and Probabilistic Neural Network (PNN) [9] classifiers are compared.

2 System Description

The test system included a rig to hold and rotate the apples in steps of 90 degrees around the stem-calyx
axis. The rig was mounted in a black felt covered enclosure with a 20 watt ring shape fluorescent light with the camera mounted in the centre of the ring looking down at the fruit 70 cms away. There were four colour images taken of each apple in 90 degree rotations to ensure the whole apple surface was captured. This simulated the concept of taking four simultaneous images of an apple from four directions as it sits on a conveyor surface.

The data set was constructed using 200 Granny Smith apples grown in Manjimup, Western Australia. Some of these apples were purposely mishandled and allowed to sit for four to five days to create enough samples of bruised fruit before taking images.

Figure 1 gives a block diagram of the image capturing through to final classification. For each apple image the background around the apple was first removed to isolate the apple in a preprocessing stage. This preprocessing stage was done using standard image processing techniques given that the apple and background colours were significantly and unambiguously different. Next, the RGB colour image was transformed to a special monochrome image crafted to enhance the bruised regions on the apple. From this a number of simple statistical features were taken from areas bounded by rings and sectors superimposed on the apple area. These features were then input to a single classifier used to determine one of four classes as follows:

1) High grade fruit
2) High grade fruit with bruising or blemishes
3) Off-grade fruit
4) Off-grade fruit with bruising or blemishes

3 Feature Selection

The image colours of the four classes are well separated and clustered in the RGB colour space. This indicates that colour is a good feature to use for the classifier. There is a decrease in intensity of all image colours in bruised areas but there is a more proportionate decrease in red and blue compared to green. This means that bruised areas are both colour and intensity sensitive. Consequently, it is possible to transform the colour image to a monochrome image without losing discriminating information.

After the image background was removed to reveal the apple the RGB apple image was transformed into a suitable monochrome image according to the colour ratio transformation equation (1).

$$m_{\text{mon}}(x,y) = \frac{\text{green}(x,y)}{\text{red}(x,y) + \text{blue}(x,y)} \quad (1)$$

This RGB colour to monochrome transformation has been specially selected for Granny Smith apples which have a predominant green colour. Equation (1) provides a good degree of invariance to illumination level. Next, a set of four uniformly spaced circles and two diameters at 90 degrees to each other and centred at the apple silhouette centroid, as shown in Figure 2, were overlayed onto the apple. The outer circle exactly encloses the apple silhouette. The contours of the test apple silhouettes were reasonable circular as they had a mean circularity value of 0.987 with a variance of 0.04. Circularity is defined by equation (2) such that it has a value of 1.0 for a perfect circle.

$$\text{circularity} = \frac{\text{perimeter}^2}{4\pi \text{ area}} \quad (2)$$

![Fig. 1 Apple Grading System Block Diagram](image)

![Fig. 2 Feature Extraction Grid](image)
From each of the sixteen apple surface areas, enclosed by the grid formed by the circles and diameters, two global features were extracted. The two features were simply the mean $m_{ntc}(x,y)$ and minimum $m_{ntc}(x,y)$ values in each area. The resulting feature pairs in each ring region were ordered by magnitude to achieve rotation invariance. The four sets of four ring pairs were then combined to form a 32 element feature vector. Many other combinations of ring and sector numbers were tested but the optimum combination was found to be four rings and four sectors as described above.

## 4 Test Results

An inexperienced grader looking at 80 apple images (20 for each of the four categories) achieved the classification results summarised in Table 1. A grader having eight years of experience looking at the same images achieved the classification results summarised in Table 2.

### Table 1  Inexperienced Human Grader

<table>
<thead>
<tr>
<th>Features</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 High Grade (HG)</td>
<td>9</td>
<td>1</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>2 HG + bruising/blemish</td>
<td>8</td>
<td>19</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>3 Off-Grade (OG)</td>
<td>3</td>
<td>8</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>4 OG + bruising/blemish</td>
<td>7</td>
<td>19</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Correct Grades = 90%, Correct Bruise = 76%,
Total Correct = 69%

### Table 2  Experienced Human Grader

<table>
<thead>
<tr>
<th>Features</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 High Grade (HG)</td>
<td>14</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 HG + bruising/blemish</td>
<td>4</td>
<td>19</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>3 Off-Grade (OG)</td>
<td>2</td>
<td>15</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>4 OG + bruising/blemish</td>
<td>1</td>
<td>1</td>
<td>15</td>
<td></td>
</tr>
</tbody>
</table>

Correct Grades = 89%, Correct Bruise = 87%,
Total Correct = 78%

Classification tests were performed for various sets of features and for the five classifiers. The best classifier, the PNN classifier, used with the optimum feature set described in section 3.0 above produced the results summarised in Table 3.

### Table 3  PNN Machine Grader

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Colour Grade</th>
<th>Bruise Detection</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-means, 4 means</td>
<td>100%</td>
<td>77%</td>
</tr>
<tr>
<td>Fuzzy c-means, fuzz. = 0.5</td>
<td>100%</td>
<td>77%</td>
</tr>
<tr>
<td>KNN, 10 nearest neighb.</td>
<td>100%</td>
<td>83%</td>
</tr>
<tr>
<td>MLP, 8-7-4</td>
<td>99.5%</td>
<td>87%</td>
</tr>
<tr>
<td>PNN, $\sigma = 0.05$</td>
<td>100%</td>
<td>90%</td>
</tr>
</tbody>
</table>

Correct Grades = 100%, Correct Bruise = 89%,
Total Correct = 89%

### Table 4  Classifier Comparisons

Features based on a two dimensional Fourier transformation of a monochrome image as described in [10] were also tested for comparison. These features produced very poor results, giving only a 63% accuracy for colour grading and 63% for bruise classification. Using the optimum features, the best classification results achieved with each of the five classifiers for colour grading and bruise/blemish detection performed separately are summarised in Table 4. The parameters for each classifier were:

1. K-means using 4 means
2. Fuzzy c-means with fuzziness = 0.5
3. KNN using 10 nearest neighbours
4. MLP with 8, 7, 4 nodes in layers 1, 2, 3
5. PNN with $\sigma = 0.05$

## 5 Conclusions

The optimal system used in this study achieved a 10% improvement over an expert human grader for colour grade classification and 5% improvement for bruise/blemish detection. These are very encouraging results however, they are only based to the performance of one human grader with eight years of experience and only looking at the apple images. Other factors to consider are that the system has only been optimised for green Granny Smith apples and a relatively small data set of 200 apples has been used. Nevertheless, the optimal features are computationally simple to compute and therefore would be suitable to use as a basis for a
real-time system implementation using relatively inexpensive image capturing and processing equipment. For real-time implementation there would be an extra need for image blur compensation if the images are taken of moving fruit.

As demonstrated in this application, the PNN classifier often performs better than other types of classifiers, especially when there are only a small number of training samples available. However, when there are large numbers of training samples the computational efficiency of the PNN is severely reduced. Fortunately, for many applications, it is possible to reduce the PNN size quite dramatically without sacrificing any performance [11].

References:


