Navel Orange Blemish Identification for Quality Grading System

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Abstract. A novel automated blemish detection system for ripe and unripe oranges is proposed in this paper. The algorithm is unique in that it does not rely on the global variations between pixels depicting the colours of an orange. By utilizing a priori knowledge of the properties of rounded convex objects, we introduce a set of colour classes that effectively 'peels-off' the orange skin in order of increasing intensity layers. These layers are then examined independently, allowing us to scrutinize the skin more accurately for any blemishes present locally at the layer's intensity variation range. The efficacy of the algorithm is demonstrated using 170 images captured with a commercial fruit sorting machine as the benchmarking test set. Our results show that the system correctly classified 96% of good oranges and 97% of blemished oranges. The proposed system does not require any training.

Keywords: Orange Blemish Identification, Fruit Grading, Image Processing.

1 Introduction

Orange is an important horticultural produce around the world amounting to millions of tons per annum and is projected to grow by as much as 64 million by 2010 [1]. Their value however is greatly affected by fruit diseases and damages due to transport and handling. Traditional inspection of fruits by human experts is considered to be very time-consuming and subjective [2, 3]. On the other hand, there are not many robust and accurate grading systems evaluating fruit defects comprehensively. Therefore, quick, accurate, consistent and more elaborate automated defect inspection systems are of paramount importance to the growing market.

Several machine vision systems were suggested for sorting oranges [4-10]. However, most of the existing algorithms are not able to explicitly mark the pixels corresponding to the blemishes, but could only provide a final answer (i.e. good or bad orange). Moreover, most of these systems are not easily customizable to meet the evolving requirements set by the market because they rely on extensive training with thousands of examples [11]. There are some commercially available fruit sorting

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machines that can be modified quickly to meet changing requirements [12] but those generally requires a supervisor monitoring the machine.

Upon examining the aforementioned algorithms, a novel system for grading oranges into different quality bands, according to their surface characteristics, is devised and presented in this paper. Both ripe and unripe oranges comprise the benchmarking dataset. It was observed that unripe oranges are more difficult to analyze for defect detection due to the colour transition areas. In addition, global variation between pixels from the same orange is deemed not to be sufficient to classify defects correctly. Most of the existing algorithms disregard this significant issue. However, the novel algorithm takes full advantage of the global intensity variation for blemish detection purposes. We provide evidence of the merits of using this global intensity variation in our experiments.

2 The Algorithms

There is a limit to most existing orange blemish detection algorithms. Any two pixels in an orange image having about the same colour will almost always be classified as belonging to the same category (either a blemish or not). This however presents a big problem, as depicted in Figure 1, it is possible to have several pixels depicting more or less the same colour channel values, but they should belong to different categories. In the figure, pixel A reflects R=134, G=86, B=24 and should be classified as a normal skin. On the other hand, Pixel B is described to have colour channel values very close to Pixel A, but should be classified as belonging to a blemish. Note that this problem stems from the illumination of the fruit and does not change when using a different colour space such as HSI. One potential solution is to use an edge detector to find the discontinuities in colour and detect blemishes based on the difference between neighboring pixels. This approach however tend to detect 'false blemishes' on unripe (green) oranges where a sharp discontinuity may occur between green and orange spots on the fruit. In light of this problem, this research utilizes a priori knowledge of the local intensity variation observed on rounded convex objects to classify the aforementioned pixels correctly.

For any rounded convex object, the intensity gradually increases from the edges to the center in a two-dimensional image as showed in Fig. 1. The proposed algorithm

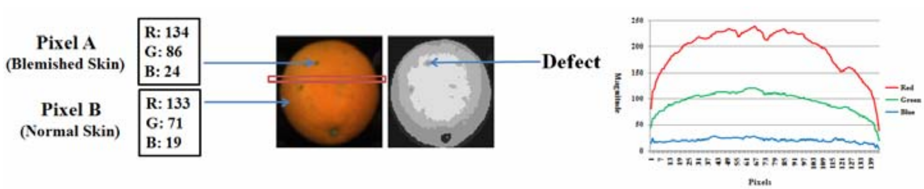

Fig. 1. Blemish detection based on a specified local image variation range. Original image of an orange (left) and partitioning (right) defects are visible as 'holes' in the top partition. With pixel values of blemished and good regions and RGB values variations along a line crossing the fruit (far right).

partitions the given image into eight orange colour classes. This in turn would generate different layers/classes using average intensities for a given image (illustrated in Fig. 1). These layers are then refined further to eliminate extraneous layers. Finally, the blemishes are detected by employing a convex hull approach on the top-most layer. Any discontinuities between successive layers/classes will be detected as blemishes.

2.1 System Architecture

A block schematic of a typical fruit grading system is shown in Fig. 2. This paper expands the blemish detection part of the system. Stem detection, blemish quantification and grading are left for other research.

Fig. 2. Block schematic of the novel orange grading algorithm

The novel blemish detection algorithm simulates how humans make observations of the local intensity variations phenomenon. Humans do not judge the colours of the orange skin by using absolute pixel values per se (i.e. RGB) but instead consider the neighboring orange surface characteristic. The stem and navel of the orange will be detected as blemishes and a second pass looking at the identified blemishes will be needed to exclude these parts from the total defect score for the fruit.

Quantifying blemishes is a necessary precursor to grading the oranges. Here, the percentage of blemishes over the whole orange is computed as the main grading feature. In addition, the different quality bands can be adjusted easily according to the requirement set by the market.

2.2 Blemish Detection

The heart of the algorithm deals with partitioning with a set of thresholds. On a clean orange without blemishes, these thresholds will generate a set of 'concentric rings', with each ring being of a darker colour as we move away from the centre of the orange. Blemishes, however, will be seen as pixels belonging to a dark ring inside a brighter ring as shown in the right side image of Fig. 1. Section 2.2.1 explains an algorithm for generating these thresholds, while Section 2.2.2 explains how the 'rings' are used for blemish detection.

2.2.1 Orange Partitioning

2.2.1.1 Orange Colour Classes. Otsu's thresholding method [13] is used here independently for each of the colour channels to automatically find a threshold that will isolate the orange fruit from the background. Otsu's thresholding method assumes that the image to be thresholded contains two classes of pixels (i.e. foreground=1 and background=0). Using the three thresholds, each pixel can be classified into one of 8 colour classes using the following formula.

$$ClassNo_{(i,j)} = 4Red_{(i,j)} + 2Green_{(i,j)} + Blue_{(i,j)} + 1 \quad \text{for } 1 \le i \le Rows, 1 \le j \le Columns \tag{1}$$

Each of these orange colour classes produces different results in colour and brightness. For instance, the combination of red and green colour is greater than the combination of blue and green colour. For other fruits, the order of the orange colour classes has to be changed accordingly to match the incremental sequence. Due to the observed nature of the orange skin colours, the different orange colour class described above is ordered incrementally according to their average magnitudes.

After classifying all the pixels comprising the entire orange image according to the 8 orange colour classes, the next objective is to merge the classes according to a similarity measure based on the following: orange class mean per channel, standard deviation per channel, squared mean difference (SMD) between colour classes per channel and quadratic mean of the combined SMD for all RGB channels, quadratic mean of the combined standard deviation for all RGB channels. The merging of the colour classes will eventually lead to the extraction of the topmost layer that will serve as the main focus of inspection.

2.2.1.2 Class Statistics. The mean and standard deviation (SD) of each channel inside each class are
calculated.

$$\mu = \frac{\sum_{i=1}^{n} P_i}{n} \tag{2}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(P_i - \mu)^2}{n}} \tag{3}$$

Where P is the pixel value from one colour channel and *n* is the number of pixels.

Squared mean difference SMD is defined as follows:

$$SMD = (\mu_A - \mu_B)^2 \tag{4}$$

where A *and B represents any one of the 8 orange colour classes, and* A ≠ B.

SMD is a measure of the squared difference between two class means. A small-valued SMD indicates that the two classes are similar to each other.

The class statistics are all tripled for all 3 channels. These are all converted into a single number by taking the quadratic mean (QM) of the value among all 3 channels.

$$QM_V = \sqrt{\frac{\Sigma V^2}{3}} \tag{5}$$

2.2.1.3 Closest Neighbor Class. Finding the closest neighbor class requires computing for the minimum between the QM-SMD values of one class against the rest of the other classes, and its own QM-SD. If QM-SD < QM-SMD, then the class is its own closest neighbor.

2.2.1.4 Class Merging. After determining the closest neighbor for each class, the classes are merged together with their closest neighbor and their corresponding class mean are recalculated. There is a possibility however that some classes will not be merged with other classes, and some classes might also disappear when their class mean is zero. At the end of this stage we will have up to 8 classes. For each class an upper threshold is calculated as the average between this class mean and the next class mean.

$$T_i = \frac{(M_{i+1} + M_i)}{2} \tag{6}$$

And each pixel is then reclassified using the set of new thresholds.

2.2.2 Blemish Pixels Identification

2.2.2.1 Top Layer Slicing. The top layer slicing phase of the algorithm is important as this defines the region of inspection. After class merging and pixel reclassification, the newly-derived orange colour classes organize itself automatically in an incrementing intensity fashion. An example of which is shown in Fig. 3 - a grey scale image generated after pixel reclassification is depicted in the figure.

Only the topmost layer is analyzed and the reasons are explained as follow:

1. The lighting condition is better on the top layer of the orange.
2. Noise is filtered out, such as background pixels.
3. The orange is rotated on the conveying system, so unprocessed parts can be analyzed in the next image as there are 25 images taken for each orange fruit.
4. Unnecessary computations are reduced for unstable data.

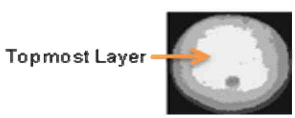

Fig. 3. Topmost layer

2.2.2.2 Blemish Segmentation. The blemishes are identified by employing a convex hull approach [14] on the topmost layer. The convex hull of the top layer is calculated and then the original layer is subtracted from the convex hull. The resulting pixels are identified as blemishes as seen in Fig. 4. To avoid false positives around the edge of the top layer, a filtering step is added before convex hull calculation.

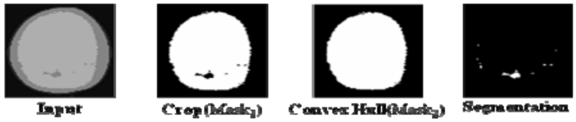

Fig. 4. Blemish segmentation on the topmost layer

3 Results

Fig. 5 shows some sample blemishes detected using this algorithm for ripe and unripe oranges. A simple grading scheme was implemented grading each image by the percentage of pixels that are classified as blemished. If at least 1% of the pixels were blemished, then the image is considered to reflect a blemished fruit. Using this classification requirement, 100 images of good oranges and 70 blemished ones were tested and the results are in table 2 which indicates high classification accuracy.

Table 1. Summary of classification results using the novel algorithm

Fruit Image Types	No. of Images	No. of Correctly Classified Images	No. of Wrongly Classified Images	% of Correct Classification
Good Orange	100	96	4	96%
Blemished Orange	70	68	2	97%

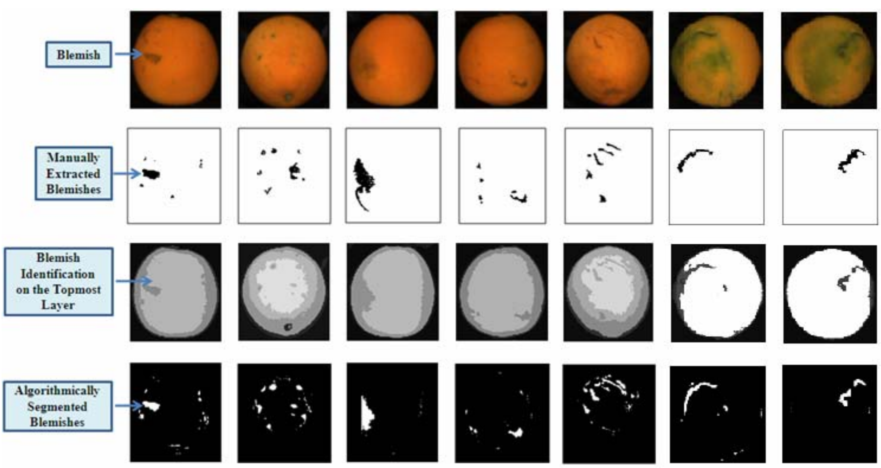

Fig. 5. Blemish identification for ripe and unripe oranges. The first row contains five ripe and two unripe blemished oranges. The second row contains manually extracted blemishes by vision experts. The third row contains processed images generated by the novel algorithm. The fourth row contains the segmented blemishes.

4 Conclusion and Future Work

An automated intelligent blemish detection system for ripe and unripe oranges is proposed in this research. The main impetus that led to the development of the novel algorithm is the observation that global variations between pixels depicting the same orange fruit are not sufficient for classifying defects. Most existing fruit grading algorithms are not addressing this significant issue and one solution to the problem is presented here. Usual approaches are also plagued with rigorous and lengthy training requirements. On the contrary, the proposed algorithm does not rely on any computationally expensive training. Lastly, some existing algorithms are able to grade fruits into different quality bands (i.e. histogram-based analysis, etc.). However, such algorithms cannot locate explicitly where the blemishes are on the fruit. On the other hand, the algorithm presented here is able to locate the blemish and measure its area with high level of accuracy. This enables a second stage classifier (not discussed in this paper) to process the potential blemishes and classify them in order to eliminate normal feature (stem and calyx ends) and to assign each blemish with a severity index for further grading of the fruit. In the current implementation all defect types contribute roughly equally to the final grading decision. However it would be fairly easy to add a severity index to types of defects. The grade is computed as a measure of the size of these surface defects over the whole orange.

For future works, we envisage that the novel algorithm may be suitable for grading some other fruits that have the rounded convex surface property. However, the orange colour class proposed here will have to be modified slightly to be adapted for grading other fruits. Moreover, an extension of the proposed research would be to improve the grade calculation by incorporating some measure of severity for the blemishes, based on their relative intensities. In effect, it is generally true that the darker the blemishes are, the more severe the damage is.

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