Detection of Visual Defects in Citrus Fruits: Multivariate Image Analysis vs Graph Image Segmentation

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Abstract. This paper presents an application of visual quality control in orange post-harvesting comparing two different approaches. These approaches correspond to two very different methodologies released in the area of Computer Vision. The first approach is based on Multivariate Image Analysis (MIA) and was originally developed for the detection of defects in random color textures. It uses Principal Component Analysis and the T^2 statistic to map the defective areas. The second approach is based on Graph Image Segmentation (GIS). It is an efficient segmentation algorithm that uses a graph-based representation of the image and a predicate to measure the evidence of boundaries between adjacent regions. While the MIA approach performs novelty detection on defects using a trained model of sound color textures, the GIS approach is strictly an unsupervised method with no training required on sound or defective areas. Both methods are compared through experimental work performed on a ground truth of 120 samples of citrus coming from four different cultivars. Although the GIS approach is faster and achieves better results in defect detection, the MIA method provides less false detections and does not need to use the hypothesis that the bigger area in samples always correspond to the non-damaged area.

Keywords: Fruit Inspection, Automatic Quality Control, Multivariate Image Analysis, Principal Component Analysis, Unsupervised Methods

1 Introduction

Quality control in the agro-industry is becoming of paramount importance in order to decrease production costs and increase quality standards. In the packing lines, where external quality attributes are currently inspected visually, machine vision is providing a way to perform this task automatically. The detection of blemishes is one of the most important factors in the commercial quality of fruit. Blemishes in citrus can be due to several causes; medfly egg deposition, green mould by Penicillium digitatum, oleocellosis (rind oil spot), scale, scarring, thrips scarring, chilling injury, stem injury, sooty mould, anthracnose and phytotoxicity. Figure 1 shows four different types of defects (blemishes) in citrus.

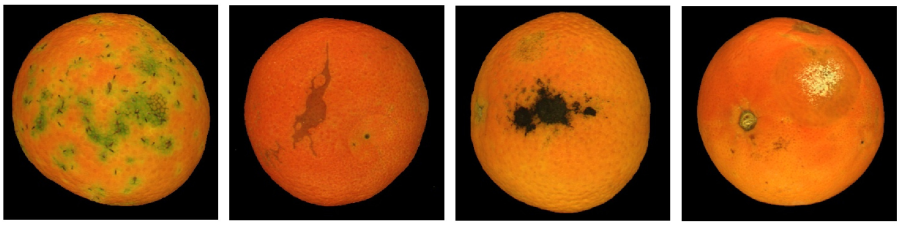

Fig. 1. Some blemishes in citrus. From left to right; scale, thrips scarring, sooty mould and green mould.

The automatic detection of visual defects in orange post-harvest, performed to classify the fruit depending on their appearance, is a major problem. Species and cultivars of citrus present great unpredictability in colors and textures in both, sound and defective areas. Thus, the inspection system will need frequent training to adapt to the visual features of new cultivars and even different batches within the same cultivar [1]. In addition, as the training process will be performed by non-specialized operators at the inspection lines, we need to select an unsupervised methodology (no labeling process required) that leads to an easy-to-train inspection system. Real-time compliance is also an important issue so that the overall production can be inspected at on-line rates. Thus, approaches with low computational costs are valuable. In the present paper, we study and compare two methods that offer these features, they are unsupervised , easy-to-train and also provide low computational costs in comparison with similar-in-purpose methods in literature.

The first method [2] is based on a Multivariate Image Analysis (MIA) strategy developed in the area of applied statistics [3–5]. This strategy differs from traditional image analysis, where the image is considered a single sample from which a vector of features is extracted and then used for classification or comparison purposes. In MIA, the image is considered a sample of size equal to the number of pixels that compose the image. Principal Component Analysis (PCA) is applied to the raw data of pixels and then statistic measures are used to perform the image analysis. The method was originally developed as a general approach for the detection of defects in random color textures, which is a Computer Vision issue where several works have been released recently in literature. We chose this kind of method because it fits the needs for the detection of blemishes (visual defects) in citrus, where sound peel areas and damaged areas are in fact random color textures. With regard to the other literature methods for the detection of defects in random color textures, this method presents the following advantages; it uses one of the simplest approaches providing low computational costs, and also, it is unsupervised and only needs few samples to train the system [2]. In order to better compile defects and parts of defects of different sizes we introduce a multiresolution scheme which minimizes the computational effort. The method is applied at different scales gathering the results in one map of defects. In the paper, we call this method MIA-DDRCT (MIA Defect Detection on Random Color Textures).

The second method we study [6] is a Graph Image Segmentation (GIS) approach which belongs to the set of methods that use a graph representation of the image and a given criteria to segment the image into regions (e.g. [7, 8]). It is an efficient segmentation algorithm based on a predicate which is defined to measure the evidence of a boundary between two adjacent regions. This predicate measures inter-regions differences in the neighborhood of boundaries as well as intra-region differences. This way, local and non-local criteria are introduced. We chose this method because it is a recent work on the Computer Vision topic of image segmentation which improves results of previous methods [6]. The GIS method is highly efficient and achieves a running time nearly linear with the number of pixels in the image. Also, it is strictly unsupervised because it does not need to learn about sound or defective areas. If we set the hypothesis that the bigger part in samples correspond to the sound non-damaged area, then the rest of regions will correspond to defects. In this case, we only need to adjust two parameters in the method: $sigma$, which is used to smooth the image before being segmented, and the k value of a threshold function where larger values of k result in larger regions. The hypothesis of the bigger area in samples being the sound area is reasonable and has been used before [1]. In the paper, we call this method EGIS (Efficient Graph Image Segmentation).

Next section shows the experimental work performed to evaluate and compare the approaches. Conclusions are reported in final section.

2 Experimental work

2.1 Ground truth

The set of fruit used to carry out the experiments consisted of a total of 120 oranges and mandarins coming from four different cultivars: Clemenules, Marisol, Fortune, and Valencia (30 samples per cultivar). The fruit was randomly collected from a citrus packing house. Five fruits of each cultivar belonged to the extra category, thus, they were fully free of defects. The other 25 fruits of each cultivar fitted secondary commercial categories and had several skin defects, trying to represent the cause of most important losses during post-harvesting (see Section 1).

2.2 MIA-DDRCT approach

The first step in the experimental work for this approach was to select a set of defect-free samples for each cultivar, in order to build the corresponding model of sound color textures. A total of 64 different sound patches were collected for each cultivar (see Figure 2). We used patches instead of complete samples in order to introduce in the model more different types of sound peels and collect as much as possible the variability of colors and textures.

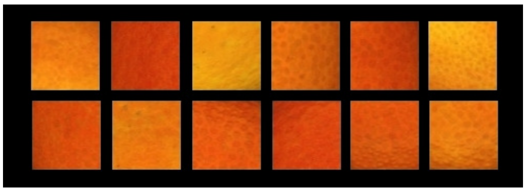

Fig. 2. Several sound patches of Clemenules cultivar.

Then, to tune the parameters, we designed a set of experiments that involved to apply the method to the ground truth of each cultivar and extract the corresponding defect maps, but varying in each experiment; the number of principal eigenvectors chosen to build the reference eigenspace, the percentile used to set the T^2 threshold, and the combination of scales used in the multiresolution scheme. The number of principal eigenvectors were varied in [1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27], the percentile in [90, 95, 99], and the set of scales in [(0.25,0.12), (0.50, 0.12), (0.50, 0.25), (1.00, 0.12), (1.00, 0.25), (1.00, 0.50), (0.50, 0.25, 0.12), (1.00, 0.25, 0.12), (1.00, 0.50, 0.12), (1.00, 0.50, 0.25), (1.0, 0.50, 0.25, 0.12)]. Thus, a total number of 462 experiments were carried out for each cultivar. To tune the parameters, that is, to select the values that maximize the quality of defect maps, we marked manually the defective areas in the samples and then compared with the achieved defect maps using three measures; Precision, Recall and F-Score.

$$Precision = \frac{tp}{tp + fp}, \quad Recall = \frac{tp}{tp + fn} \tag{1}$$

$$FScore = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{2}$$

where tp (true positives) is the number of pixels marked and correctly detected, fp (false positives) is the number of pixels not marked but detected, and fn (false negatives) is the number of pixels marked but not detected. Precision is a measure of exactness (fidelity), Recall is a measure of completeness, and the F-score combines both through their harmonic mean. Once the set of experiments was carried out for each cultivar, mean values of previous measures were computed. Then, we selected the most balanced result for each cultivar. Table 1 shows the best combination of factors for each cultivar and the corresponding mean values of Precision, Recall and F-Score.

Table 1. Best combinations of factors (MIA-DDRCT).

Cultivar	#EigenVectors	Percentile	Scales	Precision	Recall	F-Score
Clemenules	11	95	(0.50, 0.25)	0.60	0.61	0.54
Fortune	17	90	(0.50, 0.25)	0.54	0.69	0.56
Marisol	23	90	(0.50, 0.25)	0.62	0.58	0.53
Valencia	27	95	(0.50, 0.12)	0.64	0.67	0.62
T.Mean				**0.60**	**0.64**	**0.56**

Table 2. Detection results on individual defects (MIA-DDRCT).

Cultivar	Defects	Detected	False Detections
Clemenules	238	211 (88.7%)	04 (1.7%)
Fortune	172	159 (92.4%)	10 (5.5%)
Marisol	195	185 (94.9%)	07 (3.5%)
Valencia	138	125 (90.6%)	06 (4.2%)
Total	**743**	**680 (91.5%)**	**27 (3.8%)**

Once the parameters were tuned, from the marked defects and the achieved defect maps we counted the actual defects, the correctly detected defects and the false detections for each cultivar. These results are shown in Table 2 (percentage of false detections is provided with regards to the number of detected defects plus the false detections, that is, the total number of defects extracted by the method).

2.3 EGIS approach

In this approach there is no training stage and also no model of sound color textures is built. Instead, the method tries to segment the sample (the image) into regions in such a way that adjacent regions have a different visual appearance but it remains similar within them. Thus, in order to extract the defects it is necessary to set the hypothesis that bigger regions in samples always correspond to the sound area (the background is not considered).

Since no training is performed, we went directly to tune the parameters of the method for each cultivar. Parameters are *sigma*, which is used to smooth the image before being segmented, and the k value of the threshold function. In [6] the recommended values for *sigma* and k are respectively 0.5 and 500, then, we varied the parameters around these central values. For each cultivar a set of experiments was performed varying *sigma* in [0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70, 0.75], and k in [200, 250, 300, 350, 400, 450, 500, 550, 600, 650, 700, 750], which led to 132 different experiments. As the in previous approach, parameters were tuned by comparing the manually marked defects with regard to those achieved by the method. This comparison was performed again through the measures of Precision, Recall and F-Score. Tables 3 and 4 correspond to Tables 1 and 2 of previous approach. These tables show that the

EGIS approach is better in fitting the marked defects and also in defect detection, although it produces more false detections.

Table 3. Best combinations of factors (EGIS).

Cultivar	**sigma**	***k***	**Precision**	**Recall**	**F-Score**
Clemenules	0.50	350	0.75	0.75	0.71
Fortune	0.45	350	0.72	0.73	0.66
Marisol	0.60	250	0.63	0.65	0.58
Valencia	0.65	450	0.77	0.74	0.72
T.Mean			**0.72**	**0.72**	**0.67**

Table 4. Detection results on individual defects (EGIS).

Cultivar	**Defects**	**Detected**	**False Detections**
Clemenules	238	220 (92.4%)	09 (3.6%)
Fortune	172	164 (95.4%)	12 (6.5%)
Marisol	195	182 (93.3%)	17 (8.2%)
Valencia	138	129 (93.5%)	08 (5.5%)
Total	**743**	**695 (93.5%)**	**46 (6.2%)**

A major difference between both approaches arises when we study their timing costs. Using an standard PC, we measured for both methods the mean timing cost of 20 executions performed on the same sample of clemenules cultivar. While the MIA-DDRCT method achieved a mean timing of 588,5 ms, the EGIS method achieved 162.5 ms. Nevertheless and despite the difference, both methods can meet the real-time requirements at production lines (5 pieces per second) since their timing costs can be drastically reduced by using simple and cheap parallelization techniques based on computer clustering. Figure 3 shows the results achieved by both approaches on two different samples.

3 Conclusions

In this paper, we have presented an application of visual quality control in orange post-harvesting comparing two different approaches of Computer Vision. A general approach based on a Multivariate Image Analysis strategy for the detection of defects in random color textures (MIA-DDRCT), and a generic, graph-based and efficient approach to image segmentation (EGIS). Both methods have been compared through an experimental work performed on a ground truth composed by 120 samples of citrus coming from four different varieties.

First, a set of experiments were designed to tune-up the parameters in both methods. For each cultivar, the parameters of the corresponding method were varied in a wide range. This led to an extend number of experiments; 462 for the MIA-DDRCT method and 132 for the EGIS method. Then, the parameters were tuned using Precision, Recall and F-Score, three measures that compare the difference among the defects manually marked and the defects extracted by the methods. Since higher values of these measures were achieved by the EGIS method, we can conclude that this approach fits better the marked defects.

Then, for the best combinations of parameters for each cultivar in both methods, we collected the defect detection results. We counted the actual defects, the correctly detected defects and the false detections. In this case, the EGIS method achieved better performance in the correct detection ratio (93.5% versus 91.5%), while MIA-DDRCT was better providing less false detections (3.8% versus 6.2%). With regards to timing costs, the EGIS method performs 3.6 times faster than MIA-DDRCT, although both methods can easily achieve real-time compliance by introducing simple parallelization techniques. Finally, the MIA-DDRCT approach has the advantage that does not need to use the hypothesis that the bigger area in samples correspond to the sound area, unlike it occurs in EGIS method.

References

1. J. Blasco, N. Aleixos and E. Moltó. Computer vision detection of peel defects in citrus by means of a region oriented segmentation algorithm. *Journal of Food Engineering*, 81(3):535–543, 2007.
2. F. López-García, J. M. Prats, A. Ferrer and J. M. Valiente. Defect Detection in Random Colour Textures using the MIA T^2 Defect Maps. *Lecture Notes in Computer Science*, 4142:752–763, 2006.
3. M. H. Bharati and J. F. MacGregor. Texture analysis of images using Principal Component Analysis. *In SPIE/Photonics Conference on Process Imaging for Automatic Control*, :27–37, 2000.
4. P. Geladi and H. Granh. Multivariate Image Analysis. Wiley, Chichester, England, 1996.
5. J. M. Prats-Montalbán and A. Ferrer. Integration of colour and textural information in multivariate image analysis: defect detection and classification issues. *Journal of Chemometrics*, 21(1-2):10–23, 2007.
6. P. F. Felzenszwalb and D. P. Huttenlocher. Efficient Graph-Based Image Segmentation. *International Journal of Computer Vision*, 59(2):167–181, 2004.
7. R. Urquhart. Graph theoretical clustering based on limited neighborhood sets. *Pattern Recognition*, 15(3):173–187, 1982.
8. C. T. Zahn. Graph-theoretic methods for detecting and describing gestalt clusters. *IEEE Transactions on Computing*, 20(1):68–86, 1971.

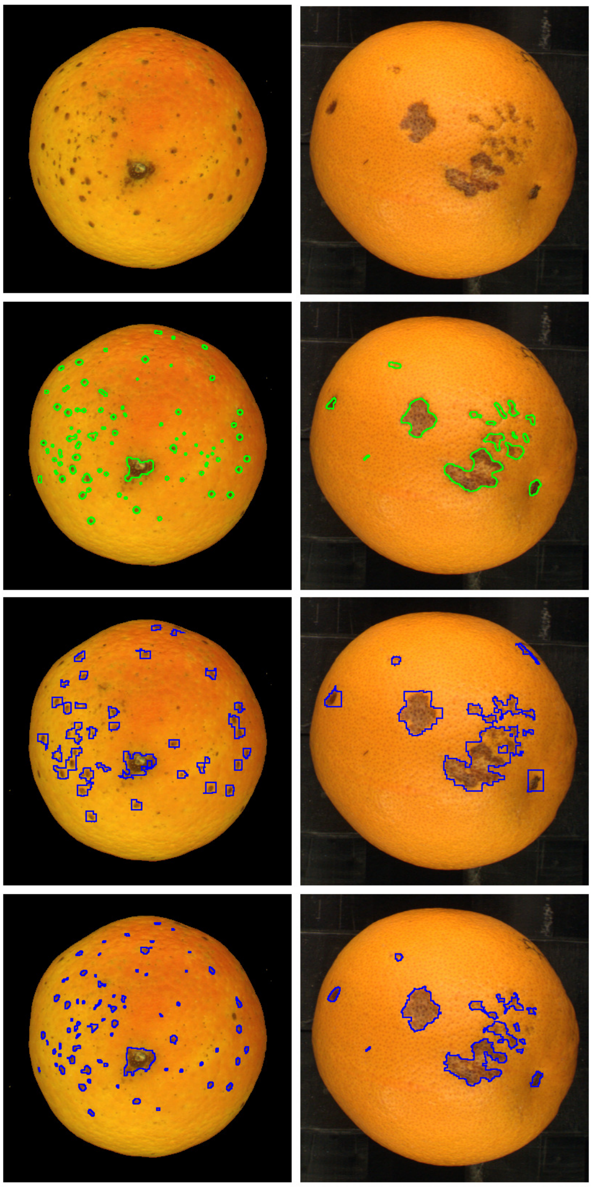

Fig. 3. MIA-DDRCT versus EGIS. From top to bottom; original, manually marked defects, MIA-DDRCT and EGIS results