THRESHOLDING-BASED SEGMENTATION AND APPLE GRADING BY MACHINE VISION

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ABSTRACT

In this paper, a computer vision based system is introduced to automatically grade apple fruits. Segmentation of defected skin is done by three global thresholding techniques (Otsu, isodata and entropy). Stem-end/calyx regions falsely classified as defect are removed. Segmentations were visually best with isodata technique applied on 750nm filter image. Statistical features are extracted from the segmented areas and then fruit is graded by a supervised classifier. Linear discriminant, nearest neighbor, fuzzy nearest neighbor, adaboost and support vector machines classifiers are tested for fruit grading, where the latter outperformed others with 89 % recognition.

1. INTRODUCTION

Computer vision based quality sorting of apple fruits is a hard but necessary task for increasing the speed of sorting as well as eliminating the human error in the process. Segmentation of skin defects of apples is one of the major problems of this field where research still continues to accurately segment and identify these defects. In order to segment defects Leemans et al. introduced a Gaussian model of skin color for 'Golden Delicious' [1], and a Bayesian classification method for 'Jonagold' apples [2], where healthy skin presenting patches was segmented as defected in the former and segmentation of russet defects and color transition areas of skin were problematic in the latter. Rennick et al. used a controlled acquisition system and different classifiers to classify skin color and detect blemishes of 'Granny Smith' apples [3]. Yang introduced an automatic system to detect patch-like defects on apples, where he used flooding algorithm to segment defects, structural light and neural networks to find stem-ends and calyxes and snakes algorithm to refine defected areas [4]. Unay and Gosselin introduced a neural network based system to segment defects on 'Jonagold' apples, where segmentation was accurate, but misclassification of stem-end, calyx areas as defects occured [5].

2. METHODS

2.1 Image Acquisition and Database

Database consists of one-view images of 'Jonagold' apples taken from diffusely illuminated environment by a high resolution monochrome digital camera with four interference band-pass filters centered at 450nm (BL), 500nm (GR), 750nm (RE), and 800nm (IR) with respective bandwidths of 80, 40, 80, and 50 nm. Each filter image is composed of 430x560 pixels with 8 bits-per-pixel resolution (Figure 1). 280 of the fruits were healthy whereas 246 of them included several skin defects (russet, recent bruises, rot, scald, hail damage, scar tissue, limb rubs,...) in varying size and shapes. 'Jonagold' variety is selected, instead of mono-colored ones, because it has a bi-colored skin causing more difficulties in segmentation due to color transition areas. Some RGB images of the database can be observed in Figure 2.

Image acquisition and database collection of this work are done in Mechanics and Construction Department of Gembloux Agricultural University of Belgium, and related details can be found in the works of Kleynen et al. [6], [7].

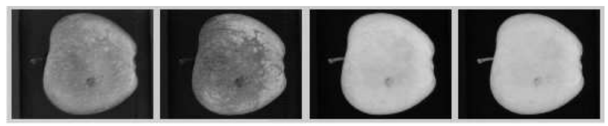

Figure 1: Filter images of a fruit. Left to right: BL, GR, RE, and IR filters.

Figure 2: Original (RGB) images of some defected apples.

2.2 Pre-Processing

The database is composed of images of apple views on a dark, uniform colored (i.e. low intensity) background. Therefore, fruit area can be separated from background by thresholding the RE filter image at intensity value of $\approx 11,77$ %. Our visual observations have shown that fixed thresholding can remove low intensity regions like some defects, stem-ends or calyxes. Hence, a morphological filling operation is also applied to remove these holes.

Our initial observations revealed that segmentation was problematic at the far edges of fruit probably due to illumination artifacts. Therefore, after background removal, fruit area is eroded by a rectangular structuring element with size adaptive to fruit size. Dimensions of the structuring element are calculated as 15 % of the horizontal (a) and vertical (b) dimensions of fruit bounding-box.

2.3 Defect Segmentation

Thresholding can be applied locally, i.e. within a neighborhood of each pixel, or globally. Due to highly varying defect sizes, it will be impossible to find one neighborhood size that works for all. Thus, following global thresholding techniques are tested for defect segmentation in this work:

- *Otsu* : Otsu's method is still among the most referenced methods in segmentation [8]. It is based on minimizing within-class variances of foreground and background pixels.
- *Entropy* : Kapur et al. explained foreground and background of an image as different signals [9]. Therefore, optimal threshold is the one maximizing the sum of the two class entropies (Eq. 1).

$$H = max\Big[-\sum_{i=0}^{T_{opt}} p_i log(p_i) - \sum_{i=T_{opt}+1}^{255} p_i log(p_i)\Big] \quad (1)$$

- *Isodata* : Ridler and Calvard assumed image as a two-class Gaussian mixture model and proposed an iterative technique, which calculates a new threshold by averaging the foreground and background class means at each iteration [10]. If change in thresholds between two consecutive iterations is small enough (0.04 %), then algorithm stops.

Above thresholding techniques are applicable on gray-level (2-dimensional) images. However in a multi-spectral imaging system, one can either combine the filter images to get a final gray-level image or select one of the filter images by a criterion. As the optimal combination is arduous, in this work we consider using filter images separately and try to select the optimum pair of filter image and thresholding technique.

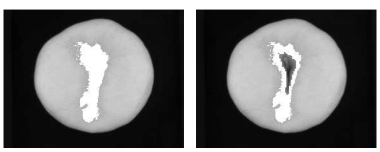

Figure 3: Example of stem-end/calyx removal. Before the removal on the left, and stem-end/calyx removed on the right. Defected area displayed in white in both images.

Stem-end and calyx, which are natural parts of apple fruit, appear as dark blobs on the images like some of the true defects. But, threshold-based segmentation does not consider presence-absence of these regions, while partitioning fruit area into defected and healthy parts. Thus, segmentation should be refined to remove stem-end/calyx.

Stem-end/calyx recognition method, which was previously introduced by the authors [11] and found to be highly accurate, is used in this work. It starts with background removal and threshold-based object segmentation. Then, statistical, textural and shape features are extracted from each segmented object and these features are introduced to support vector machines classifier, which discriminates true recognitions from false ones. So, the regions identified as stem-end/calyx by this method are removed from the formerly detected segmentation result. Figure 3 displays an example of such a refinement step, which demonstrates the improvement in the defect segmentation.

2.4 Feature Extraction

Main goal of our project is to provide a fast algorithm for fruit classification. Therefore, *average*, *standard deviation*, and *median* values are calculated over the segmented area of each fruit from all filter images. In addition to these 12 features, *defected ratio*, which is the ratio of defected pixels of the fruit, is also computed. Thus, each fruit is represented by 13 features, which are normalized to have an average of zero and standard deviation of one before the classification step.

2.5 Fruit Classification

The following supervised classifiers are tested in this paper.

- *Linear Discriminant Classifier* (LDC) searches for a linear decision boundary that separates the feature space into two half-spaces by minimizing the criterion function

$$g(x) = w^t x + w_0 \quad (2)$$

- *Nearest Neighbor Classifier* (k-NN) assigns an object to the most represented category among the k (5) nearest samples of that object. Similarity measure used to find nearest samples is the Euclidean distance.
- *Fuzzy Nearest Neighbor Classifier* (fuzzy k-NN) is the fuzzified version of k-NN. Fuzziness is acquired using the distance information of k (5) nearest neighbors to the new sample by,

$$u_i(x) = \frac{\sum_{j=1}^{k} u_{ij} \left(\|x - x_j\|\right)^{\frac{-2}{m-1}}}{\sum_{j=1}^{k} \left(\|x - x_j\|\right)^{\frac{-2}{m-1}}} \quad (3)$$

$u_i(x)$ is the predicted membership value of test sample x for class i, u_{ij} is the membership (either 0 or 1) of j^{th} neighbor to the i^{th} class and m is the *fuzzifier* parameter (set to 2) that determines how heavily the distance is weighted.
- *Adaptive Boosting* (AdaBoost) tries to form a final strong classifier (g) from an ensemble of weak learners (h_t) by continuously adding these weak learners until the desired training error is reached [12]. Thus, decision for a test sample x is taken by:

$$g(x) = sgn\big[\sum_{t=1}^{t_{max}} \alpha_t h_t(x)\big] \quad (4)$$

where α_t are the coefficients found by boosting process, t_{max} is the number of weak learners and sgn returns the sign of the value.
- *Support Vector Machines* (SVM) is a statistical learning method based on structural risk minimization [13]. In the binary case, SVM tries to find the hyperplane that separates the classes with maximum *margin* by non-linear mapping. For a test sample x, classification is done by:

$$y = sgn\big(\sum_{i=1}^{N} \alpha_i y_i K(s_i, x)\big) \quad (5)$$

$$K(s_i, x) = e^{-\frac{\|s_i - x\|^2}{2\sigma^2}} \quad (6)$$

where N is the number of training samples, y_i is the class label, $K(s_i, x)$ is the kernel function and α_i is the Lagrangian multiplier bound by $0 \leq \alpha_i \leq C$. x_i's for which

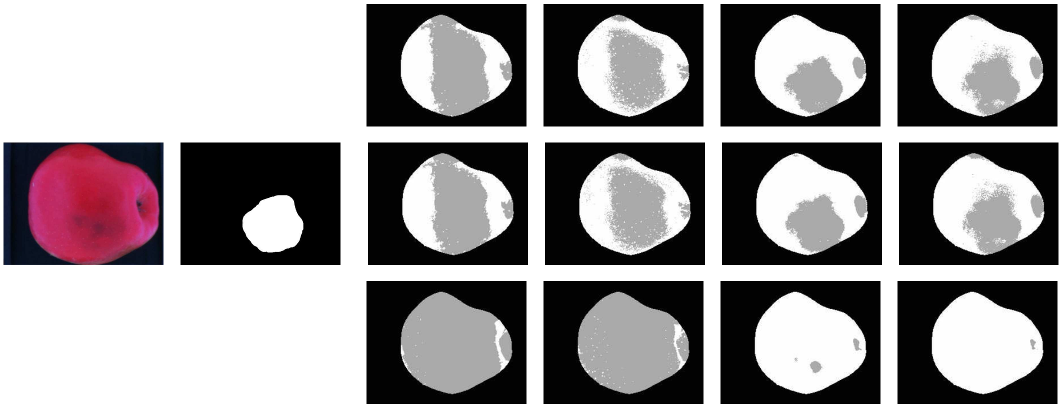

Figure 4: Segmentation results of thresholding methods on a bruised apple. Original RGB image and the manual segmentation (ground truth) of the fruit are on the left. Subsequent synthetic images show defected regions in gray and healthy ones in white. Each row belongs to a thresholding method (top-to-bottom: otsu, isodata, entropy) and each column shows a band (left-to-right: BL, GR, RE, IR).

$\alpha_i > 0$ are called the support vectors. Gaussian radial basis function kernel (Eq. 6) and $C = \infty$ are chosen for this work.

Evaluation of the classification process is measured by K-fold cross-validation method, with K=5. Furthermore, samples of the dataset are randomly ordered before being introduced to the classifier, to prevent biased classification for sample order.

In this research, libraries of Almeida [14] and Räetsch [12] are used for SVM and AdaBoost classifications, respectively. The proposed system is implemented under Matlab 6 R12.1 environment [15].

3. RESULTS AND DISCUSSION

Defect segmentation results of a bruised fruit using thresholding techniques on filter images are displayed in Figure 4. Bruise is selected for display, because it is one of the most common defects of apple fruits. As an initial observation, in the results of BL and GR filter images, false segmentations are observed. This is probably because in these filter images (i.e. in the wavelength range of [410-510] nm) contrast between healthy skin and the defect is low. Within the results of RE and IR filter images, those of entropy technique are visually unacceptable; almost no part of defect is found. On the other hand, otsu and isodata techniques provide satisfactory results, favorably on RE filter image. Although results of bruise type of defect are discussed here only, above observations are mostly consistent within the database, i.e. our visual examinations on the results of all images of the database confirm that isodata technique should be applied on RE filter image for the best output.

Figure 5 provides more segmentation results of fruits with different defects produced by isodata technique on RE and IR filter images. Scald (top-left) and hail damage perfusion (bottom-left) defects are partially segmented in both filter images. Segmentation of frost damage (mid-left) and rot (top-right) defects are acceptable for RE, whereas results of IR are under-segmented. Finally, for bruise (mid-right) and flesh damage (bottom-right) defects none of the segmentations are satisfactory. In general, results of RE filter image are visually better than those of IR. Results displayed here are before the SC removal step, therefore some stem-end regions are observed as defect, which are corrected later on.

Following segmentation, SC removal and feature extraction steps, fruits are graded as healthy or defected by different supervised classifiers, performances of which are observed in Table 1. As we go from simple to sophisticated classifiers, recognitions increase. LDC (simple) performs around 79 % and nearest neighbor classifiers (more sophisticated) around 83 %, whereas AdaBoost and SVM (most sophisticated) reach to 88-89 % rates. Fuzziness does not have significant impact on recognition. Especially in the results of AdaBoost and SVM, superiority of isodata method and RE filter image are obvious, which is consistent with our visual observations. Highest recognition rate is observed by SVM classifier on isodata method and RE filter image with 89.2 %.

4. CONCLUSION

In this article a computer vision based automatic sorting system for apple fruits is introduced. The fruit area is extracted from the background and it is eroded to reduce undesired effects of illumination. Then, defected areas of fruit are segmented by three global thresholding methods applied on filter images separately. Visual results showed that segmentation accuracy was better on RE and IR filter images. Furthermore, isodata thresholding method was found to outperform others. As stem-end or calyx regions also appear as defects in the segmentation, these parts are removed by a method previously introduced by the authors. Finally, statistical features are extracted from segmented defects and fed to several supervised classifiers for fruit grading by binary classification (defected or healthy). Highest recognition rate is observed by support vector machines classifier with 89.2 %. Observations on the performances of classifiers not only confirmed superiority of isodata method and RE filter image, but also revealed that more sophisticated classifiers lead to better recognition rates.

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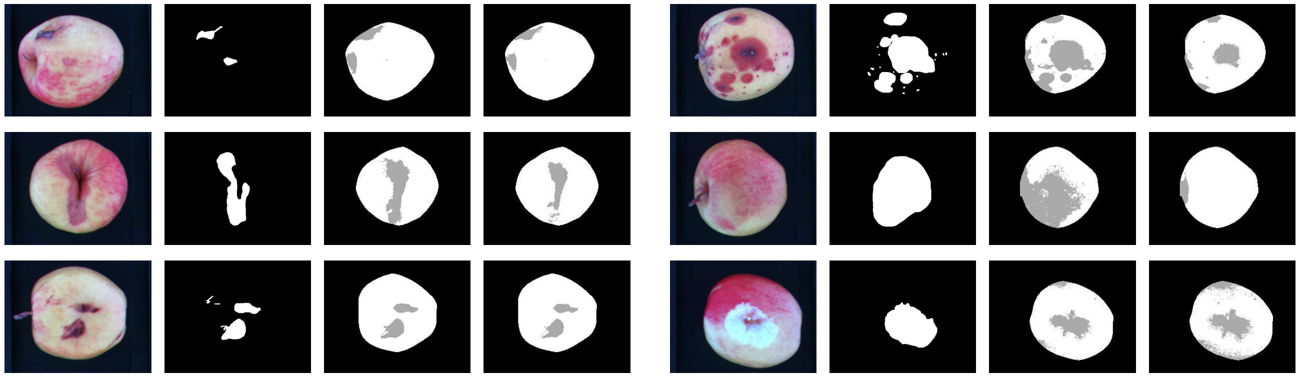

Figure 5: Results of segmentation by isodata thresholding on RE and IR filter images. Fruits displayed are defected by scald (top-left), rot (top-right), frost damage (mid-left), bruise (mid-right), hail damage perfusion (bottom-left) and flesh damage (bottom-right). For each fruit its original RGB image, its manual segmentation (ground truth) and its segmentation results (from RE filter image on the left and from IR on the right) are displayed in a row. Defected areas are displayed in white in ground truth images, whereas segmentations show defected regions in gray color and healthy ones in white.

band	method	LDC	5-NN	Fuzzy 5-NN	AdaBoost	SVM
RE	otsu	81.8	84.4	83.8	87.5	87.8
	isodata	78.5	83.5	83.5	88.4	**89.2**
	entropy	78.0	79.1	79.5	84.5	83.8
IR	otsu	78.9	82.9	83.5	86.3	86.0
	isodata	75.7	81.6	82.1	88.2	87.6
	entropy	78.9	78.0	78.3	82.9	81.9

Table 1: Classification performances of classifiers in correct recognition percentages.

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