ARTIFICIAL NEURAL NETWORK-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 sort apple fruits. An artificial neural network segments the defected regions on fruit by pixel-wise processing. Statistical features are extracted from the defected regions 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 last two are found to perform best with 90 % recognition.

1. INTRODUCTION

Computer vision based quality sorting of apple fruits is necessary for increasing the speed of sorting and eliminating the human error in the process. Research still continues to accurately segment and identify skin defects of apples. For this aim 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 area [4]. Unay and Gosselin introduced a neural network based system to segment defects on 'Jonagold' apples, where segmentation was accurate, but misclassification of stem-ends, calyxes occurred [5].

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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 450 nm (BL), 500 nm (GR), 750 nm (RE), and 800 nm (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 the related details can be found in the works of Kleynen et al. [6], [7].

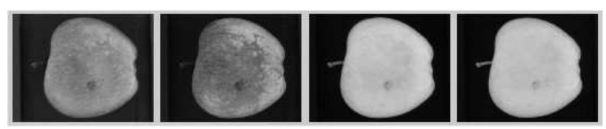

Fig. 1. Filter images of a fruit. Left to right: BL, GR, RE, and IR filters.

Fig. 2. Original (RGB) images of some defected apples.

2.2. Pre-processing

Images of apples are taken on a dark, uniform colored 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 threshold can remove low intensity regions like some defects, stem-ends or calyxes. Hence, a morphological filling operation is also applied to remove these holes.

Initial observations revealed that segmentation was problematic at far edges of fruit probably due to illumination artifacts. Therefore, after background removal, fruit area is eroded by a rectangular structuring element with size (15 % of bounding-box of fruit) adaptive to fruit size.

2.3. Defect segmentation

Segmentation of defects is proposed at pixel level, therefore for each pixel of the fruit its intensity values from four filters are used as local features. In addition, average and standard deviation of intensity values of the fruit are also calculated for each filter image, making up the global features. It was previously shown that neural networks sometimes misclassifies healthy tissue closer to the edges of fruit with only the local and global features, so a new feature related to pixels' location was introduced by the authors [5]. This new feature is inversely and linearly related to the distance of each pixel from the geometric center of the fruit. Hence, each pixel is introduced to the neural networks by 13 features.

Artificial neural network used for segmentation is a 2-layer, back-propagated network of perceptron neurons (BPNN), which makes binary decision (defected-healthy) for each pixel introduced. It has 13 and 2 neurons in the input and output layers, respectively. Different number of hidden neurons are tested, but segmentation performance is found to be independent of their quantity above 5. That's why, results obtained by 5 hidden neurons are presented in this paper. BPNN has an adaptive learning rate and uses cross-validation technique, i.e. training and validation sets do not overlap.

Stem-ends/calyxes (SC), natural parts of apple fruit, appear as dark blobs on images like some of the true defects. But, BPNN does not consider presence/absence of these regions, while partitioning fruit skin into defected and healthy parts. Thus, segmentation should be refined. SC recognition method, used in this work, was previously introduced by the authors [8] and found to be highly accurate. It starts with background removal and threshold-based object segmentation. Then, statistical, textural and shape features are extracted from each object and they are introduced to support vector machines classifier, which discriminates true recognitions from false ones. So, the regions identified as SC by this method are removed from the segmentation result. Figure 3 displays an example of such a refinement step.

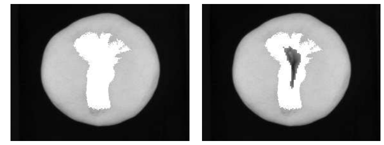

Fig. 3. Example of stem-end/calyx removal. Before the removal on the left, and SC removed on the right. Defected area displayed in white in both images.

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 work.

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

- *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,

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

  $u_i(x)$ 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

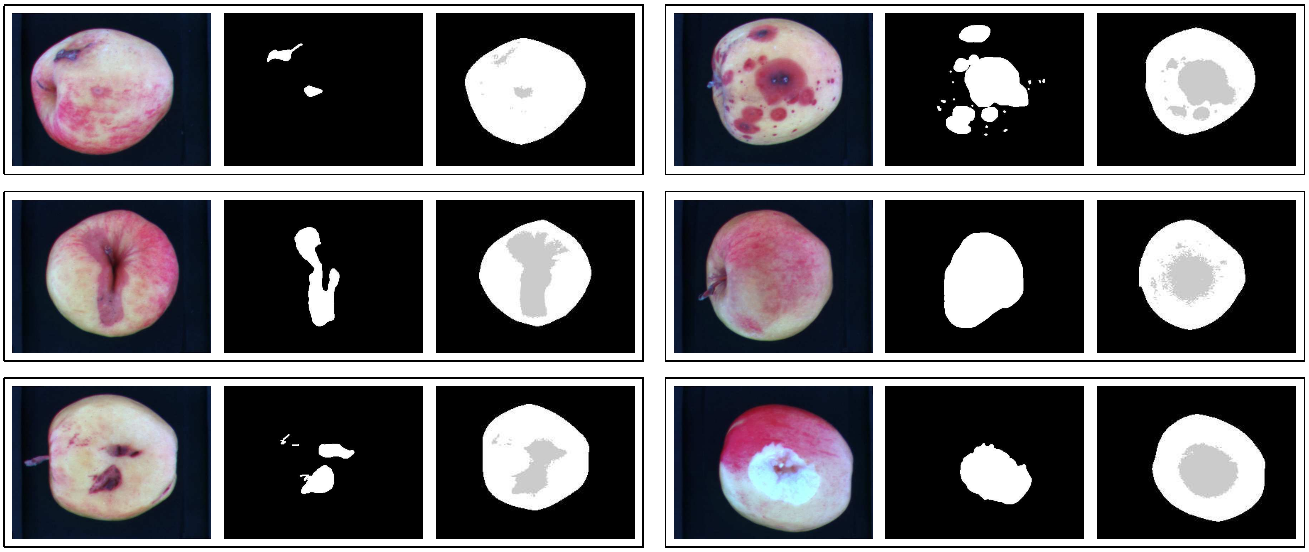

Fig. 4. Results of segmentation by artificial neural network. Fruits displayed are defected by scald (top-left), rot (top-right), frost damage (mid-left), bruise (mid-right), hail damage perfusion (bottom-left) and flesh damage (bottom-right). For each fruit its original RGB image, its manual segmentation (ground truth) and its segmentation result 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.

until the desired training error is reached [9]. Thus, decision for a test sample x is taken by:

$$g(x) = sgn\big[\sum_{t=1}^{t_{max}} \alpha_t h_t(x)\big] \qquad (2)$$

where α_i are the coefficients found by boosting process and t_{max} is the number of weak learners.

- *Support Vector Machines* (SVM), is a statistical learning method based on structural risk minimization procedure [10]. In the binary case, SVM tries to find the hyperplane that separates the classes with maximum *margin*. For a test sample x, classification is done by:

$$y = sgn\big(\sum_{i=1}^{N} \alpha_i y_i K(s_i, x)\big) \qquad (3)$$

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 $\alpha_i > 0$ are called the support vectors. Gaussian radial basis function kernel and $C = \infty$ is 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 [11] and Räetsch [9] are used for SVM and AdaBoost classifications, respectively. The proposed system is implemented under Matlab 6 R12.1 environment.

3. RESULTS AND DISCUSSION

Figure 4 displays examples of defect segmentation performed by BPNN classifier. Generally, segmentations of defects are successful. We observe under-segmentation in mid-right result, which is probably due to the variation in skin color and the type of defect(bruise) well known to be arduous to segment. In bottom-left (frost damage) defected area is over-segmented, where we end up with a bigger defect instead of two smaller ones. Neither the skin color between the two defects vary much, nor we use neighborhood information in local features that could lead to touching. So, we suspect that global features have biased the segmentation. Sometimes there exist under-segmentations, due to the combined effect of distance feature and the erosion step, like in the top-right result. The results shown are before the SC removal step, therefore segmented result of fruit with frost damage (mid-left) include stem-end too, which is removed later on.

After the segmentation step, features are extracted from segmented regions and fruits are sorted into defected-healthy classes by several supervised classifiers. Results of this test

classifiers		LDC		5-NN		Fuzzy 5-NN		AdaBoost		SVM	
		ground truth		ground truth		ground truth		ground truth		ground truth	
classes		D	H	D	H	D	H	D	H	D	H
confusion	D	227	51	213	27	211	26	216	21	220	25
matrices	H	19	229	33	253	35	254	30	259	26	255
class %		92.3	81.8	86.6	90.4	85.8	90.7	87.8	92.5	89.4	91.1
overall %		86.7		88.6		88.4		90.3		90.3	

Table 1. Performances of different classifiers for fruit grading. 'D' refers to defected class, and 'H' to healthy one.

are introduced in Table 1. As expected, the worst classifier in overall performance is the LDC. Then, come the nearest neighbor classifiers. Fuzziness does not improve recognition. AdaBoost and SVM classifiers perform best with 90.3 % overall recognition. From these two, SVM is considered to be more suitable to our application, because it does not require previous training sets, but just the related support vectors when it has to be improved by a new training set.

4. CONCLUSION

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. After this preprocessing, defected areas of fruit are segmented by an artificial neural network classifier. Visual results of this segmentation are found to be quite successful. After segmentation step, statistical features are extracted from defected regions and fed to several supervised classifiers for fruit sorting by binary classification (defected or healthy). Highest recognition rate is observed with adaboost and support vector machines classifiers by 90.3 %. Recognition rates of all classifiers vary between 86 % and 90 %, which shows that binary sorting task is not very complicated for sophisticated classifiers like SVM or adaboost. However, our future work will be to sort fruits into more than two classes, which will better clarify the difference between simple and sophisticated classifiers in performance.

5. ACKNOWLEDGEMENTS

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