APPLE STEM AND CALYX RECOGNITION BY DECISION TREES

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ABSTRACT
In this paper, a decision tree-based approach for recognizing stem and calyx regions of apples by computer vision is proposed. The method starts with background removal and object segmentation by thresholding. Statistical, textural and shape features are extracted from each segmented object and these features are introduced to two decision tree algorithms: CART and C4.5. Feature selection is accomplished by sequential floating forward selection method. Analysis showed that feature selection improves accuracy of both system. Eventhough CART performed slightly better than C4.5 after feature selection, McNemar's test found them statistically indifferent.

KEY WORDS
segmentation; classification; feature selection; CART; C4.5; McNemar

1 Introduction

In machine vision-based fruit grading field, discrimination of stems and calyxes (SC) from defects is an important and open problem, because confusion can lead to incorrect grading. Different pattern recognition-based approaches have been proposed to solve this problem. Wen and Tao [1] made use of histogram densities to discriminate SCs from defects in a rule-based system, while Li et al. [2] employed fractal dimensions with artificial neural networks. Leemans and Destain [3] used a correlation-based pattern matching technique to localize SCs. In a recent work, Unay and Gosselin [4] compared discriminations of several classifiers for the same problem.
In this paper we propose a decision tree-based approach to recognize stems and calyxes.

2 Methods

Architecture of the proposed system is composed of background removal, object segmentation, features extraction (including selection) and classification steps (Figure 1).

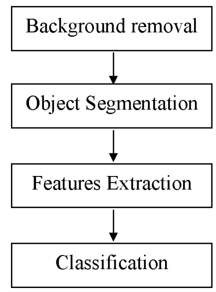

Figure 1. Proposed system architecture.

2.1 Image database

Database consists of images of 819 apples of 'Jonagold' variety acquired by a multi-spectral vision system (filters centered at 450, 500, 750 and 800 nm with respective bandwidths of 80, 40, 80 and 50 nm) from one-view at the Mechanics and Construction Department of Gembloux Agricultural University of Belgium (Figure 2) [5]. 'Jonagold' variety is used, instead of mono-colored ones, because it has a bi-colored skin causing more difficulties in segmentation due to color transition areas. Each filter image has a dimension of 430x560 pixels with 8 bits/pixel resolution. In order to reduce computational cost of the whole process, images are first down-sampled to 128x128 pixels by nearest neighbor interpolation.

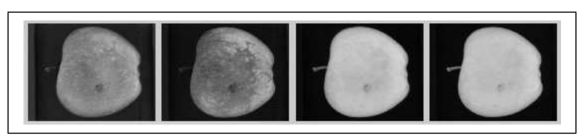

Figure 2. Images of an apple. Left to right: 450, 500, 750 and 800nm filters.

Some fruits used have healthy skin, while others contain natural defects of various size and kind. 293 images of the database were from SCs that are purposely placed in front of the camera with various orientations. Besides, SCs were also present in some of the remaining images.

2.2 Background removal

Images of the database have a low, uniform intensity background. Therefore, fruit area can be separated by thresholding the 750 nm filter image at intensity value of $\approx 11,77$ %. Visual observations showed that this fixed thresholding

statistical	$\mu_{450-800}$	average
	$\sigma_{450-800}$	standard deviation
	$min_{450-800}$	minimum
	$max_{450-800}$	maximum
	$grad_{450-800}$	gradient
	$skew_{450-800}$	skewness
	$kurt_{450-800}$	kurtosis
textural	$\phi_{450-800}$	invariant moment
shape	*S*	area
	P	perimeter
	C	circularity

Table 1. Features extracted from each object.

sometimes removes low intensity regions like some defects or SCs. Hence, a morphological filling operation is applied to correct such false removals.

2.3 Object segmentation

Our initial efforts 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 of size adaptive to fruit size. Result of this erosion step is the region-of-inspection (ROI), which is then used as a mask to compute average (ρ) and standard deviation (ϵ) of intensity values of fruit. Consequently, segmentation of objects (candidate SC's) is achieved by thresholding the masked fruit area with

$$T_0 = \rho - 2 * \epsilon \tag{1}$$

where pixels of intensity less than T_0 are believed to belong to an object. Finally, adaptive spatial cleaning is applied to remove very small objects and refine segmentation. Hence, result is the binary segmentation image.

2.4 Features extraction

7 statistical, 1 textural, and 3 shape features are extracted from each segmented object area (Table 1). As statistical and textural ones depend on pixel intensity values, their computation is repeated with each filter image. In the end, each object is represented by a total of 35 features. Moreover, features are normalized to have a mean of 0 and standard deviation of 1.

2.5 Features selection

In real-world problems, relevant features are generally not known beforehand, which results in extraction of excessive features. However, each additional feature will be a computational burden to the system and irrelevant/redundant features can introduce noise. Therefore, feature selection is important to find most relevant feature subset and limit computation time.

Sequential floating forward selection (SFFS) of [6] is a popular feature selection method that starts with an empty subset, iteratively adds features that minimize recognition error one-by-one while removing any previously added feature after each addition if its removal decreases error. A recent work [7] showed that SFFS is a good choice for SC recognition by nearest neighbor and support vector classifiers, thus it is tested in this work.

2.6 Classification

Classification stage is applied to discriminate true segmentations from false ones found by object segmentation step, hence it is a binary decision. *Decision trees* build classification models in a tree structure (Figure 3) using a "divide-and-conquer" strategy. They divide a complex problem into simpler sub-problems, solutions of which are then combined to provide an answer for the complex problem. Two very popular decision tree algorithms are: CART [8] and C4.5 [9], where the former uses Gini's index and the latter uses gain ratio as splitting criterions.

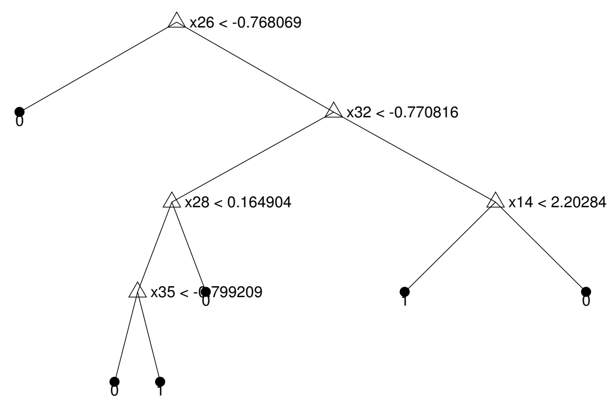

Figure 3. Example of a decision tree.

Performance estimation of classification is measured by 5-fold cross-validation method, in order to use samples for both training and testing without an overlap. Furthermore, samples are randomly ordered before being introduced to the decision tree algorithms, to prevent biased recognition with respect to sample order.

2.7 Statistical Significance

The aim of using a statistical test is to decide if the decision tree systems perform significantly different from each other. McNemar's test [10], assuming both systems are evaluated on same data, is suitable for this. McNemar's value is calculated by

$$\text{McNemar's value} = \frac{(|n_{01} - n_{10}| - 1)^2}{n_{01} + n_{10}} \tag{2}$$

where n_{01} and n_{10} refer to the number of samples misclassified by system A but not by B and by system B but not by A, respectively. If McNemar's value is greater than 3.8415, then the two systems are said to be different with 5 % level of significance.

3 Results and Discussion

Object segmentation is performed on each four filter images individually and visual evaluation showed that results from 750 nm filter were equal or superior than those of others. Thus, 750 nm filter image is used for segmentation. Figure 4 shows some examples of segmentation. In general, segmentation is encouraging. But, sometimes objects are partially segmented like in the middle image. There are also some false SC's like on the right. So, results of object segmentation should further be refined by classification.

Figure 4. Examples of object segmentation. Contours of segmented objects displayed over 750nm filter images.

To serve as a reference for classification, segmented objects are manually sorted into 'SC' (segmented object is a true stem or calyx) and 'notSC' classes. In the end 427 objects were assigned to 'SC' class while 255 to 'notSC'.

classifiers		CART		C4.5	
		ground truth		ground truth	
classified		'SC'	'notSC'	'SC'	'notSC'
confusion matrices	'SC'	383	34	397	36
	'notSC'	44	221	30	219
class %		89.7	86.7	93.0	85.9
overall %		88.6		90.3	

Table 2. Confusion matrices of decision tree algorithms for stem/calyx recognition.

Beforehand, feature selection step is ignored and all features are introduced to the decision tree algorithms and their performances are observed. Table 2 displays confusion matrices of the two algorithms with respective recognition rates. Both algorithms perform more than 85 % recognition for individual classes, while C4.5 slightly outperforms CART in terms of overall accuracy.

Next, performances of algorithms are tested together with SFFS method to examine if a small subset of features is advantageous in terms of classification accuracy. Evaluation of overall recognition rate for C4.5 and CART with number of features added is displayed in Figure 5, where a recently obtained result for linear discriminant classifier (LDC) [4] is also displayed for comparison. For decision tree algorithms a quasi-optimal value is quickly reached with few change after 10 features. They are less sensitive to feature selection than LDC due to the intrinsic feature selection of their construction probably. In general, both CART and C4.5 outperform LDC in terms of recognition. Inconsistently, CART slightly outperforms C4.5 this time, which may be due to the SFFS feature selection method that is known to find sub-optimal solutions.

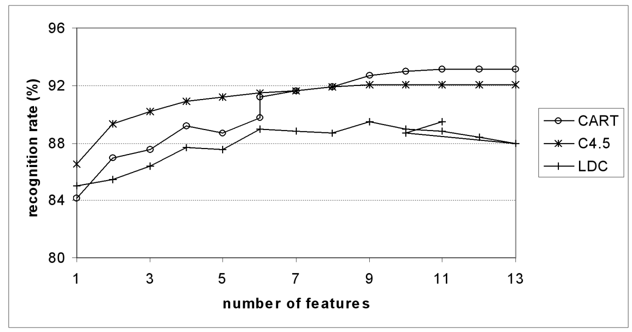

Figure 5. Effect of feature selection on recognition rates of algorithms.

C4.5 reaches to its highest recognition rate at 9 features point, while CART reaches its own peak at 11 features. Confusion matrices of both algorithms at these points with selected features are displayed in Table 3. In general, feature subsets are not similar (only 3 in common: μ_{450}, ϕ_{450} and ϕ_{800}) and shape features are not favored by the algorithms (except S of C4.5). Both algorithms perform similarly for 'SC' class, while CART is more accurate for 'notSC'. Overall recognition rates are higher than those achieved without feature selection (see Table 2), which confirms necessity of feature selection.

Thorough observation on misclassifications of both CART and C4.5 revealed conclusions that are consistent with those introduced by Unay and Gosselin [4]: Recognition accuracy is related to the location and quality of the segmented objects. If an object is closer to the edge of fruit, then it is likely to be missed. Also if segmentation is erroneous, then recognition is degraded.

Statistical comparison of accuracies of CART and C4.5 with best features subsets resulted in a McNemar's value of 1.05. As this value is lower than 3.8415, the two systems are not significantly different.

4 Conclusions

Discrimination of stems and calyxes from surface defects of apples by computer vision is crucial for fruit inspection systems. In this paper we proposed a decision tree-based approach for this discrimination using images of a multi-spectral vision system. Segmentation is achieved by

classifiers		CART		C4.5	
features		μ_{450}, max_{450}, $grad_{450}$, ϕ_{450} min_{500}, $grad_{500}$, max_{750}, min_{800} $skew_{800}$, $kurt_{800}$, ϕ_{800}		μ_{450}, ϕ_{450}, max_{500}, $skew_{500}$ $kurt_{500}$, σ_{750}, $grad_{750}$, ϕ_{800}, S	
		ground truth		ground truth	
classified		'SC'	'notSC'	'SC'	'notSC'
confusion matrices	'SC'	407	25	406	33
	'notSC'	20	230	21	222
class %		95.3	90.2	95.1	87.1
overall %		93.4		92.1	

Table 3. Confusion matrices of decision tree algorithms for stem/calyx recognition with best feature subset.

thresholding and morphological filling operations. Segmented objects are manually classified to serve as a reference database. Then, statistical, textural and shape features are extracted from each segmented object. Features are introduced to the two decision tree algorithms: CART and C4.5, where the latter slightly outperformed the former in terms of overall accuracy. In order to test the effect of feature selection on performances of CART and C4.5, sequential floating forward selection method is employed. It is observed that feature selection removed irrelevant/redundant features and lead to improved overall recognition rates. CART is observed to slightly outperform C4.5 this time with 93.4 % overall recognition, but two systems were not significantly different with respect to McNemar's test. Misclassifications realized by both systems were related to the location of segmented objects and quality of segmentation process.

5 Acknowledgements

This research is funded by the General Directorate of Technology, Research and Energy of the Walloon Region of Belgium with Convention No 9813783.

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