STEM-END/CALYX DETECTION IN APPLE FRUITS

Comparison of Feature Selection Methods and Classifiers

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Abstract A multiple classifier system to localize stem-ends and calyxes of apple fruits was introduced previously. In this paper we not only introduce a new decision step to this system, but also provide comparisons of several feature selection algorithms and classifiers used. Our results prove that floating forward selection is the best within heuristic methods and support vector machines are better than nearest neighbor classifier in discriminating stem-ends/calyxes from defects.

Keywords: Apples, stem-end, calyx, detection, machine vision, feature selection

Introduction

Machine vision-based fruit grading is an important and necessary task for fruit marketing. In this area discrimination of stem-ends or calyxes from defects, which can lead to incorrect grading of fruit, is still an open problem. Some researchers used special illumination to find stem-ends and calyxes [11], [7]. Li introduced fractal dimensions with artificial neural networks to discriminate them from defects [8]. Leemans and Destain used pattern matching to localize calyxes and stem-ends [10]. Unay and Gosselin proposed a multiple classifier system to discriminate stem-ends/calyxes from defects [13].

1. Methods

Image Database

Database consists of images of 819 'Jonagold' apples acquired by a ccd-camera and four bandpass filters(centered at 450, 500, 750, and 800 nm) from one-view in a diffusely illuminated environment at the Agricultural University of Gembloux, Belgium [1]. Each image has a dimension of 430x560 pixels with 8 bits-per-pixel resolution.

Defected and stem-end/calyx regions within the database are manually segmented by O. Kleynen and D. Unay, respectively and are used for evaluation.

System Architecture

Overall system for stem-end/calyx identification, proposed by the authors before [13], is used in this work (Figure 1).

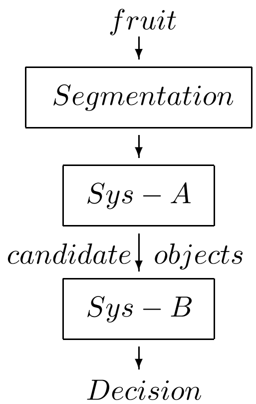

Figure 1 Architecture of the system recognizing stem-end / calyx of apple fruits, proposed previously by the authors [13]. Inspection area is extracted in *Segmentation* step, candidate regions are found in *Sys-A*, candidate regions are recognized in *Sys-B*, and stem-end/calyx of fruit is found in *Decision* step.

In *Segmentation* step, fruit area is extracted by thresholding, morphological filling [12], and erosion steps giving out the region-of-interest for *Sys-A*. Then, *Sys-A* does a pixel-based search of the fruit skin for potential stem-end/calyx objects by an artificial neural network. Objects smaller than 100 pixels found by *Sys-A* are removed (Our observations revealed that, stem-ends and calyxes in our database are far bigger than this threshold). *Sys-B* extracts features from the candidate objects provided by *Sys-A* and decides if a candidate object is really a 'stem-end/calyx' or not, providing a score value for each object.
If more than one objects are classified as stem-end/calyx by *Sys-B*, then the one with the lowest score is selected as stem-end/calyx of the fruit in *Decision* step. Calculation of score depends on the classifier used. For KNN, it is the distance of the sample from its nearest neighbors that are in the same class with the sample. SVM gives out a prediction value for each sample according to its support vectors. For 2-class case if this value is lower than zero than sample is classified to one class, else it is assigned to the other. So, absolute of this prediction value is used as score with SVM.

Feature Extraction

In *Sys-A*, each pixel is represented by its intensity value plus average and standard deviation of intensities of fruit skin, which are calculated from the image of filter centered at 800nm.
In *Sys-B*, following features are extracted from each candidate object. Aver-

ages and ranges of intensities of objects after several filtering techniques applied ($f_1 - f_8$), invariant moments of Hu ($f_9 - f_{15}$) [3], textural features of Haralick from Gray-Level Co-occurrence Matrices (GLCM) ($f_{16} - f_{26}$) [4], fractal dimension values of Kaplan ($f_{27} - f_{29}$) [5], averages and ranges of coefficients of Daubechies wavelet decomposition ($f_{30} - f_{69}$) [6].
Aim of this paper is not to focus on feature extraction and due to the limited space of this paper, details of features will not be further covered here. For a more detailed explanation on feature extraction, please refer to [13].

Feature Selection

In *Sys-B*, there are 69 possible features that can be used by the classifier. However this feature set contains irrelevant features as well as relevant ones and accuracy of a classifier is exponentially degraded as more irrelevant features are introduced. A feature selection method can avoid this and find a subset of best discriminating features. Exhaustive search of feature space guarantees optimal solution, but it is impractical as there exists 2^{69} possible subsets for our case. Therefore, following heuristic selection methods are used:

Stepwise Forward Selection (SFS): Starts with an empty set and successively adds features.

Stepwise Backward Selection (SBS): Starts with a full set and successively removes features.

Stepwise Floating Forward Selection (SFFS): Successively adds features like in SFS, but after each addition step removes any previously added feature if their removal decreases error [15].

Plus L Take Away R (PLTAR): Successively adds L and removes R features at each search step.

It should be noted that features are normalized before being introduced to the classifiers. In order to eliminate intersection of training and test sets, and to have realistic results with our small database, leave-one-out method is used throughout this work.

Classifiers

Artificial Neural Network: A two-layer artificial neural network is used in *Sys-A* for fruit skin classification. It is a feed-forward network of perceptron neurons with adaptive learning rate, it has 10 hidden nodes and it uses cross-validation technique.

K-Nearest Neighbor: The classifier used in *Sys-B* is a nearest neighbor classifier with Euclidean distance metric.

Support Vector Machine: Support vector machine (SVM) of Almeida is also tested in *Sys-B* instead of nearest neighbor classifier [14]. A 2^{nd}-order polynomial kernel is used with SVM for simplicity.

2. Results

Images of 616 fruits are introduced to the system and *Sys-A* found candidate objects within 327 of those, where 80 of them did not include any stem-end/calyx region actually (false alarms of *Sys-A*). Some of the candidate objects found by *Sys-A* can be observed in Figure 2. As the system is designed to work automatically, all the objects found by *Sys-A* will be introduced to *Sys-B* for *Decision*. So, accuracy of *Sys-A* highly effects the difficulty of the problem for *Sys-B*. Especially if the candidate objects found by *Sys-A* are actually a part of a bigger object (part of a defect, like in the left image or part of an object due to roi extraction like in the right image). Despite these disadvantages, *Sys-A* did not miss any of the stem-ends or calyxes existing within the images of 616 fruits. In our previous work, *Sys-B* was found to be more accurate when a

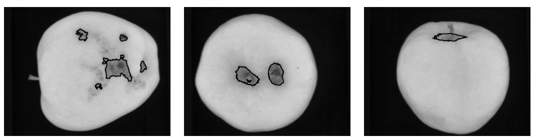

Figure 2 Examples of candidate objects found by Sys-A. Objects are contoured in black and displayed with the fruit image

subset of features found by SFS are used instead of one [13]. So, performance of *Sys-B* is tested with features found by several features selection methods. Figure 3 shows best results of each method in terms of classification error and number of features selected. KNN with 5 neighbors is used as classifier. Results show that SFFS and P2TA1 (PLTAR with L=2, R=1) methods are better than SFS and SBS in terms of low error with low number of features. But, one can never be sure how many features to add and remove in PLTAR selection method. So, SFFS method performs best (20.3% error with 12 features) within these four.

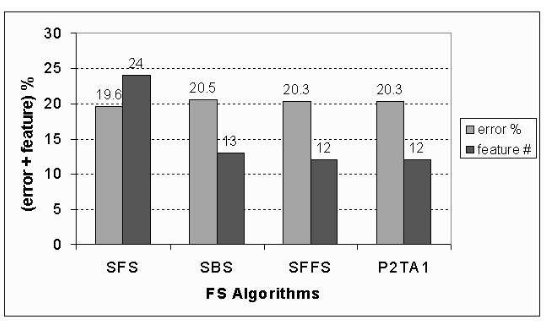

Figure 3 Performance of feature selection methods by nearest neighbor classifier with 5 neighbors. Horizontal axis shows feature selection methods and vertical axis shows classification errors with number of features selected.

SVM is a kernel-based learning machine, which has the advantages of ability to solve real-world problems and fast convergence, can be used instead of KNN classifier in *Sys-B*. So, performance of *Sys-B* is tested with SFFS feature selection method using these two classifiers. Several tests were done by KNN with various neighbors, but 21 neighbors is found to be the best. An upper bound of 100 for Lagrangian multipliers is used for SVM classifier. Figure 4 shows the evaluation of error for both classifiers with feature selection step. As observed, errors of SVM classifier are about 10% better than those of KNN generally. There are clear cut-off regions for both classifiers: KNN surpasses itself in performance if 9 or more features are introduced, whereas for SVM this cut-off is at 6 features. Best error rates reached by classifiers are 19.0% with 16 features for KNN and 9.5% with 12 features by SVM.

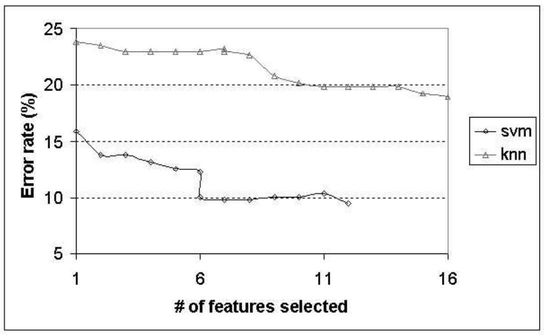

Figure 4 Performance of classifiers with SFFS feature selection method. Horizontal axis shows number of features selected and vertical axis shows classification error in percentage.

Table 1 displays the selected features and confusion matrix of the best cases among all the feature selection analysis for two classifiers. Observations show that same 9 features are selected in both tasks, where 6 of them are invariant moments of Hu. SVM outperforms KNN not only in global error rates but also in errors of classes. Error rates of 'Other' class prove the difficulty of the problem for *Sys-B* posed by *Sys-A*.

classifier	KNN		SVM	
features	$f_1, f_2, f_6, f_8 - f_{15}$ $f_{23}, f_{30}, f_{45}, f_{46}, f_{53}$		$f_1, f_5, f_6, f_{10} - f_{15}$ f_{22}, f_{46}, f_{50}	
	true classes		true classes	
graded in	SC	Other	SC	Other
SC	219	34	242	26
Other	28	46	5	54
error %	11.3	42.5	2.0	32.5
global error %	19.0		9.5	

Table 1 Confusion matrix of best-discriminating feature subset for classifiers found by SFFS selection method. 'SC' class refers to fruits having stem-end/calyx in roi and 'Other' class refers to those which don't have any.

3. Conclusions

A multiple classifier approach for recognizing stem-ends/calyxes in apple fruits was introduced by the authors before. In that previous work fruit-wise decision was missing. Therefore a new decision step, which uses score values of objects calculated by *Sys-B*, is introduced here. Several heuristic feature selection methods are tested and stepwise floating forward selection method is found to be the best. Results of feature selection methods other that heuristic approaches can be tested. Support vector machine of Almeida is used instead of nearest neighbor classifier in the system and found to perform better. Effect of using kernels other than polynomial ones and different bound values of Lagrangian multipliers on the performance of SVM has to be tested.

4. Acknowledgements

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