A STUDY ON QUALITY GRADING OF 'JONAGOLD' APPLES

D. UNAY - B. GOSSELIN

unay@tcts.fpms.ac.be - gosselin@tcts.fpms.ac.be
TCTS Lab, Faculte Polytechnique de Mons
Initialis Scientific Parc, Copernic Avenue 1, B-7000, Mons, Belgium

ABSTRACT

In this paper preliminary results on quality grading of 'Jonagold' apples are presented. Apple area is divided into subregions from where various features are extracted. Another segmentation method, 'geometric centers', is also introduced. Effects of direct vs separate principle components analysis and k-nearest neighbor vs neural network classifiers on the performance are discussed.

1. INTRODUCTION

Quality classification and defect segmentation of apples is a hard task due to multi-colored skin of some kinds, stem-calyx parts or concavity of apples leading to misclassifications, and defects highly varying in types, sizes.

Leemans et al.[1]-[2] applied Gaussian and Bayesian-based pixel classification methods on 'Golden Delicious' and 'Jonagold' apples. Nakano[3] used neural networks for color grading of 'San Fuji' apples. Rennick et al.[4] used a controlled acquisition system and classified 'Granny Smith' apples with different classifiers. Miller et al.[5] used spectral reflectance properties of apples, whereas Yang and Marchant[6] used snakes and a flooding algorithm to detect blemishes. Wen and Tao[7] and Pla et al.[8] both built automated apple sorting systems, where the system of latter one is applicable to many other vegetables.

2. DATABASE

The database consists of 280 healthy, 246 defect, 148 stem, and 145 calyx images of 'Jonagold' apples taken by a ccd-camera from one-view in a diffusely illuminated environment. Four filters at 450, 500, 750, and 800 nm were used in the acquisition system yielding to red, green, blue, and infra-red bands (Figure 1).

All the images contain stem-calyx regions either in the center or at the edge, however stem-calyx images mentioned above refer to ones with stem-calyx regions in the center view. Defect images include various kinds of defects like bruise, rot, russet, scald, limb rub, hail damage...

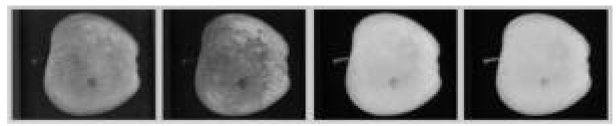

Fig. 1. Images of a defected apple. From left to right: blue, green, red, and infra-red bands.

3. IMAGE SEGMENTATION

In 2D image processing, working with rectangular regions is highly preferred due to their low computational cost compared to circular, hexagonal,... ones[10].

Images of the database contain apple views in black background. After thresholding infra-red band and applying morphological 'flood-fill' operation, resulting binary image contains only the apple region. Starting from the bounding box of this binary image, it is possible to fit a rectangle inside the circular apple region maximizing the *'used-area'* ratio (Figure 2). This ratio, which is about 60% in average for our database, is found by dividing the area of the rectangle with the total area of the apple in the view. The rectangle can then be divided into equal-sized subregions. In this paper we present the results found by 5x5 subregions fit into the rectangle.

Representing an apple view by such a rectangle means modelling an apple, a sphere-like object, by a cube. For such a model to be realistic, at least 6 different views are needed. This project is still in progress and current approach is concentrated on 4-view image acquisition. So, to realistically represent an apple with four views it is necessary to increase the *'used-area'* ratio. Here we propose *'geometric centers'* method which is simply dividing the object into regions using geometric centers. Split the object into four pie regions with horizontal and vertical borders at its geometric center (1^{st}-level). Then find geometric centers of each region and split into four (2^{nd}-level). Continue splitting until a stopping criteria. This method needs all pixels to be passed for each split-level, which is computationally expensive. However preliminary tests show that it is possible to increase the *'used-area'* ratio to 85% with only 3^{rd}-level

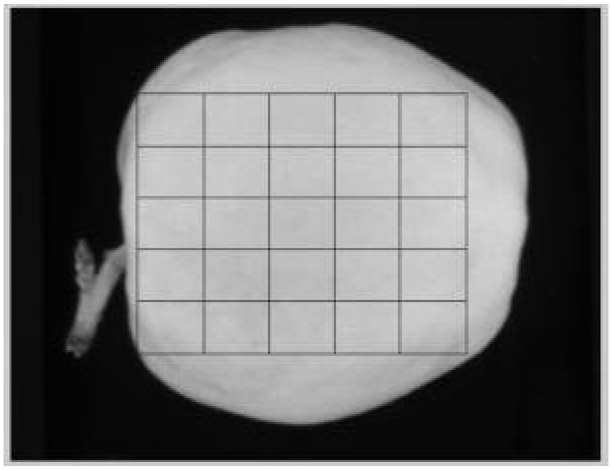

Fig. 2. 5x5 subregions in an apple image.

splitting. As *'geometric centers'* method is not used in this study, we will not go into further details.

4. FEATURE EXTRACTION

Statistical, textural and spectral types of features are extracted from each rectangular subregion. Statistical features are the mean, variance, minimum and maximum values. Textural features are Haralick's [9] energy, entropy, inertia and local homogeneity found from the co-occurance matrices of 1-pixel distance and four different orientations(0°, 45°, 90°, 135°). Resulting textural features are the averages of the values found from each orientation. Spectral features are the averages of the 2^{nd}-order Coiflet wavelet coefficients. 4 statistical, 4 textural and 14 spectral make a total of 22 features for each subregion.

Principal Components Analysis (PCA), also known as Karhunen-Love transformation, is applied on the features of each subregion to remove correlation and reduce dimensionality. PCA is simply multiplying the feature matrix by eigen vector matrix of the covariance matrix of it. Dimensionality reduction is done from variances of the eigen values. Advantage of separate PCA analysis for pixel-based apple quality grading was shown in Unay and Gosselin[11]. So, two approaches are used in this study: direct and separate. In the former all the 22 features of a subregion were introduced to PCA analysis together, whereas features of different types are introduced separetely in the latter.

After PCA analysis, a method widely used in Discrete Pulse Code Modulation technique was applied on the feature matrix. Average of features through subregions are calculated for each color-band. The new feature matrix is then composed of these averages and deviations of originals from them.

5. CLASSIFIERS

The aim of this paper is to introduce preliminary results obtained by image processing methods rather than concentrating on classifiers. Two classifiers implemented by the authors are used in this work: k-nearest neighbor (KNN) and single-layer perceptron (SLP). The former one, which uses Euclidean as distance measure, is chosen due to its tendency to nearly-optimal solutions at large sample limits, low computational cost and easy implementation. The latter one, is a feed-forward network with back-propagated error and adaptive learning rate and uses cross-validation between training and validation sets while training process. Considering the small dataset, SLP is thought to be enough in these preliminary tests.

6. RESULTS

Following results are of 2(healthy or defect), 3(healthy or defect or stem/calyx), and 4-class(healthy or defect or stem or calyx) recognition tasks, where equal number of samples are selected from each class to enable equal distribution. In each recognition task, $(1/4)^{th}$ of each class of the dataset is assigned as test set, $(9/16)^{th}$ as training set and $(3/16)^{th}$ as validation set leading to non-overlapping sets.

6.1. Direct PCA vs Separate PCA

Table 1 shows the best true-classification results of direct and separate PCA methods for 2-class recognition task in percentages.

	PCA	
	direct	separate
training	95.3	98.6
validation	92.4	94.6
test	91.9	94.3
healthy	92.1	96.8
defect	91.7	91.7

Table 1. Best results of 2-class recognition task.

Test rates show that separate PCA analysis performs 2.4% better than the direct one. This increase is also observable in the rates of healthy class, whereas the ones of defect class are constant. All the recognitions are higher than 90% regardless of the method indicating that it is possible to reach high results in 2-class task with our approach.

Best recognitions of test set with direct/separate PCA analysis are 81.1% / 83.8% and 66.2% / 70.3% for 3 and 4-class tasks, respectively. These values also justify that separate PCA analysis is better than the other.

6.2. KNN vs SLP

Within the direct PCA results of SLP for 2-class task, the worst performing one (5 linearly combined features from each region) was selected and its features were fed to the k-nearest neighbor classifier. Table 2 shows the recognition results of KNN classifier with varying neighbors as well as of SLP one to permit comparison.

method	neigh.	test	healthy	defect
KNN	1	58.5	76.2	40.0
	5	60.2	92.1	26.7
	10	63.4	96.8	28.3
	15	61.0	100.0	20.0
	20	59.4	100.0	16.7
	25	56.9	100.0	11.7
SLP	-	78.1	76.2	80.0

Table 2. Comparison of KNN and SLP classifiers by direct PCA method.

Best test rate of KNN classifier (63.4% with 10 neighbors) is 14.7% lower than that of SLP. As the number of neighbors increase, KNN performs better rates, but after 10-neighbors level it tends to classify each sample to healthy class and performs closer to 50%. Eventhough KNN outperforms SLP in recognition of healthy samples, its best rate for defect samples (40%) is half of that of SLP (80%).

7. CONCLUSION

It is shown that by using 5x5 non-overlapping subregions and approximately 60% of the apple region it is possible to reach high recognitions for healthy-defect decisions in 'Jonagold' apples. Separate PCA analysis outperforms the direct one for all (2, 3, and 4-class) decision tasks. KNN cannot reach to the performance of SLP, proving that quality grading of 'Jonagold' apples is a hard task.

Main goal of this project is to make a fully automatic and very fast (10 apples/sec) grading system. Results are promising, but it is necessary to examine the effects of varying subregion numbers, and 'geometric centers' method on performance. Multi-layer perceptrons should be tried regarding the size of available database and allowed recognition time. Then our studies will concentrate on classifying various defect types with different classifiers.

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