Automated Skin Defect Identification System for Fruit Grading Based on Discrete Curvelet Transform

Suchitra A. Khoje[1], Dr. S. K. Bodhe[2], Dr. Alpana Adsul[3],
[1]Research Scholar, Symbiosis International University,
Lavale, Pune, Maharashtra, India-11042
Email : suchiamol08@gmail.com
[2]Principal, College of Engineering, Pandharpur, India,
[2]Director, Bosh Technology, Pune, Maharashtra, India.
Email: skbodhe@gmail.com
[3]Assistant Professor, Sinhgad Institute of Technology and Science,
Narhe, Pune, Maharashtra, India.
Email : alpana.adsul@gmail.com

***Abstract*—**

The purpose of this study was to develop a methodology for assessing fruit quality objectively using texture analysis based on Curvelet Transform. Being a multiresolution approach, curvelets have the capability to examine fruit surface at low and high resolution to extract both global and local details about fruit surface.

The fruit images were acquired using a CCD color camera and guava and lemon were analyzed by experimentation. Textural measures based on curvelet transform such as energy, entropy, mean and standard deviation were used to characterize fruits' surface texture. The discriminating powers of these features for fruit quality grading is investigated. The acquired features were subjected to classifiers such as Support Vector Machines (SVM) and Probabilistic Neural Networks (PNN) and the performance of classifiers was tested for the two category grading of fruits namely healthy and defected. The results showed that best SVM classification was obtained with an accuracy of 96%. The study concludes that curvelet based textural features gives promising insights to estimate fruit's skin damages.

Keywords: Discrete Curvelet Transform, Textural features, machine vision, SVM, PNN

I. INTRODUCTION

Computer vision systems have proven their dominance in automating visual inspection in the industry[1]. One meticulous implementation is the inspection of the quality of biological products, which naturally vary in the color, shapes, sizes and environments[2].

The food industry has widely used machine vision for quality inspection of fruits, vegetable and processed food. The final application of such systems includes grading, estimation of the quality parameter from external or internal parameters[3]. The overall appearance of fruit object is a combination of its chromatic attributes (color) and its geometric attributes (shape, size, texture), together with the presence of defects that can diminish the external quality. The food industry is limited by international standards concerning quality. In this context, appearance measurement techniques must be used to guarantee good external quality of produce that meets the quality standards[4].

Skin damages and bruise detection are a vital factor for quality evaluation of fruits. Various approaches were opted by researchers for bruise detection. Rehkugler & Throop[5] investigated methods for bruise detection in apples using Interferential filters. A prior knowledge of the properties of a round convex object was used to detect blemished oranges[6]. Leemans and Destain[7] graded bi-colored apples into two quality categories using Quadratic Discriminant Classifier (QDC). A region-oriented segmentation algorithm was tested by J. Blasco[8] for detecting the most common peel defects of citrus fruits.

Much research has focused on the infrared[9] and hyper spectral imaging[10] for fruit grading. But we have limited the scope by focusing on computer vision based techniques used for defect detection of fruits.

The objective of this work is to detect external defects in fruit images using computer vision. Textural features such as energy and entropy, lower order statistical features mean and standard deviation based on discrete curvelet Transform are calculated. Finally, this information is combined using classifiers to recognize defected fruits from healthy one.

Fig. 1 shows the schematic diagram of proposed curvelet based fruit grading method. First, curvelet transform is applied to decompose an image in various curvelet subbands at scale S=2. Then, energy, entropy, mean and standard deviation computed from curvelet coefficients are used to extract textural properties of healthy and defected fruit. These four extracted features are independently tested on two classifiers, Support Vector Machines (SVM) and Probabilistic Neural Networks (PNN). Overall classification rates (percentage of correctly classified fruits) achieved with these classifiers for combined features range from 89 to 91 %.

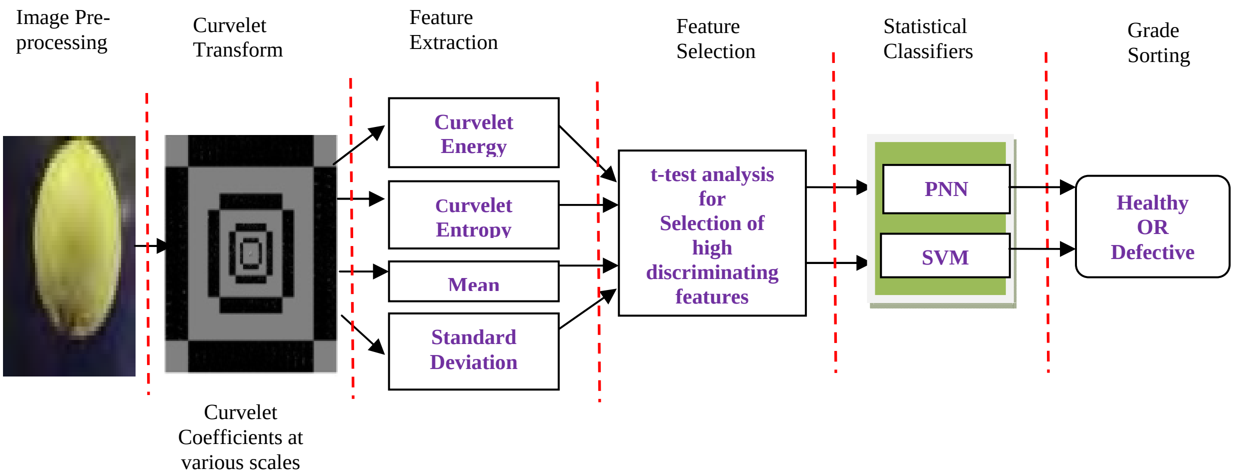

Fig.1 Schematic diagram of proposed curvelet based fruit grading method.

This paper is organized as follows: section 2 discusses materials and methods which includes a brief overview of curvelet transform and texture features analysis of fruit images. Experimental results and discussions are presented in section 3 and finally, section 4 concludes the paper and outlines directions for future work.

II. MATERIALS AND METHODS

A computer vision based fruit blemish inspection system should start with segmentation, followed by extraction of texture features and then lead to achieve correct grading of fruits into corresponding quality categories. But here, more emphasis laid on the fruit grading part of the problem. Hence, simple segmentation process is facilitated with the assumption of the in-line sorting machine.

A. Sample Collection:

This work is aimed at grading of tropical fruits of Maharashtra such as Guava (Psidium guajava L) and Lemon (citrus fruit).

For this, a total of 300 guavas and 1040 lemons of different varieties and ripeness levels were collected at random from orchards. Guavas were collected from the orchards of Ichalkaranji, Sangali, Kolhapur (Maharashtra, India) and Borgaon (District: Chikodi, Karnataka, India). Lemon fruits were obtained from a local market in Pune (India). All the fruits were harvested during the production season 2012-2013.

In this study, rather than sampling the fruits randomly, we intentionally selected healthy and defected samples as a training set to cover the maximum range of defects. Obviously, establishing distinguishing boundaries using texture features requires inspection and grading by an experienced human expert. Thus fruits were first classified manually by professional inspectors into two categories as” healthy” and “defective”.

A database of fruit images was formulated by acquiring an image for each fruit by placing it over a black sheet. A uniform diffused illumination system was used and the distance from the camera to the sample was kept constant while capturing clear images of the fruits. These images formed the database to be used for extracting texture features from the fruit samples and to design a classifier to sort them.

B. Image Acquisition

Fruit images are captured using an image acquisition system which consisted of the following elements:

- The image acquisition system used in this study consists of a CCD camera, a lighting system composed of backlighting and a personal computer. The system has a CCD camera to capture the scene that consists of fruit. The camera is connected to a personal computer. Sony (DSC-W290) camera with resolution of 12.1 Megapixels is used in the setup.
- An image processing software package
  All the algorithms for image pre-processing and segmentation, color transformations, texture feature extraction and classification are written in MATLAB v7.0 (Math Works, Inc., USA). Fast discrete Curvelet transform is calculated using CurveLab Toolbox, Version 2.1.3.

C. Image Preprocessing

The captured image from experimental setup was in RGB color space. For extraction of texture features, the image was converted to grayscale using 'rgb2gray' MATLAB function.

To avoid computational delays associated with further image processing analysis, the images were resized to obtain 256×256 pixel images.

D. Discrete Curvelet Transform

Curvelet transform has two forms namely Continuous and Discrete Curvelet Transform. The former transform divides the image on frequency domain along the annular radial angle using window, while the later, divides the image using same-center square. Thus the later one is more suitable in image processing[11].

Curvelet transform has redundant information which can offer sparse representation of signals that have edges along the regular curve. Hence, curvelet transform was redesigned later and introduced as Fast Discrete Curvelet Transform (FDCT).

The first generation of Curvelet Transform used a complex series of steps involving the ridgelet analysis of the radon transform of an image. Thus the performance was extremely slow. This second generation curvelet transforms meant to be simpler to understand and use; as it discarded the use of the Ridgelet Transform, thus reducing the amount of redundancy in the transform and increasing the speed significantly as compared to its first generation version.

In order to implement curvelet transform, first 2D Fast Fourier Transform (FFT) of the image is taken. Then the 2D Fourier frequency plane is divided into wedges (like the shaded region in Fig.2). The parabolic shape of wedges is the result of partitioning the Fourier plane into radial (concentric circles) and angular divisions. The concentric circles are responsible for the decomposition of an image into multiple scales (used for band passing the image at different scales) and the angular divisions that partition the band passed image into different angles or orientations. Thus, to deal with a particular wedge; there is a need to define it at scale j and angle θ.

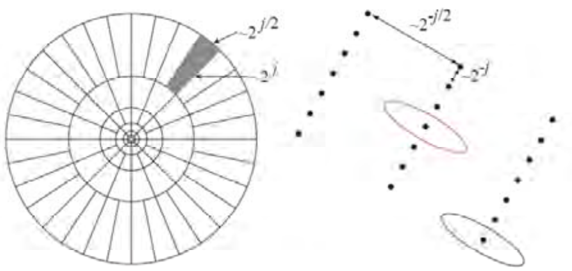

Fig. 2 curvelet transform in frequency domain (left) and in the spatial domain (right) [11]

Two implementations of Discrete curvelet transform are proposed[11]. The first digital implementation is based on unequal-spaced fast Fourier transforms (USFFT) while the second is based on the wrapping of particularly selected Fourier samples. The two implementations give same output but differ by the choice of spatial grid used to translate curvelets at each scale and angle.

In the first algorithm (FDCT via USFFT), the Curvelet coefficients are found by irregular sampling of the Fourier coefficients of an image. In this research, we have implemented the Curvelets via USFFT using Curvelab Toolbox version 2.1.3 of MATLAB.

These digital transformations are linear and take as input Cartesian arrays of the form [t1, t2], $0 \leq t1, t2 < n$, which allows us to think of the output as a collection of coefficients, cD(j, l, k) obtained by,

$$C^D(j,l,k) = \sum_{0 \leq t1, t2 < n} f[t1,t2]\overline{\varphi^D_{j,l,k}[t1,t2]} \qquad \ldots\ldots(1)$$

where each cD(j,l,k) is a digital curvelet waveform. The curvelet coefficients used in this study were obtained at the second resolution level.

E. Curvelet based Feature Extraction

The curvelet transform extracts the structural information of an image along radial 'wedges' in the frequency domain. This extracted information from the curvelet transform can be analyzed statistically to reduce the feature dimension to generate texture features. Mostly used statistical measures for texture classification in image processing include mean, standard deviation, energy, entropy, contrast, homogeneity, variance, correlation, sum-mean, cluster tendency, and inverse difference moment[12]. However, not all of these statistical measures are suitable as they are being applied to the curvelet transform, which extracts contrast of pixel pairs in radial ‘wedges’.

Four statistical curvelet-based texture descriptors namely, mean, standard deviation, energy, entropy were selected to investigate their discriminating power for fruit quality grading. Each of these features was computed from the curvelet coefficient matrix.

III. RESULTS AND DISCUSSIONS

A. *Curvelet based textural Feature values of fruits*

The curvelet based textural feature values (mean, std_dev, energy, entropy) were derived from two quality grades of fruit. Differences in these values were compared by t-test with significance level $p<0.05$ and given in Table 1.

For all textural features excluding standard deviation, there were significant differences between two qualities of the fruit. Thus, it can be observed that separation occurs between two qualities using mean, energy and entropy features. Thus, these three texture features are conclusive to classify the fruit in two qualities.

TABLE I
Curvelet Transform based texture features of fruits for two quality grades

Fruit	**Grade**	**Curvelet Transform based Texture Features**			
		Mean	**Std_dev**	**Energy**	**Entropy**
Guava	Healthy	38.1320±39.8075a	31.648±29.693a	1±0a	0.0580±0.0595a
	Defective	48.1270±50.8061b	32.963±30.183a	0.9992±0.001b	0.1519±0.2240b
Lemon	Healthy	36.1727±35.6785a	21.435±19.590a	1±0a	0.04560±0.0444a
	Defective	46.8270±48.6789b	22.333±20.111a	0.9902±0.000b	0.1734±0.2456b

Different lower case letters (a,b) indicate differences (p<0.005)by Duncan’s Test among different quality grades.

B. *Classification model based on selected features*

Vapnik[13] has described a statistical learning algorithm SVM which is a valuable tool used in data mining. SVM with various kernel functions such as linear, polynomial, radial basis function has demonstrated a good performance in different food classification research[14,15].

In this study, we developed SVM classifier with radial basis kernel function based on curvelet features for the automatic detection of defected fruit. SVM classifier was implemented in two steps: training and testing phase. For validation purpose, specifically 10-fold cross validation method was opted. The testing sample was randomly partitioned into 10 equal size subsamples and out of the 10 subsamples, a single subsample was retained as the validation data for testing the model, and the remaining 9 subsamples were used as training data.

The process was then repeated 10 times, with each of the 10 subsamples used exactly once as the validation data. The ten results from the folds were then averaged to get single estimation.

Table II shows a confusion matrix showing classification accuracy of the SVM classifier for detecting defects in fruits. The radial Basis kernel of the SVM classifier gives an accuracy of 91.42% and 95% for classifying Guava and Lemon respectively.

TABLE II
The success rate for two category fruit grading based on SVM classifier

Fruit	**True Categories**	**Graded in**		**Total fruits**	**Overall Accuracy (%)**
		Defective	**Healthy**		
Guava	Defective	160	0	160	91.42%
	Healthy	24	116	140	
Lemon	Defective	252	48	300	91.72%
	Healthy	4	736	740	

C. *Comparison of classification accuracy using different classifiers*

SVM classifier with radial basis kernel is compared with Artificial Neural Network. The probabilistic neural network was designed with some common parameters as shown in Table III.

TABLE III
Common parameter values used for all the PNN configurations

Parameter	Value
Learning Rate	0.1
Maximum number of epochs	5000
Performance Function	'SSE'
Number of neurons in input layer	600
Number of neurons in output layer	2

Table IV shows classification results for both classifiers. According to Table IV, an SVM classifier combined to mean, energy and entropy features achieved 91.41% and 91.72% for Guava and Lemon respectively. In addition, the classification accuracy of Probabilistic Neural Networks based on these three features was 85.71% and 80% for healthy and defective guavas, and the total accuracy rate was only 82.85% , as shown in the table IV. For probabilistic Neural networks, the classification accuracy was 80% and 98.91% for healthy and defective guavas, and the total accuracy rate was only 89.45%.

The results of this study show that SVM classifier with radial basis kernel function combined with mean, energy and entropy features are qualified to separate the defected fruit. Therefore, an SVM classifier combined with curvelet based statistical features is recommended for the detection of defected fruit in this study.

TABLE IV
Performance comparison of two classifiers

Fruit	Classification methods	Success Rate (%)		Total Accuracy
		Healthy	Defective	
Guavas	SVM	82.85%	100%	91.42%
	ANN	85.71%	80%	82.85%
Lemon	SVM	99.45%	84%	91.72%
	ANN	80%	98.91%	89.45%

IV. CONCLUSION

A new approach to classify the quality grade of guava and lemon fruit was developed using the SVM classifier based on curvelet transform based features. The three statistical features such as mean, energy and entropy showed high discrimination power in sorting fruit grades.

The probabilistic neural network classifier based on these statistics features achieved 82.85% and 89.45% for guavas and lemon respectively. However, the SVM classifier with a classification accuracy of 91.42% and 91.72% was found to be better than Probabilistic neural network classifier.

In our future work, we plan to use this method to detect skin damages on other fruits.

REFERENCES

[1] Ponsa D, Benavente R, Lumbreras F, Martınez J, Roca X,' Quality control of safety belts by machine vision inspection for real-time production', Optical Engineering, 42(2003), 1114–1120.

[2] Zheng C, Sun D W, Zheng L,'Recent developments and applications of image features for food quality evaluation and inspection e a review', Trends in Food Science & Technology,17(2010), 642–655.

[3] Cubero S., Aleixos N, Molt E,Gmez-Sanchis, J, Blasco J, 'Advances in machine vision applications for automatic inspection and quality evaluation of fruits and vegetables', Food Bioprocess Technol,(2010) 1–18.

[4] Blasco J, Aleixos N, Gómez-Sanchis J, Moltó E,'Recognition and classification of external skin damage in citrus fruits using multispectral data and morphological features', Biosystems Engineering, 103(2009)137–145.

[5] Rehkugler G E, Throop J A ,' Apple sorting with machine vision. Transactions of the ASAE, 29(1986), 1388–1397.

[6] MingHui Liu, Gadi Ben Tal,Napoleon H Reyes, Andre L C Barczak,'Navel Ornage Blemish Identification for Quality Grading System',Neural Information Processing Lecture Notes in Computer Science, 5864 (2009) 675-682.

[7] Leemans V, Destain M F, 'A real-time grading method of apples based on features extracted from defects', J. Food Eng. 61(2004), 83–89.

[8] J Blasco, N Aleixos, E Moltó, Computer vision detection of peel defects in citrus by means of a region oriented segmentation algorithm, Journal of Food Engineering, 81(2007) 535-543.

[9] Aleixos N, Blasco J, Navarron F, Molto E,'Multispectral inspection of citrus in real-time using machine vision and digital signal processors', Computers and Electronics in Agriculture, 33(2002) 121–137.

[10] Peirs A, Scheerlinck N, De Baerdemaeker J, Nicolai B M,'Quality determination of apple fruits with a hyperspectral imaging system', AgEng 02. Budapest, Hungary.EurAgEng Paper No. 02-PH-028.

[11] E. J. Candes, L. Demanet, D. L. Donoho, "Fast discrete curvelet transforms," Applied and C omputational Mathematics, 2005, pp.1-43.

[12] Haralick R M , Shapiro L G ,'Computer and Robot Vision', Addison-Wesley Publishing Co., (1992).

[13] Vapnik V, Statistical Learning theory, 1998, John Wiley, New York.

[14] Wu D, Yang H, Chen X, He Y, Li X, 'Application of image texture for the sorting of tea categories using multi-spectral imaging technique and support vector machine', Journal of Food Engineering, 88(2008), 474–483.
[15] Xie L, Ying Y, Yin T,'Classification of tomatoes with different genotypes by visible and short-wave near-infrared spectroscopy with least-squares support vector machines and other chemometrics', Journal of Food Engineering 94(2009), 34–39.
[16] Fernando Mendoza, Petr Dejmek, José M. Aguilera, 'Calibrated color measurements of agricultural foods using image analysis', Postharvest Biology and Technology, 41(2006) 285-295.