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Comparison of Citrus Fruit Surface Defect Classification using Discrete Wavelet Transform, Stationary Wavelet Transform and Wavelet Packet Transform Based Features

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Abstract: The aim of this study is to classify the citrus fruit images based on the external defect using the features extracted in the spectral domain (transform based) and to compare the performance of each of the feature set. Automatic classification of agricultural produce by machine vision technology plays a very important role as it improves the quality of grading. Multi resolution analysis using wavelets yields better results for pattern recognition and object classification. This study details about an image processing method applied for classifying three external surface defects of citrus fruit using wavelet transforms based features and an artificial neural network. The Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT) and Wavelet Packet Transform (WPT) features viz. mean and standard deviation of the details and approximations were extracted from citrus fruit images and used for classifying the defects. The DWT and SWT features were extracted from 40x40 sub-windows of the fruit image. The WPT features were extracted from the full fruit image of size 640x480. The classification results pertaining to the three wavelet transforms are reported and discussed.

Keywords: Artificial neural network, citrus fruit defects, feature extraction

INTRODUCTION

Classification of agricultural produces according to the type of defects seen on the external surface helps in automatic grading and sorting in the food processing and packing industry. Citrus fruits have growing demand owing to the nutritive value they have Ladaniya and Shyam (1999). The defects of citrus fruits appearing on the surface can be identified by the color difference from the normal skin surface. In manual sorting, due to fatigue (Qingzhong *et al*., 2002; Zhiqing and Yang, 1999) some of the defective fruits may be accepted wrongly and hence may pass the line, resulting in fatal consequences. Also manual-sorting process is very slow and the classification may not always be uniform as the decision taken by individuals, greatly differ. Hence automatic grading and sorting plays an important role, which minimizes the shortcomings of manual sorting (Devrim and Bernard, 2004; Upchurch *et al*., 1997). With advances in the machine vision technology, it is proved that the efficiency of the grading system has improved leading to good pricing of the products. Machine vision technology incorporates the image processing techniques to identify and classify the defects.

In manual inspection, the external defects are usually identified by the scale of skin discoloration seen by an individual, which is due to the browning reactions of the injured tissues (Reyer *et al*., 1996). In imaging, this discoloration appears as differences in reflectance from normal surfaces. But, the natural variation of color in the fruit surface can cause difficulties in the separation of defected area from the normal surfaces using image analysis. Image processing can be done in either of the two domains namely spatial and frequency (Rafael and Richard, 2003). The spatial domain refers to the image plane itself. Frequency domain processing techniques are based on modifying the Fourier transform of an image. Arthur (2003) Information, which is compact in the spatial domain, is not compact in the frequency domain and vice-versa. Moving from one domain to another provides clarity in features, which may not be obvious in the previous domain (Brooks *et al*., 2001). Images of natural products like fruits and vegetables greatly differ in color. So analyzing them with the images is not very easy as natural variation in color may result in poor segmentation, which may mislead the classification results. Texture analysis can be used for such applications wherein the area of interest cannot be segregated from the normal region by segmentation process alone. Texture classification methods are grouped into four major categories based on the types of features they associate with a texture such as statistical, structural, model-based and transform based (Vijayarekha and Govindaraj, 2004). In the transform-based methods, the most common

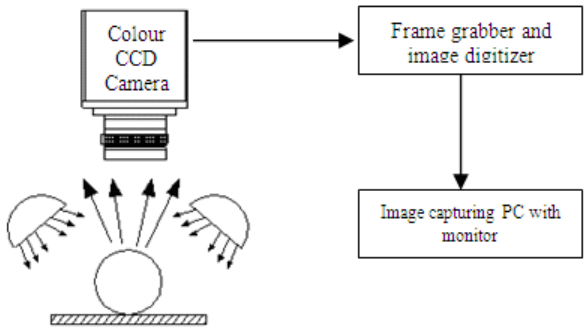


Fig. 1: Experimental set-up for imaging system

approach is to decompose the given input image into frequency sub-bands from which the features associated with textures present in the image can be extracted. This study aims at extracting the features of the images of the citrus fruit using the discrete wavelet transform, stationary wavelet transform and wavelet packet transform and to compare the performance of them. This study was conducted in Central Electronics Engineering Research Institute (CSIR) Lab, Taramani.

Types of citrus fruit external defects: Decay terminates the life of a citrus fruit after harvest. The major post harvest diseases are diplodia and phomopsis stem-end rot, splitting, pitting, green and blue mold, sour and brown rots, anthracnose and alternaria rot etc., Stephen and Timmer (2001). Among the various defects reported, we could resource and procure mandarin fruits with three types of defects viz. pitting, splitting and stem end rot. Pitting is caused due to oil gland collapse of many small circular pits associated with mechanical damage or reduced gas exchange (Offers, 1987). Pits can coalesce to form irregular patches and brown to black blemishes. Splitting is caused due the inability of the outer skin of the fruit to hold the weight of the fruit. The outer skin of the fruit splits and the inner fruit gets exposed. Unlike the other types of the defects, the defective region is brighter compared with the healthy tissues. Stem-end rot is of two types, viz. phomopsis stem end rot and diplodia stem end rot. In the initial stages of the infection, both types of stem end rot are similar. With phomopsis stem-end rot the infected tissue shrinks the affected area, which becomes tan to dark brown and a clear line of demarcation is formed at the junction between diseased and healthy skin. In images, the difference in texture can be distinguished by finding the edges, which separates the two textures. These are characterized by abrupt changes in the gray level. The analysis in the frequency domain makes use of these abrupt changes, called the frequency components. A high value of the wavelet coefficient represents the presence of more edges in the image indicating a texture, which is not uniform whereas a low value of the WT coefficient represents a smooth texture indicating no textural difference.

MATERIALS AND METHODS

Fruit samples and imaging setup: A total of 23 mandarin fruits were collected from the market, out of which 20 nos. were defective fruits and 3 nos. were good ones. Among the defective fruits 8 had pitting, 7 had stem end rot and 5 had splitting. The defects present in the fruits were identified manually based on the internet downloaded images and the images seen in the published literature. Figure 1 shows the imaging system, which consists of a color CCD camera (Pulnix TMC-6700 CL), a camera link interface compatible frame grabber card (NI-1428), an illumination source and a personal computer system (Pentium III @ 800 MHz).

Pulnix TMC-6700 CL is a progressive scan color camera with asynchronous reset capability and has camera link communication interface to the PC system through the frame grabber card. The camera has 1/2” format CCD sensor having 648 H x 484 V pixels resolution. A C-mount lens of focal length 6 mm was used. The illumination source used in the imaging system has incandescent and fluorescent lamps operating at 230V AC. Images were taken for all the 23 mandarin fruits. Mandarin fruits were placed on a vertical stand, one fruit at a time in the field of view of the camera and proper illumination was ensured. About three images were captured for each of the fruit sample at different fruit positions. Using Matlab 6.1, three image-preprocessing steps were performed. As a first step, the colour images were converted to gray scale images. Secondly the images were denoised using median filtering. Thirdly, the filtered images were segmented to check for the presence of the defect. The fruit images were considered to have external defect if the percentage of defect which is the result of the segmentation was above the set threshold value.

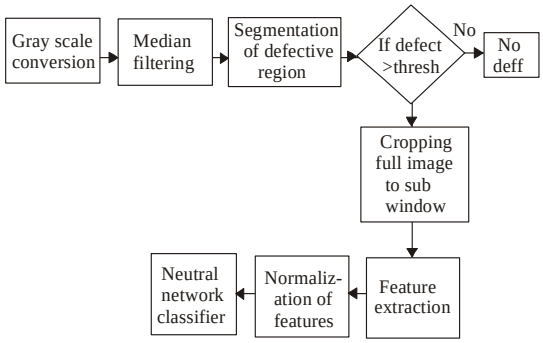


Fig. 2: Steps involved in image analysis

Citrus fruit defect classification system: The fruit images which were found to have external defect were taken for processing. Feature extraction was done in two ways:

- For features with DWT and SWT coefficients, the full fruit image was divided into sub windows of size 40x40
- For WPT features the full fruit image was taken for feature extraction

Using Daubechies wavelets, the coefficients of the three-wavelet transforms were calculated to get the three feature sets independently. The steps followed starting from segmentation to defect classification is shown in Fig. 2

DWT feature extraction and classification: Discrete Wavelet Transform (DWT) resembles the human visual system by providing a tractable way of decomposing an image into a number of frequency sub-bands at different scales. As micro-textures or macro-textures have non-uniform gray level variations, they are statistically characterized by the features in approximation and detail images. In other words, the values in the sub-band images or their combinations or the derived features from these bands uniquely characterize a texture.

Cropped sub windows of size 40x40 of the citrus fruit images (640x480) having defects were used for training and validation. A total of 145 cropped images were considered out of which 58 correspond to pitting defect, 43 belonged to splitting and 44 represented stem end rot defect. Thirteen images from each defect were reserved for validation and the remaining images from each defect type [45 for pitting, 30 for splitting and 31 for stem end rot] were used as training data. This amounts to 25% reservation of the samples available for validation.

Discrete wavelet transform was taken up to three levels using Daubechies 4 wavelet. We get four images one approximation also called as coarse image and three detail images viz. horizontal detail, vertical detail and diagonal detail. Two features for the four windows yields eight features for one level of decomposition. For the successive decomposition levels only the coarse image of the previous level is used. So the approximation image of the first level is decomposed to get the second level and the approximation of the second level is decomposed to get the third level of decomposition. For the approximation and details of images of the three level decomposition, the mean and standard deviations (Arivazhagan and Ganesan, 2003) were calculated using Eq. (1) and (2), which form the textural features. The mean is a measure of central tendency, portraying the average behavior whereas the standard deviation is a measure of spread portraying the spread around the mean. Twenty four features were extracted from the twelve images (approximation, horizontal detail, vertical detail and diagonal detail windows for three levels):

$$Mean(m) = (1/N)\sum_{i,j=1}^{N} p(i,j) \quad (1)$$

$$Standard\ deviation = \left[(1/N)\sum_{i,j=1}^{N}\left[p(i,j)-m\right]^2\right]^{0.5} \quad (2)$$

where, p (i, j) is the coefficient of the Wavelet Transformed (DWT) sub image at location (i, j) and N is the total number of pixels.

The approximation and detail sub windows from the first level of DWT decompositions for three different defects are shown in Fig. 3, 4 and 5. Figure 3a, 4a and 5a are the defective sub windows of size 40x40 cropped from the fruit image. Figure 3b, 4b and 5b are the approximation windows, Fig. 3c, 4c and 5c are the horizontal detail windows, Fig. 3d, 4d and 5d are the vertical detail windows and the Fig. 3e, 4e and 5e are the diagonal detail windows. The features, taken up to three levels of decomposition of the sub windows form the features (2x4x3 = 24).

The normalized features are used to train the neural network. If the features of one class is arranged continuously followed by the features of the other class and is given as training input to the neural network, there is a possibility that the neural network start to memorize the patterns instead of learning. Hence the inputs were arranged randomly and fed as training set. The input layer of the neural network was designed with 24 input neurons which were the same as the number of features extracted from the wavelet decomposition. As the number of pattern classes to be classified is three, the same will be the number of neurons in the output layer.

The features are normalized using the formula (x-m)/s σ

The weights were initialized randomly and checked for the convergence of the neural network by trial and error method. The best weight vector which results in better convergence with minimum error was stored. To

(a) (b) (c) (d) (e)

Fig. 3: DWT decomposition for pitting

(a) (b) (c) (d) (e)

Fig. 4: DWT decomposition for splitting defect

(a) (b) (c) (d) (e)

Fig. 5: DWT decomposition for stem end defect

Table 1: Confusion matrix for the DWT training set

	Pitting	Splitting	Stem end rot
Pitting	10	3	0
Splitting	4	9	0
Stem end rot	2	2	9

decide upon the number of units in the hidden layer, trial and error method was used. The error must be minimum for the net with the chosen number of hidden neurons and it was found to be 10. The training algorithm used was back propagation with momentum and adaptive learning. Tangent sigmoid functions, which are the best non-linear transfer function were used for both the hidden and output layers.

When the full image of the citrus fruit is considered, 40x40 sub windows are cropped and feature extraction is done only for the sub windows having the fruit region, as shown in Fig. 6. This minimizes the time taken for classification. The defect present in each of the sub windows can be identified when the normalized values of the mean and the standard deviation of the wavelet-transformed windows are given as input to the trained neural net.

The confusion matrix for the DWT training set is given in Table 1.

SWT features: Stationary Wavelet Transform (SWT) can be implemented for any arbitrary size of image as no down sampling process is used and the transformation is also called undecimated wavelet transform (Gnanadurai and Sadasivam, 2005). SWT is advantageous over DWT as it has better edge detecting capability and the denoising quality. The basic computational step of a DWT is a convolution followed by decimation. The decimation retains even indexed elements. Decimation could be carried out by choosing odd indexed elements instead of even indexed elements. If all different possible decompositions are performed on the original signal, then it will result in 2J different decompositions, for a given maximum level J. Let Єj = 1 or 0 the choice of odd or even indexed elements at step j. Every decomposition is labeled by a sequence of zeros and ones Є = Є1, Є2,…, Єj. It is possible to calculate all the Є decimated DWT for a given signal of length N by computing the approximation and detail coefficients for every possible sequence Є. All the Є decimated DWT can be obtained by convolving the signal with the appropriate filters as in DWT but without decimation (down sampling). Hence the approximation and detail coefficients at level 1 are both of size N. This transform is called Є decimated DWT or SWT. SWT is very efficient for textural analysis and enhancement processes (Vijayarekha and Govindaraj, 2005).

Sub windows which were used for training, validation and testing of DWT features were used for SWT too. Stationary wavelet transform was taken up to three levels using Daubechies 4 wavelet. For the approximation and details of images of the three level decomposition, the mean and standard deviations (Arivazhagan and Ganesan, 2003) were calculated (24

Table 2: Confusion matrix for the SWT training set

	Pitting	Splitting	Stem end rot
Pitting	10	0	3
Splitting	2	11	0
Stem end rot	0	0	13

features for the 12 windows which include approximation, horizontal detail, vertical detail and diagonal detail for the three levels) using Eq. (1) and (2), which form the textural features. Normalization of the input and randomization of input were performed as was done with DWT features. The neural network was constructed in the same way as it was done for DWT. For SWT feature set, the number of neurons in the hidden layer was found to be 6. The training algorithm used was back propagation with momentum and adaptive learning. Tangent sigmoid functions, which are the best non-linear transfer function, were used for both layers. When it comes to full fruit image classification, the same procedure was followed as that for the DWT features. The confusion matrix for the SWT training set is given in Table 2.

WPT features: If greater control over the partitioning of the time frequency plane is required, wavelet packet decomposition can be preferred. When the detail images are also decomposed further, we obtain the tree-structured decomposition. Wavelet packet transform not only makes use of the low frequency approximation sub windows but also uses the high frequency detail sub windows, which results in the next higher level of decomposition. Full fruit images were used for wavelet packet decomposition. Wavelet packet decomposition involves in down sampling of both the approximation as well as the detail sub windows and so the size of the decomposed windows becomes halved. The attributes obtained from the decomposition of such small detail windows will not be useful. Hence full images were preferred to extract the WPT features, the full fruit images were decomposed till three levels with Daubechies 10 wavelet.

Four sub windows from each of the four windows (approximation, horizontal detail, vertical detail and diagonal detail) of the second level decomposition results in sixteen windows in third level of decomposition. Mean and standard deviations (Arivazhagan and Ganesan, 2003) were calculated using Eq. (1) and (2), for all the 16 sub windows, which form the textural features. The extracted features are normalized and are used to train the neural network. The neural network was constructed with 32 input neurons, three output neurons and 10 hidden neurons. The training algorithm used was back propagation with momentum and adaptive learning. Tangent sigmoidal function was used as transfer function for both the layers. For the test fruit images, the procedure

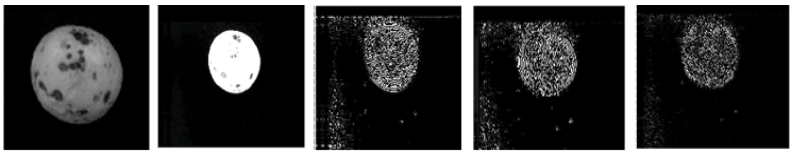


Fig. 6: WPT decomposition of pitting (second level)

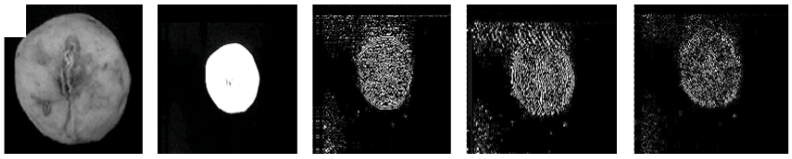


Fig. 7: WPT decomposition of splitting (second level)

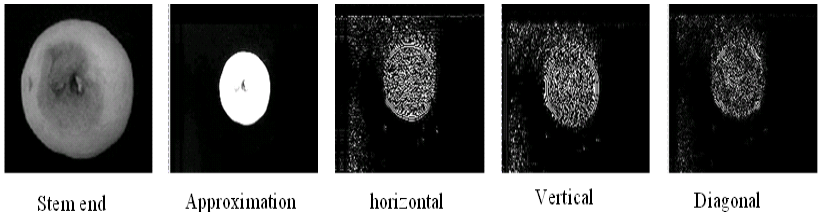


Fig. 8: WPT decomposition of stem end rot (second level)

Table 3: Confusion matrix for the WPT training set

	Pitting	Splitting	Stem end rot
Pitting	5	1	0
Splitting	5	1	0
Stem end rot	0	2	4

used for DWT & SWT is followed to extract the textural features the coefficients of the wavelet packet transformed images are used to calculate the mean and the standard deviation and are normalized before being given as input to the trained neural net. The trained neural net acts as a classifier to find the defect present in the fruit. Defective citrus fruit images with defects such as pitting, splitting and stem end rot, with the second level wavelet packet decomposition are given in Fig. 6, 7 and 8.

The confusion matrix for the WPT training set is given in Table 3.

RESULTS AND DISCUSSION

Totally 49 full fruit images covering the three defects corresponding to the 23 mandarin fruits were used for defect identification and classification. Out of 49 images, 19 images had pitting defect, 10 images contained stem-end rot defect, 12 images correspond to splitting defect and 8 images had no defect. The segmentation phase isolates the defective region from the good one, thereby identifying whether the fruit has external defect or not. If the segmented fruit area is above the set threshold value, the classification process will be carried out. The results of classification of the citrus fruits based on the external defects using the three feature sets are given in Table 4.

The statistical method deals with the occurrence of gray level pairs. Sometimes the natural variation of color in fruit surface may have intensity values, which may mislead the classification. In the case of the wavelet transform this misclassification is avoided as the transformation coefficients depends on the energy peaks, which arises due to the changeovers or high frequency components indicating the presence of edges resulting in better identification. Referring to Table 4, the classification rate for the DWT features is comparatively less for all the defect classes except for pitting because of the decimation process involved. This is because the minute edge information will be lost during the decimation.

The classification percentage using SWT features is found to be better when compared with the classification results of DWT and WPT features. Since there is no decimation, even the subtle variation in the edges can be identified by SWT, this leads to better classification when compared to DWT & WPT. The percentage of classification using SWT features is about 70 for stem end rot defect. It is so because of the images which had two different textures in it. As the number of cropped windows having texture resembling the pitting defect is more than the number of cropped windows which has the stem end rot defect, the system has identified the image of the full fruit image as pitting defect.

Table 4: Classification percentage using DWT, SWT & WPT

		Defect classification in percentage		
S. No		DWT	SWT	WPT
1	Pitting	94.73	95.23	84.21
2	Splitting	80.00	100.00	100.00
3	Stem end rot	20.00	70.00	50.00

As reported in the Table 4, the classification percentage for stem end rot defect using SWT features is still on higher side when compared with the classification results based on DWT and WPT features. The results obtained for the classification using WPT features for pitting and splitting defect classes were good. The percentage classification of stem-end rot affected fruits was only 50%. This is because of the fact that some test samples of the stem-end rot defect class were fully rotten and those images did not have textural difference on the fruit area. For wavelet packet transformation full fruit image was considered. The intensity variation in images of such fully rotten fruits was poor and the edges were not prominently defined. Hence, the edge detecting capability of WPT could not be utilized fully on such images, which resulted in poor classification rate. The test images of stem-end rot defect, which were not having defect at the edges leads to correct identification. The success percentage of classification for stem-end rot defect class can be improved by using more number of such images for training, testing and validating the algorithm.

As 40x40 windows were taken for feature extraction in the case of both DWT and SWT, even for the occurrence of a small defect the classification was fairly good. Sometimes the subtle changes in the variation of the natural color of the fruit will be misleading when sub windows are considered. This causes misclassification otherwise called classification errors in SWT and DWT features. In the case of WPT the classification depends on the defect present in the image of the full fruit. Hence misclassification becomes inevitable in the case of WPT when dual defects occur in the fruit. Sample images with the defect identified by the ANN classifier using the three feature sets are given in Table 5.

CONCLUSION

The texture analyzing capability of the wavelet transform was exploited for defect classification of citrus fruits and to analyze the efficacy of different feature sets. Performance of DWT, SWT and WPT feature sets were checked with neural network classifier. The fruits with defects were first identified in the segmentation phase.The images of the fruits, which had defects, were classified using the three feature sets. The comparison of the overall classification rate shows that SWT performs well compared with the other two feature sets. Because of the decimation involved in DWT and WPT, the details pertaining to the small edges between the defect and the good regions may get lost. But SWT does not involve

Table 5: Defect classification with actual defect and the input images

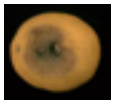
			Defect classified based on		
S.No	Fruit image	Actual defect	DWT features	SWT features	WPT Features
1		Stem end rot	Splitting	Stem end rot	Stem end rot
2		Stem end rot	Splitting	Pitting	Pitting
3		Splitting	Splitting	Pitting	Splitting
4		Splitting	Pitting	Pitting and splitting	Splitting
5		Pitting	Pitting	Pitting	Pitting
6		Pitting	Splitting	Pitting	Pitting
7		Stem end rot	Stem end and pitting	Pitting	Pitting
8		Stem end rot	Splitting	Stem end rot	---
9		Pitting	Pitting	Pitting	Pitting
10		Pitting	Pitting	Pitting	Pitting

Table 5: (Continue)

11	Splitting	Pitting and splitting	Splitting	Splitting
				
12	Splitting	Splitting and pitting	Splitting	Splitting
				

decimation and hence the details of the edges are preserved leading to better classification.

Even though the defect classification is 100% for splitting defect using SWT and WPT features, because of the rottenness appearing near the split surface of the fruit, the number of windows showing pitting defect was more. Since the texture of pitting defect is distinct from the fruit texture, the classification percentage for pitting is more when compared to the other defects As the texture difference between the normal skin of the fruit in image and pitting defect infected area of the image is more, the edges of such defects are prominent. Defect classification using the three wavelet transformations, which are mainly based on the energy peaks due to changeover of gray levels gives a good result

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