International Journal of Computer Applications (0975 - 8887)
Volume 53 - No. 3, September 2012

Performance Comparison of Fourier Transform and Its Derivatives as Shape Descriptors for Mango Grading

Suchitra Khoje
Research Scholar,
Symbiosis International University,
Lavale, Pune.

Shrikant Bodhe, PhD.
Principal,
College of engineering ,
Pandharpur.

ABSTRACT

Mango is a tropical fruit of India which plays a major role in earning foreign currency by export. The export sector of India is paying attention towards it because of its commercial significance. Image has assorted inbuilt features which reflect its content such as color, texture, shape, and spatial relationship features, etc. How to organize and utilize these features effectively in agriculture era is a valuable research topic. Shape is a first quality factor to be considered by consumer while purchasing mango fruit. The purpose of this research work is to explore image processing algorithms and techniques to sort misshapen mango fruits based on their shape features. The developed algorithm would be first step in automated grading and sorting machines in export industries. It can provide a base for fully automatic grading system using computer vision.

A shape based mango fruit sorting using computer vision is discussed in this paper. Shape features (Region based and contour based) are designed using Fourier Transform. Wavelet based descriptor is derived from basic Fourier transform to catch local shape details. A two layered radial basis neural network is developed to classify well formed and deformed mango fruits. The experiment results show performance comparison of all Fourier based shape descriptors. Wavelet Fourier Descriptor outperforms region based and contour based Fourier descriptor with classification efficiency of 89.83%.

Keywords:

Shape descriptor, Mango fruit grading, Neural network.

1. INTRODUCTION

The mango is a fleshy fruit belonging to the genus Magnifera and is native to the Indian subcontinent from where it spread all over the world. It is one of the most cultivated fruits of the tropical world. It is recognized and honored by Government of India as the National Fruit of India. It is grown in almost all states of India. India shares about 56% of total mango production in world [8] Andhra Pradesh tops in total production, whereas Uttar Pradesh tops area wise.

Shape is important aspect that is considered by a consumer while purchasing any fruit [11] and so it is of importance while assessing fruit quality. Abnormality in shape ultimately leads to rejection of foreign consignment. A cost effective and objective computer vision system is needed to segregate misshapen mango fruits. There are two major categories to characterize fruit shape such as size dependent measurements and size independent measurements.

Size dependant measurements are formed by descriptors which include compactness, elongation, convexity, roughness, etc. These descriptors are based on combinations of size measurements. Because of irregularity in biological shapes, they cannot be characterized by only size dependant measurements. Thus, Size-independent measurements (SIM), including region-based and boundary-based methods, have been developed [15]. Contour based shape descriptors can be applied to applications where shape contours are extracted by using contour tracing techniques [3]. Zhang [14] evaluated and compared two shape descriptors namely Fourier (FD) and Curvature scale space descriptor (CSSD) and concluded that Fourier Descriptor is found to be superior over CSSD. Thus FD is a most favorite shape descriptors and even modified Fourier based descriptor [13, 5, 6].

The region based methods consists of statistics of spatial information of pixel inside the object [1, 2]. This method is very effective to distinguish one shape from another. The boundary-based method obtains shape measurements by first representing the boundary and then analyzing it. This method includes Fourier Transform, autoregressive models, etc. Fourier Descriptors have been used by Currie [4] to develop apple classification system.

As local and sharp irregularities of boundary are not well captured by Fourier analysis; alternatively wavelet descriptor has been popular to catch local feature at multiple scales. Wavelet based shape descriptor was proposed by Slamet [9] to describe papaya shape. A new wavelet-based function for shape representation using only approximation coefficients was introduced by Rube [10] which is affine invariant.

In recent years, for content based image retrieval, computer vision techniques are developed by researchers using shape descriptors. This is the first attempt to use these shape descriptors for mango grading purpose. It is well-known that neural networks are good to perform non-linear mappings in pattern classification [7]. In this study, radial basis neural network is used to identify deformed shaped fruits.

The aim of this study is to evaluate the irregularity of the mango fruit shape using Fourier Based shape descriptors and neural networks. Thus aiming at more reliable, accurate and more sophisticated automated classification system for mango fruit. Mango cultivators produced in kokan area (Sindhudurga

District) of India are considered for experimentation.

2. SHAPE SIGNATURES

Shape signature represents shape by one dimension function. It is derived from shape boundaries. They provide information about the shape's features. Despite the fact that shape signatures can be used to describe a shape alone, they are often used as a preprocessing tool for other algorithms that extract features. Several shape signatures have been used to derive shape descriptors such as complex coordinates, centroid function, chord length signatures, curvature signature etc. However, FDs derived from different signatures can have significant different effect on the result of shape retrieval [14].

A contour *C* can be denoted as an ordered sequence of N coordinate points,

C=$\lambda_t = (x(t), y(t), t = 0, 1, , N-1)$, where *C* is closed. i.e.λ_i+$N = \lambda_i$. Let us see how shape signature is derived from contour *C*. We discuss here two shape signatures namely complex coordinate and centroid distance signature.

2.1 Complex Coordinate

It is simply a complex number generated from boundary points.

$$r(t) = [x(t) - x_c] + i[y(t) - y_c] \tag{1}$$

Where (x_c, y_c) is centroid of the shape and can be given as average of boundary points.

$$x_c = \frac{1}{N}\sum_{t=0}^{N-1} x(t) \quad and \quad y_c = \frac{1}{N}\sum_{t=0}^{N-1} y(t) \tag{2}$$

2.2 Centroid distance signature

The centroid distance function is expressed by the distance of the boundary points to the centroid$(x_c, y_c)$of the shape.

$$r(t) = \sqrt{[x(t) - x_c]^2 + [y(t) - y_c]^2} \tag{3}$$

Fig. 1 shows centroid distance signatures of the tree mangoes. The position of centroid, the center of gravity is fixed in relation to any shape. Since this shape signature is only dependent on the location of the centroid and the points on the boundary, it is invariant to the translation of the shape. To make them rotation invariant, starting point of the original shape can be identified on the rotated shape. This signature alone is not invariant to a change in starting point or scaling so we apply the Fourier transformation, normalize the coefficients, and then take the magnitude of these normalized coefficients to obtain a descriptor that is invariant to translation, rotation, scaling, and change of starting point.

3. SHAPE DESCRIPTORS

Fourier descriptor (FD)is one of the widely used shape descriptors. In general, the FD is obtained by applying a Fourier transform on a shape signature. A shape signature is any 1-D function representing 2-D areas or boundaries which is uniquely describes shape. The performance of FD method is affected by the shape signature as different shape signatures give different FD. Many shape signatures, such as complex coordinates, centroid distance, tangent angle, curvature, cumulative angle and so on, have been proposed for deriving FD. Zhang [16]compared six different FDs which are derived from different shape signatures. They concluded that FD derived from centroid distance function and proposed area function are the most suitable for shape representation.

3.1 Generic Fourier descriptor(GFD)

All pixels within shape region are considered in region based shape descriptor. Most commonly used region based descriptors are Zernike moments, Legendre moments, Generic Fourier Descriptors, and Wavelet Descriptors. Region based Fourier descriptor is called as generic FD as it can be applied to any application of shape representation and classification.

Shape analysis using Fourier Transform is backed by well developed and well-understood Fourier Theory. However, it is not desirable to acquire shape features using FT directly, because the acquired features are not rotation invariant and not compact. Therefore, a modified polar Fourier Transform (MPFT) is proposed by treating the polar image in polar space as a normal two-dimensional rectangular polar image [13].

If we plot a polar image into Cartesian space, it is the normal rectangular image. Therefore, if we apply 2-D Fourier Transform on this rectangular image, the polar FT has the similar form to the normal 2-D discrete FT in Cartesian space.

For a given shape image *F(x, y)*, the modified polar FT is obtained as,

$$pf(\rho, \phi) = \sum_r \sum_i F(r, \theta_i) \exp[j2\pi(\frac{r}{R}\rho + \frac{2\pi i}{T}\phi)] \tag{4}$$

where 0 $\leq$ r(t)=$\sqrt{[x(t) - x_c]^2 + [y(t) - y_c]^2}$ and θ_i=i($\frac{2\pi}{T}$) where (0$\leq i \leq T$);0$\leq \rho \leq$R ; 0 $\leq \phi <$ T and (x_c, y_c) is the center of mass of the shape; *R* and *T* are the radial and angular resolutions.

The physical meanings of ρ and ϕ are clear; they are the ρ^{th} radial frequency and the ϕ^{th} angular frequency selected to describe shape. The determination of the number of ρ and ϕ for shape description is physically achievable, because shape features are normally captured by the few lower frequencies.
The acquired Fourier coefficients are translation invariant. Rotation and scaling invariance are achieved by the following normalization:

GFD=$\frac{|pf(0,0)|}{area}, \frac{|pf(0,1)|}{|pf(0,0)|}, \ldots, \frac{|pf(0,n)|}{|pf(0,0)|}, \ldots \frac{|pf(m,0)|}{|pf(0,0)|} \ldots \frac{|pf(m,n)|}{|pf(0,0)|}$

where area is the area of the bounding circle in which the polar image resides;*m* is the maximum number of the radial frequencies selected and n is the maximum number of angular frequencies selected. Finally *m* and *n* can be adjusted to achieve hierarchical coarse to fine representation requirement. The advantage of MPFT over FT is that the acquired spectrum is rotation invariant and more concentrated to the origin. MPFT is also more advantageous than conventional polar FT, because both the radial features and the circular features captured by the coefficients are physically meaningful [13].

3.2 Contour Based Fourier Descriptors (FD)

In most of the applications, region of shape is not important; only outline or boundary is enough to describe that shape; such kind of shape descriptors are called as contour based shape descriptor. Simple one dimension Fourier transforms is used by researchers to represent shape. Fourier Descriptor is obtained by taking Fourier transform of shape signature. Discrete Fourier Transform (DFT) and Inverse Fourier Transform (IDFT) is given

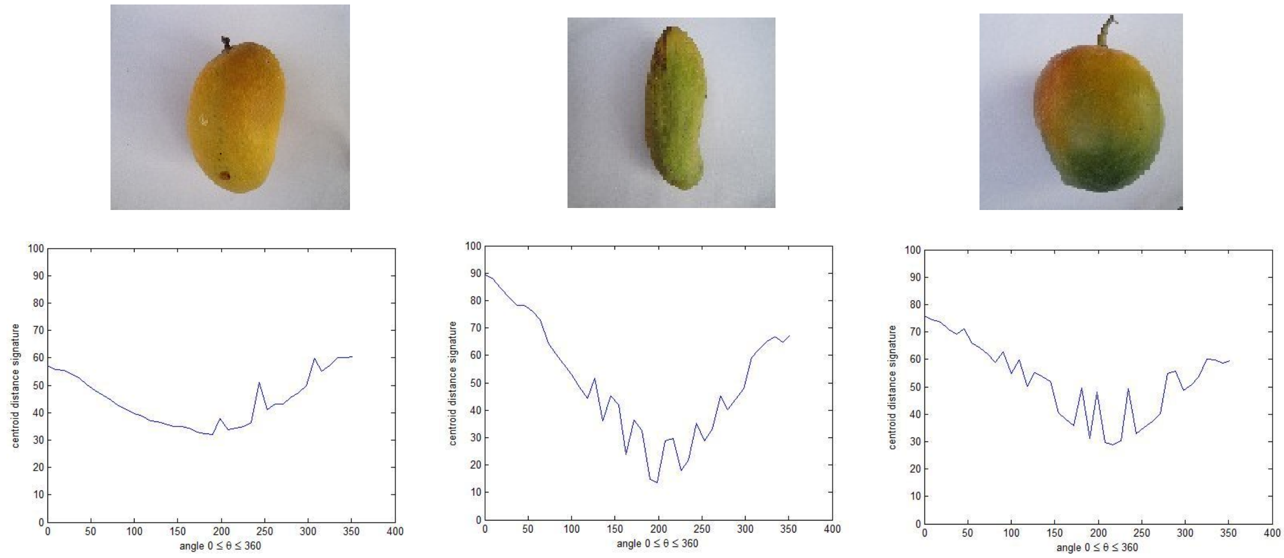

Fig. 1. Three mango shapes on the top and their respective centroid distance signature at bottom

by f(k) and r(t)respectively.

$$f(k) = \frac{1}{N}\sum_{t=0}^{N-1} r(t) \exp \frac{-j2\pi kt}{N} \tag{5}$$

where *K=-N/2,......N/2-1*

$$r(t) = \frac{1}{N}\sum_{k=0}^{N-1} f(k) \exp \frac{j2\pi kt}{N} \tag{6}$$

where *t=-N/2,......N/2-1*

Contour of shape in spectral domain is represented by Fourier coefficients *f(k)*. For scale invariance, all coefficients are normalized by dividing them by magnitude of first coefficient. Phase of coefficients gives you rotation information so to achieve rotation invariance phase information is ignored. Reseachers Zhang and Liu [14] concluded that FD outperforms than any other contour based shape descriptor. But for disjoint shapes, contour based descriptors are not suitable.

3.3 Wavelet Based Fourier descriptor (WFD)

Wavelet Descriptor is wavelet transformed coefficients applied on contour of shape. Wavelet transform analyse image information at different resolution by dilating the scale of the wavelet function and constructs time scale representation of signal. Thus relates local properties of the signal to the evolution of wavelet transform coefficients when the scale varies. It outperforms Fourier transform as it captures both frequency and location information. Wavelet coefficients are generated from mother wavelet function as shown by equation 7.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \int_R Z(t) \psi \frac{t-b}{a} dt \tag{7}$$

Where b is shifting parameter, a is scaling parameter, and $\sqrt{a}$ for energy normalization at different scale. For any specific scale a, wavelet coefficients can be obtained.

Wavelet Fourier descriptors [12] are obtained by applying Fourier transform on wavelet coefficients $\psi_{a,b}$ and is defined as(8),

$$f^a(k) = \frac{1}{N}\sum_{b=0}^{N-1} \psi_{a,b}(t) \exp \frac{-j2\pi b}{N} \tag{8}$$

Thus advantage of multi scale representation and Fourier shape descriptors are combined in this descriptor. WFDs are invariant to translation because of centroid function and to make it rotation invariant, we ignore phase information. For scale invariance we have to normalize this descriptor.

Shape contour is represented in frequency domain using WFD. Wavelet gives two kinds of coefficient namely approximation and detailed. Detailed coefficients give finer details about object shape. By applying Fourier Transform, we get N number of coefficients. Depending upon our interest, we can limit these numbers of coefficients.

4. MATERIALS AND METHODS

The samples of mangoes with various shapes used in this study were collected from mango orchard of Devgad, Ratnagiri, Kankavali, Vengurla. Database of 300 images, consisting of Alphonso (150), Piary (50), Totapuri(40), Langada(30), Dashhari(30) was created.

4.1 Data Acquisition

Mango fruit samples of various shapes and sizes were collected from an orchard. The mango images were snapshot by Sony digital color camera (resolution of 12 Megapixels) as shown in figure 2 at random orientation from perpendicular views with proper lightening conditions.

4.2 Image Preprocessing

The captured image from experimental set-up is in RGB color space which is converted to gray scale to simplify computations. By means of selective threshold based segmentation and some preprocessing image operations such as ”imfill” and ”erode”, background is totally removed. This resized image is used for extracting shape features for further classification. Then outline of mango image is detected in terms of contour information as

Fig. 2. Mango database of different varieties (From left to right: Alphonso, Piary, Totapuri, Langada, Dashhari)

Fig. 3. Contour Extraction of well formed and deformed shaped mango fruit

shown in figure 3. Then this contour is analysed using various shape descriptors.

4.3 Feature Extraction

Shape features are calculated using three different shape descriptors namely Fourier Descriptor, Generic Fourier Descriptor and Wavelet Fourier Descriptor. Centroid distance is used as shape signature by all three shape descriptors. Initially, according to human experts deformed images are sorted out from database. Neural network with Radial Basis Function is selected as classifier. Total 20 boundary points from contour image were considered to define shape of mango fruit. All these descriptor's features are input to neural network for grading purpose. Invariance of these descriptors regarding rotation, scale and translation was also tested by giving images of same fruit with various scale and rotation.

4.4 Radial Basis Function Neural network based classification

Radial basis function materialized as variant of artificial neural network in late 80s. RBFs are rooted in two layered neural network; where each hidden layer implements a radial activated function. The output unit is a weighted sum of hidden unit outputs as shown in figure 4. RBF neural network converts non-linear input into linear output.

Radial basis function has been employed for functional approximation in pattern recognition where inputs are feature vectors and each corresponds to a class. Various functions are used to activate radial basis function. Activation function of hidden layer computes the Euclidean distance between the input feature vector and the center of that unit. In pattern classification, Gaussian function is preferred and thus output is limited to the interval [0,1]by a sigmoid function.
Modelling given function of mapping is done through training of neural network. Thus weights and topology to model such mapping have to be found. RBF neural networks are fast learners as it establishes local mapping.

4.5 Classifier Design:

To design radial basis function neural network, number of input node in input layer is equal to input feature vectors. Length of shape descriptor is limited to 20. So feature vector of length 20 coefficient is input to neural network. The number of output node is equal to number of classes in which data to be classified. Thus two output nodes are needed to identify well-formed and deformed shapes. As it is two layered network, there are two

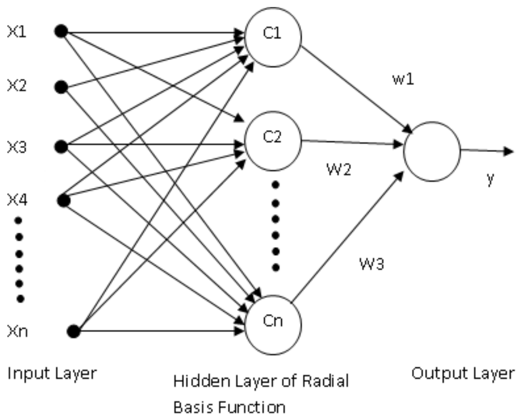

Fig. 4. Radial Basis Function Neural network

layers of hidden network where in first tier, number of neurons are equal to number of epochs required to train network and second tier consists of 2 neurons respectively.

4.5.1 Training and Testing:. The radial basis neural network is trained for all five varieties of mango namely Alphonso, Piary, Totapuri, Langada, Dashhari with total 150 samples representing approximately 30 samples each. The shape descriptor coefficients are used as input to neural network.
For testing purpose, random sample from untrained database is selected for classification. The neural network is trained with learning rate of 0.1.

5. RESULTS AND DISCUSSIONS

This section gives experimental results of shape based classification of mango fruit. The algorithms were developed for shape feature extraction using Fourier Descriptor, Generic Fourier Descriptor and Wavelet Fourier Descriptor. Experimental results show that Segmentation operation dominantly affects contour tracing process. Outline based Fourier descriptor gives result with minimum computation as compared to Generic Fourier Descriptor which considers all pixels within a shape for representation. Because of multi resolution capability, Wavelet combined with Fourier Descriptor improves result for shape classification.

Classifier performance:
Half the samples are used for training and remaining for testing. To evaluate classification performance of grading systems, classification performance metric is used which is given by

equation 9.

$$\eta(\%) = \frac{m-n}{m} X100 \qquad (9)$$

Where *m* is total number of classified images and *n* is total number of wrongly classified images. The test result of shape classification based on three descriptors using radial basis neural network are summarized in Table 1, which shows performance comparison of all three Fourier based shape descriptors.
Shape classification experiment was carried out by changing the length of WFD coefficient and number of epoch required to train neural network were observed as shown in Table 2. Classification efficiency is seen to remain constant for 20 and more WFD coefficients.

6. CONCLUSION

Most of the literature concluded that FD is a powerful tool to classify different shapes. To take advantages of multi-resolution, we modify FD by adding wavelet transform to it. We observed that WFD outperforms both Fourier descriptors. From Table 2, it can also be concluded that with increasing number of WFD coefficients, the number of epochs required to train the network shows significant decrease.

In FD, computational complexity is less as it operates on only boundary points, but in GFD as all pixels are considered while computing shape, it takes more computational time. WFD takes extra computation to apply Wavelet transform along with Fourier transform, so computational complexity lies between FD and GFD.

It is observed that, the performance of WFD is nearly 90% for shape grading; which is better than FD and GFD. Shape classification experiment was carried out by changing wavelet scale, but there is no significant change in classification efficiency. Thus it is concluded that, as mango fruit shape is not complex, there is no significant impact on classification accuracy by applying wavelets at higher scale.

In future work, a size based classification of mango fruit using shape analysis will be investigated for quality grading.

7. ACKNOWLEDGEMENT

The author would like to thank the Regional Fruit Research Center, Vengurle (Dist: Sindhudurg, Maharshtra) for providing relevant information about mango fruit quality standards and assessment. Also author thank to exporter mango orchard owners Mr. Bhooshan Pdmakar Nabar and Santosh Naik(Vengurle), Shailesh Nursery (Malkapur)for providing mango fruit samples with variety of shapes and discussing export mechanism.

8. REFERENCES

[1] Du and Sun D.W. Recent development in the applications of image processing techniques for food quality evaluation. *Trends in Food Science and Technology*, 2004.

[2] Du and Sun D W. Shape extraction and classification of pizza base using computer vision. *Journal of Food Engineering*, .

[3] T.D. Haig, Y. Attikiouzel, and M.D. Alde. Border following: new definition gives improved borders. *IEEE Proceedings on Communications Speech and Vision*, 1992.

[4] Currie A J, Ganeshanandam S, Noiton D A, Garrick D, Shelbourne CJA, and Orgaguzie N. Quantitative evaluation of apple fruit shape (malusdomestica borkh.) by principal component analysis of fourier descriptors. *Biomedical and Life Sciences, Euphytica*, 2000.

[5] Kunttu, L. Lepisto, and J. Rauhamaa. Fourier-based object description in defect image retrieval. *Journal of machine vision and Applications*, 2006.

[6] Kunttu, L. Lepisto, and J. Rauhamaa. Shape-based retrieval of industrial surface defects using angular radius fourier descriptor. *IET Image Process*, 2007.

[7] T. Morimoto, T. Takeuchi, and H. Miyata. Pattern recognition of fruit shape based on the concept of chaos and neural networks. *Computers and Electronics in Agriculture*, 2000.

[8] G.M. Naidu and G.R.Naidu. Marketing strategies for exporting mangoes and mango products from india. *ISHS Acta Horticulturae 820:VIII International Mango Symposium*, 2006.

[9] Slamet Riyadi. Wavelet-based feature extraction technique for fruit shape classification. *Proceeding of the 5th International Symposium on Mechatronics and its applications (ISMA08) Amman, Jordan.*, 2008.

[10] Ibrahim El Rube. Wavelet approximation-based affine invariant shape representation functions. *IEEE Transactions on Pattern Analysis And Machine Intelligence*, 2006.

[11] Leemans V and Destain MF. A real-time grading method of apple based on features extracted from defects. *Journal of Food Engineering*, 2004.

[12] Raj Bahadur Yadav, Naveen K. Nishchal, Arun K. Gupta, and Vinod K. Rastogi. Retrieval and classification of shape-based objects using fourier,generic fourier, and wavelet-fourier descriptors technique: A comparative study. *Science Direct Optics and Lasers in Engineering*, 2007.

[13] D. Zhang and G. Lu. Shape-based image retrieval using generic fourier descriptor. *Signal Procesing: Image Communication (Elsevier)*, 2002.

[14] D. Zhang and G. Lu. A comparative study on shape retrieval using fourier descriptors with different shape signatures. *Journal of Visual Communication and Image Represenatation*, 2003.

[15] D. Zhang and G. Lu. Review of shape representation and description techniques,pattern recognition. *Journal of Pattern recognition*, 2004.

[16] Dengsheng Zhang and Guojun Lu. Study and evaluation of different fourier methods for image retrieval. *Image and Vision Computing*, 2005.

Table 1. Classification accuracy used as metric for shape classification using FD, GFD and WFD techniques.

Sr. No.	Shape Descriptor	Average Classification Efficiency
1	Fourier descriptor	85%
2	Generic Fourier Descriptor	86.44%
3	Wavelet Fourier Descriptor	89.83%

Table 2. Impact of number of WFD coefficients on Training performance of neural networks and Classification accuracy.

Sr. No.	Number of WFD Coefficients	Number of epochs required to train Radial basis neural network.	Average classification Efficiency(%)
1	5	37	77.97
2	10	37	83.05
3	15	37	86.44
4	20	37	89.93
5	25	37	89.93
6	30	37	89.93
7	35	31	89.93
8	40	18	89.93
9	45	18	89.93
10	50	18	89.93