Dokuz Eylül Üniversitesi Mühendislik Fakültesi Fen ve Mühendislik Dergisi
Dokuz Eylul University Faculty of Engineering Journal of Science and Engineering

Basılı/Printed ISSN: 1302-9304. Elektronik/Online ISSN: 2547-958X

Parameter Selection in Elliptical Fourier Series for Leaf Classification

Eliptik Fourier Serilerinde Yaprak Sınıflandırma İçin Parametre Seçimi

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Geliş Tarihi / Received: 10.02.2021
Kabul Tarihi / Accepted: 10.02.2022
Araştırma Makalesi/Research Article
DOI:10.21205/deufmd.2022247104
Atıf şekli/ How to cite: ATASOY, H., KUTLU, Y. (2022). Parameter Selection in Elliptical Fourier Series for Leaf Classification. DEUFMD, 24(71), 375-381.

Abstract

Elliptical Fourier series method is a relatively old but powerful method in contour analysis. We have previously implemented this method as a module for a computer program called “BioMorph”. There are two significant parameters in this module; the first one is the number of harmonics (sine-cosine terms) that are calculated to form a function which represents the contour. The second parameter is the number of samples that are collected by sampling the function which is a continuous function of sums of sine and cosine terms. In this study, the effects of those two parameters to leaf classification are investigated. Also classification results obtained using reconstructed coordinates and using magnitudes of Fourier coefficients are compared. While the highest classification accuracy is obtained as 75,197% with minimum 15 sine-cosine terms and 20 samples per contour using reconstructed coordinates, it is obtained as 69,953% using magnitudes of Fourier coefficients with minimum 29 terms.

Anahtar Kelimeler: *fourier series, contour analysis, contour classification*

Öz

Eliptik Fourier serileri metodu kontur analizinde göreceli olarak eski ancak güçlü bir yöntemdir. Bu metodu daha önce “BioMorp” isimli bir bilgisayar programı için bir modül olarak hazırlamıştık. Bu modülün iki önemli parametresi mevcuttur; birincisi konturu temsil edecek fonksiyonu meydana getiren harmoniklerin sayısıdır (sinüs-kosinüs terimleri). İkinci parametre, sinüs ve kosinüs terimlerinin sürekli toplamı olan fonksiyonun örneklenmesi ile elde edilen örneklerin sayısıdır. Bu çalışmada, bu iki parametrenin yaprak sınıflandırma üzerindeki etkileri incelenmiştir. Ayrıca koordinatların yeniden yapılandırılmasıyla elde edilen sonuçlar ile Fourier katsayılarının genlikleri kullanılarak elde edilen sonuçlar karşılaştırılmıştır. Koordinatların yeniden yapılandırılması ile minimum 15 sinüs-kosinüs terimi ve kontur başına 20 örnek kullanıldığında elde edilen en yüksek başarım değeri 75,197% iken, Fourier katsayılarının genlikleri kullanıldığında minimum 29 terim ile 69,953% olarak ölçülmüştür.

Keywords: *fourier serileri, kontur analizi, kontur sınıflandırma*

1. Introduction

Plant recognition is one of the challenging tasks in botany. Leaves are recognized by human using many properties like shape, smell, texture, color etc. Since visual information of plant leaves help to recognize plants, plant or leaf recognition has attracted attention also from image processing community.

Since classification of samples in a set is highly dependent on representation of these samples, it is important to provide a distinctive representation of leaves. There are many methods mostly utilize contours of leaves or features obtained from textures or regional properties. Contour is a distinctive property that is easy to capture and relatively less sensitive to noise or other environmental conditions like light or shadows. But in many of the novel studies, combinations of multiple features are used to represent samples in a dataset.

2. Related Work

Although there are novel approaches based on deep neural networks proposed for classification of biological structures in images [1-7], shape, contour or texture-based methods are still popular and powerful methods for simpler representations and classifications of visual objects [8-13].

Yang et al. proposed two methods; multiscale triangle descriptor (MTD) for shape characteristics and local binary pattern histogram Fourier (LBP-HF) for texture characteristics of plant leaves. Then they combined them to obtain a robust descriptor [8]. Zhang et al. proposed a method to segment leaves from complicated backgrounds and used both local binary patterns (LBP) features and Fourier descriptors as inputs for their classification process [9]. Turkoglu & Hanbay proposed three novel versions of local binary patterns to recognize plants based on their leaves [10]. In their study, they used all R, G, B channels instead of working on gray level of images. Zhang et al. proposed a set of features to improve the performance of plant recognition based on leaves [11]. They used combination of local margin features and global shape features. Kadir et al. used polar Fourier transform along with color, geometric and texture features to classify leaves [12]. Kalyoncu & Toygar, used combination of well-known features like convexity, perimeter ratio, multiscale distance matrix and improved the performance of their leaf classifier [13].

There are studies also on recognition of different object types. Zheng et al. used weighted Fourier descriptors and wavelet-like features for object recognition [14]. Zare & Zahiri used amplitudes of Fourier coefficients to recognize Farsi sign language in real-time successfully [15].

Fourier series are useful for representing time series as a set of coefficients, reducing noise or samples. It is easy to apply this method to any series of values supposing the series is a time series. But in most of the studies utilizing Fourier series or Fourier descriptors, no information is given about how many terms are used or how many samples per contour are used and why. In this study, effects of two significant parameters of Fourier series (number of terms and number of samples) on leaf classification using contours of leaves are investigated. Also choosing those values dependent on number of samples of the contour itself is discussed in the lights of the results.

The rest of the paper is structured as follows: The dataset and the methods used are described in the next section. The experimental results are given and discussed in the 'Results' section. Finally, the study is summarized and concluded in the last section.

3. Material and Method

3.1. Dataset

A subset of the Flavia leaf dataset [16] is used in the experiments. This dataset contains 1907 images of 32 kinds of plant leaves (Table 1) in RGB format. All the images in the dataset have plain white (red: 255, green: 255, blue: 255) background and taken under different lighting conditions.

3.2. Preprocess

Since some leaves in the dataset have the same color as the background in some of their pixels, considering pure white as the background color, produces bad results while binarizing the leaves, in some of the images. Therefore, the images are converted to grayscale level first. Then histogram equalization is applied. The pixel value at the location x=500, y=5 where none of the images in the dataset has any pixel belongs to a leaf at is considered as the color of the background. After the binarization, 3 dilations followed by 3 erosions are applied on the binary images to autofill possible holes on binary representations of the leaves.

Table 1. Leaf kinds and number of leaves (#) in the Flavia dataset

Leaf kind	#	Leaf kind	#
Anhui Barberry	65	Goldenrain Tree	59
Beale's Barberry	55	Japan Arrowwood	60
Big-Fruited Holly	50	Japanese Cheesewood	63
Camphortree	65	Japanese Flowering Cherry	55
Canadian Poplar	64	Japanese Maple	56
Castor Aralia	52	Nanmu	62
Chinese Cinnamon	55	Oleander	66
Chinese Horse Chestnut	63	Peach	54
Chinese Redbud	72	Pubescent Bamboo	59
Chinese Toon	65	Southern Magnolia	57
Chinese Tulip Tree	53	Sweet Osmanthus	56
Crape Myrtle, Crepe Myrtle	61	Tangerine	56
Deodar	77	Trident Maple	53
Ford Woodlotus	52	True İndigo	73
Ginkgo, Maidenhair Tree	62	Wintersweet	52
Glossy Privet	55	Yew Plum Pine	60

3.3. Feature Extraction

Two feature sets are extracted. For the first set, image is preprocessed and binarized. Contours are extracted and Cartesian coordinates are transformed to polar coordinates. Then the obtained ρ vector is normalized dividing it to its length $|\rho|$. After the normalization, approximated vector ρ' is obtained resampling Fourier series of the normalized ρ vector. Thus, each leaf image is represented with one ρ' vector.

Magnitudes of Fourier coefficients obtained removing phase information (Eq. 1) are used as the second feature set, without requiring reconstruction of the signal.

$$\sqrt{a_n + b_n} \quad (1)$$

Extraction of two feature sets are summarized in Figure 1.

3.3.1. Polar Coordinates of Contour Points

Contours are sets of points that represents contour of objects in images. These points are 2-dimensional and each dimension can be considered as a time series. A slight change in orientation or location will change all the coordinates on Cartesian system. The leaves in the dataset are not in a precisely fixed location, size and orientation. Therefore, instead of using Cartesian coordinates of the contours, these coordinates (x, y) can easily be transformed to polar coordinates (θ, ρ) as shown in Eq. 2. In a polar coordinate system, ρ values do not change when the location is changed.

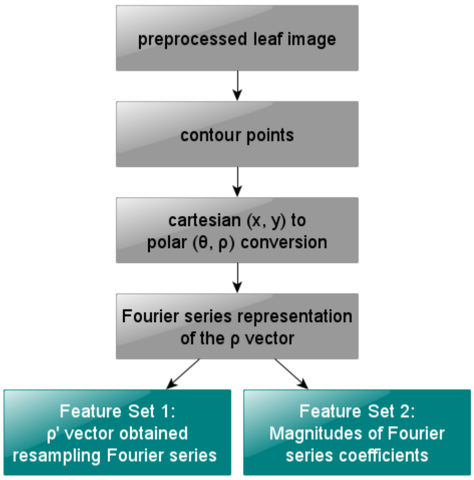

Figure 1. Feature extraction

$$(\theta, \rho) = \left(\tan^{-1}\frac{y-y_c}{x-x_c}, \sqrt{(x-x_c)^2 + (y-y_c)^2}\right) \quad (2)$$

where x_c and y_c are cartesian coordinates of the center of the contour (Eq. 3).

$$(x_c, y_c) = \left(\frac{1}{N}\sum_{n=1}^{N} x_n, \frac{1}{N}\sum_{n=1}^{N} y_n\right) \quad (3)$$

where N is the number of points.

A sample from the subset and obtained θ and ρ values are given in Figure 2. As shown in that figure, θ values have a sharp change while the transition from 0 to 2π. This transition is not easily representable by sine or cosine terms. Also, θ and ρ are not completely independent values. Therefore, ρ without θ can represent the contours without losing much information. Therefore, ρ values are considered as time series to be approximated using Fourier series, without θ values, in this study.

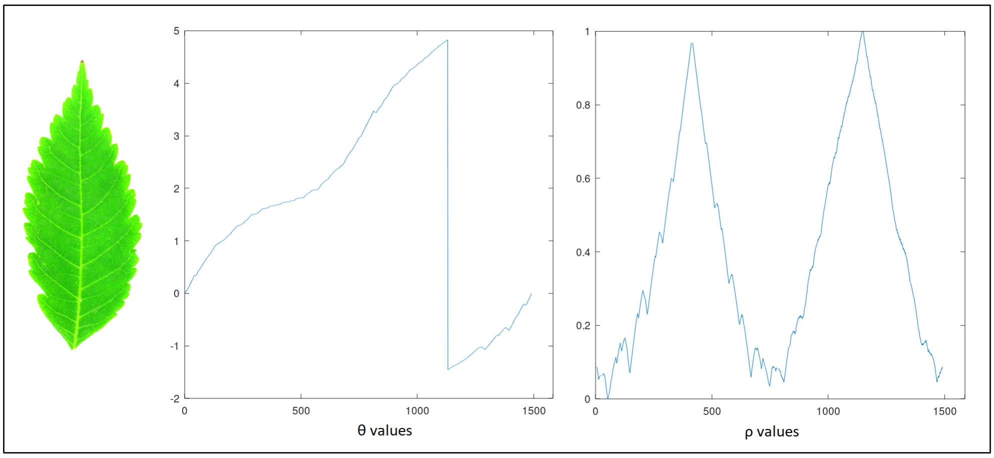

Figure 2. One sample from the subset and θ and ρ values of its contour.

3.3.2. Fourier Series

Fourier series method is very useful for representing a signal as a set of terms or to approximate a signal with less values. A periodic function $f(x)$ on an interval $[0,\ 2L]$ can be represented by infinite sums of cosine and sine terms multiplied by coefficients a_n and b_n as shown in Eq. 4-7 [17].

$$f(x) = \frac{1}{2}a_0 + \sum_{n=1}^{\infty} a_n \cos(n\pi x) + \sum_{n=1}^{\infty} b_n \sin(n\pi x) \tag{4}$$

$$a_0 = \frac{1}{L}\int_0^{2L} f(x)dx \tag{5}$$

$$a_n = \frac{1}{L}\int_0^{2L} f(x)\cos(n\pi x)dx \tag{6}$$

$$b_n = \frac{1}{L}\int_0^{2L} f(x)\sin(n\pi x)dx \tag{7}$$

In fact, the function of a contour is nothing more than a set of discrete samples for the computer when Fourier series will be calculated on. If these samples are assumed to be on an interval $[0, 2L]$, L equals to $M/2$ where M is the number of samples to be collected. Therefore, the reconstructed function $f'(x)$ can be defined as shown in Eq. 8.

$$f'(x) = \frac{1}{2}a_0 + \sum_{n=1}^{N} a_n \cos\left(\frac{n\pi x}{L}\right) + \sum_{n=1}^{N} b_n \sin\left(\frac{n\pi x}{L}\right),\ x \in [0, 2L] \tag{8}$$

where N is the number of sine and cosine terms.

There are two significant parameters while approximating functions using Fourier series. The first one is the number of sine-cosine terms (N). The approximation gets finer as N is increased. The second significant parameter is the number of samples (M) that will be collected during reconstruction. Thus, each sample in the dataset will be represented by M samples. Similarly, the approximation gets finer as M is increased. Nevertheless, it is important to use as small as possible values of N and M, since higher values increase both computational cost of this process and number of values to deal with after the reconstruction.

3.4. Classification

1907 images consist from 32 classes of leaves are preprocessed, binarized and features are extracted with the parameters N and M ranged from 2 to 30. Thus, each leaf image is represented with one ρ' vector.

Obtained ρ' vectors are classified considering each one as a feature vector, according to the kinds of the leaves. The classifications are performed using the k-nearest neighbors algorithm (k=3) with 10-fold cross validation.

The k-nearest neighbors algorithm is one of the most straightforward algorithms based on distances. According to this algorithm, class of the new sample is determined according to the most similar k samples in dataset. The Euclidian distance (Eq. 9) which is one of the most commonly-used similarity measures is used in this study.

$$d(x,y) = \sqrt{\sum_{i=1}^{n}\left(x_i^2 - y_i^2\right)} \quad (9)$$

k-fold cross validation is used to ensure that all the samples in the dataset are used for both training and classification. In cross-validation, the dataset is divided into k folds. In each step of k steps one-fold is excluded from the training process and used to test the accuracy of the classifier that is trained by the remaining k-1 folds. After k steps, all the folds are used for both training and test. A commonly-used value for k is 10 and this is selected according to the number of samples in the dataset. To leave at least 20 test samples in every step, k is selected as 10 in this study.

Each classification result is given as the ratio between the total number of truly classified instances which equals to the total number of true positives (TP) and true negatives (TN) and the total number of all the instances which equals to all true and false positives and negatives (FP and FN) (Eq. 10).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

The classifications are re-performed using the second feature set that contains only magnitudes of Fourier series coefficients, with the parameter N in the same range.

The results are given and discussed in the following section.

4. Results

841 experiments using reconstructed ρ values and 49 experiments using magnitudes of Fourier coefficients are conducted in total. Ten-fold cross validation is performed for each of the N and M values separately.

The accuracies for all the experiments are presented in Figure 3 and Figure 4.

The optimal expectation is to obtain the highest accuracy with the least possible N and M values. The highest accuracy is obtained as 75,197% with minimum N=15 and M=20. Thus, at least 15 sine-cosine terms were sufficient to distinguish classes of the leaves. Also 20 samples from the reconstructed contour of each leaf were sufficient to represent distinguishing properties of the contours. Increasing the number of samples or terms has no positive effect over the classification accuracy when the optimal values are exceeded. Therefore, those values should not be chosen much greater than the optimal values.

On the other hand, when magnitudes of the coefficients are used without phase information, the highest accuracy is obtained as 69,953 using 29 sine-cosine term coefficients (Figure 4). When all the results are considered, 20 values obtained using reconstructed coordinates provide better representation of leaves than 29 values obtained using magnitudes of Fourier coefficients.

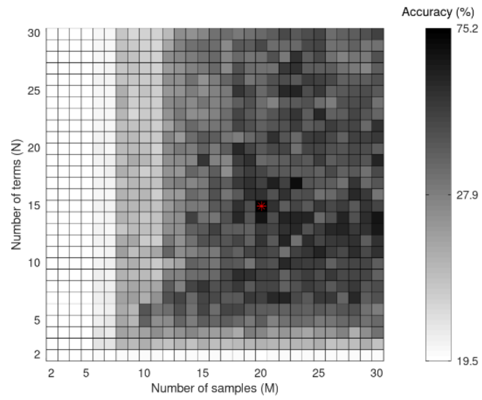

Figure 3. Accuracies obtained using reconstructed ρ values with various N and M values and minimum N and M (15 and 20 respectively) that give the maximum accuracy 75,197%.

The results also show that, increasing the number of terms while the number of samples is kept constant below the optimal value, the accuracy drops significantly. This is because collecting a smaller number of samples which means low sampling rate, causes the samples to be slightly random while Fourier series capture more detail as the number of sine-cosine terms are increased. Additionally, since each sine-cosine term is capable of holding more frequency information than the previous one, more terms make the results more sensitive to noise.

Figure 4. Accuracies obtained using magnitudes of Fourier coefficients with various N values and minimum N (29) that gives the maximum accuracy 69,953%.

Features derived from elliptic Fourier series have been usually used along with other features such as features derived from texture, color or statistical information calculated on pixel values. Because they are not capable of capturing texture or color features. In one of the studies that classify the same leaf dataset, Kadir et al. [12] has obtained an accuracy of 74,6877% using only polar Fourier transform (PFT) in one of their experiments. While PFT uses all pixels that belongs to leaves, in this study, only contour pixels are used.

5. Discussion and Conclusion

In this paper, minimum values and effects of two significant parameters that should be chosen carefully while using Fourier series for representation of leaves or similar biological structures are investigated. 841 experiments are conducted using reconstructed ρ values for each double combination of N and M values ranged from ranged from 2 to 30. Additionally, 49 experiments are conducted using magnitudes of Fourier coefficients for each value of N ranged from 2 to 50. Results show that, N, which represents the number of sine-cosine terms can be chosen as at least 15 to represent the leaves successfully. Similarly, the minimum values of M which is the number of samples that will be sampled from obtained Fourier series should be at least 20 to represent shape of leaves without losing its distinguishing properties. Also, it is shown that increasing those values has no effect on the results while greater values mean more computational cost and longer processing time.

Although computational cost is higher when using reconstructed coordinates, they provide better accuracies than using only magnitudes of Fourier coefficients.

On the other hand, the number of samples are different on each contour and more than 1000 points per contour are obtained for each leaf on the dataset. Nevertheless, only 20 values are sufficient to represent the contour without losing information that helps the classifier to distinguish the leaves.

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