# Leaf Recognition for Accurate Plant Classification

UNIVERSITY OF
KWAZULU-NATAL

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**By**

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**UNIVERSITY OF KWAZULU-NATAL**

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## DECLARATION

The research described in this thesis was conducted at the University of KwaZulu-Natal under the supervision of Prof. Serestina Viriri and Prof. Deshendran Moodley. I hereby declare that all the materials incorporated in this thesis are my own original work except where acknowledgement is made by name or in the form of a reference. The work contained herein has not been submitted in part or whole for a degree at any other university.

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Date: December 2016

As the candidate's supervisor, I have approved / disapproved this dissertation for submission

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Date: December 2016

Signed:..........................
**Prof. Deshendran Moodley**
Date: December 2016

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**DECLARATION 2 - PUBLICATION**

DETAILS OF CONTRIBUTION TO PUBLICATIONS that form part and/or include research presented in this thesis (include publications in preparation, submitted, in press and published and give details of the contributions of each author to the experimental work and writing of each publication)

A. Kala, Jules Raymond, Serestina Viriri, and Jules Raymond Tapamo. "An approximation based algorithm for minimum bounding rectangle computation." In 2014 IEEE 6th International Conference on Adaptive Science & Technology (ICAST), pp. 1-6. IEEE, 2014.

B. Kala, Jules R., Serestina Viriri, and Deshendran Moodley. "Sinuosity Coefficients for Leaf Shape Characterisation." In Advances in Nature and Biologically Inspired Computing, pp. 141-150. Springer International Publishing, 2016.

C. Kala, Jules Raymond, Serestina Viriri, Deshendran Moodley, and Jules Raymond Tapamo. "Leaf Classification Using Convexity Measure of Polygons.". Lecture Notes in Computer Science(LNCS). In International Conference on Image and Signal Processing, pp. 51-60. Springer International Publishing, 2016.

D. Kala, Jules Raymond, Serestina Viriri, Deshendran Moodley. "Leaf Classification Using Convexity Moments of Polygons.". Lecture Notes in Computer Science(LNCS). In 12th International Symposium on Visual Computing (ISVC), Springer International Publishing, 2016.

E. Kala, Jules Raymond, Serestina Viriri, Deshendran Moodley. "Plant Species Classification Using Sinuosity Coefficients of Leaf Images." *(under Review)*

Signed:...........................

*This work is dedicated to God, ALL MIGHTY*
*And*
*to the memory of my late father, Pierre Kala Kamdjoug*

## ABSTRACT

Plants are the most important living organisms on our planet because they are sources of energy and protect our planet against global warming. Botanists were the first scientist to design techniques for plant species recognition using leaves. Although many techniques for plant recognition using leaf images have been proposed in the literature, the precision and the quality of feature descriptors for shape, texture, and color remain the major challenges. This thesis investigates the precision of geometric shape features extraction and improved the determination of the Minimum Bounding Rectangle (MBR). The comparison of the proposed improved MBR determination method to Chaudhuri's method is performed using Mean Absolute Error (MAE) generated by each method on each edge point of the MBR. On the top left point of the determined MBR, Chaudhuri's method has the MAE value of 26.37 and the proposed method has the MAE value of 8.14.

This thesis also investigates the use of the Convexity Measure of Polygons for the characterization of the degree of convexity of a given leaf shape. Promising results are obtained when using the Convexity Measure of Polygons combined with other geometric features to characterize leave images, and a classification rate of 92% was obtained with a Multilayer Perceptron Neural Network classifier. After observing the limitations of the Convexity Measure of Polygons, a new shape feature called Convexity Moments of Polygons is presented in this thesis. This new feature has the invariant properties of the Convexity Measure of Polygons, but is more precise because it uses more than one value to characterize the degree of convexity of a given shape. Promising results are obtained when using the Convexity Moments of Polygons combined with other geometric features to characterize the leaf images and a classification rate of 95% was obtained with the Multilayer Perceptron Neural Network classifier.

Leaf boundaries carry valuable information that can be used to distinguish between plant species. In this thesis, a new boundary-based shape characterization method called Sinuosity Coefficients is proposed. This method has been used in many fields of science like Geography to describe rivers meandering. The Sinuosity Coefficients is scale and translation invariant. Promising results are obtained when using Sinuosity Coefficients combined with other geometric features to characterize the leaf images, a classification rate of 80% was obtained with the Multilayer Perceptron Neural Network classifier.

Finally, this thesis implements a model for plant classification using leaf images, where an input leaf image is described using the Convexity Moments, the Sinuosity Coefficients and the geometric features to generate a feature vector for the recognition of plant species using a Radial Basis Neural Network. With the model designed and implemented the overall classification rate of 97% was obtained.

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I am very grateful to my supervisors for the help and the support I received from them during my research. I would like to express my gratitude to my family and friends for all the support and encouragements.

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# List of Abbreviations

- **AUC** Area under the ROC curve.
- **CCD** Centroid Contour Distance.
- **CNN** Convolutionnal Neural Network.
- **CSS** Curvature Scale Space.
- **DAG-MLSTSVM** Multi-Class Least Square Twin Support Vector Machine.
- **GFD** Generic Fourier Descriptors.
- **MAE** Mean Absolute Error.
- **MBR** Minimum Bounding Rectangle.
- **MLP** Multi Layer Perceptron.
- **MMC** Moving Media Center.
- **MSE** Mean Square Error.
- **PCA** Principal Component Analysis.
- **RBF** Radial Basis Neural Network.
- **RBPNN** Radial Basis Probabilistic Neural Network.
- **RGB** Red Green Blue.
- **ROC** Received Operating Characteristic.

# Chapter 1

# General Introduction

## 1.1 Introduction

The use of image processing in the process of plant recognition has become a very important research topic in recent years [28] because of the variety of plant species, the availability of many leaf image databases and the advance in computational power. In order to help scientists and non-scientist to easily recognize a given plant species, new tools and processes need to be designed.

The value of a system for the recognition of plant species can greatly be increased if it helps to precisely identify a given plant species. The main purpose of a system for plant species recognition using leaf image is to narrow down the possible plant species and improve the recognition process, using information such as shape, color and texture.

In a typical plant recognition system using leaf images, the user has a leaf image as input, that he or she is interested in and wants to find the associated plant species. Possible application areas of plant classification include environmental protection, farming, medical science, remote sensing, geographic information system, education and museum catalogues. There are already some systems that facilitate plant recognition using leaf images [69].

Conventional shape descriptors are proving to be incapable of capturing certain variations on the leaf shape, especially if each shape descriptor produces a single value. It is demonstrated that leaves with different shape can produce the same shape feature; this explains the necessity to combine many shape features to characterize a given leaf image. To overcome the problems posed by single value, shape descriptors, features such as the 7 invariants moments, designed by Hu, are used to characterize a given leaf shape [56].

Leaf teeth patterns have been investigated by very few authors. It is claimed that there is no algorithm able to accurately characterize teeth pattern on a plant leaf [28]. The design of new shape descriptors emerged as an alternative research area to address the problem of leaf shape characterization [63]. Features such as Convexity Measure of Polygons [136] are also used to characterize a shape, but they are found to be efficient when combined with other shape features.

In the general framework for plant classification using leaf images, first a noise removal algorithm is applied to the leaf image, followed by the binarization, then the edge detection algorithm is applied to the binary image to extract the boundary and finally, the feature extraction is applied to the boundary. After the features of the leaf image are extracted, the classification is performed using the extracted features for the recognition.

## 1.2 Motivation

More than 300000 plant species have been identified and grouped using the systematic plant classification designed by Linnaeus [76]. Even for a trained botanist, it is very difficult to apply the classification model of Linnaeus, because of the number of rules and the fact that these rules require strong observation capabilities from the botanists. Image processing techniques are introduced to facilitate the recognition process of plant species, by automating the analysis of plant parts such as leaves and stem, to improve the recognition rate and time respectively [69].

Therefore, an appropriate system with features extraction and the classification algorithms is required. The features combined for the description of a given leaf image should be simple enough so that it can be easily computed and applicable to different types of leaf images. In order to reliably identify a given plant, botanists need a fast and accurate method for the characterization of leaf images.

## 1.3 Problem Statement

Plant recognition using leaf images has been a challenging problem due to the wide variety of plant species and the limitation of the leaf image 2D used to represent a plant leaf which is a 3D structure by nature [28]. Although existing methods have made progress in the field, the recognition of plant species using leaf images remains an ongoing research topic as there is a need for further improvement.

Plant recognition using leaf images is roughly organized into the following categories, based on the processing order.

- Shape.
- Veins extraction and characterization
- Margin analysis
- Texture feature

- Other surface-based methods
- Classifiers

During the process of leaf recognition, feature extraction has received the highest attention among all other steps used in the recognition process. Early works on leaf recognition focused on using low-level features like shape, color and texture, to characterize leaf images. A histogram of RGB values [130] or values of other color models such as color moments [87], co-occurrence of color [121] and invariant color model [109] are the techniques used to extract color features from a given leaf image. Even though color is very important in visual perception, it cannot always be used to recognize leaf images because leaf color changes during the seasons, as shown in Figure 1.1, where the fresh and the dry version of the same leaf presents different colors.

Figure 1.1. Dry and fresh leaves

In computer vision, texture was proved to be very useful to solve many problems, like remote sensing and inspection. Because of that, it became an obvious choice for the design of a system for plant recognition using leaf images. The applications of texture to analyzed leaf images include, Gabor Filter [77], Low's texture energy maps [40] and wavelet coefficients [79]. As a color feature, texture features have problems in finding similarities between leaf images, mostly because of the windowing approach used to extract texture features.

The most popular approaches for leave images, characterization are the shape features. But image segmentation is a very difficult problem, especially if the input image has a complicated background [122]. That complexity makes it difficult to accurately compute shape features. Some applications of leaf characterization using shape include, Elliptic Fourier Descriptors (EFD), contour signature, landmark and linear measurements, shape features, polygon fitting and fractal dimension.

The application of EFD to leaf shape analysis is based on the analysis of shape on the frequency domain. The EFD harmonic numbers and the coefficients are used to generate the shape features [52, 68, 127].

Contour signature is based on the analysis of the sequence of points representing the leaf shape boundary. The Centroid Contour Distance (CCD) [82, 125] is an example of contour signature techniques used for a leaf shape analysis.

The main issue when recognizing plant species using leaf images is the differentiation of plant species that look alike. Landmark and linear measurements are used to differentiate the leaves of plant species that look alike. Landmark features are presented in [28].

Shape features, such as Rectangularity, Circularity and Aspect Ratio are very similar to linear features and are used to represent a given shape using a single value. Polygon Fitting and Fractal dimension are real numbers used to quantify the dimensionality of a given shape, and can be used as input to a classifier. Minkowski-Bouligan multi-scale is the method used in [8, 16, 81] to generate fractal dimension features for a leaf shape analysis. Polygonal representation was applied in [35, 58] using a series of superimposed triangles for the classification.

Veins are the leaf vessels which transport nutrients, water and minerals. Botanists found that the pattern of veins on a given leaf are unique and can be used to differentiate plant species. Vein analysis was used in [28, 86] to recognize plant species. The issue with vein analysis is the segmentation process required to magnify the vein on a given leaf; this process sometimes requires a chemical treatment.

Leaf margins are very useful for botanists because they can use them to recognize a given plant and to have an idea of the plant environment. In [38, 105, 108] authors performed the analysis of teeth and tooth pattern to recognize leaf images.

Leaf hair, surface gland and stomata are some of the surface-based features of a plant leaf that can be used to recognize a given plant species. The 3D nature of some of these features makes it difficult to use them. Authors in [25, 80, 113] use a method such as quantitative hair analysis to characterize a given plant leaf.

The last phase in the recognition process is the classification. In this phase, a given leaf based on the input feature is assigned to the corresponding group based on the input feature. In [36, 51, 129] authors designed new classification techniques, such as the Moving Media Center hypersphere (MMC) to improve the recognition of plant leaves.

## 1.4 Thesis Objectives

This research aims to propose an accurate plant recognition model using leaf images by accurately characterizing a given leaf shape. The specific objectives of this research are:

1. To introduce new shape features to accurately describe a given leaf shape and compare them with other shape features.

2. To design new features for the characterization of the leaf boundary.

3. To design an accurate and time efficient model for plant classification using leaf images.

## 1.5 Thesis Contributions

The major contributions of this thesis include:

1. An improvement of Chaudhuri method for the determination of the Minimum Bounding Rectangle (MBR), by using a construction based technique for the determination of the rectangle corner points. The proposed improvement, reduce significantly the error inccured when using Chaudhuri method for the determination of the MBR.
2. The design of a boundary based shape characterizer: the Sinuosity Coefficients. The Sinuosity Coefficients are used to evaluate the degree of meandering of a given shape, they are obtained by dividing the shape into sections and evaluating the degree of meandering of each section. The sinuosity Coefficients is a set of values representing the degree of meandering of a given leaf shape.
3. Investigate the application of the Convexity Measure of polygons for the characterization of a leaf shape. The main limitation of the Convexity Measure of Polygons is the fact that it uses a single value to characterize a given shape. To address the limitation of the Convexity Measure of Polygons the Convexity Moments of Polygons were designed by considering all the values generated during the determination of the Convexity Measure of Polygon and calculating new values such as the Mean, Min, Standard deviation, Mode to represent the degree of convexity of a given shape.
4. The design of an accurate model for plant classification using leaf images, based on the combination of Geometric features, Convexity Moments of Polygons, Sinuosity Coefficients and the RBF classifier. Each component of the model was selected based on their capability, accuracy and robustness when characterizing and recognizing input leaf images.

## 1.6 Thesis Outline

Chapter 2 presents a review of the state of plant classification using leaf images, other approaches used to analyze and represent plant leaves, a review of classifiers used for the recognition of plant species. In Chapter 3, the preprocessing and shape descriptor methods are presented, they all grouped as background for the study. In Chapter 4, the comparison of the MBR determination algorithms is performed. Chapter 5 presents the Convexity Measure of Polygons and the Convexity Moments of Polygons, when applied to leaf characterization. The Sinuosity Coefficients are presented in Chapter 6, Chapter 7 presents the experimental results and discussion of this study. Chapter 8 draws the conclusion and outline the future works of this study.

# Chapter 2

# Literature Review

## 2.1 Introduction

For more than a decade, the use of leaf images to recognize plant species has been explored in image processing. Each author performing plants classification research using leaf images, focused their work on two main streams. The first of these streams is the leaf analysis approach in which the authors are designing or combining lower level features, such as shape, texture or color descriptors to recognize leaf images. The second stream is based on the improvement of an existing classifier or the design of a new classifier to recognize leaf images. Based on these observations a taxonomy of the contributions in the field of plants classification is proposed in Figure 2.1.

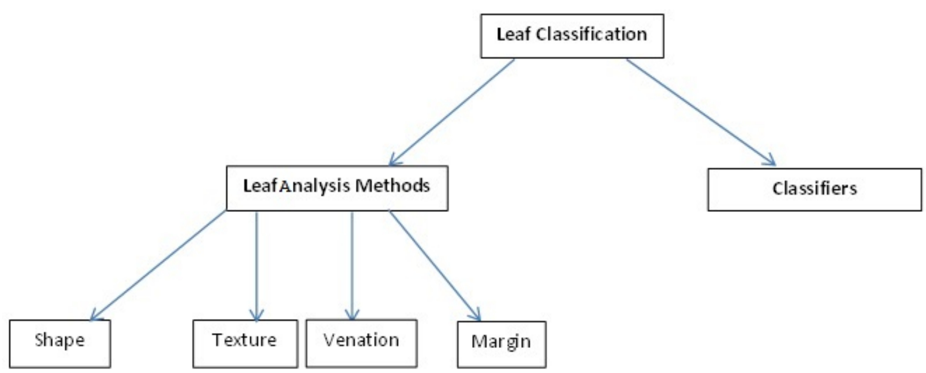



Figure 2.1. Overview of the literature on leaf classification

## 2.2 Leaf Analysis Methods

In plant morphometric research there are many aspects of plant structure and appearance, such as leaf shape, texture and vein structure, that are used to recognize a given plant [28]. Leaf shape, texture, vein structure and leaf margin are of great importance to discriminate between plant species. In the literature, leaf shape received more attention than any other characteristics when using image processing techniques for the recognition process. The characterization and extraction of these characters from the plant leaf is another larger and more complex system that comes with his challenges.

### 2.2.1 Shape descriptors

There are many reasons why leaf shape is used for the recognition of plant species. The discriminative power of the shape, as presented by [134] is one of the main reasons why it is popular in the field of leaf recognition. It is possible to find leaves from the same plant with different details, as shown in Figure 2.2, but when the species are different, the shapes are often also different, as presented in Figure 2.3. This property is used by botanists to recognize plant species. Leaf shape is the

Figure 2.2. Sample of leaf images from a single Quersus Nigra [28]

characteristic that non-experts mostly use to recognize plant species compared to the margin and vein structure. Shape characteristics are easy to extract, especially if the considered leaf image has a uniform background. The availability of well-known shape descriptors is another reason why shape features are so popular in the leaf recognition process. Many botanists are familiar with the shape features used in image processing. Figure 2.4, below, describes some features of a leaf, using botanical terms.

The age and diseases are some of the causes of irregular variations observed in leaf shape, but the general structure of the leaf remains unchanged. Leaf recognition using color can be affected by their age because most leaves turn brown with age.

#### Elliptic Fourier Descriptors

Khul et al., [68] states that Elliptic Fourier Descriptors (EFD) are the most popular shape descriptors used for leaf image recognition. With EFD, leaf shape is analyzed in the frequency domain, rather than the spatial domain.The leaf image outline is described using a set of Fourier harmonics; only 4 coefficients will be used to

Figure 2.3. Sample of leaf shapes [28]

describe each harmonic. The Fourier descriptors are formed by a set of coefficients. The quality of EFD depends on the number of harmonics, the higher the number of harmonics, the better the description will be. It is demonstrated in [52] that 10 Fourier harmonics are necessary to accurately discriminate between plant species, but it requires the use of Principal Component Analysis (PCA) to reduce the size of the feature vector, and hence improve the recognition rate. White et al., [127] were the first authors to use the EFD and they demonstrated that it outperforms the landmark approach and that the EFD are rotation translation and scale-invariant. The main advantage of EFD is the possibility to reconstruct the shape using the descriptors, as shown in Figure 2.5.

A comparison of EFD with other shape descriptors was performed by MCLellan et al., [81]. The capability of EFD to discriminate between plant species was also proved. Additionally, the authors identified some key points on leaf shapes that can be used to differentiate most leaves with regular lobes. EFD was found to be equivalent to the methods (such as centroid radi) used for the comparison. The combination of EFD with the simple shape analysis method designed by Goodal et al., [47], was investigated by Hearn et al., [52] to recognize 2420 leaf images of 151 different species composing a database created by the authors. A recognition rate of 72% was obtained. One of the successful applications of EFD to leaf classification was designed by Du et al., [37]. They achieved a classification rate greater than 80% with the Radial Basis Probabilistic Neural Network (RBPNN). In recent years, the application of EFD to plant classification, using leaf images, was performed by Tomaszewski et al., [119], who used EFD to analyze the changes in shape between dried and fresh leaves. The authors concluded that the change in shape is directional and, during the recognition process of leaf images, shape features are better than

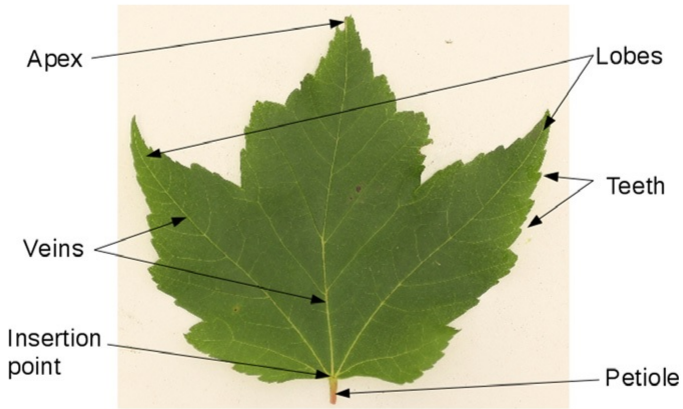



Figure 2.4. Leaf parts [28]

texture and color features. N Liu et al., [77], N Ahmed et al., [3] are other recent examples of applications of EFD to plant classification using leaf images. Ray et al., [102] extended the work on eigenshape analysis, which is a method closely related to EFD, and applied it to leaf shape analysis. The proposed approach is based on the use of recognizable landmarks to divide a given leaf boundary into segments. The main issue with this method is the use of landmarks because it is almost impossible to identify similar landmarks when leaf images are from different plant species.

### Contour Signature

Many authors in [82, 84] used Contour Signature to characterize leaf shape. A shape Contour Signature is a sequence of values calculated by using points taken on a given shape, beginning at a reference point and tracing the outline either clockwise or anti-clockwise direction.

The Centroid-Contour distance (CCD) is one of the simplest applications of the contour signature [82]. In the CCD, the signature is represented by the sequence of distances between the shape centroid and the points forming the shape. Another example of CCD is the centroid angles and the sequence of tangents of a given shape. EFD and CCD are used for the representation of shape as vectors which satisfies the rotation, translation and scale invariant. The scale invariant is obtained after normalization.

In an attempt to increase the recognition rate of leaf images using CCD, Meade et al., [82] correlated the frequency of points on the shape with the curvature extend, to identify a consistent starting point for CCD and avoid the signature alignment before they could compare leaf shapes. Authors such as Wang et al., [124, 125], applied a thinning-based method to the leaf shape.

A time-series shapelet method was used by Ye et al., [131] on CCD to recognize leaf shapes using matching approaches. For the allowed time-series to be applied,

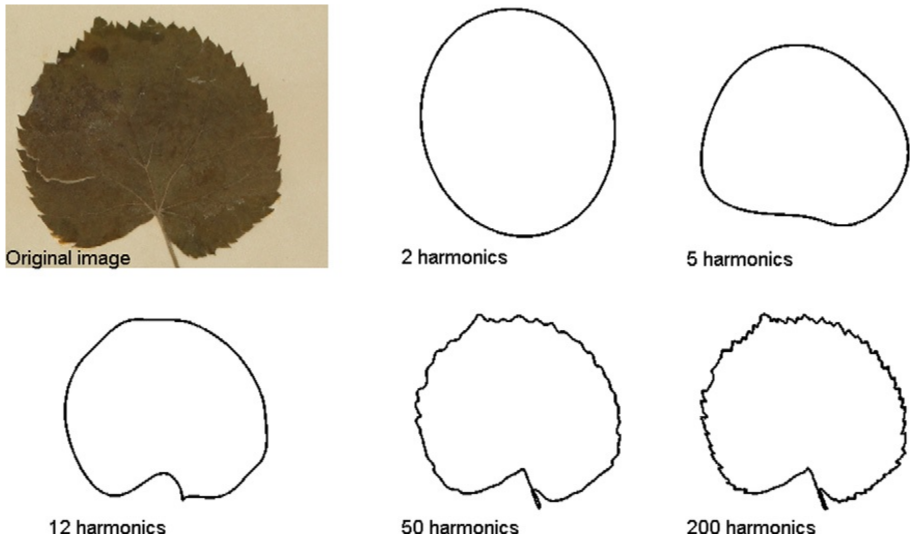



Figure 2.5. Fourier description of a given leaf shape, when more harmonics are used, the better the description [28]

local features need to be matched rather than compared to enable the time-series analysis. The self-intersection is the major difficulty in the application of CCD to shape analysis. Self-intersection is a region of the leaf where part of the leaf overlaps with another part of the same leaf.

Mokhtarian et al., [84] proposed a solution to the issue of self-intersection on leaf images. The proposed solution is based on the consideration that the darker regions of the leaf image are the overlapping regions; they use these regions to extract the overlap and use the Curvature Scale Space (CSS) to compare the regions. The drawback of this method is the need for a specific type of illumination to make the darker regions visible.

### Landmark and linear measurements

Landmarks and linear measurement are also used to characterize plant leaves. Between related organisms there is a biologically defined point that can be used to differentiate them; it is the landmark. A suitable set of landmarks to solve a specific problem requires the knowledge of an expert in the specific domain of the problem.

Bookstein et al., [13] used local maxima or local minima as landmarks for the characterization of a given shape. The organism shape will be characterized using linear and angular measurement between landmarks.

Landmarks are easily understood by humans and have been applied successfully for the recognition of animal species. To differentiate between two closely related species of Dioscorea, Haigh et al., [50] use leaves length combined with the measurement of petiole and flower.

Jensen et al., [61] use the angle and distances separating manually located leaf edges. The variations were also studied using wrap deformation. Young et al., [132] use the landmark method for the analysis of the variation between plants of the same species growing in different conditions. The authors' experiment also considered the images of plants at different ages to see which age provides better accuracy.

Ling et al., [74] uses a closely related method of the landmark method known as inerdistance for the recognition of leaf images. The inerdistance method looks at the shortest routes between shape points without passing outside of the shape.

Because of the automatic detection of landmarks (leaf apex, leaf tips), error, created during the construction of the leaf images database (irregularities in the leaf structure) and the fact that, when a given leaf is asymmetric and the main vein does not align with the shape's primary axis, it is difficult to measure the length of the leaf. These are the limitations of the landmark methods and are the reason why landmark and linear measurement methods often involve manual interactions.

The inconsistency in available landmarks between different species, as shown in Figure 2.3, is another major problem observed when using landmark methods. This inconsistency is the reason why most studies using landmarks require the usage of well-known landmarks.

Corney et al., [30] use landmarks such as leaf tips and petiole (it is the thin stalk that connects the leaf blade to the stem) insertion points to design a system for plant classification. In order to improve the recognition rate, they combined the landmark features with other features, such as leaf area, length, perimeter and blade length.

Phylogenetic reconstruction, using morphological data, nuclide acid or protein, has been considered to be one of the most significant developments in comparative biology in the past 30 years. The difference between these methods is the fact that they use shared derived characters for the leaf recognition.

#### Shape features

Shape features are similar to linear measurements. They are used to analyze the outline of a given shape. There are a wide variety of quantitative shape descriptors that can be easily calculated and used to describe a given shape; including, Aspect Ratio, Rectangularity, Circularity and Perimeter ratio, etc..., are some examples. Pauwels et al., [95] uses specific features, such as "lobedness measure" to quantify the dimension of the lobe of a given shape and use it for the recognition process. Other authors use more general shape descriptors, such as the Hu 7 invariant moments [56]. Hu 7 invariant moments are statistical descriptors of shapes; which are rotation, translation and scale invariant. A detailed review of invariant moments used for shape recognition is provided by Flusser et al., [41].

Lee et al., [72] show that region-based features, such as aspect ratio and compactness, are more useful than boundary-based features because boundary-based features depend on the identification of meaningful landmark points. They found out that using quantitative shape features as input for the nearest neighbor classifier produced better results than a contour-based features, on their selected data set of 60 species.

Du et al., [36] designed a classifier named Moving Media Center Hypersphere to classify leaf images, using quantitative shape features, and uses a series of hypersphere for the classification. The authors achieved a classification of 78%. Wang et al., [122] designed an improved version of this work and achieved a better classification rate. Wu et al., [128] combined shape features with an artificial neural network to recognize 32 species of Chinese leaf images and compare the result with other classifiers and found, it to outperform some of them.

Even with the promising results obtained with shape features, it is still difficult to analyze leaf variations using them. The difficulty or the impossibility of reconstructing shapes, using shape features, is the reason why understanding shapes using shape features are difficult, even if some shape features are easy to understand. The fact that there are many ways in which a given shape can be altered without changing the values of its shape feature, is another limitation of shape features.

Cope et al., [28] noticed that any attempt to describe leaf shapes using 5 -10 geometric shape features to describe a given leaf shape is not enough. McLellan et al., [81] demonstrated that some shape features are highly correlated, which contributes to making the task of selecting independent variable for the recognition very difficult.

#### Polygon fitting and fractal dimension

A real number representing how complex a given shape fills the space to which it belongs, is the fractal dimension. The fractal dimension is used to quantify the dimensionality of a given shape and can be used as input to a classifier. The Minkowski-Bouligand method is one of the popular methods used to define and calculate an object's fractal dimension. The popularity of this method is due to its precision and the multi-scale version of the method.

Leaf identification using fractal dimension has been done by many researchers. Combining of fractal dimension with other features was done by McLellan et al., [81] to analyze leaf images. The Minkowski-Bouligan multi-scale produces feature points and their position can be used for shape recognition, Plotze et al., [98] are among the first authors to use this method for shape recognition. Backes et al., [8], used the Minkowski-Bouligan multi-scale, but, in their case they compared it with the Fourie descriptor of the considered shape. Bruno et al., [16] combined a Minkowski-Bouligan multi-scale estimate of fractal dimension with linear discriminant analysis to design a system for plant identification. One of the limitations of the fractal dimension was found by McLellan et al., who show that, for any given shape its fractal dimension is highly correlated with the perimeter to area ratio.

Even with the classification rate of 100% obtained by Plotze et al., [98] on a small dataset of 10 species of Passifora, the capabilities of fractal dimension to explain shape variations remain limited. The wide variety of plant species, as shown in Figure 2.3, is the reason why a single value of complexity cannot be used to describe a given leaf. This suggests that fractal dimension can only be combined with other features to characterize leaf shape.

The polygonal representation of leaves was used by Du et al., [35] to recognize leaf shape. Im et al., [58] used a series of super-imposed triangles to describe the leaf outlines, then performed the normalization and registration of those triangles for the classification process. Im et al., [58] used this method to correctly classify 14 species of Japanese plants. However, the use of this method required the use of some approximations which may limit the applicability of the method to general shape analysis.

### 2.2.2 Vein extraction and characterization

After shape, veins are the next features used to recognize plant species. Veins are the structures used by a given leaf to transport water, minerals and other important plant substances. Researchers usually exploit the pattern of veins on the leaf to recognize them. Leaf veins can be used to differentiate plant species because the overall vein pattern remains almost the same within a given species. In order to visualize leaf veins, it is sometimes necessary to use a high definition camera to magnify them, but sometimes a given leaf needs to undergo a chemical treatment to make the veins visible. Figure 2.6 describes the type of veins on a given leaf image. Many techniques have been used for the extraction and the characterization of veins

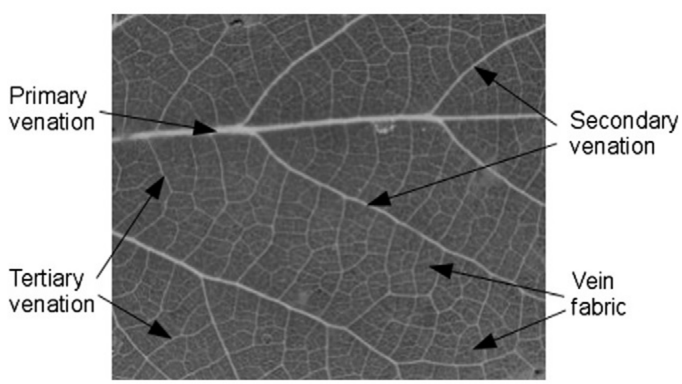



Figure 2.6. Leaf veins structures [28]

with some promising results. Clarke et al., [27] compared two manual methods for veins extraction: scalar space analysis and smooth edges detection. The results obtained with their method showed some hopes for the automatic analysis when vein structures are easily extracted. Cope et al., [29] identifies vein pixels by using a classifier improved by genetic algorithms. The proposed method was able to detect the main and secondary veins, but the method is time consuming, depends on the initial population. Li et al., [73] used Independent Component Analysis (ICA) designed by Camon to extract leaf venation. The method was not better than a simple edges detection when applied to a complete leaf image. Mullen et al., [86] used artificial ant swarms to detect the venation and outlines on the leaf image via an edges detection method. Works based on the combination of thresholding and the neural network approach produced the best results for veins extraction. Fu et al., [43] used that method to extract veins on a leaf image; however, it is important to note that the images used by Fu were taken using a fluorescent light to enhance the veins, which limit the use of the images. Furthermore, B-splines method was used by Kirshgessner et al., [67]to extract the veins on the leaf image. Morphological Laplacian operator and Fourier high pass filter were used by Plotze et al., [98] to extract leaf venation. Most studies on leaf recognition, using leaf veins, focused on the extraction and very few on the analysis. The pattern of end points and branch points of veins were used by Park et al., [93] to characterize the vein structures. Figure 2.7 presents some examples of veins structures. Nam et al., [90] applied a classification approach to a graphical representation of leaf veins to characterize their structure.

Figure 2.7. Leaf venations types [28]

### 2.2.3 Margin analysis

The outer edges of the lamina often contain a pattern of teeth, which are small serrated portions of the leaf that are distinct from the typically larger and smoother lobes. Figure 2.8 presents some leaf margins. Leaf margins have been used by very few authors to recognize leaf species, even though they are very useful features for botanists. Royer et al., [106] claim that "no computer algorithm can reliably detect leaf teeth" as yet. The possible reason for this is the fact that not all plant species have teeth, or it may be that they are damaged or missing parts before or after specimen collection, or because it is difficult to automatically acquire and measure teeth patterns.

Figure 2.8. Leaf margins types [28]

For many species, teeth are a very important feature for recognition. Botanists, use qualitative descriptors of tooth curvatures, as stated by Ellis et al., [38]. Royer et al., [105] demonstrated that the size and number of teeth are useful climate indicators and of growth patterns; they can also be used to understand prehistoric climates. The process of leaf recognition using margins requires the leaf features vector to contain margin features that are combined with other measurements. Tooth length and width, taken manually and used alongside other leave features, were used by Clark et al., [24, 25, 26] and Rumpunen et al., [108]. The superiority of multilayer perceptron classifier over a computer generated taxonomic key for identifying species using morphological traits, was demonstrated by Clark et al., [24]. The recognition of plant species using self-organized maps extracted from similar morphological traits are described in [25].

McLellan et al., [81] considered adjacent angles and used the sum of angles connecting them, and use them as features; the histogram of angles was used by Wang et al., [125]. If the leaf is sufficiently undamaged, then leaf margin and teeth number measurements are very useful features for species identification. Cope et al., [28] stated that combining leaf margin features with vein features will produce a better leaf recognition system because teeth usually have small vein patterns running through them.

Cem et al., [65] proposed a new method for leaves boundary analysis based on corner region extraction and analysis, then combined it with well-known features extraction and classification to classify plant leaves. The proposed system achieved a classification rate of 71% on leafsnap dataset.

Guillaume et al., [20] proposed a new technique based on the design of a sequence to represent leaf margins, where the teeth are viewed as symbols of a multivariate real values alphabet. The sequence obtained, is used to characterize the teeth pattern of a given leaf image, but as any shape analysis techniques the quality of the description depends on the boundary extraction (segmentation) algorithm.

### 2.2.4 Texture features

Natural and traditional texture analysis techniques can be used to recognize plant species. Multi-scale fractal dimension and deterministic tourist work for texture analysis was used by Backes et al., [8] to recognize plant species. When Gabor filter array was used by Casanova et al., [19] on a larger dataset to demonstrate the ability of the filter, to analyze leaf texture by calculating the energy for the response of each applied filter, they achieved some promising results. Wavelet transforms and support vector machines were presented by Liu et al.,[77]. A classification rate of 80% was achieved by Cope et al., [28], on a dataset of 32 species of Quersus using the co-occurrence of a different scale of Gabor Filter. Other approaches for leaves texture analysis include Grey-scale co-occurrence matrix and Fourier descriptors.

All the previous methods for leaves texture analysis were based on windowing obtained through traditional techniques. An electronic microscope was used by Ramos et al., citeramos to create leaf textural images and Backes et al., [8] used a magnified cross section of leaf epidermis. The main limitation of these methods is the difficulty to obtain them in larger scales. To provide a complete analysis of a given leaf, it might be important to combine texture features to outline-based shape analysis. To provide a complete analysis of a given leaf, it might be important to combine texture features to outline-based shape analysis.

### 2.2.5 Other surface based methods

On the leaf surface there are other features that can be used to identify a given plant species, such as leaf hair, surface gland and stomata. The 3D nature of these features is the reason why it is difficult to use them for the design of an automated system. Clark et al., [25] used quantitative hair descriptors in a self-organized map to recognize plant species. The proposed feature was manually identified and described, which made the automation almost impossible. Ma et al., [80] described a 3D imaging and modelling method of leaf shaping based on volumetric information to improve the understanding of a given leaf. The combination of many 2D images of the same scene to extract a 3D representation, followed by the use of 2D and 3D images for the segmentation using normalized cut, was performed by Teng et al., [117] to find leaf boundaries. Similarly, Song et al., [113] designed a system where stereo images were analyzed using self-organized maps and stereo matching to model a surface on which the dimension of a given plant leaf can be obtained. The stomata, which are pores used to regulate gaseous and water exchanges of a given plant, are located on the leaf surface. Research shows that the size and distribution of stomata are closely related to $CO_2$ and the climate. The review of data collected on fossil leaves, performed by Royer et al., [107] shows that the density of stomata on fossil leaves is inversely related to the local concentration of $CO_2$ for a period of time. Hetherington et al., [53] discusses the effect of environmental changes and the impact on stomata morphology. A thorough botanical description and manual measurement of leaf stomata of more than 300 species was performed by

Zarinkamar [133]. He then argued that these measurements can be used to recognize plant species. Fernandez [39] used a mathematical method to analyze a digital microscopic image. The authors analysis is based on measures such as correlation and entropy to characterize the texture and patterns found on the digitized images. Cope et al., [28] claim that combining the previous lamina features with other leaf features will certainly improve the recognition rate.

## 2.3 Other approaches for leaf analysis

### 2.3.1 Symmetry

Symmetry can be found in man-made and natural environments [78]. The ability to detect and use symmetry is innate to humans, but it is not easy to automate the detection and the analysis of this useful insight. The symmetry of plant leaves has been used by botanist for centuries during the process of plant recognition [75].

Computational Symmetry proposed by Liu [78], is one of the approaches used in Computer Vision to formalized and used symmetry for object analysis. The following points are the motivations behind the design of the Computational Symmetry.

- Symmetry can be found every where.
- Symmetry is intellectually stimulating.
- Symmetry can be useful or harmful.
- There are very few for the analysis of natural symmetry.

Liu [78], demonstrated using a series of applications that Computational Symmetry can be used in fields such as medical image analysis to detect brain cancer, by generating a line of symmetry that separate the brain in two hemispheres and compare both hemispheres to detect variations.

Milner et al., [83], proposed an application of the symmetry for plant recognition by analyzing the symmetry of the leaf veins. Compared to Liu method this method is based on the use of two values used to measure the symmetry level of the leaf veins. The first value is LoA (Local Approach) this value represent the minimum energy used to transform leaf veins into symmetric structure. The second value is GoA (Global Approach) this value gives the amount of energy globally required to transform the leaf veins into symmetric structures. Promising results were during the classification of leaf images using the two measures, these results remain lower than the one obtained with traditional approaches, but are better than the state of the art of plant characterization using symmetric measures. In this study leaf veins are not used for the recognition.

### 2.3.2 Modeling

In Computer Vision recognizing natural objects remain a very difficult task. One of the approaches used to solve the recognition problem is the use of modeling techniques such as Fractals [54]. Fractals are considered as mathematical objects representing a redundant patterns, they have been applied in many fields of science such as Physics, Computer vision and Medical sciences. L-Systems (Lindenmayer Systems) are formal grammars that can be interpreted as determining the movements of a turtle drawing algorithm [110]. The L-system is an example of fractal that have been used successfully to model and recognize natural plants and trees

Holliday et al., [54] used L-system fractals to model and recognized plants. They started by using L-system to model an input plant, extract linear features and general shape properties from the model and use them for the recognition. Due to the lack of precision of the proposed model a more precise L-system was proposed in [110].

Samal et al., [110], proposed a plant recognition system based on a stochastic L-system. The proposed L-system is used to model natural plants and features such as the length of the branch, the principal axis, the moment of inertia and the symmetry are extracted from the model and used for the recognition. The stochastic L-system has the advantage of being more precise than the context free L-system used in [54].

The leaf model created by the L-system is not precise enough to be used for the recognition of plant species. The L-system can be a very good tool for the characterization of compound leaves, which remain a challenge when recognizing plant with leaf images.

## 2.4 Classifiers

During the recognition process, classifiers such as KNN, MLP, RBF and Naive Bayes, are used to associate an input leaf image described using shape, texture or color features, to the corresponding plant species. In the literature neural network (such as MLP) and distance-based classifiers (KNN) are used for the recognition steps when leaf images are characterized using shape features. Improving the classifiers is the second direction used by the authors to increase plant recognition rate.

A classifier based on the maximum likelihood approach and well suited for mixed data types is the Logistic Classifier [5], the classification process with the Logistic Classifier maximized the expression in equation (2.1) for a 2 classes problem.

$$\max_{\Theta}\left\{\prod_{x_i^{(1)}\in w_1} q_1(x_i^{(1)};\Theta)\prod_{x_i^{(2)}\in w_2} q_2(x_i^{(2)};\Theta)\right\} \tag{2.1}$$

where:

$q_j(x;\Theta)$ = is the posterior probability of $w_j$ given x.
$\Theta$ = a set of unknown parameters.
$x_i^j$ = the ith sample from $w_j$.

K-NN and Parzen classifiers are the two well known non parametric decision rules. They are similar in nature, but in practice provides different results [60]. Both classifiers are based on the computation of the distance between the patterns in the training set and the test pattern. The two classifiers depending on the size of the training set require a large amount of computation, which can be reduced by using a Vector Quantitization technique to reduce the size of the training set [44, 45].

A Bayes classifier is an example classifier based on the construction of decision boundaries by optimizing error criterion such as MSE [60]. The goal of this type of classifier is to minimize the error between the classifier output and the target value [101].

The multilayer perceptron, is a neural network based classifier that provides in addition to classifying an input pattern a confidence in the classification, this confidence can be used to reject an input in case of doubt [60]. when it is time to handling outlier the radial basis function is better than the sigmoid function. Compare to a multilayer perceptron the radial basis neural network hidden neurons are added until a predefined performance is obtained [60].

A decision tree is a special type of classifier [15, 23, 100], its training process is based on an iterative selection of the most important features at each node. The selection criteria of the feature and the creation of the tree is based on Fisher's criterion which are: the nodes purity and the information contain. The advantages of a tree classifier are based on the speed and the ability to interpret the decision in terms of individual rules [60].

The introduction of the support vector machines by Vapnik and other authors is considered as one of the most interesting development to design classifiers [17]. With support vectors the optimization criterion is the margin width between class. For a two classes problem derived by the support vector classifier is defined by the decision function in equation(4.21).

$$D(x) = \sum_{\forall x_i \in S} \alpha_i \lambda_i K(x_i, x) + \alpha_0 \tag{2.2}$$

where:

$S$ = is the support vector set.
$\lambda_i$ = the label of the object $x_i$
$\alpha_i \geqslant 0$ = the parameter optimized during training.
$K$ = is the kernel function (it can be a dot product).

Table2.1 presents the most commonly used classifiers and some of their characteristics.

Table 2.1. Description of the Common Classification methods [60]

| Method | Property | Comments |
|---|---|---|
| Template matching | Assign patterns to the most similar template. | The templates and the metric have to be supplied by the user; the procedure may include nonlinear normalizations; scale (metric) dependent. |
| Nearest Mean Classifier | Assign patterns to the nearest class mean. | Almost no training needed; fast testing scale (metric) dependent |
| Subspace Method | Assign patterns to the nearest class subspace. | Instead of normalizing on invariants, the subspace of the invariants is used; scale(metric) dependent. |
| 1-Nearest Neighbor Rule | Assign a patterns to the class of the nearest training pattern. | No training needed; robust performance; slow testing; scale (metric) dependent. |
| k-Nearest Neighbor Rule | Assign patterns to the majority class among k nearest neighbor using a performance optimized value for k. | Asymptotically optimal; scale (metric) dependent; slow testing |
| Bayes plug-in | Assign pattern to the class which has the maximum estimated posterior probability. | Yield simple classifiers(linear or quadratic) for Gaussian distributions; sensitive to density estimation errors. |
| Logistic Classifier | Maximum likelihood rule for logistic (sigmoidal) posterior probabilities | Linear classifier; iterative procedure; optimal for a family of different distributions (Gaussian); suitable for a mixed data type |
| Parzen Classifier | Bayes plug-in rule for Parzen density estimates with performance optimized kernel. | Asymptotically optimal; scale (metric) dependent; slow testing. |
| Fisher Learner Discriminant | Linear classifier using MSE optimization | Simple and fast; similar to Bayes plug-in for Gaussian distributions with identical covariance matrices. |
| Binary decision tree | Find a set of threshold for a pattern-dependent sequence of features | Iterative training procedure; overtraining sensitive; needs pruning; fast testing. |
| Perceptron | Iterative optimization of a linear classifier | Sensitive to training parameters; may produce confidence values. |
| Multi-layer Perceptron (Feed-Forwarrd Neural Network) | Iterative MSE optimization of two or more layers of perceptrons (neurons) using sigmoid transfer functions. | Sensitive to training parameters; slow training; non linear classification function; may produce confidence values; overtraining sensitive; needs regularization. |
| Radial Basis Network | Iterative MSE optimization of two or more layers of perceptrons (neurons) using sigmoid transfer functions | Sensitive to training parameters; nonlinear classification function; may produce confidence values; overtrain-ing sensitive; needs regularization; maybe robust to outliers |
| Support Vector Classifier | Maximizes the margin between the classes by selecting a minimum number of support vectors. | Scale (metric) dependent; iterative; slow training; nonlinear; overtraining sensitive; good generalization performance. |

The following classifiers have been designed and used for leaves classification. Moving Media Center Hyperspheres (MMC), designed by Ji-Xiang et al., [36], uses a series of hyperspheres to classify leaf images using geometric features. The classification process is based on the construction of a hypersphere representing each leaf class. The center of each hypersphere is occupied by an element that is determined by using the multi-dimensional median of the element contained in the class under consideration. Ji-Xiang et al., demonstrated that MMC is close to a KNN classifier, but with the advantage that it can work with a smaller dataset and obtain better results. The Convolutional Neural Network (CNN) is a feed-forward neural network inspired from the animal visual cortex. CNN has been applied for object recognition, video analysis and natural language recognition with promising results.

In [129] CNN is used for plant classification using coloured leaf images, they use the PReLU (Parametric Rectified linear unit) instead of ReLU(Rectified Linear Unit) to construct the CNN. A classification rate of 94.5% was achieved. He et al., [51] introduced the single connected layer (SCL) for the CNN construction and demonstrated that the usage of SCL improves the classification rate. A direct, acyclic, graph-based, multi-class, least squares, twin support vector machine (DAG-MLSTSVM) was used by Tomar et al., [118] to recognize leaf images using shape and texture features.

## 2.5 Conclusion

In this chapter, a review of methods for plant classification using leaf images was presented. All the reviewed works can be organized using two main streams: the leaf analysis stream and the classifier stream. The leaf analysis stream is based on features such as shape, texture and color used to describe a given leaf image. The extraction of these features is a delicate and difficult operation, because of challenges such as noises on the input leaves image and the precision of the method used to extract the features. Color and texture features are found to be difficult to use as leaf images characterizers because when a given leaf is drying the color is changing and the texture as well. In the literature, shape features are the most popular leaf images characterizers because they can be used to characterize fresh and dry leaf images of the same species. Even with the promising results obtained with the shape features, they are sensitives to noises and the lack of precision of the extraction process is another limitation because it can affect the overall recognition rate. Other authors introduce leaf analysis techniques such as symmetry and modeling. The symmetry analysis uses the leaf symmetric property to recognized plant species, and the plant modeling provides a better understanding of plant structure and can contribute to the recognition process. The classifier stream is based on the improvement of the recognition process by improving or customizing pre-existing classifiers or by designing new classifiers. The next chapter proposed a review of shape features used for leaves image characterization.

# Chapter 3

# Background

## 3.1 Introduction

Many image databases have been created and made available online to be freely accessible. The necessity of developing effective tools to search, analyze and use those images to solve real life problems is in demand. When describing images, shape features are for many the most natural and simple features. However, describing and representing shape is a very difficult task. Certainly because most real life objects are naturally 3D and image databases contain 2D images, meaning the analysis of images is made with one dimension lost. The loss of one dimension results in a partial representation of the object. Noise, defect, distortion and occlusion are some other issues affecting the shape features extraction process. The Shape features are used to describe objects interior or boundary. Some of the commonly used shape features belong to the following families: shape signature, shape invariant, shape context, signature histogram, shape matrix and curvature. The common method used to evaluate the effectiveness of shape features is based on how they allow the retrieval of images with similar shape. Dengsheng et al., [134], state that, comparing shape features based on how they allow the retrieval of similar images, is not sufficient to evaluate the effectiveness of shape features because some important characteristics of shape features can be left out.

A good shape-base recognition system requires a shape descriptor to have a rotation, translation and scale invariant properties and be robust enough to provide an accurate description. A good shape descriptor should be able to provide a description of any object. A lower computational cost is another very important characteristic of a shape descriptor because a higher computation cost means maximum uncertainty which can affect the quality of the feature. This chapter presents the image pre-processing operations and some of the shape descriptors used for the characterization of objects.

## 3.2 Image Pre-processing

The following section provides some details on all the pre-processing techniques used during the experimentations.

### 3.2.1 Grayscale transformation

A grayscale representation of an image is used for features extraction in place of color images because they offer the advantages of not being computationally expensive and they produce images that are easy to manipulate. Color images are maybe of limited benefit for many applications and can introduce unnecessary information and increase the amount of training data necessary to achieve a good performance [66].

Kanan et al., [66] demonstrated that a grayscale transformation has a considerable impact on the quality of a given object recognition system. They also demonstrated that *Luminace*, a gray scale transformation method, produces grayscale images that are adequate for many applications.

*Luminance* presented in [99] is based on human brightness perception using a weighted combination of Red, Green and Blue (RGB) channels, as presented in equation (3.1). Luminance is the grayscale representation method use in this thesis.

$$l = 0.2989 * R + 0.5870 * G + 0.1140 * B \tag{3.1}$$

All images in the dataset are transformed from a color image into a grayscale image. In fact, converting the image into grayscale image will preserve the shape of the leaf; thereby not impacting negatively on the end result.

### 3.2.2 Image thresholding

Thresholding is the simplest segmentation technique used to create a binary representation of an input image, using equation (3.2).

$$f(x,y) = \begin{cases} 0 & if \quad f(x,y) > T \\ 255 & if \quad f(x,y) \leqslant T \end{cases} \tag{3.2}$$

The difficulty with using the thresholding method is determining the threshold ($T$) which depends on the input image.

In this thesis, the following assumptions were made for the determination of the threshold $T$.

- The input image is supposed to have two principal regions.
- If there is prior knowledge of the distribution of gray level values, it is possible to minimize the pixel classification error.

- The gray level values follow a Gaussian distribution for some special case [114].

- The probability of a given pixel value is given by the following mixture: $P(z) = P(z \mid background)P(background) + P(z \mid object)P(object)$ or

$$P(z) = P_b \frac{1}{\sqrt{2\pi\sigma_b}} e^{-\frac{(z-\mu_b)^2}{2\sigma_b^2}} + P_o \frac{1}{\sqrt{2\pi\sigma_o}} e^{-\frac{(z-\mu_o)^2}{2\sigma_o^2}} \tag{3.3}$$

  Where:
  $P_b(z)$ and $P_o(z)$ are the probability distribution of background and object.
  $\mu_b, \mu_o$ : the means of the distributions.
  $\sigma_b, \sigma o$: the standard deviations of the distributions
  $P_b, P_o$: the a-priori probabilities of background and object pixels.

The following steps can be used to determine $T$:

- Find the histogram h(z) of the input image to be binarized

- Assign values to the following parameters $(\mu_b, \mu o, \sigma_b, \sigma_o, P_b, P_o)$ such that the model $P(z) = P_b P_b(z) + P_o P_o(z)$ fits $h(z)$ minimizing $Error = \frac{1}{N}\sum_{i=1}^{N}(P(z_i) - h(z_i))^2$

- Choose $T$ based on the above formula.

### 3.2.3 Edges detection

For the edges detection purpose, Sobel operator is used, because it can detect edges and their orientation [46]. A Sobel operator is obtained from the Prewit operator by increasing the weight on the central coefficients. Haldo et al., [115] show that using 2 as a central value of the mask provides image smoothing. Sobel edges detection is implemented using the masks in Figure 3.1. Sobel operators are better localizer

| | | |
|---|---|---|
| $\frac{-1}{\sqrt{12}}$ | $\frac{-1}{\sqrt{3}}$ | $\frac{-1}{\sqrt{12}}$ |
| 0 | 0 | 0 |
| $\frac{1}{\sqrt{12}}$ | $\frac{1}{\sqrt{3}}$ | $\frac{1}{\sqrt{12}}$ |

| | | |
|---|---|---|
| $\frac{-1}{\sqrt{12}}$ | 0 | $\frac{1}{\sqrt{12}}$ |
| $\frac{-1}{\sqrt{3}}$ | 0 | $\frac{1}{\sqrt{3}}$ |
| $\frac{-1}{\sqrt{12}}$ | 0 | $\frac{1}{\sqrt{12}}$ |

Figure 3.1. 3x3 Sobel masks

and less subject to the aliasing effect because of the Gaussian shape of [1 2 1]. The Sobel filter is fast and robust.

### 3.2.4 Thinning transform

To make sure the extracted image boundary is one pixel wide, a sequential thinning by structuring element $L$ obtained from the Golay alphabet, described in equation (3.4), is applied to the extracted image boundary.

$$L_1 = \begin{bmatrix} 0 & 0 & 0 \\ * & 1 & * \\ 1 & 1 & 1 \end{bmatrix} \; L_2 = \begin{bmatrix} * & 0 & 0 \\ 1 & 1 & 0 \\ * & 1 & * \end{bmatrix} \ldots \tag{3.4}$$

## 3.3 Shape Description and Representation

All the techniques used to represent and describe shape can be organized in two classes: region-based (or interior-based) method and contour-base (or boundary-base) methods. The differences between these methods depends on the part of the object from which the shape features are extracted. Each class is further divided into structural and global method depending on whether the shape feature describes the object shape as a whole or as a combination of segments. The complete organization of shape features is presented in Figure 3.2 as described in [134]; some sections of the hierarchy will be discussed in the following sections.

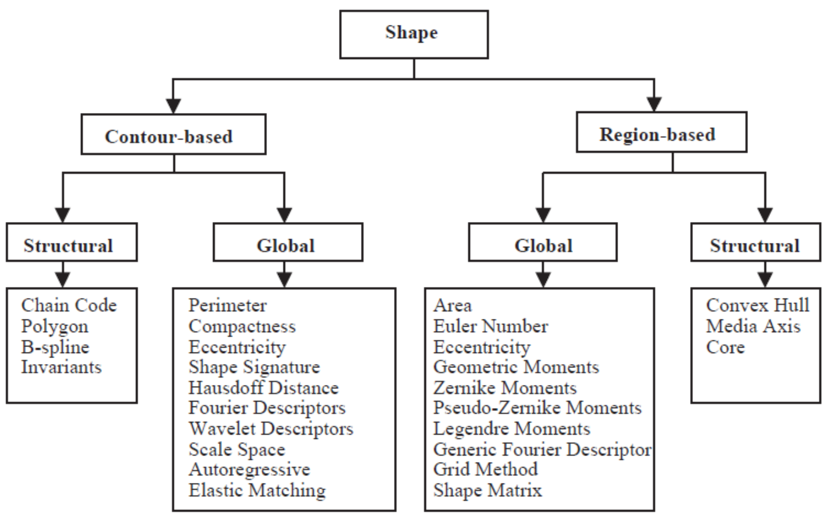



Figure 3.2. Organization of shape description and representation techniques [134]

## 3.4 Contour-based Shape Description and Representation Techniques

Structural and global modeling are the two approaches used to represent a given shape. The continuous or global approach is used to describe the integral object shape, and does not divide the object shape into sub-parts. The values generated by the global descriptors can be used to measure shape similarity [134]. The discrete or structural approach divides the object shape into segments using a specific criterion. Object shape can also be characterized using string or tree. When using string or tree to represent a given shape, evaluating shape similarity is the same as evaluating a graph similarity.

### 3.4.1 Global methods

A multi-dimensional features vector is usually generated from the shape boundary using a global contour shape representation technique. The Euclidean distance (or any other metric can be used) of two feature vectors characterizing two objects can be used to evaluate the degree of similarity of the two objects. The next section presents some global methods for shape characterization.

#### Simple shape descriptors

These are the common global feature descriptors such as, Circularity (equation (3.5)), area, Eccentricity (equation (3.6)), major axis orientation, and bending energy are some of the common examples of global shape descriptor as presented in [14].

$$Circularity = \frac{Perimeter^2}{area} \tag{3.5}$$

$$Eccentricity = \frac{Length\ of\ the\ major\ axis}{Length\ of\ the\ minor\ axis} \tag{3.6}$$

The global shape features are mostly used as filters, because they can only discriminate objects with larger shape differences. They are not suitable for standalone shape discrimination system. Figure 3.3 presents some figures with their associated circularity and eccentricity. Figure 3.3 a and 3.3 b have the same circularity; in this case, the eccentricity is a better descriptor. Peura and Livarienen [97] developed other simple descriptors, such as Convexity, Ratio of principal axis, Circular variance and Elliptic variance.

#### Shape Signature

A one-dimensional function derived from a given shape boundary points is an approach known as shape signature. The Centroid distance, complex coordinates, tangent angle, cumulative angle, curvature area and cord length, presented in [32, 135] are some examples of shape signatures. To satisfy the translation and scale invariant properties, shape signatures are usually normalized, but for the rotation invariant property, some authors use shift matching which requires the identification of the

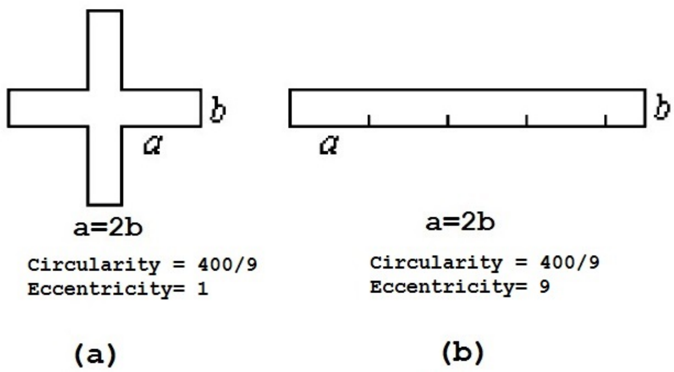



Figure 3.3. Shape Eccentricity and Circularity

best match between two shapes [134]. The problem with the matching process is the fact that it is computationally expensive, which makes it very difficult to use for real time applications. Another problem associated with shape signature features is its sensitivity to noise, which might cause some error during the recognition process. Therefore, in order to use a shape signature for object recognition, some additional processing operations, such as noise removal and thinning, are required to increase the robustness of the extracted features. One of the solutions to the rotation invariance of a shape signature descriptor is to convert the signature to a histogram.

### Boundary moments

A shape signature usually generates many values that are sometimes difficult to analyze. The Boundary moments can be used to reduce the dimensionality of a given shape boundary and improve the recognition time. Lets consider $Z(i)$ a shape signature, $m_r$ the $r^{th}$ moment, $\mu_r$ the central moment evaluates in equation (3.7), as presented in [114].

$$m_r = \frac{1}{N}\sum_{i=1}^{N}[Z(i)]^r \quad and \quad \mu_r = \frac{1}{N}\sum_{i=1}^{N}[Z(i) - m_1]^r \tag{3.7}$$

Where $N$ is the number of boundary points, $m_r$ and $\mu_r$ are generally normalized to obtain $\bar{m_r}$ and $\bar{\mu_r}$ which are rotation translation and scale invariant. The main advantage of the boundary moments is the fact that they easy to implement; but it remains difficult to link the values of the moments to the shape appearance.

### Scale space method

The scale space method was introduced because of the noise sensitivity and boundary variation problems observed when using other shape analysis methods. Object shape representation using a scale space method is done by tracking the position of the shape inflexion points using low pass Gaussian filters of variable width. As the width ($\sigma$) of the Gaussian filter increases the boundary of the generated edges become smoother and significant inflexion are eliminated as presented in Figure 3.4. The main difficulty of the scale space method is the interpretation of the final

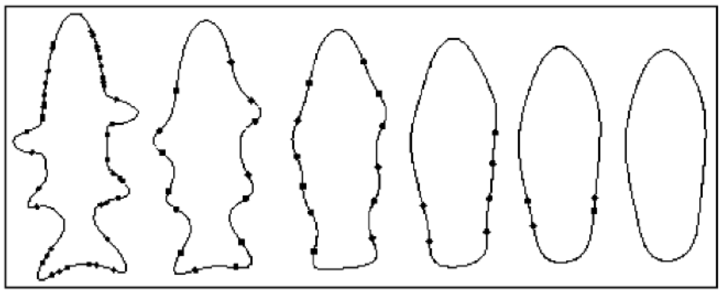


Figure 3.4. Object boundary as the value of the width ($\sigma$) increases [134]

result which is generally an interval tree. The interval tree obtained by the scale space was first interpreted by Asada and Brady in [6]. The Gaussian filter and the second derivative is used to generate the interval tree and the detection of the tree branches from higher scales to lower scales is the base for the interpretation of the interval tree. The variations are interpreted as corner, end, crank, bump/dent and smooth join. Asada and Brady's, interpretation method was extended by Mokhtarian et al., [85] into shore lines interpretation, also known as curvature scale space (CSS). Geodesic topology is another interpretation of the scale space interval tree proposed by Daoudi et al., [31]. The classification of objects using this method is based on the use of a geodesic distance measure.

### 3.4.2 Structural methods

Structural methods divide a given shape into small segments called primitives. In the literature the common method used for the boundary decomposition is the polygonal approximation, curve fitting and curvature decomposition [96]. The result of a structural method is represented as a string, as shown in equation (3.8).

$$S = s_1, s_1, ..., s_n, \tag{3.8}$$

Where $s_i$ can be a length, a maximal curvature, a bending energy, an average curvature or an orientation. The generated string $S$ can be used as the input to a given classifier. Chain code representation, polygon decomposition, smooth curve decomposition, a scale space method, syntactic analysis and shape invariant are some of the applications of structural methods for shape analysis.

### Polygon decomposition

Applied in [48, 49], shape boundary is divided into line segments by polygonal approximation. The primitives are the polygon vertices. The features extracted from each primitive is represented as four length strings which contain the distance from each vertex, the interval angle and the $x$ , $y$ coordinates. These features are not scaled, translation and rotation-invariant. The similarity between two shapes described by this method is by using the editing distance of the two strings [134].

### Smooth curve decomposition

This technique was developed by Berreti et al., [11], and is an extension of the model presented in [48]. This extension is based on the description of a given shape using a series of tokens generated from the *curvature zero crossing* points from the Gaussian smoothed boundary. Each token generated for a given shape contains features such as, maximum curvature and orientation. The weighted Euclidean distance can be used to evaluate the similarity between two tokens. The presence of the orientation in the token removes the rotation invariant property from the feature property.

### Scale space method

This method is based on a feature by feature matching followed by model matching, as presented in [11, 48]. The curvature-turned smoothing techniques are used to obtain the shape primitives. Each primitive will produce values such as segment descriptors, composed of ordinal position, segment's length and curvature-turned. To describe a given shape, a string of segment descriptors is created for each shape, as presented in equation 3.9.

$$A = (S_1^A, S_2^A, ..., S_N^A) \tag{3.9}$$

Where $N$, is the number of boundary points. The main problem with this technique is the fact that it is not scale-invariant.

### Syntactic analysis

The phenomenon supporting the composition of a natural scene is equivalent to a composition of a language, and is the base of syntactic analysis. The representation of a shape as a set of predefined primitives is the goal of a syntactic method. The syntactic analysis is based on a set of predefined primitives called codebook and the actual primitives are the codewords. Equation (3.10) presents an example of shape representation using syntactic analysis.

$$S = dbabcbabababababa \tag{3.10}$$

The shape matching (recognition) is equivalent to the string matching problem. The syntactic shape analysis is based on the theory of formal language.

## 3.5 Region-based Shape Description and Representation Techniques

The region-based techniques are based on all the pixels used to represent a given object shape; not only the boundary pixels. Moment descriptors are the common approach used in shape region descriptors. Grid Method, Convex hull, Shape matrix and Medial axis are some of the common region-based methods. Region-based methods can be divided into global and structural methods like the boundary-based methods, depending on whether the considered shape can be divided in sub-parts or not [134].

### 3.5.1 Global methods

The global methods within the region-based shape descriptors generates a numeric features vector that describes a given object shape as a whole. To evaluate the similarity between two object shapes, a metric distance can be applied to their features vector. The following lines describe some region-based methods.

#### Geometric moment invariants

Hu in [57] was the first to publish a significant paper on the use of Moment invariants for the analysis of two dimensional images in pattern recognition applications. His approach, based on equation (3.11), is inspired by the works of Boole, Cayley and Sylvester [134].

$$m_{pq} = \sum_{x}\sum_{y} x^p y^q f(x,y), p,q = 0,1,2,..... \tag{3.11}$$

Where $x, y$ represents pixels coordinates, $f(x, y)$ the pixel intensity at the coordinates $(x, y)$ and $p, q$ are used to evaluate the moment order.

The geometric moments are obtained using the combination of lower order moments and based on the desired properties, such as rotation, translation and scale-invariance. Many authors, such as Sonka et al., [114] have used the geometric moments for objects recognition. The few invariant moments derived from the lower order moments are not sufficient to describe a given shape. This represents one of the main problems faced when using geometric moments, plus and the fact that higher-order moments are difficult to derive. In [92] it was demonstrated that geometric moments are suitable for the description of simple shapes.

#### Generic Fourier descriptor

Zhang et al., [134] developed the Generic Fourier descriptors (GFD) to overcome the limitations of the Zernike moment descriptors, such as, the complexity of the kernel and the necessity to normalize the shape into a unit disk. The fact that radial and circular features captured by the Zernike moments are not consistent. The problems posed by Zernike moments can result in a significant loss of features that are important for the shape description. Equation (3.12) is used to generate the GFD of a given input 2D polar image.

$$PF_2(\rho.\phi) = \sum_r \sum_i f(r, \theta_i) exp[j2\pi(\frac{r}{R}\rho + \frac{2\pi}{T}\phi)], \quad (3.12)$$

Where $0 \leq r < R$ and $\theta_i = i(\frac{2\pi}{T})(0 \leq i < T); 0 \leq \rho < R, 0 \leq \phi < T$ The radial frequency resolution and angular frequency resolution are represented as T and R respectively. The GFD are the normalized coefficients. The advantage of GDF is the fact they easy to compute, the features generated from them are pure spectral features and they have better retrieval performance.

#### Elliptic Fourier Descriptors

The Fourier descriptor features used in this paper are derived from the coefficients of the Fourier series approximating the boundary of the leaf image; the series is described in Kuhl and Giardina [68]. The coefficients $a_n, b_n, c_n, d_n$, are described as follows:

$$a_n = \frac{L}{2n^2\pi^2} \sum_{p=1}^{P} \frac{\Delta x_p}{\Delta l_p} (Cos \frac{2n\pi l_p}{L} - b_n Cos \frac{2n\pi l_{p-1}}{L}) \quad (3.13)$$

$$b_n = \frac{L}{2n^2\pi^2} \sum_{p=1}^{P} \frac{\Delta x_p}{\Delta l_p} (Sin \frac{2n\pi l_p}{L} - b_n Sin \frac{2n\pi l_{p-1}}{L}) \quad (3.14)$$

$$c_n = \frac{L}{2n^2\pi^2} \sum_{p=1}^{P} \frac{\Delta y_p}{\Delta l_p} (Cos \frac{2n\pi l_p}{L} - b_n Cos \frac{2n\pi l_{p-1}}{L}) \quad (3.15)$$

$$d_n = \frac{L}{2n^2\pi^2} \sum_{p=1}^{P} \frac{\Delta y_p}{\Delta l_p} (Sin \frac{2n\pi l_p}{L} - b_n Sin \frac{2n\pi l_{p-1}}{L}) \quad (3.16)$$

### 3.5.2 Structural methods

Region-based structural methods divide a given object shape region into parts that can then be used to represent and describe the object shape, as with the contour structural method.

#### Convex hull

Lets consider two points $x_1$ and $x_2$ in a region $R$, if the segment $x_1x_2$ is inside the region $R$, then $R$ is said to be convex. The convex hull of a region $R$ is the smallest convex region $H$, satisfying $R \subset H$. The convex Hull is a very useful tool for the analysis of shape variation.

**Medial axis**

A skeleton can be used to describe a given region shape. In [32] a skeleton is defined as a connected set of medial lines along a considered figure limbs. In [12] Blum's medial axis transforms are used to represent the skeleton method. The bold region in Figure 3.5 is the skeleton of the rectangular shape.

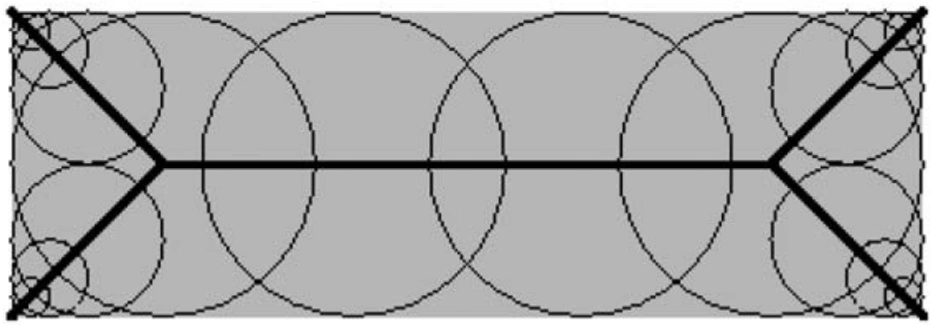


Figure 3.5. Construction of the skeleton of a rectangular shape [134]

## 3.6 The Seven Invariant Moments

Hu's seven invariant moments are computed from the central moments. They are very useful for shape description and classification [36]. The discrete form of the geometrical moment of order $p + q$ is defined as:

$$M_{pq} = \sum_{x=1}^{N} \sum_{y=1}^{M} x^p y^q. \tag{3.17}$$

where:

$p, q \quad = 0,1,2,....$
$N \times M =$ the image size.

Consequently, a set of seven invariant moments $(Ph_1, Ph_2, ..., Ph_7)$ can be derived from the normalized central moments as in [128].

## 3.7 Geometrical Features

The ***rectangularity*** $(R)$ represents the ratio between the leaf area $(A_{leaf})$ and the area of the minimum bounding rectangle. It evaluates how close the leaf shape is, to a rectangle shape.

$$R = \frac{A_{leaf}}{D_{max} \times D_{min}} \tag{3.18}$$

The ***aspect ratio*** ($A$)is the ratio between the maximum length($D_{max}$) and the minimum length($D_{min}$) of the minimum bounding rectangle

$$A = \frac{D_{max}}{D_{min}} \tag{3.19}$$

The ***sphericity*** ($S$) is expressed by the following equation:

$$S = \frac{r_i}{r_c} \tag{3.20}$$

where:

$r_i$ = represents the radius of the in-circle of the leaf.
$r_c$ = the radius of the ex-circle of the leaf.

The ratio between the length of the main inertia axis and the minor inertia axis of the leaf, determines the accent of the leaf. It evaluates how much an iconic section deviates from being circular [7].

$$E = \frac{E_A}{E_B} \tag{3.21}$$

The ***circularity*** ($C$) is defined by all the contour points of the leaf image.

$$C = \frac{\mu_R}{\sigma_R} \tag{3.22}$$

Where

$$\mu_R = \frac{1}{N} \sum_{i=0}^{N-1} ||(x_i, y_i) - (\bar{x}, \bar{y})||$$

and

$$\sigma_R = \frac{1}{N} \sum_{i=0}^{N-1} (||(x_i, y_i) - (\bar{x}, \bar{y})|| - \mu_R)^2$$

***Form Factor*** ($F$) compares the perimeter of the equivalent circle to the perimeter of the leaf shape. It is also used to describe surface irregularity and is given by the following equation:

$$F = \frac{4\pi A_{leaf}}{P^2_{leaf}} \tag{3.23}$$

***Area ratio of the convex hull*** ($CA$) is defined as the ratio between the leaf area and the area of its associated convex Hull polygon (equivalent to the surface-based Convexity Measure). It is expressed by the following equation:

$$CA = \frac{A_C}{A_{ROI}} \tag{3.24}$$

## 3.8 Other shape descriptors

In this section the application of tree-based data structure will be presented. Kd-tree is a tree based data structure that can be used for shape analysis. Kd-tree have been successfully used to solve problems (search, indexing, and space partitioning) but very few authors used the Kd-trees for shape analysis.

Bauckhage in [9], proposed a modified Kd-tree for shape analysis, the proposed Kd-tree is constructed by combining the properties of traditional tree models such as R-tree and Kd-tree. A top-down approach is used for the construction of the proposed tree model. The modified Kd-tree is used to describe both the boundary and the region of the object of interest by extracting salient points and parts of shapes. With the help of the serialization the modified Kd-tree describing a given object, can be easily transformed into feature vectors that can be submitted to a statistical classifier.

## 3.9 Conclusion

In the literature, shape features can be organized into two main groups contour-based or region-based shape representation methods. A contour-based shape feature uses the boundary pixels to characterize the object shape, and a region-based shape feature uses the interior pixel to characterize the object shape. A contour-based or region-based shape feature can be a structural method if it uses a series of values to characterize a given shape or global method if it used a single value to represent a given shape. Contour-based shape features are sensitive to small variations, are computationally expensive, require the boundary extraction algorithm to be accurate, these features are not invariant to all similarity transforms, but they provide a clear and understandable description of the object shape and can be used for the reconstruction of objects shape. Region-based shape features are easy to compute, are not computationally expensive the drawback of this method is the loss of precision. Many shape features have been designed and used to characterize objects, but the precision and the computational cost of these features remain a current problem. The next chapter described and compare methods used for the computation of the minimum bounding rectangleof an input leaf image.

# Chapter 4

# Minimum Bounding Rectangle Computation

## 4.1 Introduction

The first step in the recognition process of plant species using leaf images is the pre-processing of the input leaf images. The pre-processing step is usually followed by the feature extraction process. In the literature, shape, texture and color features are the most popular image representation methods because they are well defined and can be easily computed from raw images. In this chapter, the pre-processing step contains operations such as, thresholding to transform the input image into a binary image, boundary extraction using edges detection algorithm and a thinning operation to make sure that the output shape is one pixel wide.

The Minimum Boundary Rectangle computation is also a very important operation because the quality of many low-level features, such as, rectangularity, aspect ratio and eccentricity depend on the precision of the minimum bounding rectangle computation. For the feature extraction process, we will be discussing all the low-level features used during the experimentation. In this thesis, shape features are computed from the leaf region and the leaf boundary and used for the representation of leaf images. Our main goal was to design a system for leaves recognition using leaf shape, so only shape features were used for the construction of our system. However, all the algorithms used in this thesis for leaves features extraction can also be used for a more general problem, such as object recognition.

The rest of this chapter summarizes all the techniques used during the pre-processing step, then describes a newly developed approach for the minimum bounding rectangle computation; finally, it presents some of the low-level features used during the feature extraction process.

## 4.2 Minimum Bounding Rectangle

One of the most important tasks in computer vision is the computation of geometric features. Some of the features used to characterize shape are: aspect ratio, elongation and circularity [46, 114]. Minimum Bounding Rectangle (MBR) can be used to compute many other features, such as the real aspect ratio, rectangularity and eccentricity, which are very important tools for image analysis as they can be used in various domains [38, 89]. The MBR is defined as the smallest rectangle that contains every point in the region, with the condition that the rectangle boundaries are aligned with the major and minor axis of the object of interest [22].

The determination of the Oriented Bounding Box or Minimum Bounding Rectangle have been implemented using many Heuristic, such as $R-tress$ [104], $R^*$-trees [111], $R^+$-trees [10], the Principal Component Analysis(PCA) [34] and the Least Square method [22].

One of the popular and stable approach for the determination of the Minimum Bounding rectangle is based on the use of the Principal Components Analysis (PCA). The PCA method uses orthogonal transformations that transform a set of observations of possible correlated variables into a set of values of linearly uncorrelated variables called principal components [34]. The determination of the Minimum Bounding Rectangle of a set of points using the PCA method start with the determination of the axes of the MBR using the PCA of the set of points, followed by the determination of the Oriented Bounding Box using the projection of each point set on the axes.

This thesis presents an improvement of a method of finding MBR, proposed in [22], in order to reduce some of the defects observed due to the object initial angulation, caused by aliasing effect and obtain a result comparable to the PCA approach. MBR construction is based on the determination of the object boundaries, followed by the boundary centroid determination and the boundary orientation for the determination of the major and minor axis; the major and minor axis are then used to determine the rectangle edges [22]. Bookstein [13], Rosin [103] and Forsyth [42] conducted much important research in the domain of shape analysis. They approximated a finite set of points using a rectangle as a model. The process of constructing a rectangle using the parametric and non-parametric Bayesian paradigm is discussed in [126]. Using the perimeter and the surface of the object of interest, Alt and Hurto [4] describe an approach for fitting convex polygons in a rectangle of the smallest size. Even though these methods give the possibility of fitting a discrete set of points in a rectangle, they are computationally very expensive. The method presented in this thesis is inspired by the one in [22] with a difference in the determination of the rectangle edges. Instead of solving the systems of equations to obtain the intersection of lines, a set of approximations is used.

The rest of this section is organized as follows: First, the description of Chaudhuri's method to determine the MBR of an object and outline its drawbacks; secondly, the proposed method is discuss; then the PCA approach for the determination of the minimum bounding rectangle will be presented; followed by the experimental results of a comparative study of the methods.

### 4.2.1 Computation of the Minimum Bounding Rectangle Least Square Method

Lets consider $I$ the binary image to be processed. Given a set of boundary points $(x_i, y_i)_{i=1,\ldots,n}$ the method proposed by Chaudhuri et al., [22] for the construction of the MBR, focuses on the following:

***Determination of the boundary centroid***. The centroid, $(\bar{x}, \bar{y})$, is the average of the coordinates of the boundary points, defined as:

$$(\bar{x}, \bar{y}) = (\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i) \tag{4.1}$$

***Determination of the image orientation and the image principal axis***. These are the perpendicular axis dividing the object into four parts. To determine the principal axis, boundary point coordinates are considered and the formula given in equation (4.2) is used to obtain the object orientation, $\theta$.

$$\tan 2\theta = \frac{2\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}[(x_i - \bar{x})^2 - (y_i - \bar{y})^2]} \tag{4.2}$$

This formula is obtained by using the equation (4.3) of the line passing through the centroid with the angle $\theta$.

$$x \tan\theta - y + \bar{y} - \bar{x}\tan\theta = 0 \tag{4.3}$$

and the perpendicular distance from that line to an edge point is defined as:

$$p_i = (x_i - \bar{x})\sin\theta - (y_i - \bar{y})\sin\theta \tag{4.4}$$

***Determination of the lower and further points associated with each axis***.
These are the points associated with each principal axis. They are obtained using the following property:

$$If \quad f(a,b) \begin{cases} > 0 & \text{then } (a,b) \text{ is above} \\ = 0 & \text{then } (a,b) \text{ is on } f(x,y) = 0 \\ < 0 & \text{then } (a,b) \text{ is below} \end{cases} \tag{4.5}$$

Where $f(a,b)$ is the value obtained using equations (4.6) or (4.7) by considering the coordinates $(a,b)$ of the shape points. Considering the principal axis equations, bounding points are organized into upper and lower further points. The equations of these axes are:

$$(y-\bar{y})-\tan\theta(x-\bar{x})=0 \tag{4.6}$$

$$(y-\bar{y})+\cot\theta(x-\bar{x})=0 \tag{4.7}$$

To determine the upper and lower points, the distance associated with each lower and upper point is computed using the following equation:

$$P_i=(x_i-\bar{x})\sin\theta-(y_i-\bar{y})\cos\theta \tag{4.8}$$

***Determination of the rectangle corner points***. These points are the intersection of lines passing at the upper and lower points associated with each axis, and are obtained using the formulae in equations (4.9) to (4.12).

$$(tl_x = \frac{x_1\tan\theta+x_3\cot\theta+y_3-y_1}{\tan\theta+\cot\theta}, \quad tl_y = \frac{y_1\cot\theta+y_3\tan\theta+x_3-x_1}{\tan\theta+\cot\theta}) \tag{4.9}$$

$$(tr_x = \frac{x_1\tan\theta+x_4\cot\theta+y_4-y_1}{\tan\theta+\cot\theta}, \quad tr_y = \frac{y_1\cot\theta+y_4\tan\theta+x_4-x_1}{\tan\theta+\cot\theta}) \tag{4.10}$$

$$(bl_x = \frac{x_2\tan\theta+x_3\cot\theta+y_3-y_2}{\tan\theta+\cot\theta}, \quad bl_y = \frac{y_2\cot\theta+y_3\tan\theta+x_3-x_2}{\tan\theta+\cot\theta}) \tag{4.11}$$

$$(br_x = \frac{x_2\tan\theta+x_4\cot\theta+y_4-y_2}{\tan\theta+\cot\theta}, \quad br_y = \frac{y_2\cot\theta+y_4\tan\theta+x_4-x_2}{\tan\theta+\cot\theta}) \tag{4.12}$$

Figure 4.1 presents MBR corner point positions $tl=(tl_x,tl_y), tr=(tr_x,tr_y), bl=(bl_x,bl_y), br=(br_x,br_y)$. A drawback of this method is that it produces inaccurate values of the rectangle edge coordinates. Figure 4.2 shows an example in which the method works perfectly and another example in which it does not. This problem is due to the fact that all the formulae for the calculation of the object orientation and the coordinates of the corner points of the rectangle are in the continuous domain, and their approximation in the discrete domain does not always represent the reality.

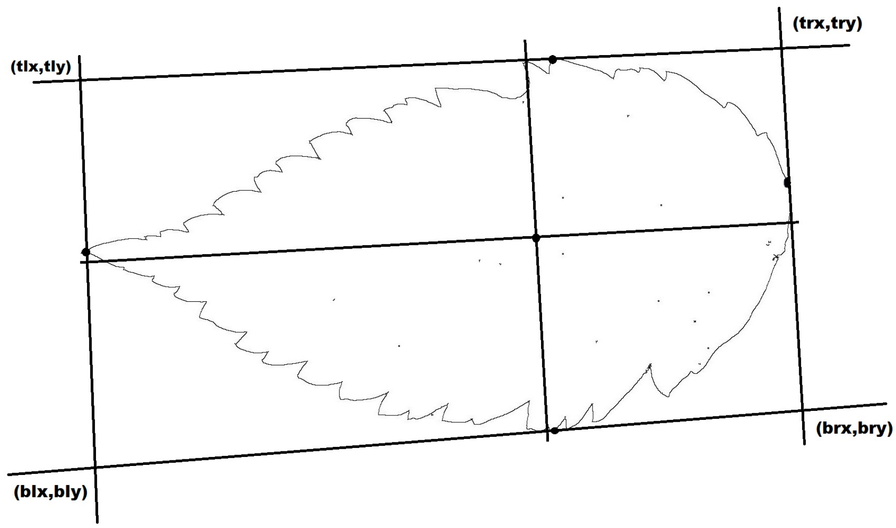



Figure 4.1. Minimum Bounding Rectangle corner point coordinates

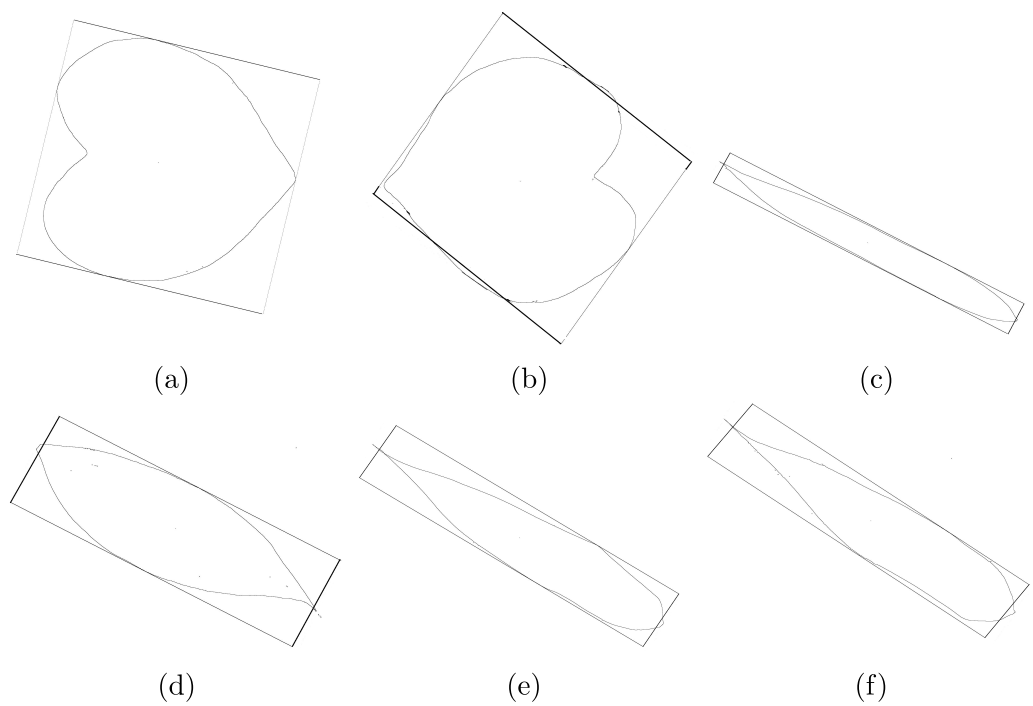



Figure 4.2. MBR construction using Chaudhuri's method. (a) MBR is accurately constructed. (b),(c),(d),(e),(f) MBR is not properly detected

### 4.2.2 Minimum Bounding Rectangle Proposed Method

This method is inspired by Chaudhuri's one. It uses equations (4.1) to (4.7) in a similar way to the previous method. The difference is in the determination of the rectangle edge points. Algorithms (1) and (2) describe the process of the construction of the rectangle edge points.

**Algorithm 1** Construction of the set A

**Input:** $Im$.

**for** $p \in Im$ **do**

  **if** $Q1(p) \approx 0$ **then**

    $A_1 = A_1 \cup \{p\}$

  **if** $Q2(p) \approx 0$ **then**

    $A_2 = A_2 \cup \{p\}$

$A = A_1 \cup A_2$

**Output:** $A, A_1, A_2$

**Algorithm 2** Determination of rectangle edge points

**Input:** $A_1, A_2$, $Im$.

$B = \emptyset$

**for** $p \in Im$ **do**

  **if** $(Q4(p) = 0) \vee (Q3(p) = 0)$ **then**

    $B = B \cup \{p\}$

  **if** $(p \in A_1) \wedge (Q3(p) = 0)$ **then**

    $tl = p$

  **if** $(p \in A_2) \wedge (Q3(p) = 0)$ **then**

    $bl = p$

  **if** $(p \in A_1) \wedge (Q4(p) = 0)$ **then**

    $tr = p$

  **if** $(p \in A_2) \wedge (Q4(p) = 0)$ **then**

    $br = p$

**Output:** $tl, bl, tr, br$, $B$

Let $Im$ be the set of all pixels of the image. $A$ is the set of pixels of the two lines associated with the upper and lower points of $Im$ with respect to the main axis and is parallel to it, respectively $(x_{uA}, y_{uA})$ and $(x_{lA}, y_{lA})$. $B$ is the set of pixels of the two lines associated with the upper and lower points of $Im$ with respect to the minor axis and is parallel to it respectively $(x_{uB}, y_{uB})$ and $(x_{lB}, y_{lB})$. Let $Q1$, $Q2$ be the equations of the lines associated with $A_1$ and $A_2$ respectively, with $A = A_1 \cup A_2$ and $Q3$ , $Q4$ the equations of the line associate to $B_3$ and $B_4$ respectively, with $B = B_3 \cup B_4$. Let $tl, tr, bl, br$ be the set of rectangle corner edge points as presented in Figure 4.1 $Q1, Q2, Q3, Q4$ are defined as:
For all $p \in Im$ with $p = (x_p, y_p)$ and $\theta$ the initial angle of the boundaries we have:

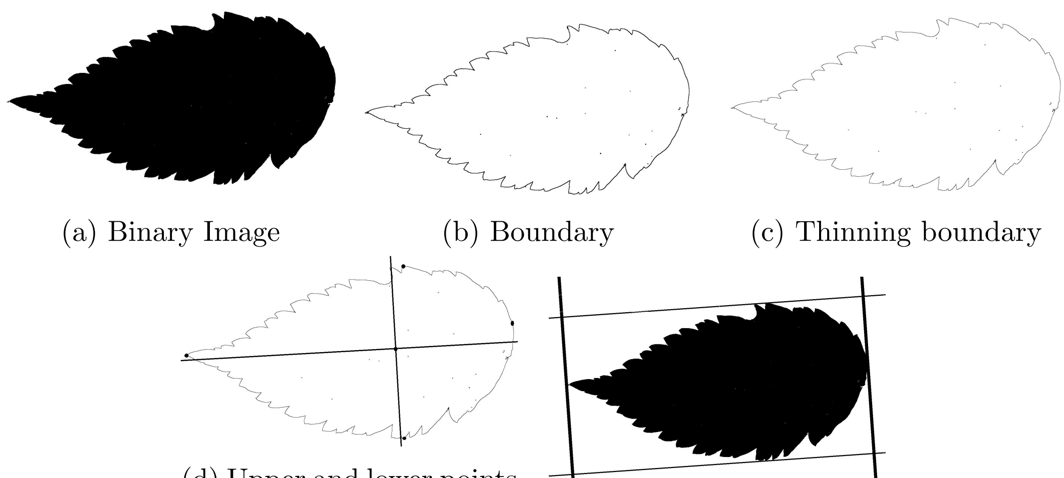
$$Q1(p) = x_p \tan\theta + y_{uA} - x_{uA} \tan\theta - y_p. \tag{4.13}$$

$$Q2(p) = x_p \tan\theta + y_{lA} - x_{lA} \tan\theta - y_p. \tag{4.14}$$

$$Q3(p) = x_p \tan\theta + y_{uB} - x_{uB} \tan\theta - y_p. \tag{4.15}$$

$$Q4(p) = x_p \tan\theta + y_{lB} - x_{lB} \tan\theta - y_p. \tag{4.16}$$

We have the following properties: $A \subset Im$ and $B \subset Im$ Algorithm (1) focusing on the determination of the set of pixels $A$. Algorithm (2) determines the rectangle edge points, by considering the intersection of $Im$, $A$ and $B$, where $Im$ is the image pixels, $B$ is the set of pixels associated with the lines parallel to the minor axis and $A$ is the set of pixels associated with the lines parallel to the major axis. Figure 4.3 represents the construction of the MBR of a given shape image using the proposed method.

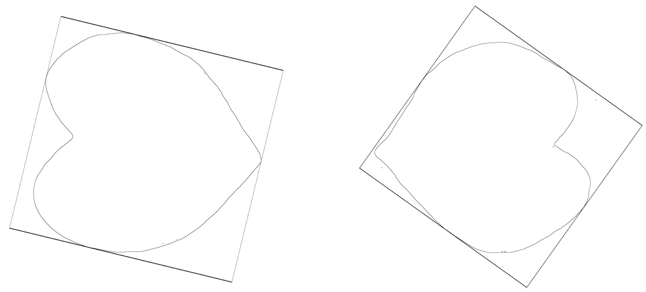


(a) Binary Image (b) Boundary (c) Thinning boundary

(d) Upper and lower points and axis (e) MBR

Figure 4.3. Process of construction of MBR from the original binary image to the drawing of MBR around the original image.

The proposed approach is applied to the images used to test Chaudhuri's method. Figure 4.5 presents the results obtained when applying algorithms (1) and (2) to an image. It can be noticed from Figures 4.2(a) and 4.5(a) that the two methods produce identical results. While the proposed method still produces good results in Fig. 4.5(b), Chaudhuri's method fails to detect correct boundaries in Figure 4.2(b). As with Chaudhuri's method, the proposed method produces MBR's corner points.



(a) (b)

Figure 4.4. MBR construction using the proposed method

### 4.2.3 Minimum Bounding Rectangle PCA Method

Performing data dimensionality reduction by identifying the most important direction is the principal motivation behind the use of the PCA [62]. PCA uses orthogonal transformations that transform a set of observations of possible correlated variables into a set of values of linearly correlated variables called principal components. It is a heuristic frequently used for the computation of the Minimum Bounding Rectangle of a set of points because of the following advantages:

- It isolate Noises.
- It Eliminate effect of rotation.
- It Separate out the redundant degree of freedom.

Lets consider $S = \{a_1, a_2, ..., a_m\}$ a set of point in $\mathbb{R}^2$ with $a_1 = (x_1, y_1)$ and $c = (\bar{x}, \bar{y})$ the centroid of $S$. The following steps need to be followed to create the Oriented Bounding Box (or the Minimum Bounding Rectangle).

#### Evaluate the coordinates of the centroid of $S$

The centroid is the average position of all point in the set $S$. Equation (4.17) describes the centroid of the points in the set $S$.

$$C = (\bar{x} = \frac{1}{m}\sum_{i=1}^{m} x_i, \bar{y} = \frac{1}{m}\sum_{i=1}^{m} y_i) \tag{4.17}$$

**Determine Covariance Matrix of the points in $S$**

The covariance is used to measure how linear is the relationship between two given variables, if the covariance is small it means the variables are independent. In the case of the set $S$ the covariance is evaluate using the matrix in equation (4.18).

$$A = \begin{bmatrix} cov(x,x) & cov(x,y) \\ cov(x,y) & cov(y,y) \end{bmatrix} \tag{4.18}$$

Where $cov(x,y)$ is describe in equation (4.19).

$$cov(x,x) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{n-1}. \tag{4.19}$$

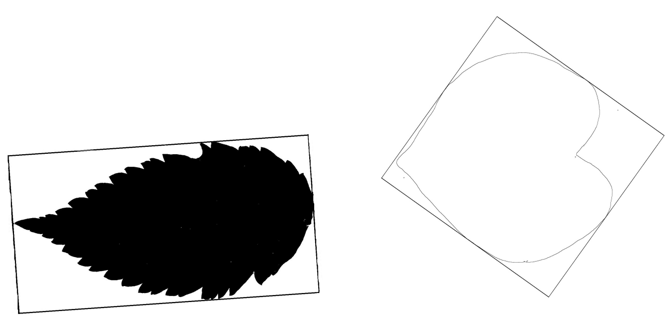
**Calculate the eigenvalues and eigenvectors of the Covariance Matrix**

At this step the eigenvalues will be used to determine the eigenvectors that defined the angular orientation of the set of points in $S$. The eigenvalues are obtained using equation (4.20). The eigenvector associate to a given eigenvalue are obtained using equation (4.21) define the orientation of the set of points.

$$det(A - \lambda I) = 0 \tag{4.20}$$

$$AV = \lambda V \tag{4.21}$$

The oriented Bounding Box is obtained by the projection of each point on the axes defined by the eigenvectors. Figure: 4.5 presents the result of the application of the application of the PCA on two leaf images to determine the Minimum Bounding Rectangle.



(a) (b)

Figure 4.5. MBR construction using the PCA Method

To achieve a better precision during the determination of the Oriented Bounding Box the process require the construction of the Convex Hull of the set of points $S$ which in return increases the the complexity of the method to $O(nlog(n)$.

## 4.3 Experimental Results and Comparative Study of the Three Methods

An experimental study based on 50 leaves of 10 different plants is conducted in order to prove the accuracy of the proposed methods. To evaluate the effectiveness of each method, we adopted the Mean Absolute Error (MAE) method. MAE measures how close points detected by each method are to the one calculated manually. Given a set of $n$ shapes $(S_i)_{i=1,\ldots,n}$, for each shape $S_i$, the four corner points $[(x_i(pos,t), y_i(pos,t))]_{pos \in \{TL,BL,TR,BR\}}$, are computed for each method. $t \in \{M, C, P\}$, where TL, BL, TR, BR represent *Top Left, Bottom Left, Top Right,and Bottom Right* respectively, and M,C and P represent *Manual, Chaudhuri and Proposed* methods respectively. The errors are calculated as follows:

- For the $x$ coordinate, $xe_i(pos,t)$, the deviation from the manually calculated coordinate is:
$$xe_i(pos,t) = |x_i(pos,t) - x_i(pos,M)| \tag{4.22}$$
- For the $y$ coordinate, $ye_i(pos,t)$, the deviation from the manually calculated coordinate is:
$$ye_i(pos,t) = |y_i(pos,t) - y_i(pos,M)| \tag{4.23}$$

where $t \in \{C, P\}$. It is then possible to compute the Mean Absolute Error for each corner point position ($pos$) and each method $t$, $MAE(pos,t)$, for all $n$ shapes as:

$$MAE(pos,t) = \frac{1}{2n}\sum_{i=1}^{n}(xe_i(pos,t) + ye_i(pos,t)) \tag{4.24}$$

The errors incurred when computing the MBR corner points of the 50 shapes presented above, are shown in Table 4.1.

Table 4.1. MAE Inccured for each method and for each corner point of the MBR

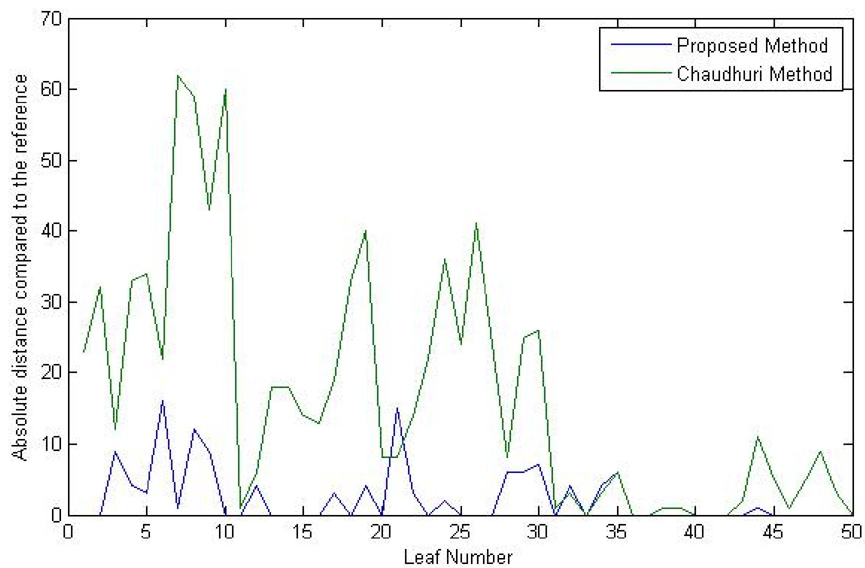
| | | Methods | | |
|---|---|---|---|---|
| | | Chaudhuri | PCA | Proposed |
| Position of the corner points | Top Left | 26.37 | 8.1 | 8.14 |
| | Top Rigth | 28.40 | 8.25 | 8.34 |
| | Bottom Left | 19.09 | 8.40 | 8.34 |
| | Bottom Right | 192.24 | 10.38 | 10.32 |

It can be seen that the proposed method consistently outperforms Chaudhuri's one. Figures 4.6a to 4.6h, show the errors incurred by each method to compute the four corner points when applied to each of the 50 leaves in the data set. They depict how the proposed method consistently computes the points more accurately. For instance, Figure 4.6h presents the leaves' numbers vs errors incurred when computing the y coordinate of the bottom right corner point of the MBR using the two methods. It shows that the error incurred by the proposed method is very close to 0, compared with Chaudhuri's one because the proposed method lowers the impact of the aliasing effect during MBR determination process. In Table: 4.1 the error inccured by the PCA method and the proposed method are very close.

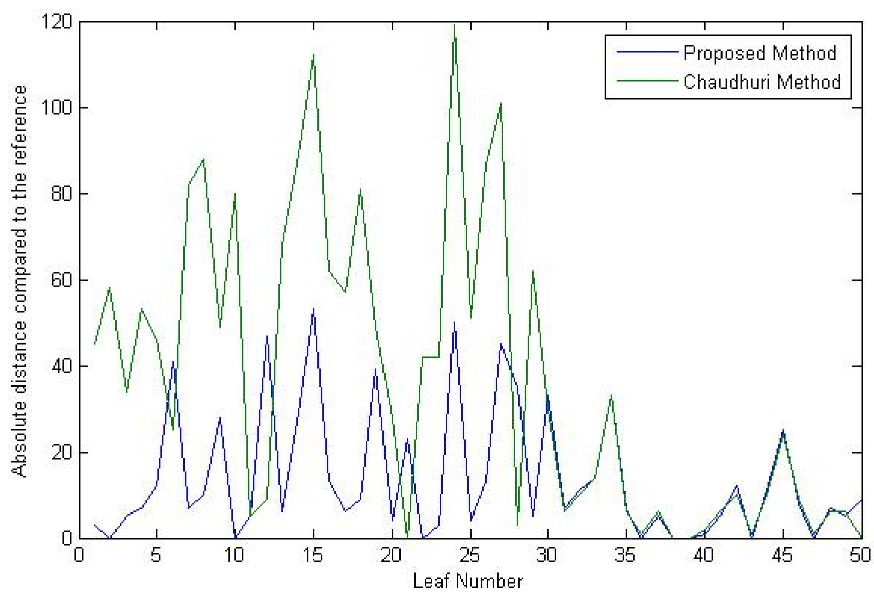
Table:4.2 summarized the comparison of the three methods, we can see that all the methods have the same complexity, but when using the Convex Hull on the PCA it increase the complexity for the PCA method. The PCA method have been applied to dimension 2, 3 and are proven to be efficients in those dimension. The proposed method and the Chaudhuri have only been applied to dimension 2.

Table 4.2. Comparison of three Methods

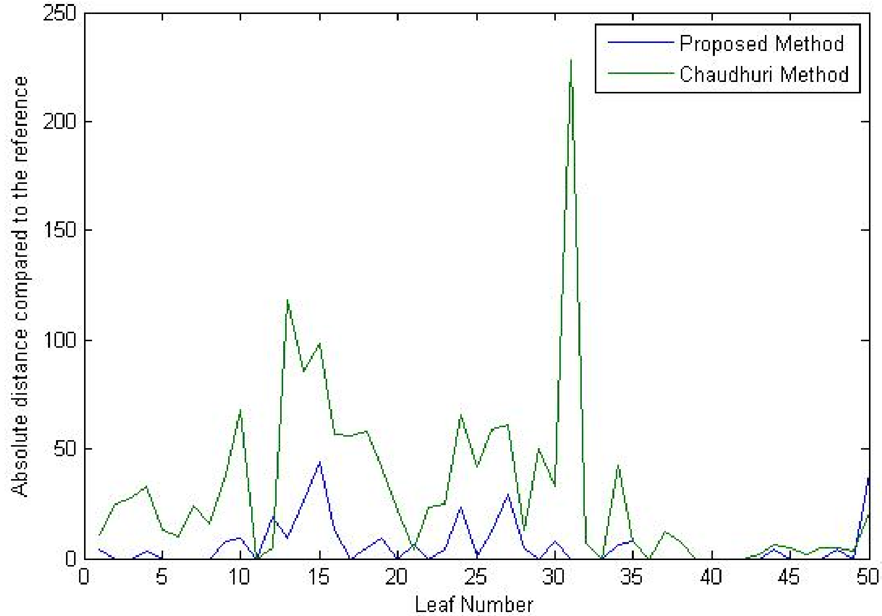
| **Proposed Method** | **PCA Method** | **Chaudhuri Method** |
|---|---|---|
| Least Square method | Principal Component analysis | Least Square method |
| Complexity:O(n) | Complexity: O(n) or O(nlog(n)) | Complexity: O(n) |
| Applicable on $\mathbb{R}^2$ | Applicable on $\mathbb{R}^d$ | Applicable on $\mathbb{R}^2$ |
| Not Sensitive to aliazing effect | Not Sensitive to aliazing effect | Sensitive to aliazing effect |
| 890 ms(for a (3000*3000pixels) image) | 860 ms(for a (3000*3000 pixels) image) | 890 ms(for a (3000*3000 pixels) image) |



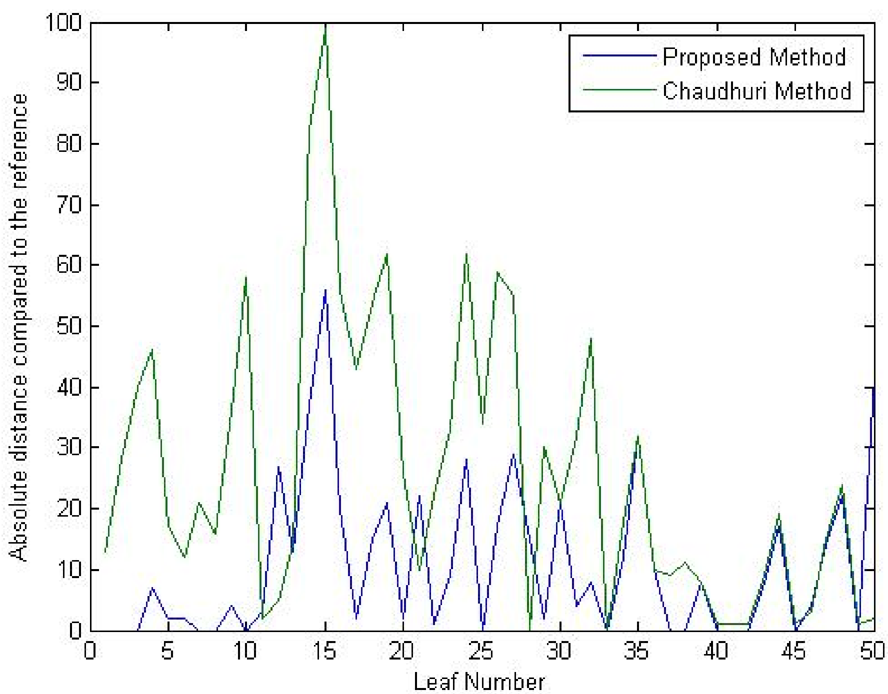

(a) Leaves numbers vs errors incurred when computing the x coordinate of the Top left corner point of the MBR using the two methods.



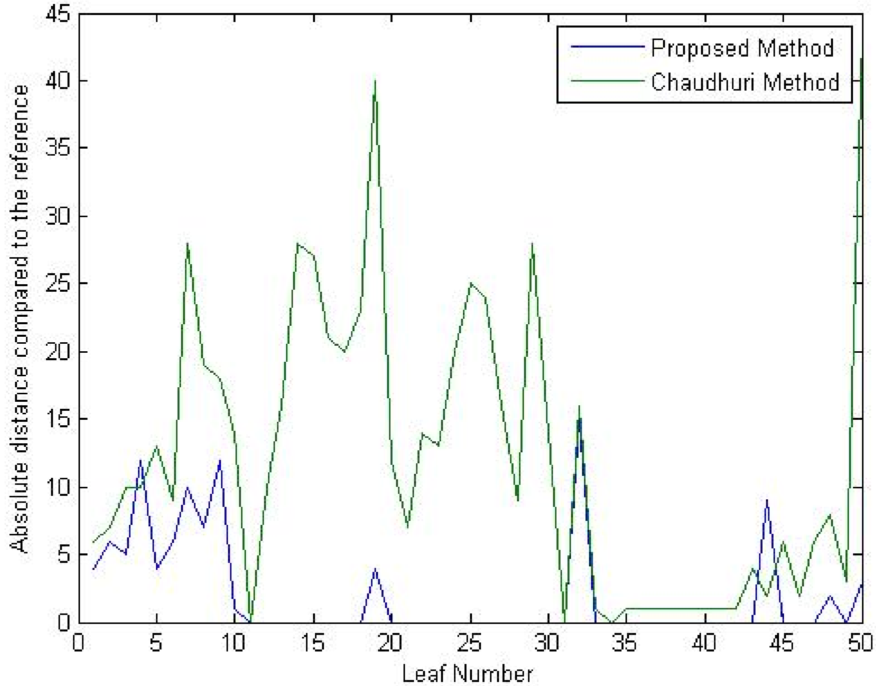

(b) Leaves numbers vs errors incurred when computing the y coordinate of the Top left corner point of the MBR using the two methods.



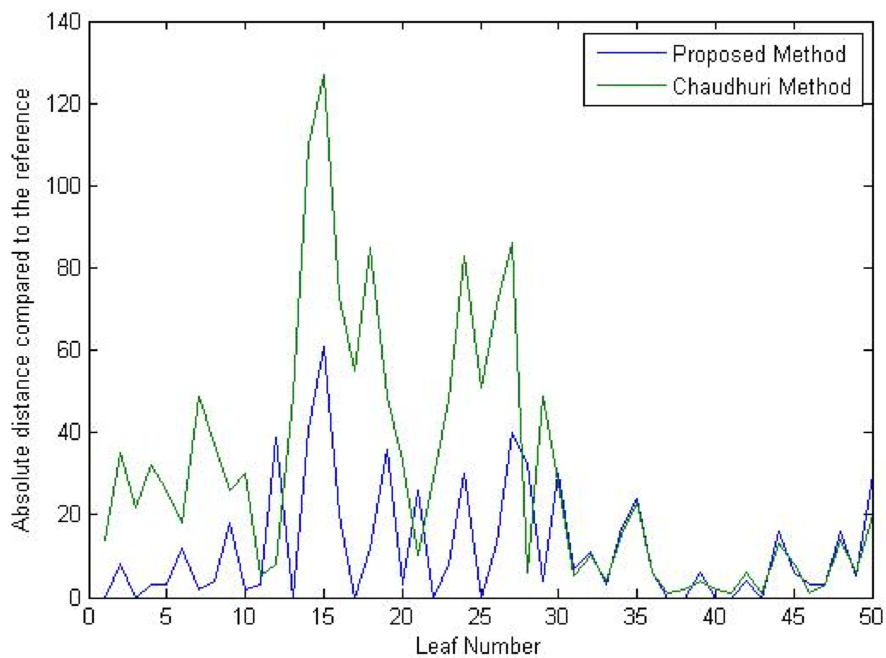

(c) Leaves numbers vs errors incurred when computing the x coordinate of the bottom left corner point of the MBR using the two methods.



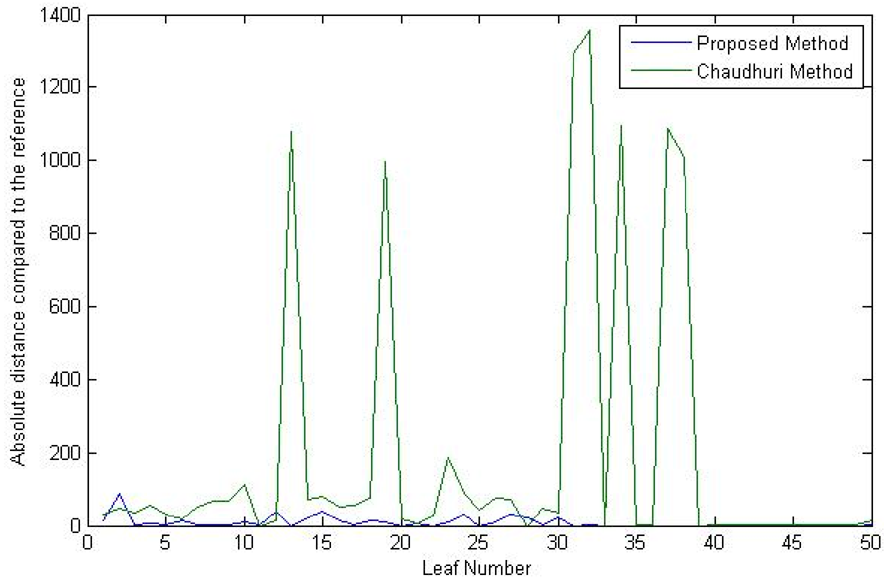

(d) Leaves numbers vs errors incurred when computing the y coordinate of the bottom left corner point of the MBR using the two methods.



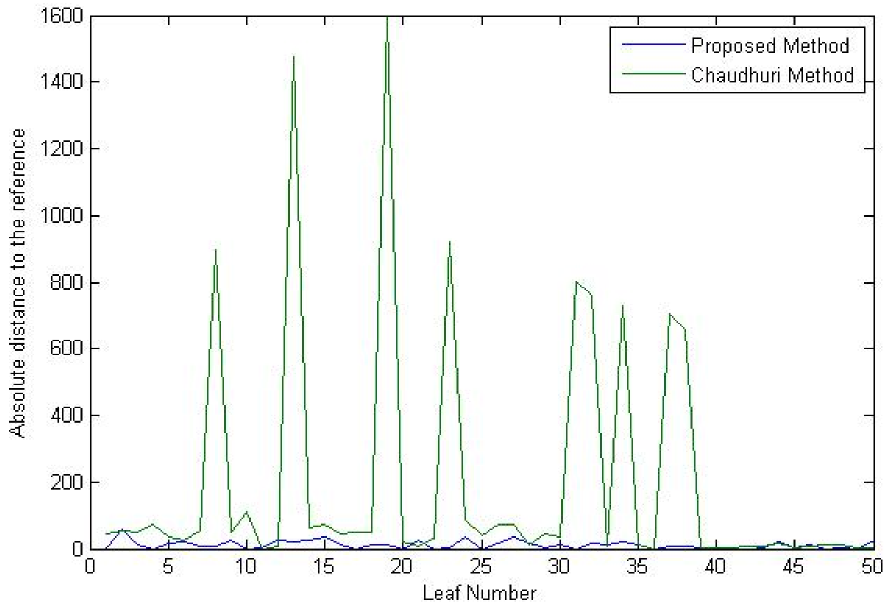

(e) Leaves numbers vs errors incurred when computing the x coordinate of the Top right corner point of the MBR using the two methods.




(f) Leaves numbers vs errors incurred when computing the y coordinate of the Top right corner point of the MBR using the two methods.




(g) Leaves numbers vs errors incurred when computing the x coordinate of the bottom right corner point of the MBR using the two methods.




(h) Leaves numbers vs errors incurred when computing the y coordinate of the bottom right corner point of the MBR using the two methods.

Figure 4.6. Leaves numbers vs errors incurred when computing MBR edges points coordinates

## 4.4 Conclusion

In this chapter, the three MBR construction algorithms were presented and compared. The MBR determination is very important for feature extraction steps. To overcome the errors committed when extracting shape features, a new method for the determination of the Minimum Bounding Rectangle is presented. The proposed method was derived from Chaudhuri et al., [22] method and has the advantage of being lesser sensitive to the aliasing effect and produces results closers to the popular PCA method. In the next chapter, the Convexity Measure of Polygons and the Convexity Moments of Polygons are described and used for the recognition of plant species using leaf images.

# Chapter 5

# Convexity Measure of Polygons and Convexity Moments of Polygons

## 5.1 Introduction

Shape features are very popular in the field of plant recognition using leaf images. However, most of the commonly used features have failed to capture certain specific variations on the leaf shape. These variations can be used to improve recognition accuracy. In this thesis, one of the solutions proposed for improvement of plant recognition using leaf images is the introduction of a boundary-based convexity estimator for the analysis of leaf shape.

A given shape can be characterized using a convexity estimator. In this thesis, a convexity estimator known as Convexity Measure of Polygons is used for the analysis of leaf shapes. The Convexity Measure is a boundary-based shape which was proved by Zunic et al., [136] to be better than a surface-based convexity estimator because it is more sensitive in measure boundary defects.

The Convexity Measure of Polygons is an improved version of the Convexity Measure based on the ratio between the Euclidean perimeter of the considered shape and the Euclidean perimeter of its associated Convex Hull. The main advantage of the Convexity Measure of Polygons is the ability to provide a convexity estimation of shape with holes, which is particularly important during the analysis of deformed leaves.

The Convexity Measure of polygons was found by Zunic et al., [136] to be ineffective when used alone to characterize objects. The authors further state that the New Convexity Measure of Polygons needs to be combined with other shape features to obtain an accurate system. Based on the limitations of the Convexity Measure of Polygons, a new shape characterizer is derived from the Convexity

Measure of Polygons. The Convexity Moments of Polygons are more accurate than the New Convexity Measure of Polygons, certainly because it uses more values to characterize a given shape.

The rest of this chapter is organized as follows: Section 2 presents the Convexity Measure of Polygons, followed by an application to the classification of leaf images. The Convexity Moments of Polygons and an application to leaf image recognition is presented in Section 3.

## 5.2 Convexity Measure of Polygons

A set of points, $A$, is convex if the straight line segment joining any two points in $A$ is contained in $A$ [136]. The Convexity Measure of Polygons, is a numerical value that is used to represent the probability that a straight line joining two points in $A$ lies entirely in $A$.
The Convexity Measure of Polygons has the following properties [136]:

- The value of the Convexity Measure is in (0,1].
- For a given shape, the Convexity Measure can be arbitrarily close to 0.
- The Convexity Measure of a convex set is equal to 1.
- The Convexity Measure is invariant under similarity transformation.

In the literature, there are two types of Convexity Measure: surface-based Convexity Measures and boundary-based Convexity Measure [136]. The first approach for the determination of the Convexity Measure of polygons was based on the convex Hull polygon(CH). $C_1$, $C_2$ and $C_3$ of a shape $S$ were defined as:

$$C_1 = \frac{Area(S)}{Area(CH(S))}. \tag{5.1}$$

$C_1$ is a surface-based Convexity Measure that is obtained by dividing the area of the shape by the surface of the associated convex Hull polygon.

$$C_2 = \frac{Area(MCS(S))}{Area(S)}. \tag{5.2}$$

$C_2$ is a surface-based Convexity Measure that is obtained by dividing the area of the minimum convex set (MCS) of shape $S$ by the surface of shape $S$.

$$C_3 = \frac{Per(CH(S))}{Per(S)}. \tag{5.3}$$

$C_3$ is a boundary-based Convexity Measure that obtained by dividing the perimeter of the convex Hull of shape $S$ by the perimeter of shape $S$.

### 5.2.1 New Convexity Measure of Polygons

The new definition of the Convexity Measure of Polygons, introduced by Zunic et al., [136] was designed because of the incapacity of other Convexity Measures to include huge defects. In addition, this measure can evaluate small variations on a shape and is the first element in the leaf feature vector used in this chapter. The Convexity Measure of Polygons defined by Zunic et al., [136] is evaluated as:

$$C\left(P\right) = \underset{\alpha\in[0,2\pi]}{min} \frac{Per_2\left(R\left(P,\alpha\right)\right)}{Per_1\left(P,\alpha\right)}, \tag{5.4}$$

where:

$\alpha$ = Rotation angle
$P$ = Shape Parameter (Polygon)
$R$ = The optimal rectangle
$Per_2$ = Perimeter by projection on axis
$Per_1$ = Euclidian perimeter

In equation (5.4), the perimeter of the polygon $P$ is fixed and the perimeter of the bounding rectangle noted $R(P, \alpha)$ depends on the value of $\alpha$. $C(P)$ is equivalent to the following equation.

$$C(P) = min\left\{\tfrac{Per_2(R(P,\alpha_i))}{Per_1(P,\alpha_i)} | i = 1, 2, ..., n\right\} \tag{5.5}$$

where

$$Per_2(R(P, \alpha_i)) = \tilde{g}_i * \cos(\alpha_i) + \tilde{f}_i * \sin(\alpha_i),$$
$$Per_1(P, \alpha_i) = \tilde{c}_j * \cos(\alpha_i) + \tilde{d}_j * \sin(\alpha_i).$$

$\tilde{g}_i, \tilde{f}_i, \tilde{c}_j, \tilde{d}_j$ are the constants obtained using the $l1$ metric (Manhattan) and $l2$ metric (Euclidean) of the rectangle edges and the polygon(shape) edges. Equation(5.8) to equation (5.9) describe each constant as demonstrated in [136].

$$\tilde{c}_j = \sum_{i=n}^{n} l_2(e_i)(a_{j,i} * cos\phi_i + b_{j,i} * sin\phi_j) \tag{5.6}$$

$$\tilde{d}_j = \sum_{i=n}^{n} l_2(e_i)(b_{j,i} * cos\phi_j - a_{j,i} * sin\phi_i) \tag{5.7}$$

$$\tilde{f}_i = \sum_{i=n}^{4} l_2(b_i)cos\phi \tag{5.8}$$

$$\tilde{g}_i = \sum_{i=n}^{4} l_2(b_i) sin\phi \tag{5.9}$$

Where $e_i, 1 \leq i \leq n$ are the shape edges. $b_i$ are the rectangle edges.

This equation(5.5) represents the computational process of $C(P)$. Figure 5.1 presents some leaves with their associated Convexity Measure.

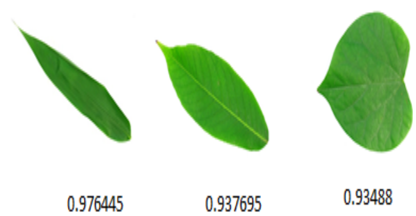



Figure 5.1. Convexity Measure of Polygon of selected leaves

In order for the Convexity Measure of Polygons (Zunic et al., [136]) to be used for shape characterisation, it has to be combined with other Convexity Measures or features to increase the recognition rate [136], this is the main limitation of the convexity measure as a feature. The Convexity Measure of Polygons only expresses how convex or concave a given shape is; however, it is also important to have another descriptor for the surface.

## 5.3 Convexity Moments of Polygons

The Convexity Moments of Polygons, designed based on the limitation of Convexity Measure of Polygons are calculated using all the values generated by the formula of the Convexity Measure of Polygons in equation (5.1). A set of statistical characterizers (mean, standard deviation, mode, min) are applied to the 361 generated values using equation(5.1) (by considering the value of the Convexity Measure for each rotation angle in $[0, 2\pi]$), to obtain the Convexity Moments of a given leaf shape. Each statistical characterizer is selected for the following purposes;

- The Mean (Arithmetic mean): to obtain a single piece of data that describes the whole set, the mean is intended to be a measure of central tendency of all the 361 values. It represents the average value of all the convexity measure calculated by equation (5.1).

$$\overline{X} = \frac{\sum x_i}{n} \tag{5.10}$$

With

$$x_i \in \left\{ \frac{Per_2(R(P,\alpha_i))}{Per_1(P,\alpha_i)} |\ i = 1, 2, ..., n \right\}$$

- The mode is the most frequently occurring value in the set $C$.

$$C = \left\{ \tfrac{Per_2(R(P,\alpha_i))}{Per_1(P,\alpha_i)} \mid i = 1, 2, ..., n \right\}$$

- The min is the smallest value in the set $C$ it is the actual value of the Convexity Measure of Polygons; it is expressed as :

$$Min = min \left\{ \tfrac{Per_2(R(P,\alpha_i))}{Per_1(P,\alpha_i)} \mid i = 1, 2, ..., n \right\}$$

- The standard deviation: to evaluate the variation between the values in the set. It expresses the average variation between the values obtain using equation (5.1)

$$\sigma = \sqrt{\frac{\sum (x_i - \overline{X})^2}{n-1}} \tag{5.11}$$

These Convexity Moments are rotation, translation and scale-invariant because they are based on the values generated by the equation (5.1) as demonstrated by Zunic et al., [136] to be rotation, translation and scale-invariant. The values used here to represent the Convexity Moments of Polygons are the one that require every few computations and provide good results as shown in Chapter 7. The Convexity Measure and the Convexity Moments of Polygons have the same complexity which is $O(n^2)$. Figure 5.2 present some images with the corresponding Convexity Moments.


Figure 5.2. Convexity Moments of Polygon of selected leaves

## 5.4 Conclusion

This chapter describes two boundary-based shape features descriptors, the Convexity Measure of Polygons and the Convexity Moments of Polygons. The Convexity Measure of Polygons is a value used to describe the degree of convexity of a leaf image and is proven to be better than the surface-based convexity measure. Based on the limitation of the Convexity Measure of Polygons, this thesis proposed the

Convexity Moments of polygons derived from the Convexity Measure of Polygons and will be proved in Chapter 7. In the next chapter, the Sinuosity Coefficients are designed and used for plant classification using leaf images.

# Chapter 6

# Sinuosity Coefficients

## 6.1 Introduction

The leaves have valuable information about the plant's environment and can help to identify the species to which a plant belongs [75]. Botanists use information from leaves, such as the tooth pattern on the leaf margin and whether or not it is jagged or smooth [94]. The sinuosity of a given curve represents the degree of meandering of that curve. Sinuosity has been extensively used in the domain of medical science for the analysis of the meandering of a spinal column [116] and in Hydrography to evaluate the degree of meandering of a river [70].

In this thesis, a typical leaf shape is divided into sections and the Sinuosity Coefficients (SC) are computed from each section to construct a set of features for leaves classification. To demonstrate the accuracy of the proposed features, all the datasets (LeafSnap, FLAVIA, UCI) will be used for the experiment. The first experiment is used to assess the ability of the SC to characterize a leaf shape. Here the leaf shape will be divided into 4 and then 8 sections to see which division provides better results. The second experiment is designed to assess whether combining the SC with other geometrical features, such as rectangularity, circularity, sphericity and aspect ratio, will improve the classification rate obtained in the previous experiment.

The rest of this chapter is organized as follows: Section 6.2 discusses the use of the sinuosity measure in the literature and presents the image preprocessing for the extraction of the Sinuosity Coefficients. In Section 6.3, the sinuosity measure and Sinuosity Coefficients are presented with the Fourier descriptors. The chapter conclusion is in Section 6.4.

## 6.2 Application of Sinuosity Measure

The sinuosity measure has been applied in many fields of science, such as Geography, Biology and Medical Science as a parameter to explain other natural phenomena; for example, the meandering of a river. In [70], the sinuosity measure was used to evaluate the degree of meandering of a river. It was explained that meandering in the case of a river is the result of an erosion process tending toward the most stable form in which the variability of certain essential properties, such as velocity and depth are minimized.

Jaekel et al., [59] presents an application of the sinuosity measure for the characterisation of the webbing on a salamander foot to demonstrate the morphological changes performed on the animal foot to adapt to a given surface. Alain T. et al., [116] developed a method for the analysis of spine meandering for the early detection of spine deformation. Because of the growing interest in spatial exploration, Lazarus et al., [71] used the sinuosity measure to demonstrate that there were rivers on the surface of Mars by analysing the planet surface to detect deep meandering shapes.

### 6.2.1 Image Preprocessing

Let $\xi$ be a leaf color image; the features for the characterization of $\xi$ will be extracted from the image greyscale. Let $I$ be the binary representation of the gray scale components of $\xi$. Considering a set of boundary points $(x_i, y_i)_{i=1,\ldots,n}$ of the binary image $I$, the elements, used for the construction of the Minimum Bounding Rectangle (MBR) in [22, 64] and describe in Chapter 4 will be used.

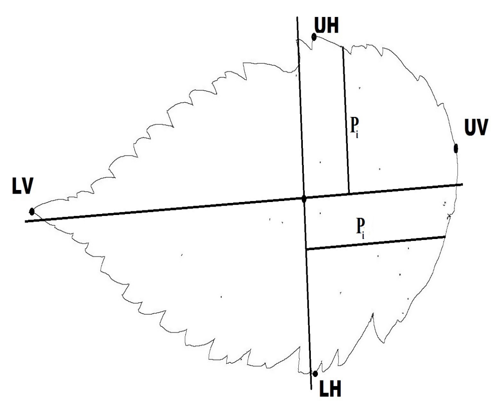



Figure 6.1. Points Maximizing the Distance $P_i$.

The considered points are the ones maximising $P_i$ on equation (4.8) on a given segment, as shown in Figure 6.1 (UH: Uppermost Horizontal point, LH: Lowermost Horizontal point, LV: Lowermost Vertical point, UV: Uppermost Vertical point).

## 6.3 Features Extraction

### 6.3.1 Sinuosity Measure

Lets consider $(x_i, y_i), i = 1, 2, ..., n$ the coordinates of points composing the curve $l$. If $l$ is a continuously differentiable curve, having at least one inflexion point, then the sinuosity of $l$ is equal to the ratio between the length of $l$ and the length of the straight line joining the two end points $A(x_0, y_0)$ and $B(x_n, y_n)$ of $l$. The sinuosity measure of the curve $l$ is expressed by the following equation:

$$S_l = \frac{\sum_{i=1}^{n} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}}{\sqrt{(x_n - x_0)^2 + (y_n - y_0)^2}} \tag{6.1}$$

The values generated by equation (6.1) are from 1 (for a straight line) to infinity (closed loop where the shortest path length is zero) or for an infinitely long curve [71]. Let us consider a curve formed by two inverted semicircles located in the same plane. The sinuosity measure of this curve is: $S = \frac{\pi}{2} \approx 1.5708$. In order to evaluate the sinuosity measure of a curve $C$, one should make sure that $C$ is continuous between its two, ends. Generally the sinuosity measure is evaluated in dimension two, but it is also valid in dimension three [116]. The basic classification of the sinuosity is either $Strong : 1 \ll S$ or $Weak : S \approx 1$). This basic classification is the point of interest of this paper because the sinuosity measure will provide the information needed for the classification of the leaf edge into two groups (smooth leaf="Weak" edge and jagged leaf="Strong" edge).

### 6.3.2 Sinuosity Coefficients

The sinuosity measure of a complete leaf boundary is infinite because leaf shape is a closed contour. In order to apply the sinuosity measure to a leaf contour, a leaf shape can be divided into four or more different parts, as presented in Figure 6.1. In order to obtain the leaf shape Sinuosity Coefficients, the sinuosity measure of each of the following curves $(UV, UH)$, $(UV, LH)$, $(LV, UH)$ and $(LV, LH)$ was evaluated using equation (6.1). The Sinuosity Coefficients of a leaf shape is a vector of sorted values of the sinuosity measure of the curves composing the leaf shape. Figure 6.2 presents some leaves with their associated Sinuosity Coefficients.

#### Translation Invariance

Let us consider the curve $(UV, UH)$ in Figure 6.3 and a distance $d$ of the line joining the two ends of the curve. Since the translation of the curve will not change the length of the curve, the expression in equation (6.1) will not change either.

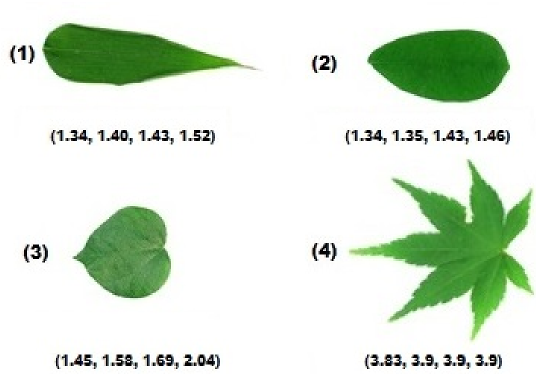



Figure 6.2. Sinuosity coefficients of four leaf shapes

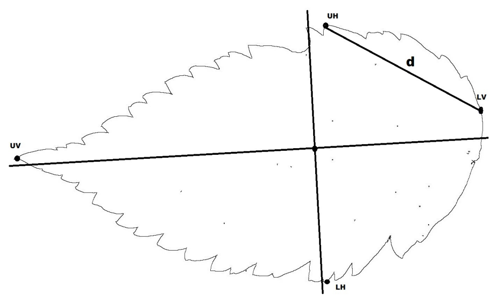



Figure 6.3. Leaf shape information

*Proof:* Let us consider $(x_i, y_i), i = 1, 2, ..., n$ as the coordinates of points composing the curve $(UV, UH)$ of the original curve and $d$ the length of the line joining the two ends of the curve. Let us consider $(UV1, UH1)$ the image of $(UV, UH)$ using the translation of vector concept $(T_x, T_y)$, $(a_i, b_i), i = 1, 2, ..., n$ points of $(UV1, UH1)$ and $d1$ the length of the line joining the two ends of $(UV1, UH1)$. Let us show that $d(UV1, UH1) = d(UV, UH)$

$$\begin{aligned} d(UV1, UH1) &= \sum_{i=1}^{n} \sqrt{(a_i - a_{i-1})^2 + (b_i - b_{i-1})^2} \\ &= \sum_{i=1}^{n} \sqrt{((x_i + T_x) - (x_{i-1} + T_x))^2 + ((y_i + T_y) - (y_{i-1} + T_y))^2} \\ &= \sum_{i=1}^{n} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} = d(UV, UH) \end{aligned}$$

which implies: $d(UV1, UH1) = d(UV, UH)$ and $d$=$d1$ since the translation maintains the shape of the curve.

Hence:

$S_l = \frac{d(UV,UH)}{d} = \frac{d(UV1,UH1)}{d1}$

**Scale Invariance**

Applying a scale to an object is to multiply the dimensions by a constant, $k$. Considering the curve $(UV, UH)$ putting it into scale $k$ means multiplying it by the

constant, $k$, which means that the shortest path joining $UV$ and $UH$ is also multiplied by $k$. Taking this information into consideration, the expression in equation (6.1) will not change, as shown in the following proof.
*Proof:* Using the scale transformation of coefficient $k$ applied to the curve $(UV, UH)$ we have the following relation:

$$\begin{aligned} d(UV1, UH1) &= \sum_{i=1}^{n} \sqrt{(a_i - a_{i-1})^2 + (b_i - b_{i-1})^2} \\ &= \sum_{i=1}^{n} \sqrt{(x_i * k - x_{i-1} * k)^2 + (y_i * k - y_{i-1} * k)^2} \\ &= \sum_{i=1}^{n} *k * \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} = k * d(UV, UH) \end{aligned}$$

$S_l = \frac{d(UV,UH)}{d} = \frac{k*d(UV,UH)}{k*d} = \frac{d(UV1,UH1)}{d1}$

## 6.4 Conclusion

Leaves boundary carries important information that can be used to differentiate between plant species. In this chapter, the Sinuosity Coefficients were used to describe the degree of meandering of leaf images. This new feature is proven theoretically to be translation and scale invariant and accurately describe leaf images. Experimentally the 8 Sinuosity Coefficients provide the best results. The next chapter describes a model for plant classification using leaf images which use the Convexity Moments of Polygons, the Sinuosity Coefficients, some geometric features and the RBF classifier.

# Chapter 7

# Results and Discussions

## 7.1 Introduction

Experimental setup, results and discussion of plant classification using leaf images are presented in this chapter. Leaf images are described using the Convexity Measure of Polygons, the Convexity Moments of Polygons and Sinuosity Coefficients, described in this thesis. A detailed discussion is done on the performance comparison of the proposed techniques to the results achieved in the literature and followed by the combination of those techniques.

## 7.2 Experimental Setup

The description of the system development environment and the performance evaluation measures used in the experiments and presented in this section.

### 7.2.1 System development environment

The algorithms for the extraction of the Convexity Measure of Polygons, the Convexity Moments of Polygons, the Sinuosity Coefficients and the determination of the Minimum Bounding Rectangle were implemented using Java on an Intel Core i7 CPU (2.93 GHz, 4.00 GB RAM).

### 7.2.2 Performance evaluation

In literature, the classification rate is the most used performance measures. To compare two leaf recognition systems, the use of the same dataset is needed. The common measures used for performance evaluation are Mean Square Error (MSE), Specificity, Sensitivity and Classification rate. These are the measures already proposed in information retrieval and pattern recognition literature to evaluate a given recognition system. These measures will be computed for a given leaf recognition system to evaluate how it performs on a given dataset. Specificity and Sensitivity are the two traditional measures used to evaluate pattern recognition problems.

The Sensitivity (Equation (7.1)) represents the proportion of positive that are recognized as such. The Specificity (Equation (7.2)) is the proportion of negative that are identified as such. For a given recognition process, a high Sensitivity implies that many leaf images are well classified.

$$Sensitivity = \frac{TruePositive}{(TruePositive + FalseNegative)} \tag{7.1}$$

$$Specificity = \frac{TrueNegative}{(TrueNegative + FalsePositive)} \tag{7.2}$$

$$Accuracy = \frac{TrueNegative + TruePositif}{(TrueNegative + TruePositif + FalsePositive + FalseNegative)} \tag{7.3}$$

For many recognition systems, the illustrations used are the ROC (Received operator curve) and the curve representing the classification rate per species.

### 7.2.3 Performance Assesment

The leaf recognition system presented in this thesis starts with an input image $\xi$. A given user provides an image to the system and receives a plant species as output. The problem of assigning a given leaf image to a possible plant species is equivalent to the similarity problem between images, which is not well defined in the literature because of the number of unjustified heuristics.

Like other approaches for plant classification using leaf images, the classifiers are trained and tested using features extracted from leaf images. Here we suppose that similar images have similar feature vectors. For example, leaves from plant of different species have different feature vectors.

Given the relevant plant species $B_1$, the irrelevant plant species $B_j, j = (2, ..., n)$ for an input image $\xi_i$ where $n$ is the total number of species. The classification error for the image $\xi_i$ is computed as:

$$\begin{aligned} P(error) \equiv \frac{1}{n}\sum_{j=2}^{n}[P(\xi_i \ \ assign \ \ to \ \ B_j \ \ belongs \ \ to \ \ B_1) \\ +P(\xi_i \ \ assign \ \ to \ \ B_1 \ \ belongs \ \ to \ \ B_j)] \end{aligned} \tag{7.4}$$

During the classification process, our goal is to minimize $P(error)$. The ideal classifier will be the one providing the smallest value for $P(error)$.

In case of a Bayes classifier, minimizing $P(error)$ in equation (7.4) should use the following rule:

$$\xi_i \;\; belongs \;\; to \begin{cases} B_1 \;\; if \;\; \forall B_j (j = 2, ..., n), P(B_1 \mid \xi_1) > P(B_j \mid \xi_1) \\ \qquad\qquad\qquad B_j \;\; otherwise \end{cases} \tag{7.5}$$

After defining the classification process, the remaining problem is the definition of the appropriate model for leaves recognition. The proposed system for plant classification using leaves images is divided into three steps:

- Image Preprocessing (Image enhancement and noise removal, segmentation)
- Feature extraction
- Classification

This thesis describes the solutions proposed for the second step and compared each solution available in the literature to finally design a model for plant recognition using leaf images, based on the combination of the design shape features.

## 7.3 Experimental Setup

### 7.3.1 Databases for experimentation

To evaluate the performance, of the proposed model, three leaf image databases were used. The leaf image databases are:

1. Flavia Database:
   FLAVIA contains more than 1600 leaf images from more than 32 different species of plants [128]. Each leaf image was capture with a high resolution camera on a uniform white background. The plants used to create FLAVIA are from the Nanjin University and the Yat-Sent arboretum. These plant species are common in the Yangtze Delta. The combination of high resolution images and the uniform background makes the feature extraction process easy. Samples of leaf images in FLAVIA are given in Appendix A.

2. UCI Database:
   UCI contains more than 400 leaf images from more than 32 different species of plants [112]. Each leaf image was captured with an IPad2 camera on a uniform colored background. The 24-bit RGB images have a resolution of 720*920 pixels. Samples of leaf images in UCI are given in Appendix B.

3. LeafSnap Database:
The LeafSnap dataset contains 185 species from the Northeastern United States [69]. LeafSnap is composed of 23147 Lab images and 7719 field images. The Lab images are high quality images of pressed leaves from the Smithsonian collection on controlled backlight and front lit versions, with several samples per species. The field images are low quality images taken using mobile phones and are characterized by a varying amount of blur, noise, shadow and illumination which further complicates the feature extraction process. Samples of leaf images in LeafSnap are given in Appendix C.

### 7.3.2 Experimental protocol

For the experimentation process, training and testing sets are separated. For a given database, the overall dataset or a randomly selected number $N$ of leaf images using equation (7.6) defined in [88], is used. Equation (7.6) is used to calculate the sample size that is representative of the overall dataset, which is the initial population. Where $n^{'}$ is the sample size in case of a finite population; $N$ is the population size(dataset size); $Z$ is the $Z-Statistic$ for a level of confidence, which is usually equal to 1.96; P is the expected proportion; $d$ is the precision generally equal to 0.05. For FLAVIA dataset, the minimum sample size obtained using the formula is equal to, 292 leaf images.

$$n^{'} = \frac{NZ^2P(1-P)}{d^2(N-1)+Z^2P(1-P)} \tag{7.6}$$

During the experimentation 2/4 of the data will be used for the training process, 1/4 for the testing and the rest for the validation process.

### 7.3.3 Classifiers

In the classification process, three well-known pattern classifiers will be used: MLP, KNN and RBF. They have been used to solve problems such as pattern classification and the approximation of functions. There are strengths and weaknesses associated with each classifier. Despite the high computational cost of the MLP and the sensitivity to the overfitting problem, the MLP has the ability to detect complex nonlinear relations between related and non-related variables. The RBF is very easy to design; the capabilities are very good and it performs robustly, even when there are noises on the input. Depending on the problem, each classifier will perform differently.

KNN is a non parametric method used for classification and regression. The quality of a KNN classifier is closely related to the number of instances to classify. In all the experiments, the MLP configuration will depend on the number of inputs. For the first two experiments based on the LeafSnap dataset, the input layer will have 4 or 8 neurons, based on the number of input features. 184 neurons were used for the output layer because there are 184 species. There will be 2 hidden layers of 100 neurons each (100 neurones were obtained experimentally as the configuration of the MLP producing the best results). The function used in the neurons in the output and hidden layer was the hyperbolic tangent function to take advantage of the differentiability and non-linearity properties. In addition the following parameters are used: 500 training epochs with a learning rate of 0.1, minimum performance gradient of 1e-6, a maximum training time of 120 Sec, a validation check of 500 and a performance goal of 0. In the case of RBF, the configuration is based on a Mean Square Error (MSE) goal of 0, spread of 0.1, 4 and also 8 neurons in the input layer for the first experiment. The proposed RBF classifier contains one hidden layer on which some neurons are added until it meets the specified mean square error goal. The training step stops when 400 neurons are reached on the hidden layer, as shown in [2]. The implementation of the classifiers that are used in this thesis are the one available in MATLAB Machine learning.

## 7.4 Exprimental Results and Discussion

### 7.4.1 Convexity Measure and Convexity Moments of Polygons

#### Convexity Measure of Polygons

The experiments were conducted using FLAVIA. The leaf database is composed of more than 1600 plant leaves from more than 30 species [128]. We randomly chose 400 leaves from 20 species, 1600 leaves from 32 species and 100 leaves from 5 species (the 1600 plant leaves from 32 species represent all the available species in FLAVIA). The experiments were organized in two phases. First, the leaves were characterized using the geometrical features and the seven invariant moments. Secondly, the seven invariant moments and the geometrical features were combined with the New Convexity Measure of Polygons to characterize a leaf image.

Table 7.1 presents the accuracy of the proposed method with and without the Convexity Measure of Polygons (Zunic et al., [136]) in the feature vector. In the first row with the Convexity Measure of Polygons, the Multi-Layer Perceptron (MLP) achieved an average of 92% of well classified leaves with an area under the Received Operating Characteristic curve (ROC) equaling 0.993. Without the Convexity Measure of Polygons, 86% of well classified leaves with the area under the ROC curve equaled 0.98.

Table 7.1. Comparative study of classifiers and Convexity Estimators

| | With the Convexity Measure | | Without the Convexity Measure of Polygons | |
|---|---|---|---|---|
| | %of good classify | AUC average | % of good classify | AUC average |
| Multilayer Perceptron(400) | 92% | 0.993 | 86% | 0.98 |
| K-Nearest Neighbour(400) | 87.5% | 0.971 | 85% | 0.921 |
| Naive Bayes(400) | 80.94% | 0.969 | 79.2% | 0.966 |
| Multilayer Perceptron(100) | 99% | 0.993 | 97% | 0.97 |
| K-Nearest Neighbour(100) | 99% | 0.971 | 97% | 0.9 |
| Naive Bayes(100) | 90% | 0.969 | 80.2% | 0.95 |
| Multilayer Perceptron(1600) | 95% | 0.993 | 92% | 0.99 |
| K-Nearest Neighbour(1600) | 92% | 0.971 | 89.5% | 0.95 |
| Naive Bayes(1600) | 89% | 0.969 | 80.2% | 0.98 |

The experimental phase is organized in three different processes to show how efficient the proposed model is when used in various conditions. Finally, to complete the experimentation, the proposed method is applied to a large dataset with 1600 leaves and a classification rate of 96% was obtained. This classification rate shows that the proposed method remains consistent, even with a larger dataset. The classification rate and the Area Under the ROC Curve (AUC) clearly show that the Convexity Measure of Polygons (Zunic et al., [136]) contributes to the improvement of the classification rate and to the efficiency, of the proposed model.

In Table 7.2 present the comparison the classification of leaf images using the combination of the Convexity Measure of Polygons and Geometric features, to other methods in the literature, the following observations can be made. As did Panagiotis et al., [120] here 100 images of leaves are used to illustrate how the proposed method is more efficient when applied to a small number of leaves. We obtained a classification rate of 99% with the Convexity Measure of Polygons (Zunic et al.). In the feature set, it shows that the Convexity Measure of Polygons contributed significantly to the discrimination process of leaf shapes, even with a small dataset. We then applied the proposed method to a medium dataset which had 400 leaves. In this case, a classification rate of 92% shows again how efficient the proposed method is when applied to a medium size dataset, when the Convexity Measure of Polygons (Zunic et al., [136]) is used.

Table 7.2. Comparative study of the proposed method with some methods in the literature

| Autors | Method | Feature | Nb Leaves | Nb species | Rate | Algorithm | Drawback | Advantages in classification |
|---|---|---|---|---|---|---|---|---|
| Panagiotis et al., [120] | Plants leaves classification based on morphological feature | Shape | 100 | 4 | 99% | NN Fuzzy | incomplete experiment | Fast classification |
| Jixian et al., [36] | Leaf shape based plant species recognition | Shape | 400 | 20 | 91% | MMC | Model evaluation | Fast with the MMC |
| Stephen et al., [128] | A leaf recognition Algorithm for plant classification using PNN | Shape | 1800 | 32 | 90% | PNN | the method is not completely automatic | Fast classification |
| Benoit et al., [33] | Weed leaf recognition in complex natural scene by model guided edge pairing | Shape | 10 | 1 | 60% | rating process | incomplete methode | Adaptative method |
| Aakif et al., [1] | SMSD, FD | Shape | 1600 | 32 | 95% | BPNN | Model evaluation | Adaptative method |
| Caglayan et al., [18] | SMSD,CM, CH | Shape+color | 1600 | 32 | 96% | RBF | Model evaluation | Adaptative method |
| Chaki et al., [21] | CT, Hu Moments | Shape | 1600 | 32 | 50% | MLP | Model evaluation | Adaptative method |
| Wang et al., [123] | ENS and CDS | Shape+Texture | 1600 | 32 | 98.8% | SVM | Model evaluation | Adaptative method |
| Hsiao et al., [55] | SIFT | Shape | 1600 | 32 | 95% | MLP | Model evaluation | Adaptative method |
| Nguyen et al., [91] | HOG | Shaper | 1600 | 32 | 85% | SVM | Model evaluation | Adaptative method |
| **Proposed approach** | **Leaf Classification using Convexity Measure of Polygons** | **Shape** | **400** | **20** | **92%** | **MLP** | **Convexity measure time complexity with big images** | **Accurate** |
| **Proposed approach** | **Leaf Classification using Convexity Measure of Polygons** | **Shape** | **1600** | **32** | **95%** | **MLP** | **Convexity measure time complexity with big images** | **Accurate** |
| **Proposed approach** | **Leaf Classification using Convexity Measure of Polygons** | **Shape** | **100** | **4** | **99%** | **MLP** | **Convexity measure time complexity with big images** | **Accurate** |

### Convexity Moments of Polygons

The experiment was conducted using the FLAVIA leaf images database presented by Wu et al., [128]. 400 leaf images of 20 species of plant were used for the experimentation. In the classification process, two pattern classifiers Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) were used.

In all experiments the MLP configuration depended on the number of inputs. For the first experiments, the input layer will have 5 neurons based on the number of input features. 20 neurons were used for the output layer because there are 20 species and there will be 2 hidden layers of 100 neurons each. The function used in the neurons in the output and hidden layer was the hyperbolic tangent function, in order to take advantage of the differentiability and non-linearity properties. In the case of RBF, the configuration is based on a Mean Square Error (MSE) goal of 0, spread of 0.1, 4 and also 8 neurons in the input layer for the first experiment. The proposed RBF classifier contains one hidden layer on which some neurons are added until it meets the specified mean square error goal.

The considered features were extracted from the leaf boundary (Convexity Measure, Convexity Moments, Geometric Features). For the first experiment, each of the leaf boundaries is described using the Convexity Moments and four geometric features as described in Chapter3. For the second experiment, each of the leaf boundaries is described using the Convexity Measure of Polygons and four geometric features. The Convexity Measure of Polygons and Convexity Moments are combined with the geometric features because Zunic et al., [136] stated that, to obtain a better classification rate, the Convexity Measure needs to be combined with other shape features. For the classification purpose, 2/4 of the dataset were used for the training process, 1/4 of the rest for the testing and the remainder for validation.

Table 7.3. Comparative study of the two shapes characterizers

| | Convexity Measure + Geometric Feature | Convexity Moments + Geometric Feature |
|---|---|---|
| Properties | (rotation, translation,scale) invariant | (rotation, translation,scale) invariant |
| Number of Features | 5 features | 7 features |
| Classification Rate | RBF(95%), Naive Bayes(68%), MLP(92%) | RBF(97%), Naive Bayes(75%), MLP(95%) |
| MSE | RBF(0.012), Naive Bayes(0.016), MLP(0.0186) | RBF(0.006), Naive Bayes(0.052), MLP(0.065) |
| Specificity | RBF(0.845), Naive Bayes(0.801), MLP(0.787) | RBF(0.918),Naive Bayes(0.879), MLP(0.854) |
| Sensitivity | RBF(0.922), Naive Bayes(0.901), MLP(0.882) | RBF(0.924), Naive Bayes(0.930), MLP(0.943) |

Table 7.3 presents the results of the classification of leaf images using the two shape features. A classification rate of 95% with the Convexity Measure of Polygons and 97% with the Convexity Moments using the Radial Basis Neural Network (RBF) classifier was obtained.

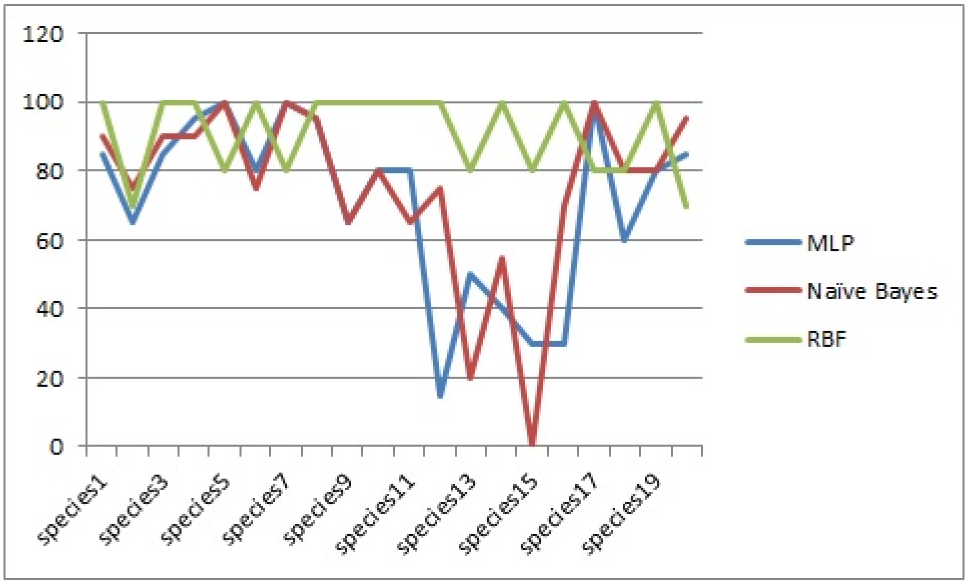



Figure 7.1. Classification rate for each species with the Convexity Moments of Polygons

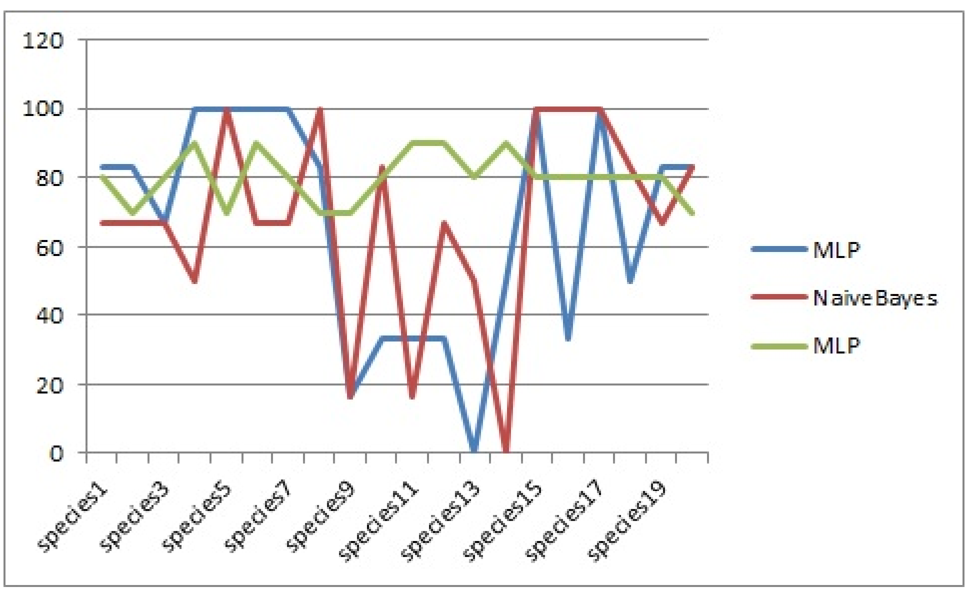



Figure 7.2. Classification rate for each species with the Convexity Measure of Polygons

Figure 7.1 and Figure 7.2 presents the classification rate per species with the Convexity Moment of Polygons and the Convexity Measure of Polygons. The recognition rate is improved when using the Convexity Moment of Polygons.

An MSE, a sensitivity and specificity of 0.012, 0.845 and 0.922 are respectively obtained using the Convexity Measure of Polygons, with the RBF as classifier. An MSE, a sensitivity and specificity of 0.006, 0.918 and 0.924 are respectively obtained with the Convexity Moments of Polygons, with the RBF as classifier. These results are proof that the Convexity Moments are better features compared with the Convexity Measure of Polygons. The good results observed with the Convexity Moments are due to the number of features used to characterize a leaf shape and because they consider the information that was left out by the Convexity Measure of Polygons.

The leaf species that were not recognized are species 3, 9, 11, 13, 15, 16 and 19 because in terms of shape the leaf look a like and produce approximately the same Convexity Measure, the Convexity Moments produces promising results with the RBF classifier but the lowest classification rate was obtained with the Naive Bayes classifier. As long as the leaf images look different the Convexity Measure will produce similar values, which means the convexity Measure alone is a weak descriptor and needs other descriptors to accurately describe a given shape. The convexity moments uses more feature features to characterize a given, as shown in Figure 7.1 these features are able to describe the small variation on the leaf shape, which makes it easy for the classifier to recognize plant species, this means the Convexity Moments are strong features.

### 7.4.2 Sinuosity Coefficients

For each selected leaf image used for the experiment, the associated grey scale image will be used during the feature extraction process. A sorted vector of sinuosity measure of each curve composing the leaf shape was extracted (Sinuosity Coefficients), followed by the extraction of the geometrical features and the 4 Fourier descriptors. For the first, second, third and fourth experiments, the geometrical features (4 features), 4 sinuosity (4 features), 8 sinuosity (8 features) and 4 Fourier descriptors (4 features) are respectively used to recognize leaf images. On the fifth, sixth and seventh experiments, the 4 sinuosity, 8 sinuosity and 4 Fourier descriptors are combined with the geometrical features to recognize leaf images. A total of 8, 12, and 8 features are used respectively for the classification.

The choice of four Fourier descriptors was made because the sinuosity measure also uses four values. The experimentation is performed using all the species in LeafSnap, FLAVIA and UCI databases. For the classification phase, 1/2 of the data set was used for training, and 1/4 for testing and the rest for validation.

Table 7.4. Performance evaluation of the three features on LeafSnap dataset

| | Geometric Features | | 4 Sinuosity Coefficients | | 8 Sinuosity Coefficients | | Fourrier Descriptors | |
|---|---|---|---|---|---|---|---|---|
| | MLP | RBF | MLP | RBF | MLP | RBF | MLP | RBF |
| MSE | 0.016 | 0.015 | 0.0274 | 0.018 | 0.006 | 0.003 | 0.007 | 0.012 |
| Specificity | 0.910 | 0.920 | 0.840 | 0.960 | 0.894 | 0.980 | 0.860 | 0.878 |
| Sensitivity | 0.921 | 0.930 | 0.940 | 0.980 | 0.974 | 0.985 | 0.950 | 0.965 |
| Classification Rate | 70% | 80% | 65% | 88% | 80% | 92% | 78% | 89% |

Table 7.5. Comparative study of the Sinuosity Coefficients and Elliptic Fourier descriptor on LeafSnap dataset

| | 4 Sinuosity Coefficients+ Geometric Features | | 8 Sinuosity Coefficients+ Geometric Features | | Fourier Descriptors+ Geometric Features | |
|---|---|---|---|---|---|---|
| | MLP | RBF | MLP | RBF | MLP | RBF |
| MSE | 0.015 | 0.047 | 0.012 | 0.004 | 0.048 | 0.005 |
| Specificity | 0.820 | 0.920 | 0.810 | 0.916 | 0.830 | 0.901 |
| Sensitivity | 0.916 | 0.967 | 0.955 | 0.987 | 0.947 | 0.970 |
| Classification Rate | 76% | 92% | 82% | 93% | 80% | 91% |

Table 7.6. Comparative study of the Sinuosity Coefficients and Elliptic Fourier descriptor on FLAVIA and UCI datasets

| | 8 Sinuosity Coefficients + Geometric features | | | | | | Elliptic Fourier Descriptors + Geometric features | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | FLAVIA | | | UCI | | | FLAVIA | | | UCI | | |
| | MLP | RBF | KNN | MLP | RBF | KNN | MLP | RBF | KNN | MLP | RBF | KNN |
| MSE | 0.007 | 0.005 | 0.001 | 0.0076 | $7.5 * 10^{-4}$ | 0.006 | 0.0012 | 0.054 | 0.013 | 0.0718 | 0.0011 | 0.0201 |
| Specificity | 0.8414 | 0.9439 | 0.776 | 0.211 | 0.9902 | 0.495 | 0.619 | 0.9232 | 0.201 | 0.1373 | 0.9740 | 0.1301 |
| Specificity | 0.9952 | 0.998 | 0.901 | 0.9935 | 0.999 | 0.950 | 0.9904 | 0.9974 | 0.9910 | 0.9927 | 0.9997 | 0.99901 |
| Classification Rate | 80% | 94% | 78% | 52% | 98% | 50% | 70% | 92% | 70% | 27% | 97% | 30% |

Table 7.4 presents the classification results when using geometrical features, 4 sinuosity, 8 sinuosity and 4 Fourier descriptors as leaf features on the LeafSnap dataset. A classification rate of 70% was obtained using the MLP (Multilayer Perceptron) and 80% when using the RBF with the geometrical features as input. A classification rate of 80% was obtained with MLP and 92% with the RBF when using the 8 Sinuosity Coefficients.

Table 7.5 presents the results of the classification when using the geometric features combined respectively to the 4 Sinuosity Coefficients, 8 Sinuosity Coefficients and to the Elliptic Fourier descriptors respectively to characterize the leaves on LeafSnap. A classification rate of 82% was obtained with MLP when using the combination of geometrical features and 8 Sinuosity Coefficients and 93% with the RBF on the database. Finally, a classification rate of 80% was obtained with MLP and 91% with RBF respectively, using the 4 Elliptic Fourier descriptors combined with the geometric features.

Table 7.6 presents the classification results when using geometrical features combined with the 8 sinuosity and 4 Fourier descriptors to characterize leaf images from FLAVIA and UCI datasets. A classification rate of 80% was obtained using the MLP (Multilayer Perceptron) and 94% when using the RBF on the FLAVIA dataset. A classification rate of 27% was obtained with MLP and 97% with the RBF when using the 4 Fourier descriptors on the UCI dataset.

The classification results of the geometric features with MLP are shown in the third row, second column and third column of Table 7.4. A classification rate of 70% is obtained, with a Mean Square Error (MSE) of 0.0160. A classification rate of 80% with an MSE of 0.015 was also obtained when the geometrical features were used to characterize the shape of a leaf image with RBF as a classifier. These results show that the boundary-based shape features are able to recognize more than half of the leaf images.

The results of the Sinuosity Coefficients and MLP classifiers are shown in the third row, column four and five of Table 7.5. A classification rate of 65% was obtained, with an MSE of 0.0274 with the MLP classifier. A classification rate of 88% with an MSE of 0.018 was also obtained with the RBF classifier. These results show that the 4 Sinuosity Coefficients capture the leaf shape, structure but not with a high precision. That precision is improved when using the 8 Sinuosity Coefficients

The classification results when the 4 Sinuosity Coefficients are combined with geometrical features using MLP as the classifier are shown in the third row and column two of Table 7.5. A classification rate of 76% and an MSE of 0.015 were obtained. A classification rate of 90% and a MSE of 0.0047 were also obtained with the RBF classifier when using the 4 Sinuosity Coefficients combined with the geometrical features to characterize the shape of the leaf images. The results in Table 7.5 shows that 4 Sinuosity Coefficients combined with the geometric features are more efficient than the 4 Sinuosity Coefficients.

From the results obtained in this study, it is clear that the Sinuosity Coefficients are good descriptors of leaf shape. However, further classification improvement was obtained by combining the 8 Sinuosity Coefficients with geometrical features compared to the combination of the geometrical features to the 4 elliptical Fourier descriptors as shown in Table 7.6. The MLP performed poorly compared to the RBF on the overall dataset. The lower results observed are due to the fact that some leaves look alike and produce similar feature values, for instance species 11, 13, 25 and 24 also because the dataset contains compound leaves which makes features extraction difficult. Compound leaf description is the weakness of the shape features because there is a high possibility that some compound are partially occluded which impact the shape description. On Table 7.6 the results of the combination of the proposed feature with other geometric features produce some promising results. Which prove that combining the proposed feature to other geometric features reduced the miss classification rate. The leaves that are creating issues are species (1, 26,17 and 38), because they look alike or are compound leaf images. The superior performance of the RBF over MLP has also been reported in the literature, as presented by Adetiba et al. [2], it is based on the ability of the RBF to detect the variations that exist between plant species and the fast training time.

### 7.4.3 Combination of Convexity Moments of Polygons and Sinuosity Coefficients

Each shape features used to construct the proposed model is selected based on the specific aspect of a given leaf shape it describes. Rectangularity, sphericity, aspect ratio and form factor represent the geometric features and are used to describe the interior of a given leaf image. Sinuosity coefficients are used to characterize the object shape boundary and provide a local value to describe each section of a given leaf shape. Convexity Moments of polygons described the overall leaf shape by providing a series of values to represent the degree of convexity of the consider leaf image. To complete the proposed model The Radial Basis neural network (RBFNN) classifier was used to associate a given input leaf image to the corresponding plant species. The structure of the proposed model is present in Figure 7.3,

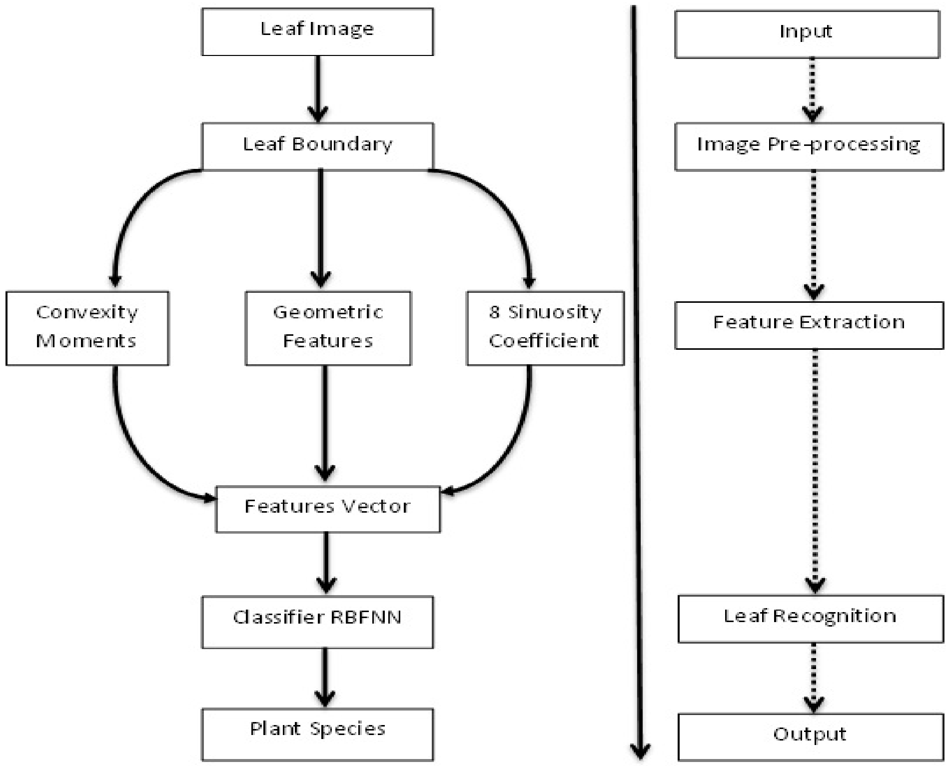



Figure 7.3. Proposed model for plant classification

The proposed system is evaluated using the complete FLAVIA dataset, the classification results are presented in Table 7.7. Where on the first line, the specificity is 0.820, the sensitivity is 0.870 and an accuracy of 78% with MLP classifier. On the third line, the specificity is 0.992, the sensitivity is 0.960 and an accuracy of 97% with RBF classifier.

Table 7.7. Experimental Results with the proposed model

| | MSE | Specificity | Sensitivity | Accuracy |
|---|---|---|---|---|
| KNN | 0.0192 | 0.820 | 0.87 | 78% |
| MLP | 0.0180 | 0.978 | 0.91 | 95% |
| RBF | 0.0160 | 0.992 | 0.96 | 97% |

These results show that the proposed model is recognizing plant species accurately, because fewer errors are made during the recognition process. The source of classification error made by the proposed model is because the database contains deform leaves (that create issues during the feature extraction), the database also contains plant species that have similar leaf shape which constituted a problem as described in [86]. The plant species such as species 11 and 13, are the example of species that were misclassified because they look a like in terms of shape.

## 7.5 Conclusion

This Chapter presents the experimentation process used to evaluate the designed shape features and the proposed model for plant classification when used to recognize plant species using leaf images. When compared to the results available in the literature, the proposed model presents some promising results. The next chapter concludes this research work and presents the future work that can be considered to further the research in the field of plant classification using leaf images.

# Chapter 8

# Conclusion and Future Works

The online availability of a wide variety of leaf images of various plant species, significantly facilitates the design of systems for plant recognition using leaf images. Plant recognition using leaf images is considered to be one of the popular research areas in computer vision. The recognition process of a given plant using an input leaf image can be divided into three phases: preprocessing, feature extraction and recognition. In the related literature, shape feature received more attention than any other feature. The popularity of shape features is because they are easy to understand and most plant species can be differentiated using their leaf shape. The issues with shape features are the fact that they are not easy to extract, they are noise-sensitive, and are sensitive to small variations. Another issue with leaf characterization is the fact that there is no efficient algorithm that can be used to characterize the tooth pattern on a given leaf boundary. During the recognition process a given leaf image is described as a set of feature values that can be used as input for a classifier.

## 8.1 Contributions

In this thesis, the goal has been the design of a shape-based plant recognition system using leaf images by focusing our attention on the feature extraction level. Furthermore, an attempt to provide a solution to the problem of leaf boundary analysis by designing new boundary-based features which also have a high potential of giving promising improvement in recognition process was proposed.

The first research attempts for the conception of a system for plant recognition using leaf images was the improvement of the Minimum Bounding Rectangle computation because many shape features (such as Rectangularity, Circularity, Aspect Ratio) are closely dependent on the minimum bounding rectangle. By improving the computational process of shape feature, we also improved leaf recognition accuracy, as presented in Chapter 3. The improvement on Chaudhuri method gave a new method that produces results comparable to the popular PCA method for the determination of the Minimum Bounding Rectangle (or the oriented Bounding Box). The MAE (Maximum Error Encure) was used to evaluate the accuracy of the method compared with a human point of view of a Minimum Bounding Rectangle, the choice of the human point of view is because there is no reference available for the construction of the Minimum Bounding Rectangle.

The second attempt was the introduction of the Convexity Measure of Polygons for the characterization of a given leaf shape. Convexity Measure of Polygons is a boundary-based shape feature and has proven to be better than the region-based Convexity Measure because it can be used to evaluate the convexity of an open shape. During the experimental process, the Convexity Measure was combined with other shape features and the model obtained yielded some promising results. A classification rate of 92% was obtained when using the geometrical feature alone to characterize a given leaf shape and a significant improvement of 3% was obtained when combining the Convexity measure of polygons with the geometric features. The Convexity Measure of Polygons provides additional information for the characterization of the leaf shape.

The Convexity Measure of Polygons uses a single value to characterize a given shape and this makes its usage difficult in characterizing a given shape. To address the problem, we derived a new shape feature known as the Convexity Moments of polygons which characterize a given shape using 4 different values compared with the use of a single value used by the Convexity Measure of Polygons. Like the Convexity Measure of Polygons, the Convexity Moments of Polygons are invariant to similarity transformations. The Convexity moments use a set of 4 values to characterize the degree of convexity of a given shape. The Convexity Moments of Polygons have proven to be better than the Convexity Measure of Polygons because they use more values to represent the convexity of a given shape. When using the Convexity Moments of Polygons a classification rate of 97% was obtained which represent a significant improvement of 5% compared to the Convexity Measure of Polygons. Both shape descriptors have the same complexity with a small variation on the running time use for the computation of the statistical descriptors.

The third attempt was the design of the Sinuosity Coefficients to address the problem of leaf boundary characterization. The Sinuosity Coefficients are values used to characterize the degree of meandering of a given leaf boundary. In order to obtain satisfactory results, the Sinuosity Coefficients need to be combined with other shape features, sinuosity measure only provides information about the boundary of a given object, not the overall structure. There is a limit to the number of times a given shape can be divided to apply the sinuosity coefficient. Experimentally, we found that the optimal number of times a given shape can be divided by 8. A classification rate of 93% was obtained when combining the Sinuosity Coefficients to other geometric features. The experiment showed the Sinuosity Coefficients combined with other geometric features are better descriptors compared to 4 Fourier descriptors combine with other geometric features.

The last attempt was the design of a model for plant classification using leaf images. The proposed model was designed by combining the Sinuosity Coefficients, Convexity Moments, other shape features (Geometric features) and the Radial Basis Function Neural Network. The choice of each of the components of the proposed models, was based on the results obtained when using each of them for the recognition of plant leaves. The proposed model has provided promising results with the leaf image database used for the experiment. An average classification rate of 97% was obtained by the proposed model.

## 8.2 Findings

The leaves that are misclassified during all the experiments are either deformed or are compound leaves. This constitutes one of the future research problem in the field of plant recognition using leaf image. The possible solution to the recognition of the deformed leaves might be the use of the symmetry because some leaves are naturally symmetric. For the compound leaf analysis a possible solution might be the use of modeling techniques that could help to understand the structure of the compound leaves hence facilitate the recognition process.

## 8.3 Future works

The future works of this thesis are based on the improvement of the proposed model, by adding textural features on the feature set, followed by the conceptualization of an ontology for plant classification. The ontology will exploit the hierarchical nature of the techniques used by botanists to recognize plant species. The use of the symmetric method to design a model for the recognition of deformed plant leaves, and the design of a model for the description of compound leaf using modeling techniques.

# Appendix A

# FLAVIA Database

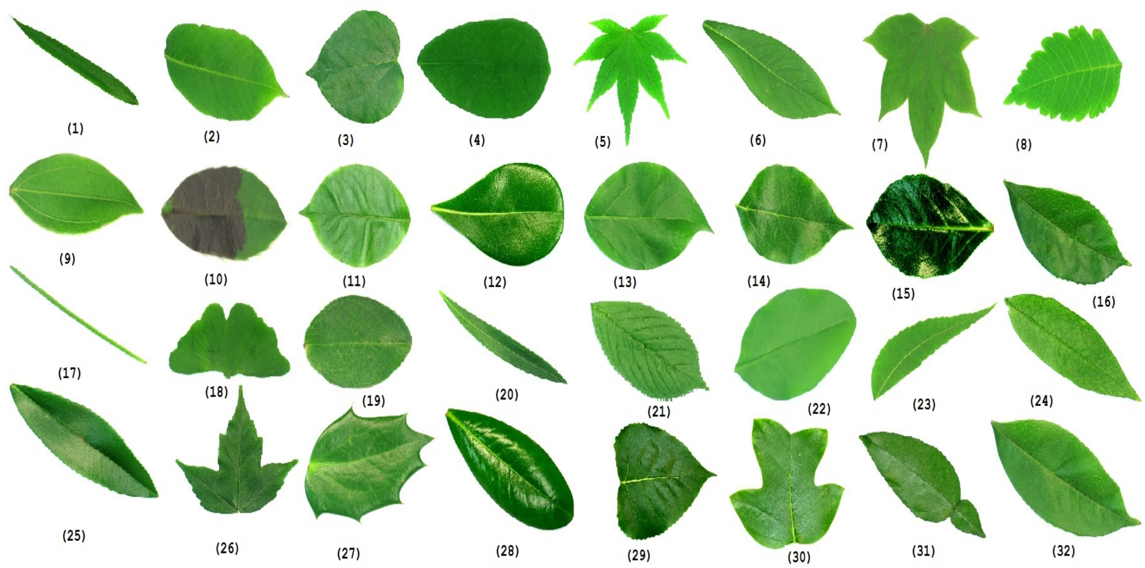



Figure 1.1. Sample of leaf images in FLAVIA Database

# Appendix B

# UCI Database

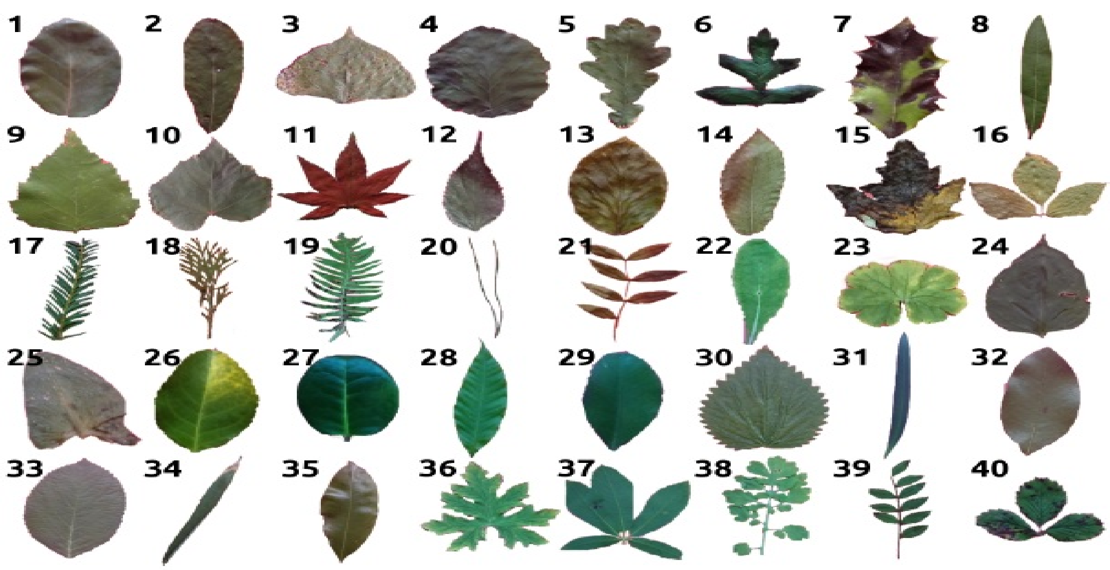



Figure 2.1. Sample of leaf images in UCI Database

# Appendix C

# LeafSnap Database

Figure 3.1. Sample of leaf images in LeafSnap Database

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