Plant leaves classification based on morphological features and a fuzzy surface selection technique

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***Abstract*— The design and implementation of an artificial vision system that extracts specific geometrical and morphological features from plant leaves is presented in this paper. A subset of significant image features are identified using a novel feature selection approach. This approach reduces the dimensionality of the feature space leading to a simplified classification scheme appropriate for real time classification applications. A feed-forward neural network is employed to perform the main classification task. The proposed system exhibits size and orientation invariance with respect to the samples and it can operate successfully even with leaves samples that are deformed due to drought or due a number of holes drilled in them. A considerably high classification ratio of 99% was achieved, even for the classification of deformed leaves.**

Index Terms - Feature selection, classification, fuzzy surface, neural networks, image processing.

I. Introduction

The classification of plant leaves is a crucial process in botany and in tea, cotton and other industries [1], [2]. Moreover, the morphological features of leaves are used for plant classification or in the early diagnosis of certain plant diseases [3].

This paper presents the design and implementation of an artificial vision system capable of extracting geometrical and morphological features from plant leaves. Initially, leaves taken from plants in the native environment and surroundings were collected and used as samples for testing the proposed system. Later, additional samples originating from diverse environments were used for classification.

The proposed system consists of: a) an artificial vision system (frame grabber and camera) b) a combination of image processing algorithms implemented in LabView [4] and c) a feed-forward neural network based classifier implemented in MatLab [5].

The image processing part is responsible for image capture and image pre-processing in order to obtain normalized features [6], [7] and for determining some critical geometrical characteristics. The study of such morphological features has been extensively used in the literature [8], [9], [10]. However, the plethora of geometrical and morphological features makes it impossible to use all available features in a certain classification problem, especially in real-time applications and, thus, some selection technique is necessary. A novel, fast and consistent approach for calculating the importance of each subset of features, that together are assumed to influence the classifier output of the image processing system the most, from a set of candidates features, is presented in this work. More specifically, a fuzzy surface technique [11] is used for building fast a coarse model of the system from a subset of the initial candidate features. A neural network is then trained with the selected morphological features and classifies the feature space to appropriate categories. Neural networks have been also used extensively for classification [12], [13].

In order to develop an efficient classifier two fundamental and contradicting modeling principles should be satisfied: a) maximization of the identification/generalization capabilities and b) minimization of the architectural complexity. Since the neural network complexity increases exponentially with the number of inputs, an input selection technique is required to identify the significant features from the plethora of candidate geometrical and morphological features. This data pre-processing task is carried out using an entirely different modeling technique to the neural network classifier modeling. This technique [11], based on fuzzy surfaces, emphasizes on the maximization of learning-generalization capabilities and ignores the complexity of the architecture for the sake of modeling celerity.

Furthermore, the proposed system is also capable of automated image capture (for 'production line' operation), counting the number of the leaves per category, counting of the holes that may be present on the leaves surface (due to diseases, malformations etc.) and morphological classification of these holes.

This paper is organized as follows: Section II provides the image processing algorithms for morphological feature extraction. Section III presents the feature selection problem and a novel fuzzy surface approach adopted for the determination of the significant subset of features. Having decided on the optimal subset of significant features, the optimal structure of the reduced dimensionality neural network classifier is presented in section IV. Section V provides a description and evaluation of the overall image processing system. Finally, the advantages of the proposed system are highlighted in the conclusions section.

II. Morphological Feature Extraction

Several morphological and geometrical features are extracted from the leaves using the proposed image processing system. These features are very important for the morphology of the leaves and they provide critical information about its visual representation [7]. The suitability of a set of such morphological features for the efficient classification of the leaves and for the detection of deformations and holes, in order to classify deformed samples, were investigated in this paper. The basic features and the respective methods for their calculation are described below:

i) *Image Thresholding:* Thresholding separates the leaves from their background producing a binary image that facilitates feature extraction and evaluation [6], [7].

ii) *Determination of the Center of Gravity:* For a leaf surface described by function $f(m,n)$, consisting of N pixels, the Center of Gravity coordinates $(\overline{m},\overline{n})$ can be calculated as [7], [14]:

$$\bar{m} = \frac{1}{N}\sum\sum_{(m,n)\in\Re} m \qquad \bar{n} = \frac{1}{N}\sum\sum_{(m,n)\in\Re} n \tag{1}$$

iii) *Moments of Inertia:* The moments of inertia for an image described as $f(x,y)$ can be defined as:

$$m_{p,q} = \int\int_R f(x,y)x^p y^q dxdy \tag{2}$$

where $p,q = 0,1,2$. In the case of binary images, the moments of inertia that are defined with respect to the center of gravity of the leaf are [6], [14]:

$$\mu_{p,q} = \sum_I\sum_J (i-\bar{m})^p(j-\bar{n})^q \tag{3}$$

iv) *Leaf orientation:* Orientation is defined as the angle between the axis exhibiting the minimum moment of inertia and the horizontal [7], [14]. It can be calculated after minimization of the following function:

$$I(\theta) = \sum\sum_{(m,n)\in\Re} [(n-\bar{n})\cos\theta - (m-\bar{m})\sin\theta]^2 \tag{4}$$

resulting in the following angle θ [14]:

$$\theta = \frac{1}{2}\tan^{-1}\left[\frac{2\cdot\mu_{1,1}}{\mu_{2,0}-\mu_{0,2}}\right] \tag{5}$$

v) *Hydraulic Radius:* It is calculated by dividing the leaf area by the leaf perimeter [6], [14], where the perimeter is calculated according to:

$$T = \int\sqrt{x^2(t)+y^2(t)}dt \tag{6}$$

and the area is calculated as shown below.

vi) *Area:* Area is defined as the complete set of pixels that constitute a leaf. It is calculated as:

$$E = \int\int_R dxdy \tag{7}$$

vii) *Diagonal:* It is defined as the diagonal of the smallest possible rectangle a leaf can be fit in [14].

viii) *Maximum Length:* This is defined as the length of the maximum horizontal cord consisting of successive pixels in the binary image of the leaf [14].

ix) *Maximum width:* This is defined as the length of the maximum vertical cord consisting of successive pixels in the binary image of the leaf [14].

x) *Waddel Disk Diameter:* This is defined as the diameter of an equivalent disk that has the same area with the leaf under examination [7], [14].

Similarly, some additional features are useful for the detection of deformations and holes on the leaf surfaces:

xi) *Edge Detection:* Leaf and hole edges are derived by the application of a non-linear convolutional filter, with two convolution kernels of the Sobel type [7], [15]. These kernels are defined as:

$$\begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{matrix} \qquad and \qquad \begin{matrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{matrix} \tag{8}$$

xii) *Equivalent Ellipse:* This is defined as that ellipse whose second moment of inertia equals that of the leaf [6], [14].

xiii) *Object Count:* For the purpose of object counting an object is defined as a set interconnected pixels.

A set of programs for the extraction of the above morphological and geometrical features, as well as for the overall image processing tasks, were developed and tested in the visual programming environment of LabView ver. 6 [4]. Moreover, the set of image processing libraries available in the programming environment of NI-IMAQ [14] were used.

III. FEATURE SELECTION

Feature selection is an important task that allows the determination of the most relevant features for pattern recognition. The objective of feature selection is to obtain a feature space with: a) low dimensionality, b) retention of sufficient information, c) enhancement of separability in feature space, and d) comparability of features among examples in same category [16], [8]. The goal of feature selection is to reduce the dimensionality of vectors associated to patterns by selecting a subset of attributes smaller than the original. The classifier performance is often improved eliminating redundant features.

These methods can be divided into *filter* and *wrapper* models. Filter models investigate indirect performance measures, mostly based on distance and information measures [17]. They study the feature selection task independently of a classifier, whereas, wrapper models use classification as a subtask, testing the classification for different subsets of features, until an optimum is found [18]. Wrapper methods are computationally feasible only for small feature vectors because they are much more time-consuming as each iteration of the method requires classifier execution and testing [8].

Feature selection methods use search strategies, which can be categorized as exhaustive (greedy algorithms), heuristic (sequential) and non-deterministic (randomized). Both Euclidean and Mahalanobis distances can be calculated, however the information of Euclidean distance is limited since it is used for uncorrelated variables [8]. In statistical analysis, forward and backward stepwise multiple regression (SMR) are widely used to select features. The output here is the smallest subset of features resulting in a correlation coefficient value that explains a significantly large amount of the variance.

Rough sets theory was also used to determine the degree of dependency of sets of attributes for selecting binary features [16]. The most popular feature selection methods in machine learning literature are variations of sequential forward search (SFS) and sequential backward search (SBS) [16]. SFS (SBS) obtains a chain of nested subsets of features by adding (subtracting) the locally best (worst) feature in the set. Finally, in [19] Lin and Cuningham proposed a very fast method for input selection introducing the fuzzy curve concept. A fuzzy curve is a non-linear continues curve, which establishes a connection between a specific input and the output, performing a projection of the multidimensional input output space on the (probed input)-output space. The height of the projected output is the measure of importance of the specific input. In this paper we introduce the fuzzy surface concept as an extension of the fuzzy curve [11], applied to image feature classification.

The fuzzy surface method can be described as follows: Assuming there exists a feature vector consisting of m-features (inputs), belonging to a certain class (single output), the behavior of a classifier for the classification of such vectors can be statistically represented by a set of q input/output observation data points, in the form $d_k = [x_{1,k}, ..x_{j,k}..., x_{m,k},\, y_k]$ where $k = 1, 2, .., q$. For each datum d_k a fuzzy rule R_k is created in the following form:

$$R_k: \text{ if } x_1 \text{ is } A_{1,k}, \text{ and}, ..., \text{and } x_m \text{ is } A_{m,k} \text{ then } y \text{ is } y_k \quad (9)$$

The membership function $\mu_{j,k}(x_j)$ of each coordinate fuzzy set $A_{j,k}$ is given by:

$$\mu_{j,k}(x_j) = \exp[-(2 \cdot \frac{x_{j,k} - x_j}{\sigma_j})^2] \,\text{where}\, j = 1, 2, ..., m \quad (10)$$

Each bell-shaped function is located at $x_{j,k}$; the parameter σ_j has a fixed value per input variable x_j, which equals $5-15\%$ of the x_j variable range. A fuzzy rule base is generated comprising q rules, R_k, $k = 1, ..., q$ in the form of Eq. (9). Having determined the product as the fuzzy implication method and using the centroid defuzzyfication technique, the output of the fuzzy model is given by the formula:

$$FS_{m,q,\ell}(\underline{x}) = \frac{\sum_{k=1}^{q} \left[\prod_{j=1}^{n} \left(\mu_{j,k}(x_{j,k}) \right) \right] \cdot y_k}{\sum_{k=1}^{q} \left[\prod_{j=1}^{n} \mu_{j,k}(x_j) \right]} \quad (11)$$

Eq. (11) provides a continuous and parameter free surface, which approximates the input output data, and behaves as a fuzzy model. The mean absolute percentage error is used to estimate the quality of the approximation:

$$E_{m,q,\ell} = \frac{100}{q} \sum_{k=1}^{q} \frac{|FS_{m,q,\ell}(\underline{x}_k) - y_k|}{|y_k|}\% \quad (12)$$

It has to be underlined that the aforementioned modeling technique is used as a parameter free coarse model, which performs the system identification process without any time-consuming adaptation processes. Parameters σ_j are used to regulate the degree of accuracy that the model approximates the input/output observation data.

Note that the fuzzy system described by Eq. (11) includes all the candidate features $x_1, x_2, ..., x_m$. A number of $m!/n!\,(m-n)!$ subsystems $FS_{n,q,\ell}(\underline{x})$ could be created, in a similar manner, by using $n < m$ features, where $\ell = 1, 2, ..., \frac{m!}{n!\,(m-n)!}$. The approximation performance of each subsystem, calculated by Eq. (12), is related to the importance of the respective fature combination. Moreover, the number n of inputs, which participate in the creation of the $FS_{n,q,\ell}(\underline{x})$, could be used as a complexity measure for the $FS_{n,q,\ell}(\underline{x})$ subsystem. Finally, in order to cope with the problem of *data over-fitting*, a relaxation strategy is adopted as follows: The observation data set of q input/output pairs is divided into two subsets, each comprising $q/2$ data points. Each fuzzy surface $FS_{n,q/2,\ell}(\underline{x})$ is built using the first q/2 data, that is, the rule base includes $q/2$ fuzzy rules in the form of Eq. (9). The performance evaluation of the respective fuzzy surface takes into account the whole data set of q data. An evaluation measure $R_{n,\ell}$, related both to the modeling performance (identification and generalization) and to the complexity of $FS_{n,q,\ell}(\underline{x})$ subsystem is defined by the formula:

$$R_{n,\ell} = w \cdot \frac{100 \cdot E_{q,n,\ell}}{E_{\max}} + (1-w) \cdot \frac{n}{m} \,|w \in (0,1) \quad (13)$$

where $E_{\max} = \max(E_{q,1,\ell}),\,|\,\ \ell = 1, ..., m$ is used as a normalization factor. The smaller is the value of $R_{n,\ell}$ the greater is the importance of the respective $FS_{n,q/2,\ell}(\underline{x})$ and the blending feature combination. Not important features participation increases both terms in Eq. (13). Entering significant inputs or deducting negligible ones decreases the $R_{n,\ell}$ value. In the case that two input combinations are equivalent in the modeling performance, the preferred combination is the one with the smaller n.

Given m candidate features, $2^m - 1$ possible feature combinations exist. The feature combination with the minimum $R_{n,\ell}$ value is the solution to the feature selection problem. In the case that the number m is a small integer (i.e. $n \leqslant 10$) the evaluation of all the combination is feasible. For larger m a non-linear optimization technique is required [11]. The best subset of features selected by the proposed fuzzy surface model, out of all the possible feature combinations presented in the previous section is:

$F = \{Moments\,of\,Inertia\,xx,\ Moments\,of\,Inertia\,yy,\ Leaf\ Area/Total\ Area,\ Hydraulic\,Radius\}$

with an evaluation measure of 1.18785, calculated according to Eq. (13). These features are used for the training of the neural network classifier.

IV. Neural Netork Design and Training

A neural network was designed for the classification of the available samples, taking as inputs the features selected by the fuzzy surface model. Neural networks are well-known for their generalization capabilities in classification problems [20], especially in the field of image processing [12], [13]. In order to avoid over-fitting, the data set was split to a training set including the first $q/2$ observation vectors and a validation set including the rest $q/2$ vectors. A classical backpropagation training algorithm was used, implemented in MatLab [5].

Using 10 neurons in the hidden layer, a classification accuracy of 99% was achieved for the validation set. It should be noted that the data set included deformed leafs or even leafs with holes drilled on their surface, as it will be shown in the next section.

V. System Description and Operation

A. A Graphical User Interface Developement

A Graphical Users Interface (GUI) was developed for the efficient interaction the image processing tasks (programs), the feature selection and classification programs with the system hardware components i.e., the SONY laboratory camera and the National Instruments frame-grabber. The proposed GUI (shown in Fig. 1) was designed using visual programming in Labview and it is the master program that invokes programs in MatLab, Labview, and IMAQ libraries. Moreover, it can control the camera and frame-grabber parameters.

Red, Green and Blue selection cursors in the proposed GUI can change the parameters for image thresholding according to the available classes, lighting conditions etc. This is followed by the calculation of the center of gravity such that the image of the leaf is moved at the center of the optical region. The image of the leaf is then rotated such that its orientation is vertical (thus avoiding various orientation and translation problems [7], [21]). Then, the morphological and geometrical feature calculation routines are invoked (for the specific subset of selected features, as described in the feature selection section). Finally, the selected features are fed to the neural network and classification results are presented.

B. System operation

The operation of the proposed image processing system was tested for a large number of leaves samples, belonging to 4 different classes. It was found that the proposed system was capable of correctly classifying the samples even in cases that leaves are deformed, or they have different orientations and sizes during image sampling. System operation is demonstrated with the following examples. Fig. 2 shows the classification procedure for a leaf sample of the 4^{th} pre-selected class, without any deformations or holes and at a random orientation with respect to the camera. Fig. 2(a) displays image snapping and Fig. 2(b) shows the result of image thresholding. The leaf orientation (angle θ, with respect to the horizontal) is calculated according to Eq. (5) and the leaf is then rotated by an angle of $(\theta - 90^0)$ so that it's final orientation is vertical, as shown in Fig. 2(c). Fig. 2(d) shows the result of edge detection, according to Eq. (8).

This completes the pre-processing step and, then, the selected features are calculated, as discussed in the feature selection section. The values of the selected features are then

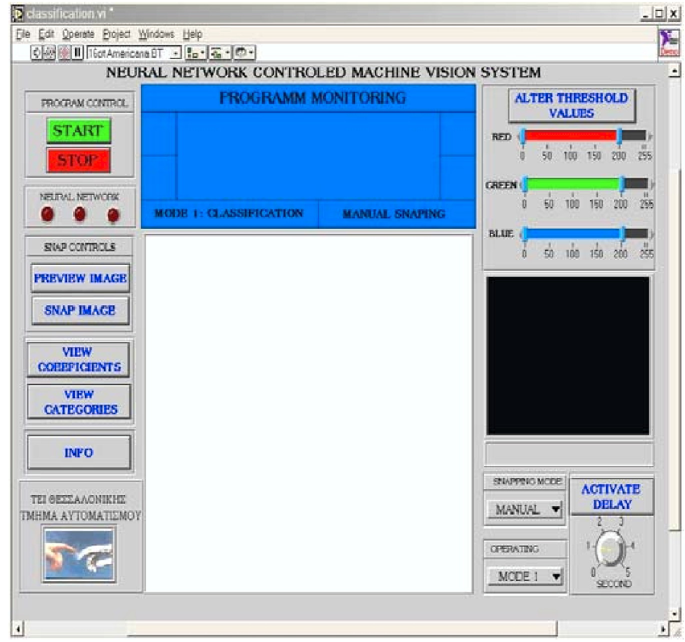

Fig. 1. The Graphical Users Interface

fed to the neural network that is invoked by the GUI and the neural network produces the classification result. The corresponding class with characteristic class descriptors is shown in Fig. 2(e).

Similarly, Fig. 3(a-e) demonstrate the operation of the proposed system for a leaf belonging to the first class. The leaf is deformed (has been dried out) and has two holes drilled on its surface. The extraction of the selected morphological features and the subsequent operation of the neural network successfully classify the leaf to the correct class, despite its severe deformations. The proposed system was tested for a variety of samples of different leaf sizes (according to their growing phase) and of different levels of deformations (due to leaves drying out or due to holes on their surface). In any case a very high classification success was achieved, at about 99%.

VI. Conclusions

Reducing the number of features for classification results in faster execution speeds and higher classification success rate. The proposed image processing system consisting of the camera and frame grabber and operating under the control of the proposed GUI that invokes the image processing libraries, feature selection and neural network classification routines can be suitable for real-time operation in several application environments.

The proposed feature selection approach results in simpler, faster and easier to train neural network architectures, when compared to neural networks used to measure the contribution of individual input features to the output of the neural network [16].

Moreover, the proposed approach compares favorably to the most popular feature selection methods in machine learning literature, i.e. the sequential forward search (SFS) and sequential

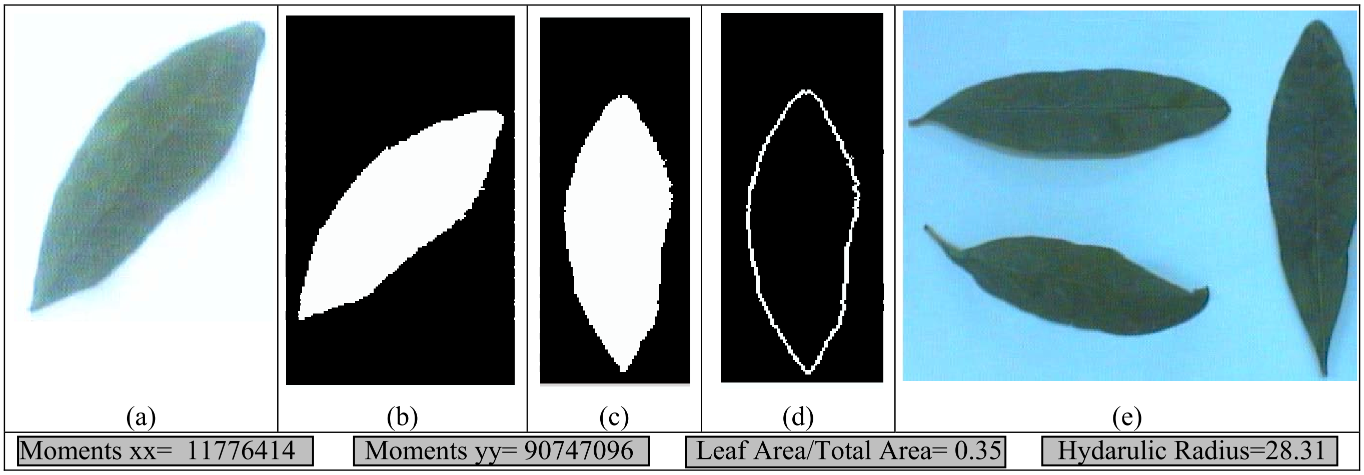

Fig. 2. Classification of a sample of the 4^{th} class

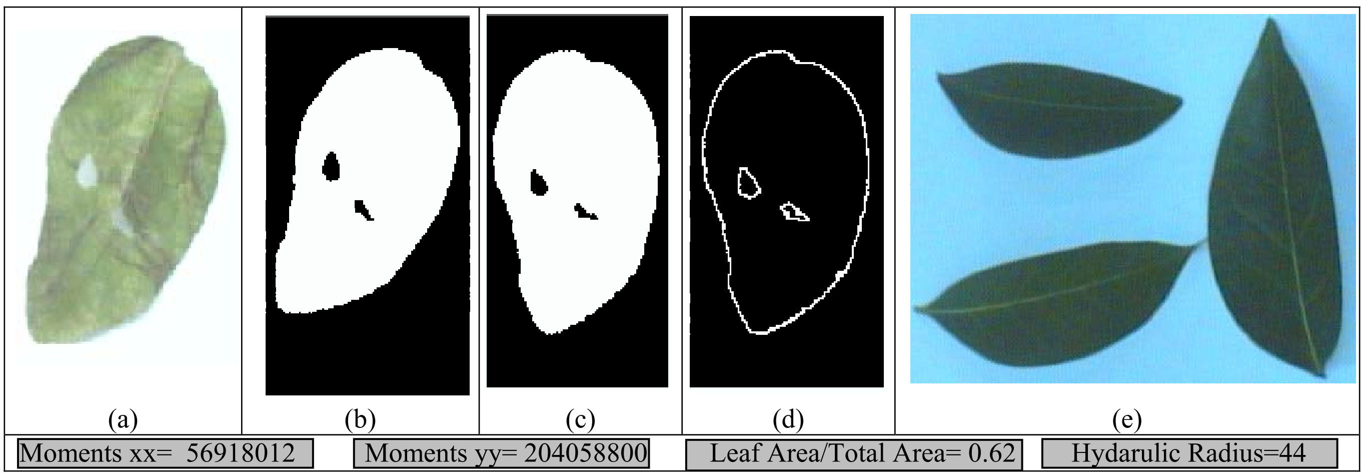

Fig. 3. Classification of a deformed sample of the 1^{st} class

backward search (SBS) [16]. The serious weakness of this approach is that it adds or subtracts one feature at a time. It results in trapping the search in local minima, because it fails to encode the probing of all the potential combinations.

Additionally, the main drawback of the forward and backward stepwise multiple regression (SMR) approaches [18], when compared to the approach presented in this paper, is that they search for interdependent features in the input space ignoring the influence of each one to the output of the system.

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