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Plants Leaves Images Segmentation Based on Pseudo Zernike Moments

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Abstract—Leaves images segmentation is an important task in the automated plant identification. Images leaf segmentation is the process of extracting the leaf from its background, which is a challenging task. In this paper, we propose an efficient and effective new approach for leaf image segmentation, we aim to separate the leaves from the background and from their shadow generated when the photo was taken. The proposed approach calculates the local descriptors for the image that will be classified for the separation of the different image's region. We use Pseudo Zernike Moments (*PZM*) as a local descriptor combined with K-means algorithm for clustering. The efficient of *PZM* for features extraction lead to very good results in very short time. The validation tests applied on a variety of images, showed the ability of the proposed approach for segmenting effectively the image. The results demonstrate a real improvement compared to those of new existing segmentation method.

***Index Terms*—**Pseudo Zernike Moments, leaves plant, image segmentation, K-means algorithm.

I. Introduction

Plants are essential creatures in our planet, they are our nearest environment on which depends several life aspects such as food, oxygen, water, medicine. In our days the plants are increasingly threatened, lead to their loss which has a devastating impact on human life. In order to protect plants we need to know more about them and disseminated more knowledge, even for non-specialists; but their large numbers and their diversity are a challenge even for the specialists who cannot know or remember only a limited number.

Plant identification methods are based on the use of taxonomy. The taxonomy is used by the specialists who examined the plants for identification. The identification methods can be divided into two broad categories: The first one is called the modern methods, but they are complex and can be handled only by specialists since they consider biological characteristics. The second one is called traditional methods based on the visual identification of the form of an important organ of the plant such as leaf, flower or fruit and identifies it through this feature.

The leaves are considered the fundamental parameter for plant identification [1], since they are available all year round in almost all seasons, they do not require three dimensional acquisitions since the form of a leaf can be retained in a two-dimensional image [2]. That's what justifies their wide applications for automatic identification which handle only two-dimensional images.

The leaves possess several characteristics such as shape, color, veins and texture [3][4]. Form is the most used feature for plant identification, it is a characteristic often inherited and not influenced by the environment [5]. Leaf shape allows a better description of the leaves from other characteristics such as color or even texture [1]. Therefore, for leaf identification we need to extract leaf from the background. The extraction of the leaf from the image and recover its form, is a very significant step in the identification process. Most of leaves images used have generally a uniform background; however the segmentation of the leaf from the background remains a challenge due to the noise produced by the brightness variation and shadow produced by the leaves themselves. Our goal is to propose an efficient method for leaf segmentation, which allows extracting leaf without shadow or background.

In this paper, we propose the use of Pseudo Zernike Moments (*PZM*) as a local descriptor of leaf form for efficient features extraction. Using the local descriptor instead of global allows more efficient feature extraction. The local features array extracted from a partitioned image for each partition. The image is represented by all features descriptors of all partitions. Image descriptors are then classified and the image's pixels are segmented into different regions based on classification results obtained by K-means algorithm [6].

The rest of this paper is organized as follows: in section 2, we present the related work. Section 3 gives a presentation of Pseudo Zernike Moments. Then, the proposed method is described in section 4. The section 5, presents some results and discussions. Finally, the paper is concluded in section 6.

II. Work Related

The plant identification process has recently been a subject of interest for many recent studies. Few of them consider the problem of leaf extraction from the background. In [7], the authors propose a Leaf snap system for Automatic Plant Species Identification, they use the Expectation Maximization (*EM*) algorithm to

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classify each pixel in image by estimating foreground and background color distributions. For scan pictures, the Otsu segmentation algorithm [8] is used in [9], the segmented image contains two classes of pixels foreground and background. In [10], for gray level images the maximally stable extremal regions algorithm is used for the segmentation of a single object over background, the algorithm computes a scan in depth, and then detects an object to be segmented when a stable number of connected components are reached. Arora et al. [11], propose to use preprocessing techniques for shadow removal, they performed Otsu threshold on the saturation space to give the shadow-free image. Arai et al. [12] propose another system to identify plants from, they combine between shape descriptors from Dyadic wavelet transformation and Zernike complex moments.

Many works on leaf identification have been focusing on the feature extraction and classification shapes. For leaf shape description two approaches can be used: the first is based on the contours and the second is based on regions [1]. The importance of leaf margins for plant identification requires the use of effective methods for the detection of different border's types [13]. It is clear that a good description using the contours requires a good extraction of the outline of the object that is in it a major segmentation problem. On the other side the contour based descriptor extracts features only from boundary, then it loses the important information carried by the region inside [14].

For the region approach the internal details of the borders are considered. Then, the shape is described by features extracted from the whole image [14]. Most commonly used methods as form descriptors are moments invariant like Hu [15], Zernike moments [16] and Pseudo Zernike Moments [17].

Hu moments are seven derived moments, easy to compute, but they don't accurately present an image[14]. Pseudo Zernike Moments allow a better representation of the features; they are more robust to noise than Zernike moments [18] and more effective since the characteristics described by lower levels of *MPZ* are better than other moments, such as Zernike moments[19]. *PZM* is considered very effective image descriptors, used for recognition as the construction of the images [18]. Pseudo Zernike Moments (*PZM*) provide a unique description of an object regardless of transformations such as rotation or translation [17]. *PZM* allows multilevel representation of the image due to the property of orthogonal with less redundancy information, robust to noise, they are rotation invariants since just the magnitude is used [20].

III. PZM AS A FORM DESCRIPTOR

Pseudo Zernike Moments are widely used as an image descriptor for object recognition. Originally proposed by Teh and Chin[17], Pseudo Zernike Moments are orthogonal moments used as a kernel for the Pseudo Zernike polynomials defined within a unit circle with polar coordinates. *PZM* are the projection of the image intensity function to Pseudo Zernike polynomials.

Pseudo Zernike Moment of order p and repetition q, calculated for a 2D image of size $N*N$ having the intensity function $f\ (r,\ \theta)$ is given by the following equation:

$$PZM_{p,q} = \frac{P+1}{\pi} \iint_{x^2+y^2\le 1} V_{pq}^*(x,y) f(x,y) dxdy \qquad (1)$$

Where $V_{p,q}^*(x,y)$ is the complex conjugate of the complex Pseudo Zernike $V_{p,q}$ polynomials (x,y), which can be separated into two functions?

$$V_{p,q}(x,y) = R_{p,q}(r) e^{jq\theta} \qquad (2)$$

Where:

- $R_{p,q}(r)$: Radial polynomial on polar coordinats *(r, θ)*.
- $e^{jq\theta}$: Angular function, $e^{jq\theta} = (\cos\theta + j\sin\theta)^q$.
- *p*: Moments order, anon-negative integer.
- *q*: Moments repetitions, integer $0 \le |q| \le p$. Only the positive values are used since negative values can be calculated using the complex conjugate:

$$PZM_{p,-q} = PZM^*_{p,q} .$$

- *j*: Imaginary number $j = \sqrt{-1}$.
- θ : angle between the vector *r* and axis X

$$\theta = \tan^{-1}\left(\frac{x}{y}\right) \text{ et } \theta \in [0, 2\pi]$$

- *r*: Length of the vector from the origin $(\bar{x}, \bar{y})$ to pixel (x,y). $r = \sqrt{x^2+y^2}$.
- $R_{p,q}$: is calculated by the equation :

$$R_{p,q}(r) = \sum_{s=0}^{p-|q|} (-1)^s \frac{(2p+1-s)!}{s!(p+|q|+1-s)!(p-|q|-s)!} r^{p-s} \qquad (3)$$

The image is described by a vector comprising the PZM for all orders and repetitions:

$$VI = \{PZM_{p,q}\},\ p = 0,\cdots,p_{\max};\ q = 0,\cdots,p \qquad (4)$$

Since $PZM_{p,q}$ are complex numbers and it's always easy to manipulate real numbers; $PZM_{p,q}$ are usually divided into two parts: real $PZM^c_{p,q}$ and imaginary $PZM^s_{p,q}$ [21][11].

$$PZM_{p,q}^{c} = \frac{2(p+1)}{\pi} \iint_{x^2+y^2\le 1} R_{p,q}(r)\cos(q\theta) f(r,\theta) dr d\theta \quad (5)$$

$$PZM_{p,q}^{s} = \frac{2(p+1)}{\pi} \iint_{x^2+y^2\le 1} R_{p,q}(r)\sin(q\theta) f(r,\theta) dr d\theta \quad (6)$$

The discrete form of Pseudo Zernike moments is given by the following equation:

$$PZM_{p,q}(f(x,y)) = \frac{p+1}{\pi} \sum_{i=0}^{N} \sum_{j=0}^{M} V_{p,q}^{*}(x,y) f(x,y) dxdy \quad (7)$$

PZM of order p contains $(p-1)^2$ linearly independent polynomials lower or equal to p orders. Different Polynomials of different orders corresponding to the different image characteristics, this advantage is due to the orthogonally of Pseudo Zernike polynomials. The moments of different orders can be calculated independently of each other, each one has different information with almost no redundancy.

Pseudo Zernike moments are defined in polar coordinates in a unit circle; then the pixels of square image have to be normalized to the interval [0, 1], $x^2 + y^2 \le 1$.

The normalization is done by a linear transformation of pixel coordinates to polar system, where the center of the image is taken as the origin of the circle.

There are two possibilities for the normalization of the image:

- *The circle within the image*: the unit circle is mapped within the image. The pixels outside the circle are ignored and will not be taken into account when calculating the *PZM*.
- *Image within the circle:* the entire image is included in the circle, and no information will be lost since all pixels are taken into account when calculating *PZM* [22].

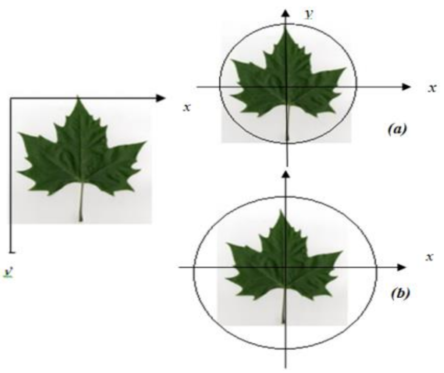

Fig.1. Image normalization methods. (a) circle within the image, (b) image within the circle

The normalized coordinates (x_c, y_c) inside the unit circle are given by:

$$x_c = \frac{2x+1-N}{D}, \; y_c = \frac{2y+1-N}{D} \quad (8)$$

Where:

- x, y : are the pixel coordinates before normalization.
- $D = N$: Case of unit circle within the images.
- $D = N\sqrt{2}$: Case of image normalized within the unit circle.

IV. PZM Based Segmentation Method

In this section, we present in detail our proposed approach of segmentation to extract leaf without shadow.

Plant leaves images segmentation is a process of two phases: the first relates to feature extraction and the second consists of classifying the pixels of the image based on the results from the first phase. In our case we start by image partitioning and normalization technique, and then we compute *PZM's* descriptors.

A. Image Partition and Normalization

The image RGB is firstly converted to grayscale image. After color space conversion the image is partitioned into windows, for each the *PZM* will be computed. Partitioning provides better local feature extraction.

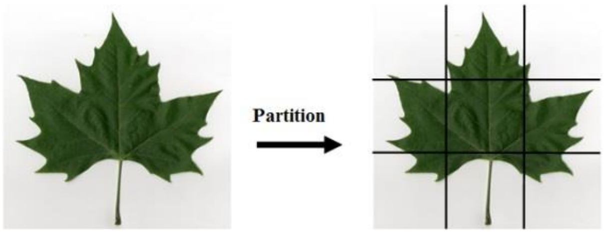

Fig.2. Image partition

For the image *I* of size $N \times M$ the windows are of equal size $W \times W$ and without recovery. The total number of windows is obtained by:

$$NBwidth = \frac{N}{W}, \; NBlength = \frac{M}{W} \quad (9)$$

$$NBblock = NBwidth \times NBlength \quad (10)$$

The window size is *W*, estimated by experimental results, the value size is *W=4* gives the best compromise between execution time and description quality.

A window in the partitioned image can be located by two coordinates (*x*,*y*) where $x \in [0, NBlength - 1]$ and $y \in [0, NBwidth - 1]$, the image intensity function *f* at the pixel (x_i, y_j) is given by the following equation:

$$f^{x,y}(x_i, y_j) = f(Wx + x_i, Wy + y_j) \quad (11)$$

$$NBlength = \frac{M}{W}$$

After partitioning the image, the coordinates of each pixel are normalized to a polar coordinate space, where

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each block of the image is mapped within a unit circle. The choice of this normalization technique is justified by the preservation of information because all pixels are taken into account when calculating the moments.

B. *Features Extraction*

The features extraction step is performed by calculating the *PZM* for each window of the partitioned images.

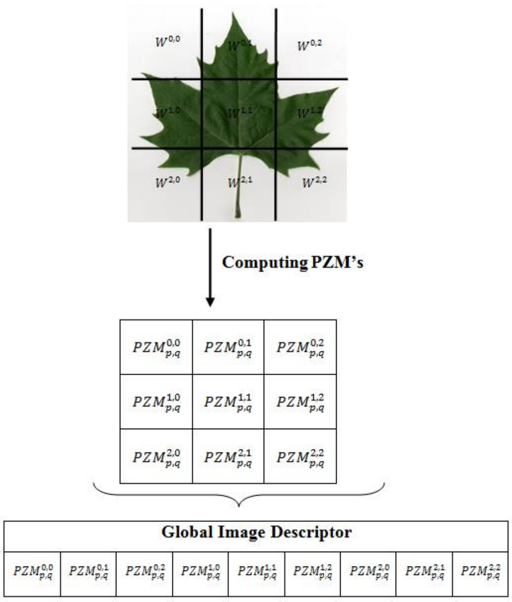


Fig.3. Image Global Descriptor calculation for one channel partitioned image using $PZM^{x,y}$

Since the *PZM* are rotation invariants only the magnitude will be considered as a feature.

The RGB image is divided into three color channel R, G and B. each channel is treated independently. After calculating the descriptors of all windows of each channel by following the same steps described above for an image with one channel. A global descriptor of a window at position (x, y) is constructed from the three descriptors of the three channel windows lying in the same position.

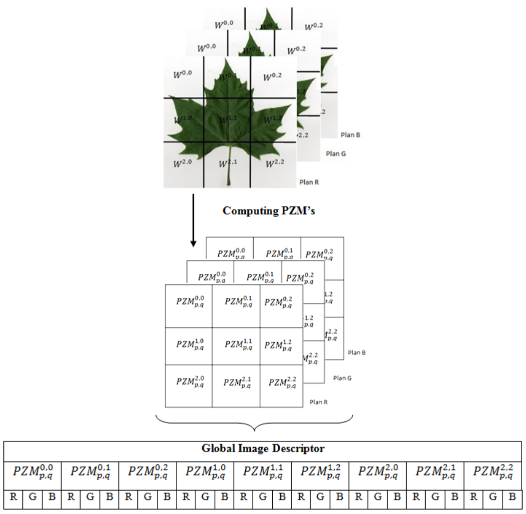


Fig.4. Calculating a partitioned RGB image descriptors using $PZM^{x,y}$

C. *Clustering*

The image descriptors are then classified with K-means algorithm [6]. The k-means algorithm is one of the most and popular clustering algorithms, it is known for its simplicity, efficiency and speed. K-means algorithm has been used in many applications and can be easily used in image segmentation.

The goal of the algorithm consists in gathering descriptors in clusters, and maximizes the similarity between descriptors in the same cluster. Let be $X=\{X1, X2,..., Xn\}$ the set of n descriptors represented by a set of data points of dimension d, to be clustered into K clusters with means μ_1, μ_2, … , μ_k . The K-means algorithm produces a partition such that the squared error between the mean of a cluster and all data in the cluster is minimized, the goal is to minimize the sum of the squared error (*SSE*) over all *K* clusters.

$$SSE = \sum_{k=1}^{K} \sum_{x_i \in C_k} \left\| x_i - \mu_k \right\|^2 \qquad (12)$$

Optimization of this objective is known as a NP-complete problem [23]. The main steps of K-means algorithm are as follows:

1. Select k data points as initial cluster centroids.
2. For each data point of the whole data set, compute the clustering criterion function with each centroid. Assign the data point to its closest cluster centroids.
3. Recalculate *k* centroids based on the data points assigned to them.
4. Repeat steps 2 and 3 until convergence.

It is obvious in this description that the result is influenced the desired number of clusters *k*. In our study, different initialization values were used for k. For scanned images the k values varied between 2 and 4. For scan-like images higher values were used. Thereafter the image is segmented according to the classification result.

V. Results and Discussions

For testing the presented method we use *Pl@ntLeaves*[1] database, containing more than 5436 images of more than 70 plants. It is included in the ImageCLEF 2012 Plant Identification Task project.

The images contained in the database are categorized into three types: Scanned Images, Scan-Like images (photographed with a uniform white background) and photographed images (in the tree with a natural background).

[1] http://imedia-ftp.inria.fr:8080/imageclef2012/ImageCLEF2012PlantIdentificationTaskFinalPackage.zip

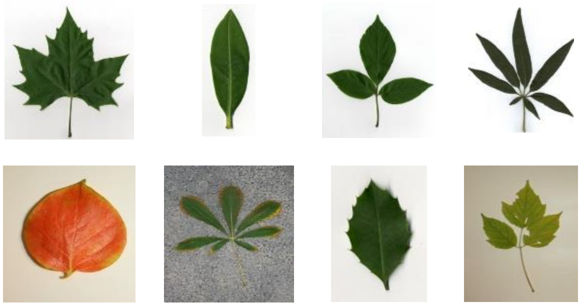


Fig.5. Different types of images in Pl@ntLeaves database images

The *Pl@ntLeaves* database contains 3070 scanned images, 897 scan-like images and 1469 photographed images.

For the experimental results both type scan and scan-like images were used. The Fig. 6. shows *PZM* based on the segmentation results of one channel images.

(a) (b)

Fig.6. Segmentation results of grayscale images using Pseudo Zernike Moments.(a) results for scanned images, (b) results for scan-like images.

The images are firstly mapped to the grayscale image, then several orders of moments were tested and order $P_{max} = 4$ was held at the end to have a quality compromise between performance and execution time.

(a) (b)

Fig.7. Segmentation results of RGB images using Pseudo Zernike Moments. (a) results for scanned images, (b) results for scan-like images

The segmentation results produced are generally good. In Fig. 7. the color space shows the best results for the segmentation of the scanned images. However for scan-like images light variance affects the segmentation results and produces worse results.

The exploitation of the information carried by the three channels improves the results of image segmentation using Pseudo Zernike moments. The Fig. 7. shows some examples of segmentation results.

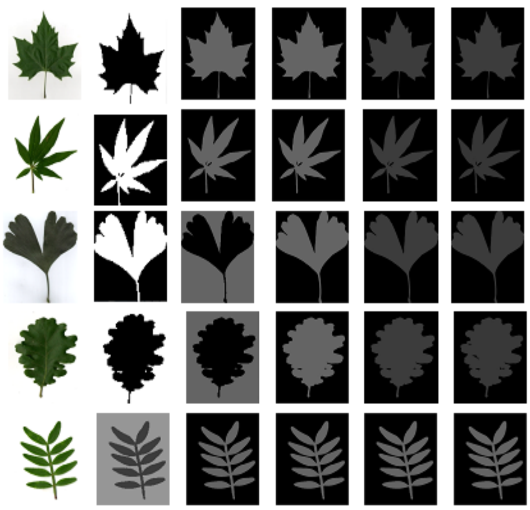
The results are compared to those produced by other methods based on different shape descriptors as the Neutrosophic sets [24], entropy and even multi-level thresholding with the same classification algorithm K-means.

Neutrosophic based segmentation is performed on RGB images, were each channel is transformed to the Neutrosophic domain. For eliminating the indeterminacy we use two methods α-mean and β-enhancement proposed by sengur [25]. The true subsets of the three channel are then classified using K-means.

Entropy based segmentation is performed by firstly eliminating the background using Otsu algorithm [8] that result a black and white image used as a binary mask image to extract the leaf and shade from the background. Each pixel not belonging to the background is considered as the center of the window of size W * W for which the entropy is calculated then the global descriptor is classified.

For Multilevel thresholding segmentation also a binary mask is used for extracting the leaf and shade, then algorithm proposed by Arora [26] is applied on the masked image. The figures (Fig. 8. and Fig. 9.) shows segmentation results of both scanned and scan-like images by the different methods.

Segmentation results of *PZM* one three channel images are the best, the neutrosophic sets produces very similar results. The results of both segmentation methods based on entropy and multi-level thresholding are very sensible to light variation.



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

Fig.8. Segmentation results of scanned images by the different methods, (a) the original images, (b) MPZ 1 channel, (c) MPZ 3 channel, (d) Neutrosophic sets, (e) entropy, (f) multi-level thresholding.

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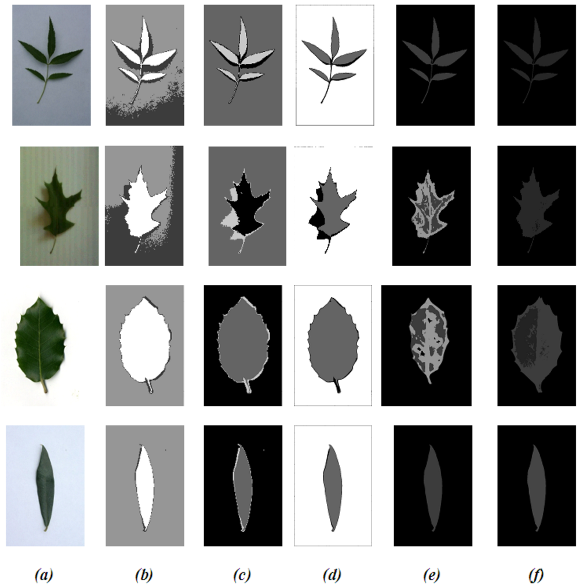

Fig.9. Segmentation results of Scan-like images, (a) the original images, (b) MPZ 1 channel, (c) MPZ 3 channel, (d) Neutrosophic sets, (e) entropy, (f) multi-level thresholding.

We have also compared our method with the method proposed in [7] which is an improvement of the EM algorithm (Expectation Maximization). EM algorithm judged by several studies [7] [27] as the most effective segmentation algorithm for leaf images.

Fig. 10. shows a comparison of results obtained by our method and those of the method in [7].

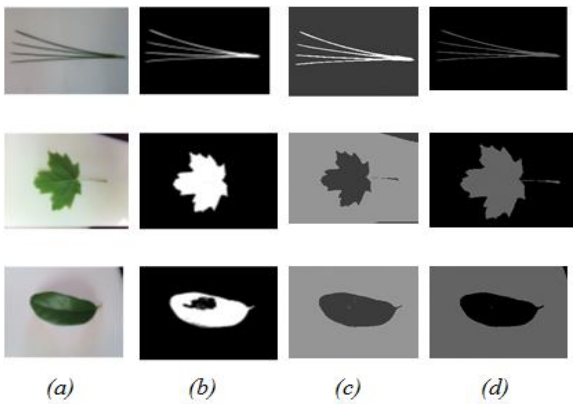

Fig.10. Comparison of segmentation results (a) The original image, (b) Segmentation results by the EM algorithm, (c) segmentation results of one channel images using Pseudo Zernike Moments, (d) Segmentation results of three channel images using Pseudo Zernike Moments.

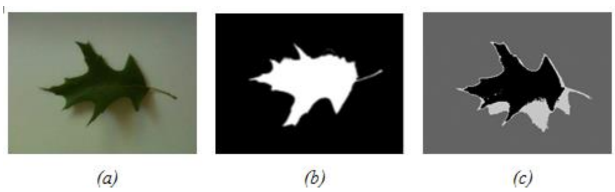

Fig.11. Segmentation results (a) the original image, (b) the segmentation result of the image by the modified EM algorithm, (c) the result of segmentation using Pseudo Zernike Moments of three channel images.

The last line shows that our method improves the results produced with less sensitivity to change of luminance.

PZM based segmentation of three channel images shows better results compared to those presented by the EM modified method [7]. The following figure shows an example of results improvement.

On the other hand, the average segmentation time (feature extraction and classification) of the different methods for the images tests is given in Fig. 12.

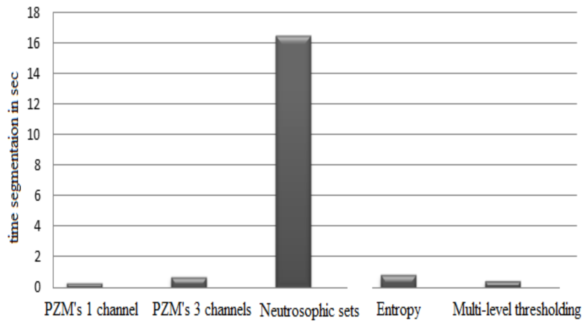

Fig.12. Average time elapsed by different methods.

In addition to the computational speed of *PZM* based segmentation it generates small descriptors that allow a faster segmentation.

Time segmentation obtained by Pseudo Zernike moments is the fastest for both scanned images and scan-like images. The Neutrosophic sets based segmentation approach is the slowest compared to the others

VI. Conclusion

In this paper, we presented the problem of identifying plants through the shape of their leaves. We aim to extract the leaf from its background, which is a challenging task due to the noise produced by the luminance variation or shadow of the leaf itself.

Our goal was to exploit the power of Pseudo Zernike moments as shape descriptors for better features extraction of leaf images. We propose the use of *PZM* as a local form descriptor of leaf form for efficient feature extraction. The image's descriptors are then classified and the image's pixels are segmented into different regions based on classification results, for the classification we have used k-means and its variant bisecting k-means for their simplicity and quality of classes produced.

We evaluated the proposed approach on varieties of images, the quality of the obtained results is very effective and correct. The segmentation results using the proposed approach are better than Neutrosophic, Entropy and Multilevel thresholding methods.

As perspectives we intend to expand our research and improve our segmentation method for photographed images where acquisition conditions and background are more complex.

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