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.

The authors propose an efficient and effective new approach for leaf image segmentation, and 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.

Pseudo Zernike Moments (*PZM*) is used 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.

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.

I. INTRODUCTION – cont.

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].

[1] K. Asrani and R. Jain, "Designing a clustered database for identification of leaves," in *Advance Computing Conference (IACC), 2013 IEEE 3rd International*, 2013, pp. 237–242.
[2] H. Hajjdiab and I. Al Maskari, "Plant species recognition using leaf contours," in *2011 IEEE International Conference on Imaging Systems and Techniques (IST)*, 2011, pp. 306–309.

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].

[3] X. Zheng and X. Wang, "Leaf Vein Extraction Based on Gray-scale Morphology," *Int. J. Image Graph. Signal Process.*, vol. 2, no. 2, p. 25, Dec. 2010.
[4] J. S. Cope, D. Corney, J. Y. Clark, P. Remagnino, and P. Wilkin, "Plant species identification using digital morphometrics: A review," *Expert Syst. Appl.*, vol. 39, no. 8, pp. 7562–7573, juin 2012.

I. INTRODUCTION – cont.

Form is the most used feature for plant identification, it is a characteristic often inherited and not influenced by the environment [5].

[5] J. B. MacQueen, "Some Methods for Classification and Analysis of MultiVariate Observations," in *Proc. of the fifth Berkeley Symposium on Mathematical Statistics and Probability*, 1967, vol. 1, pp. 281–297.

Leaf shape allows a better description of the leaves from other characteristics such as color or even texture [1].

[1] K. Asrani and R. Jain, "Designing a clustered database for identification of leaves," in *Advance Computing Conference (IACC), 2013 IEEE 3rd International*, 2013, pp. 237–242.

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.

The goal here is to propose an efficient method for leaf segmentation, which allows extracting leaf without shadow or background.

I. INTRODUCTION – cont.

The use of Pseudo Zernike Moments (*PZM*) is proposed, 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].

[6] N. Kumar, P. N. Belhumeur, A. Biswas, D. W. Jacobs, W. J. Kress, I. C. Lopez, and J. V. B. Soares, "Leafsnap: A Computer Vision System for Automatic Plant Species Identification," in *Computer Vision – ECCV 2012*, A. Fitzgibbon, S. Lazebnik, P. Perona, Y. Sato, and C. Schmid, Eds. Springer Berlin Heidelberg, 2012, pp. 502–516.

II. RELATED WORK.

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 classify each pixel in image by estimating foreground and background color distributions.

[7] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms," *Syst. Man Cybern. IEEE Trans. On*, vol. 9, pp. 62–66, 1979.

For scan pictures, the Otsu segmentation algorithm [8] is used in [9], the segmented image contains two classes of pixels foreground and background.

[8] Y. Chéné, D. Rousseau, P. Lucidarme, J. Bertheloot, V. Caffier, P. Morel, É. Belin, and F. Chapeau-Blondeau, "On the use of depth camera for 3D phenotyping of entire plants," *Comput. Electron. Agric.*, vol. 82, pp. 122–127, Mar. 2012.
[9] A. Arora, A. Gupta, N. Bagmar, S. Mishra, and A. Bhattacharya, "A Plant Identification System using Shape and Morphological Features on Segmented Leaflets: Team IITK, CLEF 2012," in *CLEF 2012 Evaluation Labs and Workshop, Online Working Notes, Rome, Italy, September 17-20, 2012*, 2012, vol. 1178.

II. RELATED WORK – cont.

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.

[10] K. Arai, I. Nugraha Abdullah, and H. Okumura, “Image Identification Based on Shape and Color Descriptors and Its Application to Ornamental Leaf,” *Int. J. Image Graph. Signal Process.*, vol. 5, no. 10, pp. 1–8, Aug. 2013.

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.

[11] N. Valliammal and S. N. Geethalakshmi, “Performance Analysis of Various Leaf Boundary Edge Detection Algorithms,” in *Proceedings of the 1st Amrita ACM-W Celebration on Women in Computing in India*, New York, NY, USA, 2010, pp. 34:1–34:6.

Arai et al. [12] propose another system to identify plants from, they combine between shape descriptors from Dyadic wavelet transformation and Zernike complex moments.

[12] C. Singh and Pooja, “Local and global features based image retrieval system using orthogonal radial moments,” *Opt. Lasers Eng.*, vol. 50, no. 5, pp. 655–667, mai 2012.

II. RELATED WORK – cont.

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].

[1] K. Asrani and R. Jain, "Designing a clustered database for identification of leaves," in *Advance Computing Conference (IACC), 2013 IEEE 3rd International*, 2013, pp. 237–242.

The importance of leaf margins for plant identification requires the use of effective methods for the detection of different border's types [13].

[13] M.-K. Hu, "Visual pattern recognition by moment invariants," *IRE Trans. Inf. Theory*, vol. 8, no. 2, pp. 179–187, 1962.

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].

[14] M. R. Teague, "Image analysis via the general theory of moments," J. Opt. Soc. Am., vol. 70, no. 8, pp. 920–930, août 1980.

II. RELATED WORK – cont.

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].

[14] M. R. Teague, "Image analysis via the general theory of moments," J. Opt. Soc. Am., vol. 70, no. 8, pp. 920–930, août 1980.

Most commonly used methods as form descriptors are moments invariant like Hu [15], Zernike moments [16] and Pseudo Zernike Moments [17].

[15] C.-H. Teh and R. T. Chin, "On image analysis by the methods of moments," IEEE Trans. Pattern Anal. Mach. Intell., vol. 10, no. 4, pp. 496–513, 1988.
[16] M. S. Al-Rawi, "Fast computation of pseudo Zernike moments," J. Real-Time Image Process., vol. 5, no. 1, pp. 3–10, Mar. 2010.
[17] A. B. J. T. Ying-Han Pang, "A discriminant pseudo Zernike moments in face recognition," J. Res. Pract. Inf. Technol., vol. 38, 2006.

II. RELATED WORK – cont.

Hu moments are seven derived moments, easy to compute, but they don't accurately present an image [14].

[14] M. R. Teague, "Image analysis via the general theory of moments," *J. Opt. Soc. Am.*, vol. 70, no. 8, pp. 920–930, août 1980.

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].

[18] C.-W. Chong, P. Raveendran, and R. Mukundan, "An Efficient Algorithm for Fast Computation of Pseudo-Zernike Moments," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 17, no. 06, pp. 1011–1023, Sep. 2003.
[19] H. R. Kanan, K. Faez, and Y. Gao, "Face recognition using adaptively weighted patch PZM array from a single exemplar image per person," *Pattern Recognit.*, vol. 41, no. 12, pp. 3799–3812, décembre 2008.

II. RELATED WORK – cont.

PZM is considered very effective image descriptors, used for recognition as the construction of the images [18].

[18] C.-W. Chong, P. Raveendran, and R. Mukundan, "An Efficient Algorithm for Fast Computation of Pseudo-Zernike Moments," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 17, no. 06, pp. 1011–1023, Sep. 2003.

Pseudo Zernike Moments (PZM) provide a unique description of an object regardless of transformations such as rotation or translation [17].

[17] A. B. J. T. Ying-Han Pang, "A discriminant pseudo Zernike moments in face recognition," J. Res. Pract. Inf. Technol., vol. 38, 2006.

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].

[20] D. J. M. Garey, "The complexity of the generalized Lloyd - Max problem (Corresp.)," *Inf. Theory IEEE Trans. On*, no. 2, pp. 255 – 256, 1982.

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.

[17] A. B. J. T. Ying-Han Pang, "A discriminant pseudo Zernike moments in face recognition," *J. Res. Pract. Inf. Technol.*, vol. 38, 2006.

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 $f(r, \vartheta)$ is given by the following equation:

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

III. PZM AS A FORM DESCRIPTOR – cont.

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 :

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

III. PZM AS A FORM DESCRIPTOR – cont.

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

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

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].

[21] F. Smarandache, *A unifying field in logics: neutrosophic logic: neutrosophy, neutrosophic set, neutrosophic probability*. Rehoboth [N.M.]: American Research Press, 2003.

[11] N. Valliammal and S. N. Geethalakshmi, "Performance Analysis of Various Leaf Boundary Edge Detection Algorithms," in Proceedings of the 1st Amrita ACM-W Celebration on Women in Computing in India, New York, NY, USA, 2010, pp. 34:1–34:6.

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

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

III. PZM AS A FORM DESCRIPTOR – cont.

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 $[0, 1], x^2 + y^2 \leq 1$.

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.

III. PZM AS A FORM DESCRIPTOR – cont.

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].

[22] A. Sengur and Y. Guo, "Color Texture Image Segmentation Based on Neutrosophic Set and Wavelet Transformation," *Comput Vis Image Underst*, vol. 115, no. 8, pp. 1134–1144, août 2011.

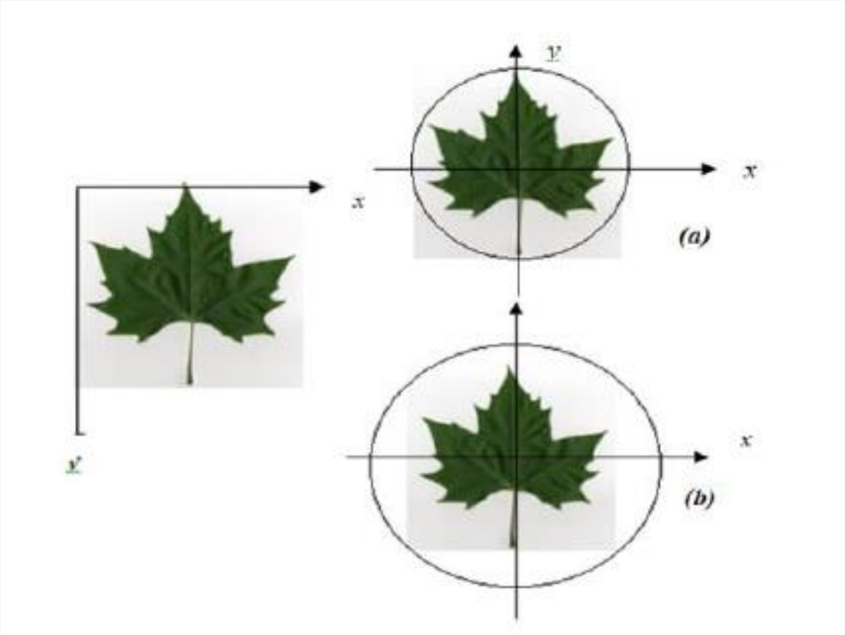

Fig.1. Image normalization methods.
(a) circle within the image,
(b) image within the circle.

III. PZM AS A FORM DESCRIPTOR – cont.

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

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

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, the proposed approach of segmentation to extract leaf without shadow is presented in detail.

Plant leaves images segmentation is a process of two phases:

- ❑ the first relates to feature extraction;
- ❑ 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.

IV. PZM BASED SEGMENTATION METHOD – cont.

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.

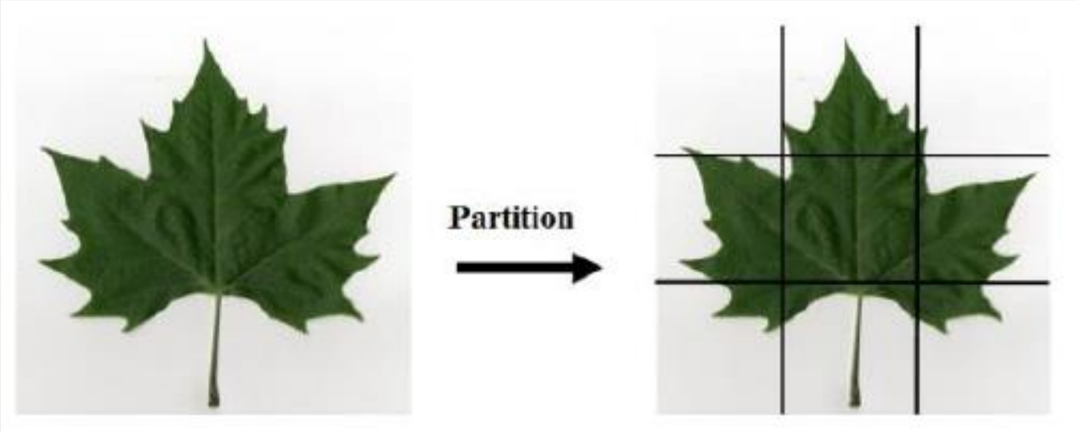

Fig. 2. Image partition

IV. PZM BASED SEGMENTATION METHOD – cont.

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:

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

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

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:

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

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

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

IV. PZM BASED SEGMENTATION METHOD – cont.

B. Features Extraction

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

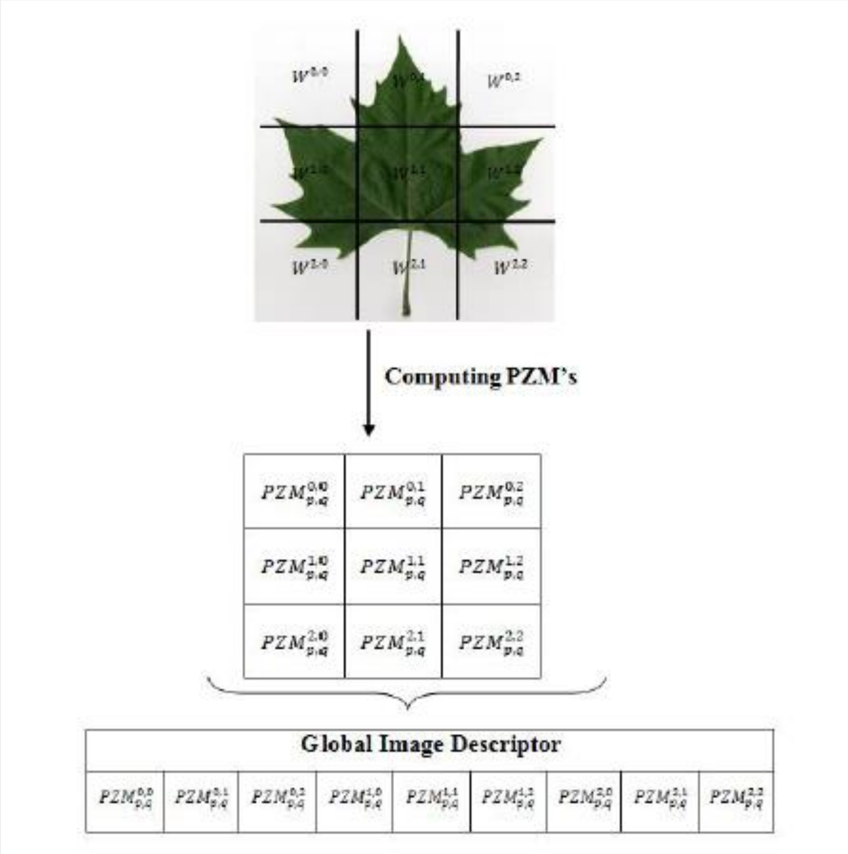

Fig. 3. Image Global Descriptor calculation for one channel partitioned image using $PZM^{x,y}$

IV. PZM BASED SEGMENTATION METHOD – cont.

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.

IV. PZM BASED SEGMENTATION METHOD – cont.

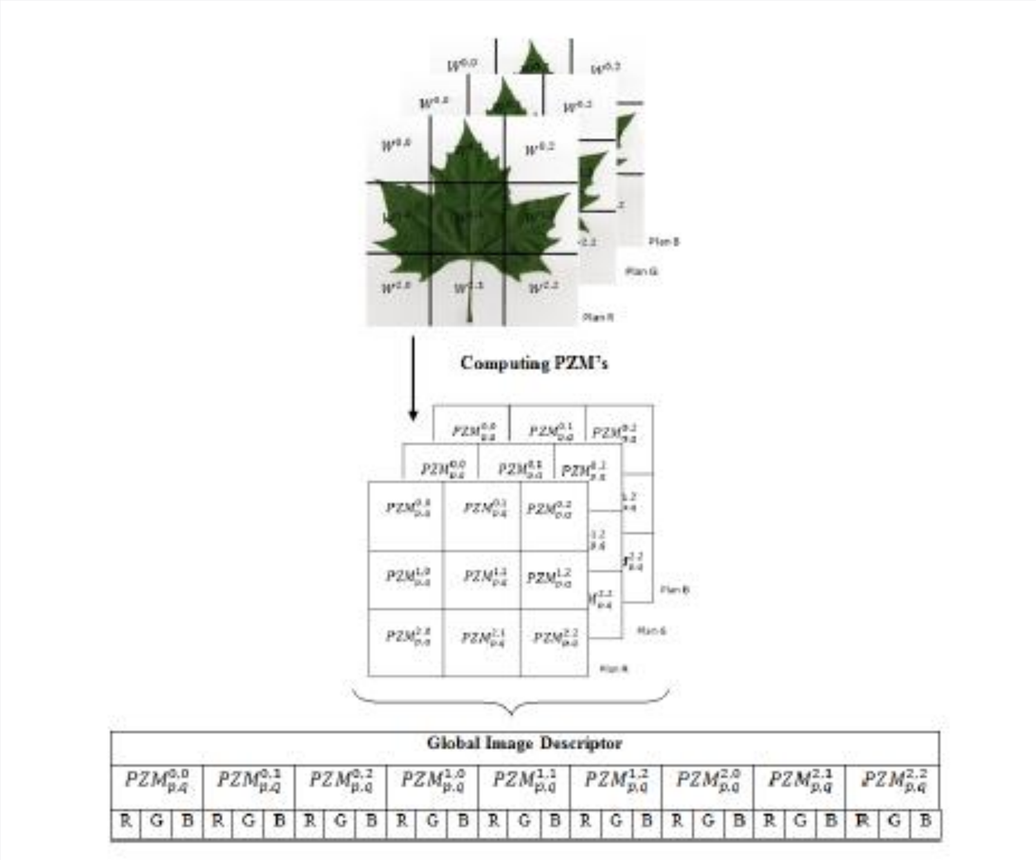

Fig. 4. Calculating a partitioned RGB image descriptors using $PZM^{x,y}$

C. Clustering

The image descriptors are then classified with K-means algorithm [6].

[6] N. Kumar, P. N. Belhumeur, A. Biswas, D. W. Jacobs, W. J. Kress, I. C. Lopez, and J. V. B. Soares, "Leafsnap: A Computer Vision System for Automatic Plant Species Identification," in *Computer Vision – ECCV 2012*, A. Fitzgibbon, S. Lazebnik, P. Perona, Y. Sato, and C. Schmid, Eds. Springer Berlin Heidelberg, 2012, pp. 502–516.

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 $X=\{X_1, X_2, ..., X_n\}$ the set of n descriptors represented by a set of data points of dimension d, to be clustered into K clusters with means $\mu_1, \mu_2, \ldots, \mu_k$.

IV. PZM BASED SEGMENTATION METHOD – cont.

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.

V. RESULTS AND DISCUSSIONS.

It is obvious in this description that the result is influenced the desired number of clusters k.

In present 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.

For testing the presented method we use Pl@ntLeaves database, containing more than 5436 images of more than 70 plants.

It is included in the ImageCLEF 2012 Plant Identification Task project.

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

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).

V. RESULTS AND DISCUSSIONS – cont.

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

V. RESULTS AND DISCUSSIONS – cont.

The Pl@ntLeaves database contains 3070 scanned images, 897 scan-like images and 1469 photographed images. For the experimental results both type scan and scanlike images were used. The Fig. 6. shows PZM based on the segmentation results of one channel images.

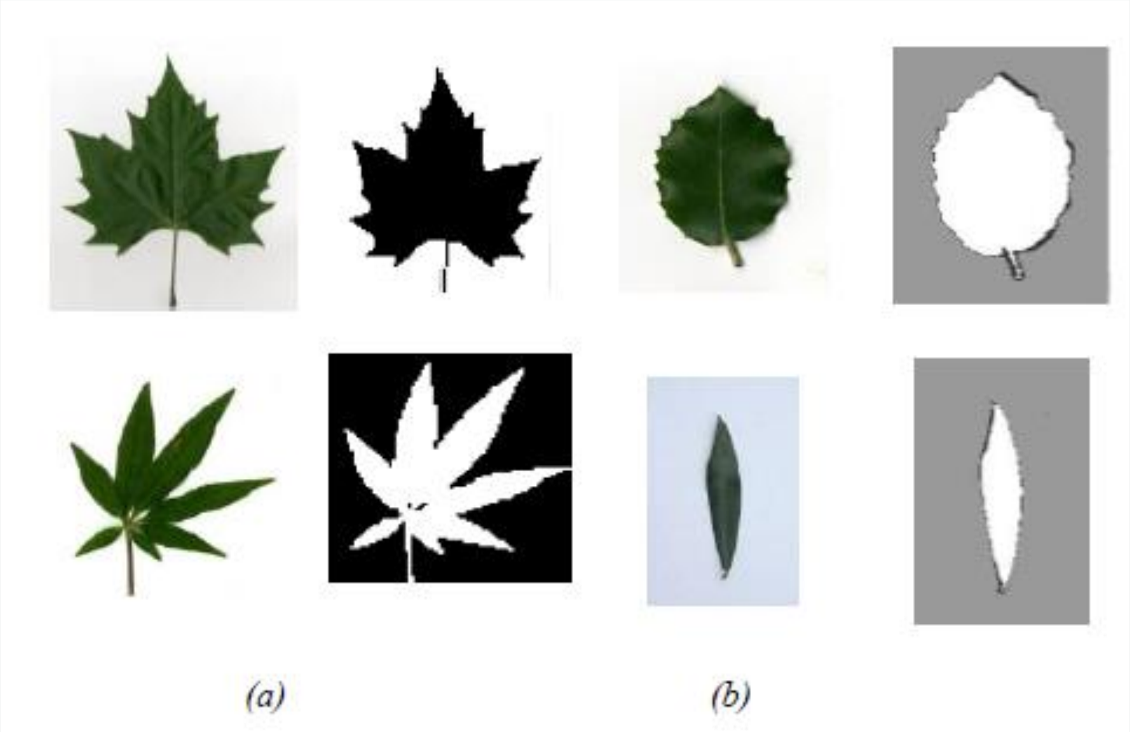

Fig. 6. Segmentation results of grayscale images using Pseudo Zernike Moments.
(a) results for scanned images, (b) results for scan-like images.

V. RESULTS AND DISCUSSIONS – cont.

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.

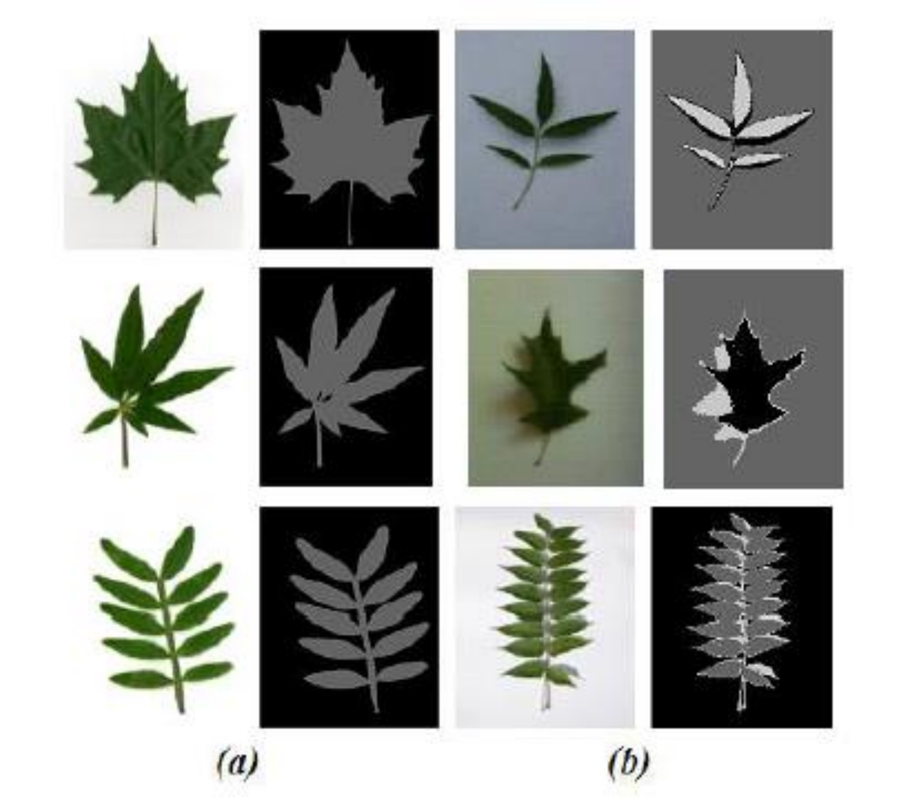

Fig. 7. Segmentation results of RGB images using Pseudo Zernike Moments.
(a) results for scanned images, (b) results for scan-like images.

V. RESULTS AND DISCUSSIONS – cont.

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 scanlike 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.

[24] P. Belhumeur, D. Chen, S. Feiner, D. Jacobs, W. Kress, H. Ling, I. Lopez, R. Ramamoorthi, S. Sheorey, S. White, and L. Zhang, "Searching the World's Herbaria: A System for Visual Identification of Plant Species," in *European Conference on Computer Vision (ECCV)*, 2008, pp. 116–129.

V. RESULTS AND DISCUSSIONS – cont.

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.

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.

[8] Y. Chéné, D. Rousseau, P. Lucidarme, J. Bertheloot, V. Caffier, P. Morel, É. Belin, and F. Chapeau-Blondeau, "On the use of depth camera for 3D phenotyping of entire plants," *Comput. Electron. Agric.*, vol. 82, pp. 122–127, Mar. 2012.

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.

V. RESULTS AND DISCUSSIONS – cont.

For Multilevel thresholding segmentation also a binary mask is used for extracting the leaf and shade, then algorithm proposed by Arora 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.

V. RESULTS AND DISCUSSIONS – cont.

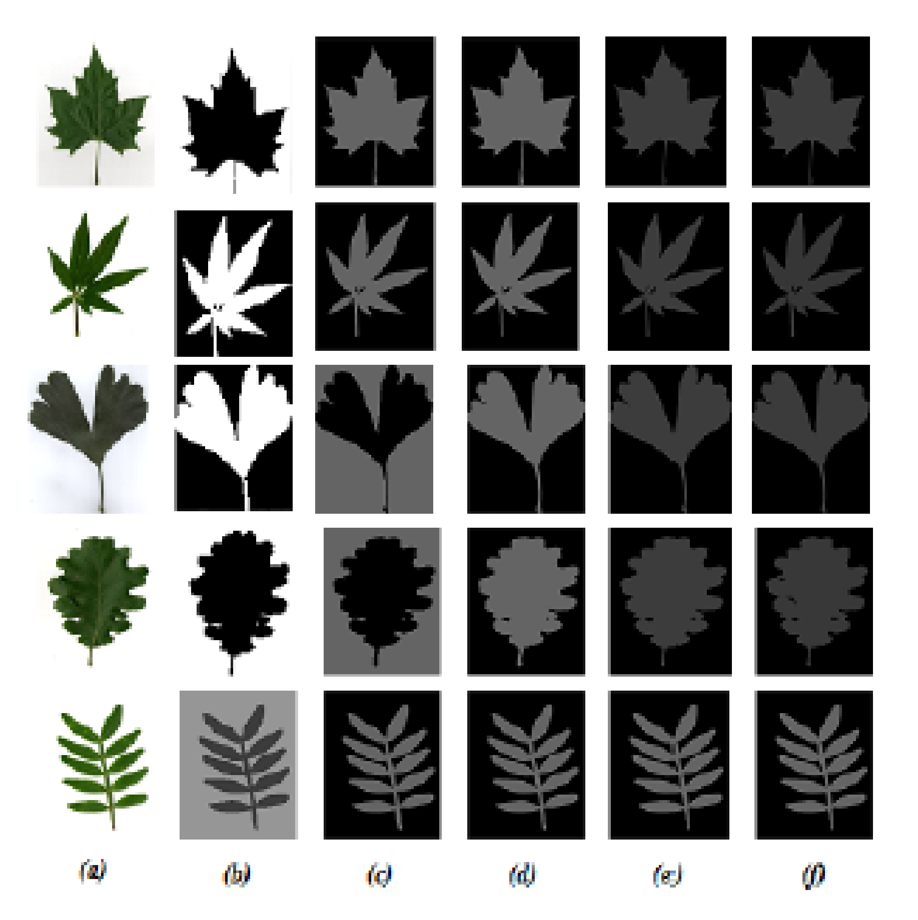

Fig. 8. Segmentation results of scanned images by the different methods, (a) the original images, (b) MPZ 1 channel, (c) MPZ 3 channel, (d) Neutrosophic sets, (e) entropy, (f) multi-level thresholding.

V. RESULTS AND DISCUSSIONS – cont.

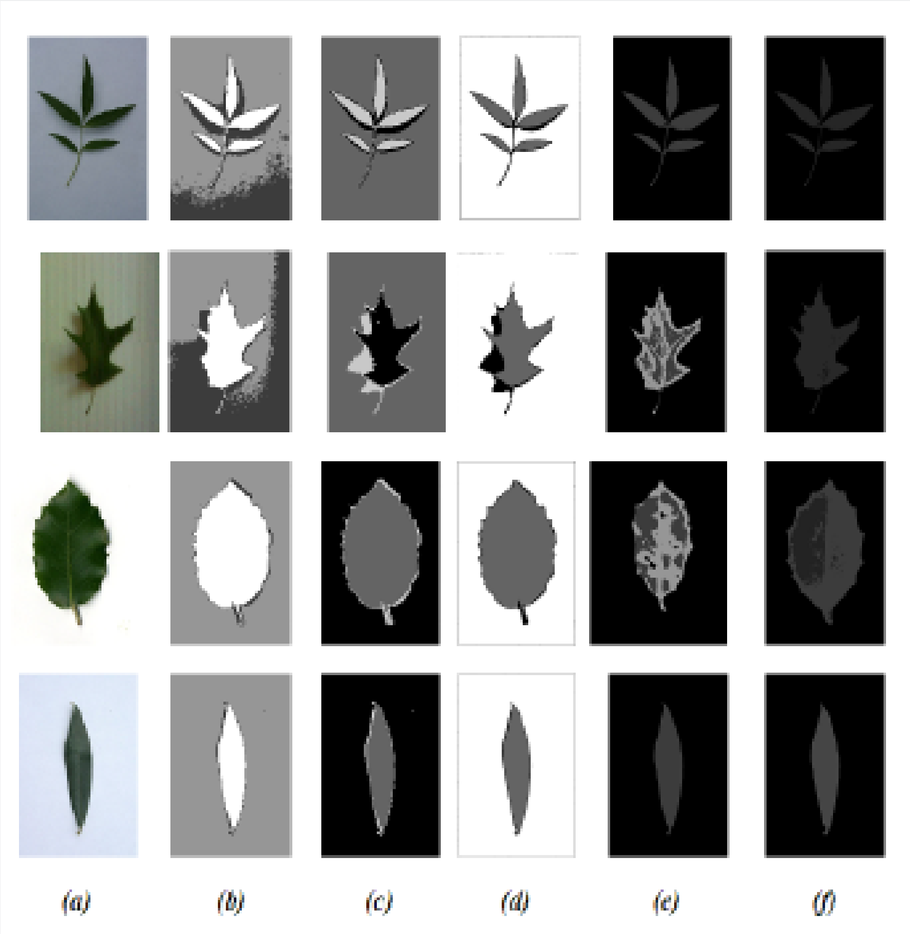

Fig. 9. Segmentation results of Scan-like images, (a) the original images, (b) MPZ 1 channel, (c) MPZ 3 channel, (d) Neutrosophic sets, (e) entropy, (f) multi-level thresholding.

V. RESULTS AND DISCUSSIONS – cont.

This method was compared with the method proposed in [7] which is an improvement of the EM algorithm (Expectation Maximization). EM algorithm is judged as the most effective segmentation algorithm for leaf images.

[7] N. Otsu, “A Threshold Selection Method from Gray-Level Histograms,” *Syst. Man Cybern. IEEE Trans. On*, vol. 9, pp. 62–66, 1979.

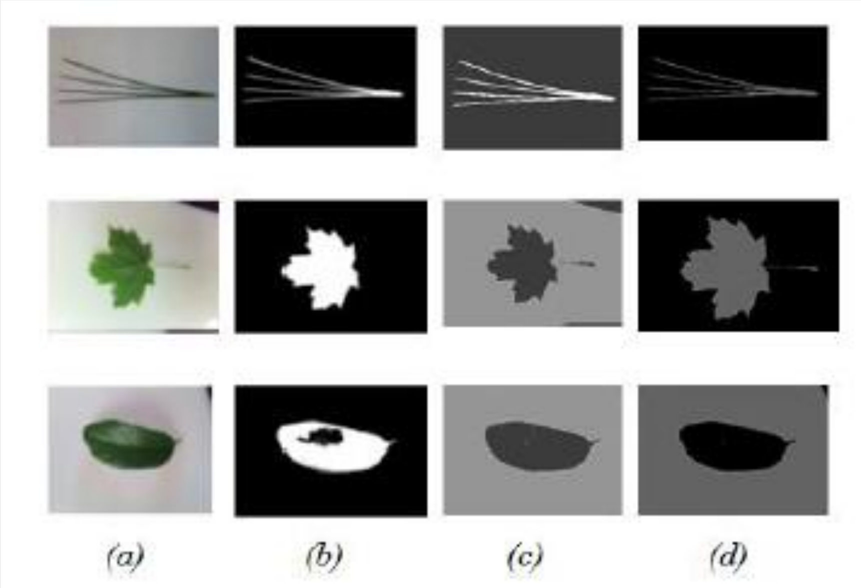

Fig.10. Comparison of segmentation results (a) The original image, (b) Segmentation results by the EM algorithm, (c) segmentation results of one channel images using Pseudo Zernike Moments, (d) Segmentation results of three channel images using Pseudo Zernike Moments.

V. RESULTS AND DISCUSSIONS – cont.

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.

The following figure shows an example of results improvement.

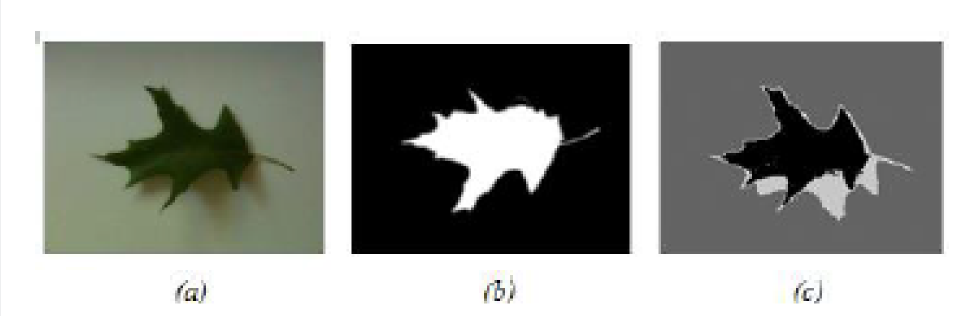

Fig.11. Segmentation results (a) the original image, (b) the segmentation result of the image by the modified EM algorithm, (c) the result of segmentation using Pseudo Zernike Moments of three channel images.

V. RESULTS AND DISCUSSIONS – cont.

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.

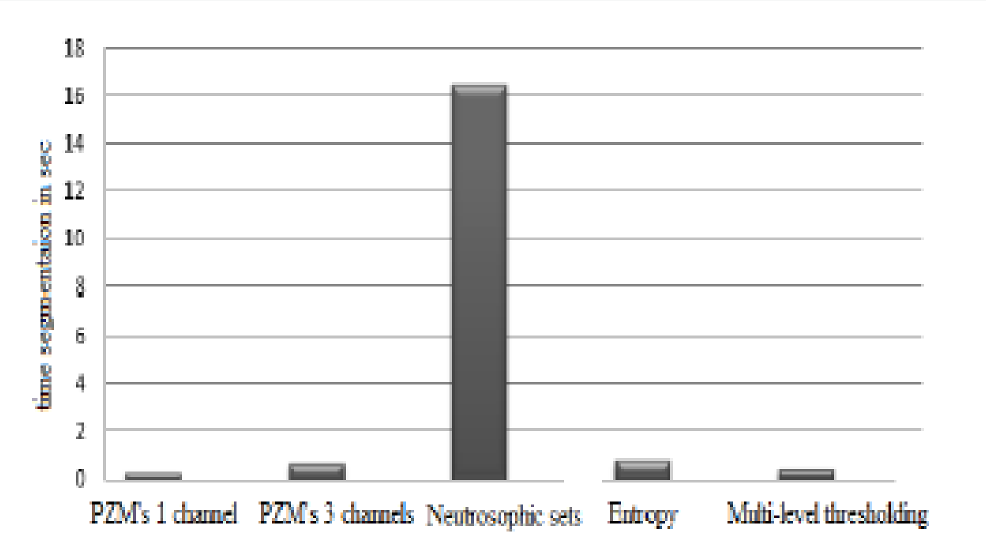

Fig.12. Average time elapsed by different methods.

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 scanlike images.

CONCLUSION.

The authors presented the problem of identifying plants through the shape of their leaves.

The aim is 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.

The goal was to exploit the power of Pseudo Zernike moments as shape descriptors for better features extraction of leaf images, proposing 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.

The segmentation results using the proposed approach are better than Neutrosophic, Entropy and Multilevel thresholding methods.

As perspectives, authors 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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