A Graph-Based Approach for Contextual Image Segmentation

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***Abstract*—Image segmentation is one of the most important tasks in Image Analysis since it allows locating the relevant regions of the images and discarding irrelevant information. Any mistake during this phase may cause serious problems to the subsequent methods of the image-based systems. The segmentation process is usually very complex since most of the images present some kind of noise. In this work, two techniques are combined to deal with such problem: one derived from the graph theory and other from the anisotropic filtering methods, both emphasizing the use of contextual information in order to classify each pixel in the image with higher precision. Given a noisy grayscale image, an anisotropic diffusion filter is applied in order to smooth the interior regions of the image, eliminating noise without loosing much information of boundary areas. After that, a graph is built based on the pixels of the obtained diffused image, linking adjacent nodes (pixels) and considering the capacity of the edges as a function of the filter properties. Then, after applying the Ford-Fulkerson algorithm, the minimum cut of the graph is found (following the *min cut-max flow* theorem), segmenting the object of interest. The results show that the proposed approach outperforms the traditional and well-referenced Otsu's method.**

***Index Terms*—Min Cut-Max Flow; Graph Theory; Anisotropic Diffusion; Image Segmentation.**

I. Introduction

Image segmentation can be defined as the task of partitioning a digital image into two or more disjoint regions (groups of pixels), which have specific characteristics: color, texture, shape, among other [1]. The segmentation process divides the image in terms of its internal semantic structures.

The image segmentation task plays an important role in many Image Analysis applications, commonly present in our daily activities. It is, generally, the first step in any attempt to analyze or interpret an image. Some kind of segmentation techniques is always found in any application involving the detection, recognition, and measurement of objects in images. It locates the regions of interest in the images also allowing discard irrelevant information [2]. An imprecise image segmentation may lead the subsequent methods to wrong results.

According to Maintz [2], many segmentation methods were proposed in the last decades. However, it is possible to classify them into some categories: threshold-; edge-; region-; clustering-; and matching-based approaches.

One of the main challenges when dealing with digital image segmentation consists in developing methods invariant to noise. Unfortunately, except the synthetic images generated through computer software, all other kinds of images, usually extracted from the real world through different kinds of sensors, tend to present noise.

In general, noise is originated from physical limitations of the capture sensors. However, some distortions in the image data can also be generated, intentionally or not, due to the manipulation process (storage, compression, errors in transmissions or processing, etc.).

Contributions: In this work a novel image segmentation approach robust to noise is proposed, which analyzes neighborhood information, through the use of concepts from graph theory and anisotropic filtering, in order to classify the image pixels more accurately. Comparing the performance of the proposed method with the traditional and well-referenced Otsu's [3] segmentation technique, the proposed approach outperforms the latter even when varying the magnitude of the Gaussian noise applied in the images of the evaluated database.

II. Technical Background

The proposed method for image segmentation presents robustness to noise since it exploits "twice" the neighborhood information in order to classify a given image pixel. First, an anisotropic diffusion is applied to the image in order to smooth internal regions of objects, preserving their boundaries. After that, a graph is built based on the generated image properties: each pixel is mapped into a node and linked with its neighbors. Then the minimum cut of this structure is found and the original image is segmented, considering again the contextual information for the segmentation.

A. Graph Cuts

Image segmentation techniques based on graphs cuts are examples of region-based methods. Unlike techniques focused on isolated pixels, i.e., in which the algorithms classify such elements analyzing them alone, the methods which use graph cuts also take into account, as mentioned, contextual information, i.e., the neighborhood of the pixels in the images, to classify them.

Greig et al. [4] were the first to propose that the minimum cut algorithm in graphs could be used to minimize certain energy functions for Computer Vision problems, i.e., traditional minimum cut algorithms on a given graph could be used to classify different regions of the image that it represents with minimal energy [5]. According to them, the energy of a given image segmentation (classification of pixels) can be represented by:

$$E(L) = \sum_{p \in P} D_p(L_p) + \sum_{(p,q) \in N} V_{p,q}(L_p, L_q) \tag{1}$$

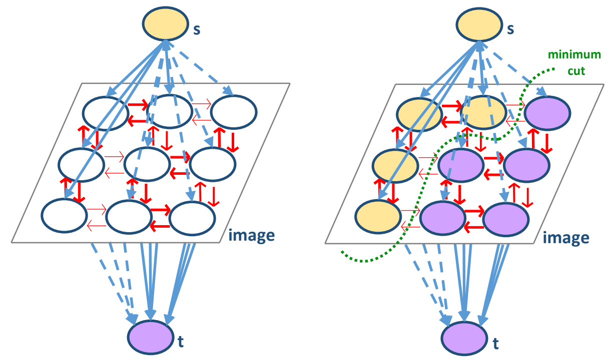
where $L = \{L_p | p \in P\}$ is the classification of the pixel p of an image P. $D_p(\cdot)$ is a penalty function based on the properties of the pixel p (e.g., grayscale value) and the label L_p associated to it (dissimilarity between the pixel characteristics and the class associated to it), and $V_{p,q}$ corresponds to the relationship of pixel p with its neighbors, i.e., the degree of similarity towards the adjacent pixels in the image (discontinuities are penalized). N is the set of all neighboring pixels p and q in the image.

In other words, $D_p(L_p)$ corresponds to the analysis of the pixel separately, i.e., how similar it is compared to the pixels of a particular class and $V_{p,q}$ compares a given pixel with its neighbors (local coherence in the image). The methods that seek the image partition (classification of the pixels in the predefined classes) attempt to minimize $E(L)$, that is, the total energy, ensuring, as good as possible, that similar (and near) pixels remain in the same class.

The complex minimization of the function $E(L)$ can be obtained by mapping the segmentation problem of a given image to the minimum cut problem in its respective graph. Considering the existence of only two distinct regions in the image (foreground and background), it is mapped to a directed graph (digraph) $G = (V, E)$ where each image pixel corresponds to a vertex $v \in V$. For a given vertex v (corresponding to a pixel p of the image) edges (called *n-links*) link v to the other graph nodes that represent the neighbors pixels of p in the given image. In addition, are inserted into the formed graph, two special nodes called terminals: s (*source*) and t (*sink*). Edges (called *t-links*) link s to all vertices correspondents to the pixels of the image and, after, all these vertices are also linked to the vertex t. With this the final graph representation of the image under analysis is obtained. The vertex s is taken as a model for the region of interest (foreground) in the image and should contain similar features to this region (e.g., similar grayscale value). The vertex t is taken for represent the background region and must also have properties similar to the pixels of this area.

A capacity (weight) value is assigned to each edge of the graph, which represents how similar two vertices connected by that edge are: the more similar (e.g., closer grayscale values), the greater the capacity value of the edge linking them. Fig. 1 illustrates the basic layout of a graph representing an image with dimensions 3×3. Thicker edges indicate higher capacity in the edge (more similar vertices). It is noteworthy to mention that, in the case of this work, the capacity value of the edge (u, v) is always equal to the capacity of the edge (v, u), although in some problems this property may not be valid.

Given a graph generated from an image, the problem of finding the minimum cut of this structure is also quite complex. However, following one of the most important theorems of graph theory and combinatorial optimization, *min cut-max flow*, one can prove that the minimum capacity cut of a given graph can be found, with polynomial complexity, by solving the maximum flow problem in such structure [6].



(a) Original graph. (b) Minimum cut.

Fig. 1. (a) Example of a graph formed from an image (size 3×3). The thinner the edge, the lower its capacity (lower similarity with the neighbor node). (b) Minimum cut, which segments the given graph (and consequently the original image) in two regions, one associated with s vertex (yellow) and the other with t (purple), by "breaking" low capacity edges optimally.

Most of algorithms that find the maximum flow (and hence the minimum cut) in graphs, follow two main approaches: methods based on the style Push-Relabel [7] and methods based on Augmented Paths of Ford-Fulkerson [8]. In this work the last algorithm for image segmentation was used.

The Ford-Fulkerson algorithm [8] finds the maximum flow in a given weighted and oriented graph (edges with capacity values) so that it is possible to obtain the minimum cut therefore efficiently (segmenting the given image). The s terminal node is considered as the source of the flows and the t vertex as the sink node, i.e., where the flows are absorbed. From the original graph G, flows are sent from s to t through not saturated edges until there is no more unsaturated path.

After finding the maximum flow of G by means of its residual graph G_f, applying a breadth-first search algorithm on G_f from the vertex s, one obtains the nodes of the graph (pixels of the image) that will be associated with the partition of s (pixels similar to s and found by the search algorithm mentioned). Vertices not achieved by the search are associated with the node t (belonging to the image region similar to t).

It is possible to show that the maximum flow value f_{max} allowed in G_f is equal to the sum of the capacities of the saturated edges departing from the partition associated with s and entering in the graph partition associated with t (this is the minimum possible cut for the graph, that is, optimum image segmentation into two heterogeneous regions).

B. Anisotropic Diffusion

From studies of methods for solving partial differential equations and iterative techniques for image filtering, the process known as anisotropic diffusion was widely disseminated by the Image Analysis community. This is mainly due to the pioneering work of Perona and Malik [9], who proposed the first computational algorithm for image smoothing based on the concept of anisotropic diffusion. This work opened the door to the application of methods based on differential equations in solving various problems in Image Processing.

The basic idea of the Perona-Malik [9] method involves discretization of the anisotropic diffusion equation given by:

$$I_t = div(c(x,y,t)\cdot\nabla I) = c(x,y,t)\cdot\nabla^2 I + \nabla c\cdot\nabla I \quad (2)$$

where div denotes the divergent operator, ∇ and ∇^2 denote, respectively, the gradient and Laplacian operators and $c(x,y,t)$ is a function that allows the diffusion coefficient to be variant both in space and time. According to [9], it is possible to show that, considering the discretization structure illustrated in Fig. 2, Eq. 2 may be written as:

$$\begin{aligned} I_{i,j}^{t+1} = I_{i,j}^t + \lambda(c_{N_{i,j}}^t\nabla_N I_{i,j}^t + c_{S_{i,j}}^t\nabla_S I_{i,j}^t + \\ c_{E_{i,j}}^t\nabla_E I_{i,j}^t + c_{W_{i,j}}^t\nabla_W I_{i,j}^t) \end{aligned} \quad (3)$$

where $I_{i,j}^t$ denotes the image intensity at the pixel (i,j) at iteration t, $\lambda\in[0;0.25]$ is the parameter that controls the velocity of the diffusion, and $\nabla_N I_{i,j}^t$, $\nabla_S I_{i,j}^t$, $\nabla_E I_{i,j}^t$ and $\nabla_W I_{i,j}^t$ corresponds to the difference of intensity between the pixel (i,j) and its neighbors:

$$\nabla_N I_{i,j}^t = I_{i-1,j} - I_{i,j} \quad (4)$$

$$\nabla_S I_{i,j}^t = I_{i+1,j} - I_{i,j} \quad (5)$$

$$\nabla_E I_{i,j}^t = I_{i,j+1} - I_{i,j} \quad (6)$$

$$\nabla_W I_{i,j}^t = I_{i,j-1} - I_{i,j} \quad (7)$$

The diffusion coefficients $c_{N_{i,j}}^t$, $c_{S_{i,j}}^t$, $c_{E_{i,j}}^t$ and $c_{W_{i,j}}^t$ are updated at each iteration as a function of the local gradient. The simplest choice for the values of these coefficients is given by [9]:

$$c_{N_{i,j}}^t = g(|\nabla_N I_{i,j}^t|) \quad (8)$$

$$c_{S_{i,j}}^t = g(|\nabla_S I_{i,j}^t|) \quad (9)$$

$$c_{E_{i,j}}^t = g(|\nabla_E I_{i,j}^t|) \quad (10)$$

$$c_{W_{i,j}}^t = g(|\nabla_W I_{i,j}^t|) \quad (11)$$

where the function $g(\cdot)$ is usually defined in one of the two forms:

$$g(\nabla I) = e^{-(\frac{||\nabla I||}{K})^2} \quad (12)$$

$$g(\nabla I) = \frac{1}{1+(\frac{||\nabla I||}{K})^2} \quad (13)$$

where K is an empirically selected parameter that controls the conductivity of the diffusion [9].

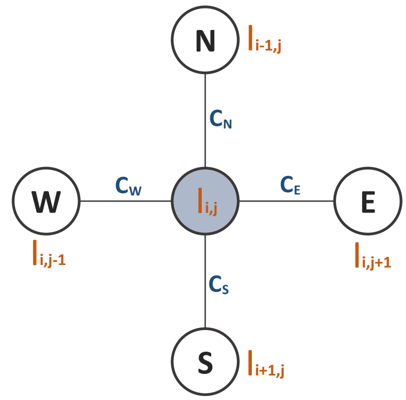


Fig. 2. Discrete structure used by Perona and Malik [9]. Actually it is based on the grayscale values of the pixels in the image - a central pixel being analyzed ($I_{i,j}$) and its four neighbors: $I_{i-1,j}$ (north); $I_{i+1,j}$ (south); $I_{i,j-1}$ (west); and $I_{i,j+1}$ (east).

III. Proposed Approach

As previously mentioned, in this work, a novel image segmentation approach is proposed, which is robust to noise and uses contextual information inherited from concepts of the graph theory and anisotropic filtering. Fig. 3 illustrates how the proposed method is organized.

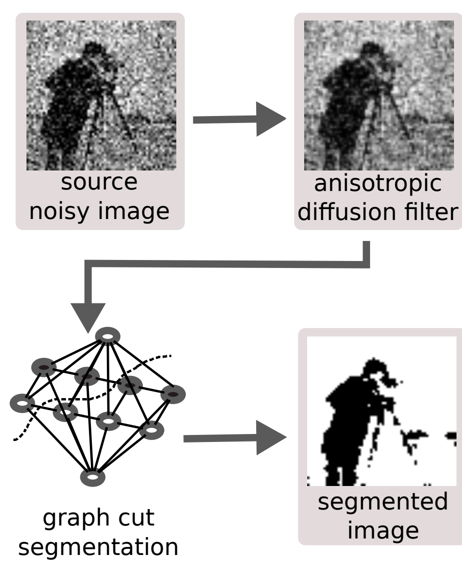


Fig. 3. Main phases of the proposed method. The images are real ones, i.e., the traditional cameraman image with Gaussian noise and its diffused and segmented images obtained through the proposed method. The noisy image is filtered using an anisotropic diffusion filter and segmented by minimum cut in its graph. As one can see, the resulting image is segmented with a good precision despite the high-intensity noise applied.

In the first step of the proposed approach, given the noisy original image, the diffusion filter is applied to it, generating a diffused image, in a single iteration, i.e., in Eq. 3, t varies from 0 (original image) to 1 (final diffused image). In order to calculate the new grayscale values of the image pixels (generating the diffused image), Eq. 12 is applied to find the

$g(\cdot)$ values. In this equation, the K parameter indicates, as said, the conductivity (magnitude) of the diffusion, especially in interior regions: the higher K, the higher the magnitude of the diffusion transformation. In this work K was set to 80, a relatively high value, found empirically but also by observing the properties of all the images of the assessed database (including the noisy ones): fore and background relatively well-delimited and internal regions with homogeneous pixels (the grayscale distribution of the fore and background pixels are relatively different, even with the Gaussian noise applied to the images - relatively low variance values). Some studies analyze the definition of K for each level of noise [10].

After finding the diffused image, two regions (9×9 pixels) are marked on it by selecting their central pixels, one representing the object and other the background. The dimensions of the regions were empirically defined in order to improve the estimation of the average grayscale value of such regions presenting better results than when working with traditional neighborhood dimensions (e.g., 3×3 and 5×5 pixels). Then the average intensity is calculated for each region, based on the grayscale values of the selected pixels in each of them. In a third step, a directed graph is created from the diffused image as explained in subsection II-A.

It is important to note that the capacities of the edges (*n-links*) of the graph, generated based on the diffused image, are based on the grayscale values of the pixels in this transformed image. As shown in Fig. 2, each graph node (pixel) is linked with its four immediate neighbors: north, south, east and west ones. The capacities of the edges, i.e., c_N, c_S, c_E and c_W are calculated based on Eqs. 8 to 11.

This way and as briefly mentioned, in the proposed approach it is emphasized twice the contextual information in the pixel classification task (in foreground or background classes): besides of considering the neighborhood information to segment each image pixel inherited from the minimum graph cut algorithm, since in this technique each pixel is connected with its four adjacent neighbors and, the more similar their grayscale values, the thicker the edges that link them (making more difficult to separate near and similar pixels in the two image classes - foreground and background - preserving the homogeneous regions in the image, i.e., similar and near pixels tend to remain together), the use of the Eqs. 8 to Eq 11 as the capacities of the graph, improve the results since their also encode relevant contextual information, i.e., grayscale values near the pixel being analyzed, also considering the diffusion coefficient of the filtering technique.

The capacities of the *t-links*, i.e., the edges that connect the terminal vertices (*s* and *t*) to all inner vertices are calculated using the likelihood function expressed by Eqs. 14 and 15:

$$w_s = \frac{1}{\sqrt{2\pi\sigma_s^2}} \exp\left\{\frac{-1}{2\sigma_s^2}\left(I_p - \mu_s\right)^2\right\} \tag{14}$$

$$w_t = \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left\{\frac{-1}{2\sigma_t^2}\left(I_p - \mu_t\right)^2\right\} \tag{15}$$

where I_p represents the gray level value on pixel p and μ_s is the average intensity of the marked image region associated with object (terminal vertex *s*), as well as μ_t is the average intensity of the marked region associated with background (terminal vertex *t*).

Finally, after building the whole graph, the fourth step of the proposed method consists in segmenting the image based on its prepared digraph and, for this, the Ford-Fulkerson [8] algorithm is applied, as described in subsection II-A.

IV. Experimental Evaluation

For the experiments, a leaf image database [11] with 10 grayscale images of plant leaves was used. Gaussian noises with zero mean and variance ranging from 0.02 to 0.60, considering intervals of 0.02 (resulting in 30 different variance values), were applied to the 10 original images, generating a total of 300 noisy images (10 noisy images per variance value). Tab. II shows the original images of the database and some of their noisy versions. The proposed approach was implemented using the Python programming language.

Given a fixed variance value, for each one of the 10 noisy images generated from the 10 original ones, the proposed method was applied and the resulting Kappa coefficients were calculated. The same was done with the Otsu's [3] technique in order to compare their accuracies through the Kappa metric. To calculate the Kappa coefficient for each image (and for each method) the segmented image were compared with a ground-truth manually segmented image, previously prepared. Kappa was calculated following Eq. 16:

$$\hat{K} = \frac{N\sum_{i=1}^{C} M_{ii} - \sum_{i=1}^{C} x_{i+}x_{+i}}{N^2 - \sum_{i=1}^{C} x_{i+}x_{+i}} \tag{16}$$

where M is the confusion matrix obtained by comparing the ground-truth and the segmented image, x_{i+} is the sum of the elements from the i^{th} row of M, x_{+i} is the sum of the elements from the i^{th} column of M, C is the number of classes, in this work $C = 2$ (fore and background), and N is the total number of observations (pixels in each image).

This coefficient, $\hat{K} \in [0;1]$, is commonly applied in the assessment of image segmentation methods in the literature, which defines an agreement level between the ground-truth segmented image and the (semi-) automatic segmented image. The higher the Kappa, the better the performance. Besides the numerical quantitative analysis of the proposed approach using the Kappa coefficient (Eq. 16), a visual analysis of the images was also performed, considering the visual aspects of segmentation (presence of isolated pixels, etc.).

V. Results and Discussion

As mentioned in section IV, to access the performance of the proposed method while segmenting noisy images, it was used a leaf image database [11] with 10 original images. Tab. III shows visual results obtained by applying both tested methods (proposed and Otsu's one) to segment the noisy images generated. One can see the original images from the database, their manual segmentation (ground-truth) and the segmented images by the proposed approach and Otsu's method varying the levels of noise (values of variance).

It is possible to observe that the method of this work outperforms the Otsu's segmentation technique, even visually. While the Otsu's method presented lots of misclassified isolated pixels in fore and background for both low and high values of variance of the Gaussian noise, the proposed technique, by exploiting contextual information, eliminate these isolated pixels, detecting with better accuracy the background (white region), which does not present spurious pixels (it looks "clean" in all segmented noisy images). The foreground (black region) is also well segmented by the proposed approach: the object is only degraded for high levels of variance (e.g., $\sigma^2 = 0.18$) but it is important to note, however, that usually the Gaussian noise of the real images presents low variance.

Sometimes really thin parts of the object in the images may not be preserved by the proposed approach (e.g., the petioles of the leaves) when their grayscale values are different from the values of the other pixels of the object. However, it possibly can be avoided by applying morphological operations.

Besides the visual comparison, as said, a traditional metric was used for quantitative analysis of the image segmentation techniques: the Kappa coefficient, which is calculated for a given segmented image as shown in section IV. Given the 10 original images, different levels of Gaussian noise were applied to them. For each level, the Kappa coefficients for all the 10 noisy images generated were calculated (considering the segmented ground-truth image) and their mean value was found. So, for each method (proposed and Otsu's one) and for each level of noise, the mean Kappa for the respective 10 noisy images, generated from the original ones, was obtained. By varying the variance parameter from 0.02 to 0.6 (intervals of 0.02), the curves of Fig. 4 were built.

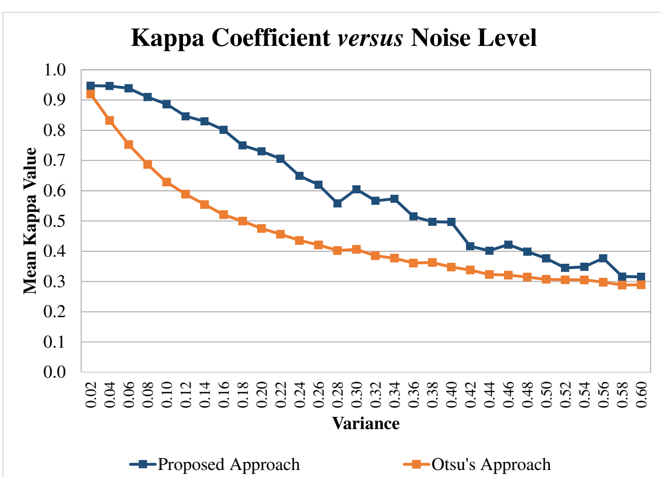


Fig. 4. Accuracy in terms of the Kappa coefficient for the proposed and Otsu's methods varying the level of noise (variance value of the Gaussian noise applied) in the images of the database. The higher the curve the better the approach. As one can see, the proposed technique presented the best results for all variance values, especially for low noise level.

As can be seen in Fig. 4, the proposed approach outperforms the Otsu's method especially for low but also for high levels of noise. In general, real images present relative low levels of noise - variances at low values (at the initial part of the tested interval). At higher values (like $\sigma^2 = 0.6$), it is difficult, even to a human specialist, to segment the object of interest.

VI. Conclusion and Future Works

In this paper, a new graph-based approach for noisy image segmentation based on contextual information is proposed. The proposed method gives an especial emphasis to the neighborhood information to correctly classify a given image pixel under analysis (in fore or background), preserving, with more accuracy, homogeneous and contiguous regions in the images, avoiding the presence of spurious isolated pixels.

The results show that the proposed method outperforms the Otsu's technique, a traditional and well-referenced image segmentation approach, even visually. The Kappa coefficients calculated after segmenting the noisy images generated from 10 grayscale images of a leaf image database for the proposed method are much superior than the ones obtained by the Otsu's technique, especially for low values of variance of the Gaussian noise applied.

Based on all the results, it is also possible to conclude that contextual features, as the ones considered by the proposed method, are a rich source of information and can benefit a lot the image segmentation process, preserving interior regions.

As future works, the performance of the proposed method will be compared with the results of other important approaches, such as the recently proposed median-based versions of the Otsu's method. The proposed technique will be assessed on other image databases. Morphological operations will be evaluated in order to avoid elimination of thin parts of the objects and new graph models as well as normalized cuts, for image representation, will be studied.

References

[1] B. Basavaprasad and M. Ravi, "A comparative study on classification of image segmentation methods with a focus on graph based techniques," *Int. J. of Research in Eng. and Tech.*, vol. 3, no. 3, pp. 310–315, 2014.

[2] T. Maintz, *Digital and Medical Image Processing*. 2005.

[3] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Trans. on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62-66, 1979.

[4] D. Greig, B. Porteous and A. Seheult, "Exact maximum *a posteriori* estimation for binary images," *J. R. Stat. Soc.*, vol. 51, pp. 271-279, 1989.

[5] Y. Boykov and M. Jolly, "Interactive graph cuts for optimal boundary and region segmentation of objects in N-D images," *International Conference on Computer Vision*, vol. 1, pp. 105-112, 2001.

[6] Y. Boykov and V. Kolmogorov, "An experimental comparison of min-cut/max-flow algorithms for energy minimization in vision," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 9, pp. 1124-1137, 2004.

[7] A. V. Goldberg and R. E. Tarjan, "A new approach to the maximum-flow problem", *Journal of the ACM*, vol. 35, no. 4, pp. 921-940, 1988.

[8] L. Ford and D. Fulkerson, *Flows in Networks*. US: Princeton Press, 1962.

[9] P. Perona and J. Malik, "Scale-space and edge detection using anisotropic diffusion", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 12, no. 7, pp. 629 – 639, 1990.

[10] A. C. Filho, "Filtro de difusão anisotópica anômala como método de melhoramento de imagens de ressonância magnética nuclear ponderada em difusão", M.Sc. dissertation, University of São Paulo, 2013.

[11] V. E. Waghmare, *Leaf Shape Databases*. Available at: http://www.imageprocessingplace.com/downloads_V3/root_downloads/image_databases/leaf shape database/leaf_shapes_downloads.htm. 2016.

TABLE II

SUBSET OF NOISY IMAGE DATABASE USED IN THIS WORK. THE FIRST ROW PRESENTS THE 10 ORIGINAL LEAVES IMAGES. THE SECOND, THIRD AND FOURTH ROWS PRESENT THE RESULTS FROM THE ORIGINAL IMAGES AFTER APPLYING GAUSSIAN NOISE WITH ZERO MEAN AND $\sigma^2 = 0.02$, $\sigma^2 = 0.10$ AND $\sigma^2 = 0.18$, RESPECTIVELY.

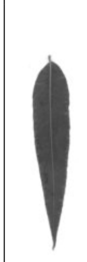
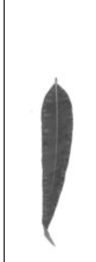
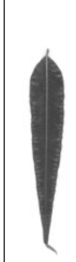
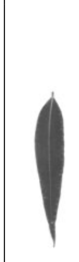
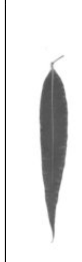
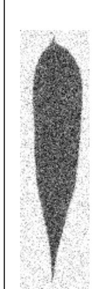
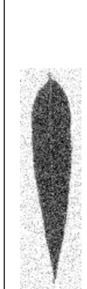
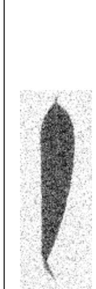
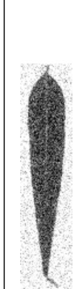
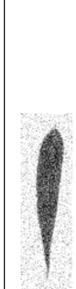
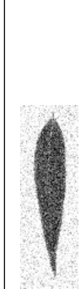
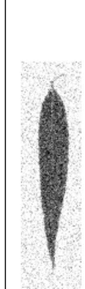
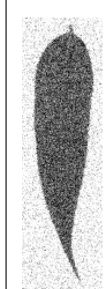
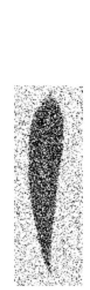
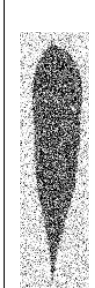
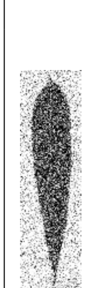
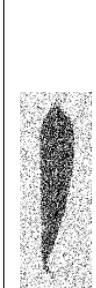
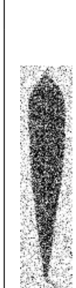
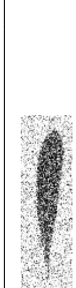
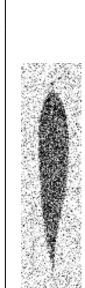
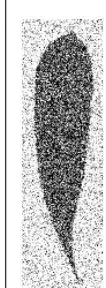
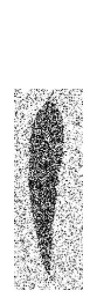
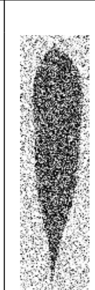
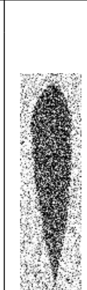
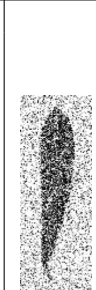
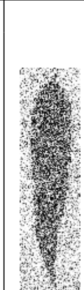
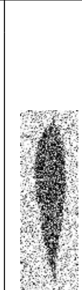
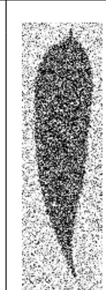
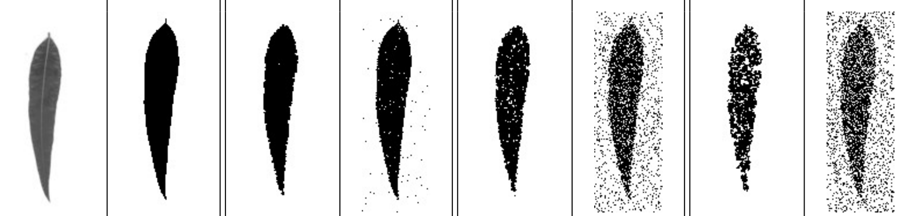
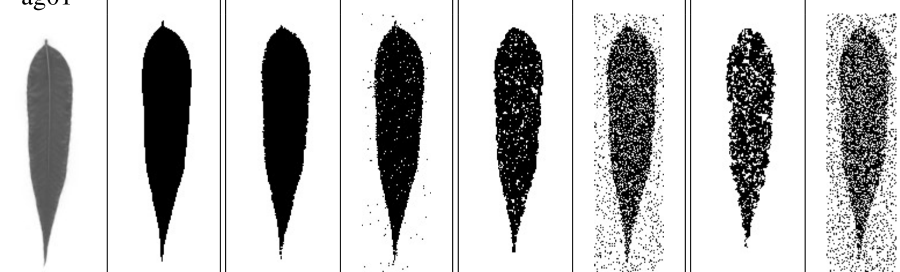
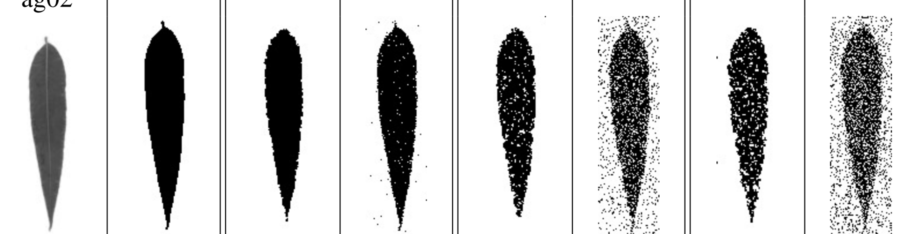
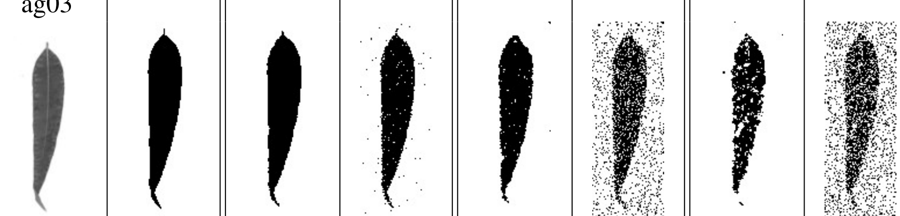
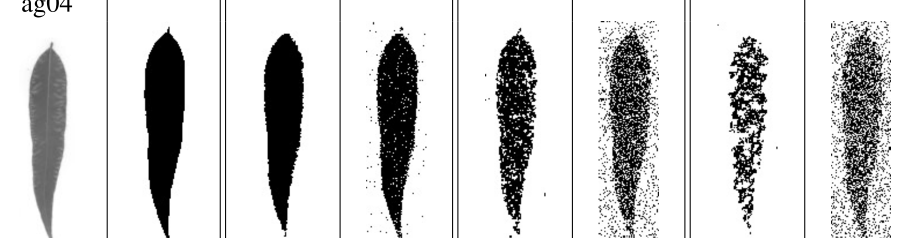
	ag01	ag02	ag03	ag04	ag05	ag06	ag07	ag08	ag09	ag10
Original										
$\sigma^2 = 0.02$										
$\sigma^2 = 0.10$										
$\sigma^2 = 0.18$										

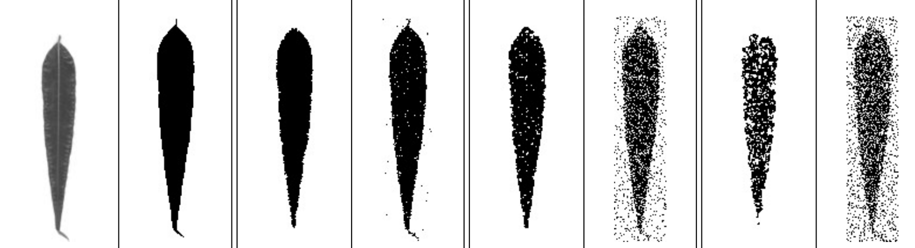
TABLE III

VISUAL EVALUATION OF THE GRAPH-BASED APPROACH FOR CONTEXTUAL IMAGE SEGMENTATION. IN THE FIRST COLUMN ARE PRESENTED THE 10 ORIGINAL LEAVES IMAGES. THE SECOND COLUMN PRESENTS THE MANUALLY SEGMENTED IMAGES (BY A HUMAN EXPERT), WHICH IS CONSIDERED THE GROUND-TRUTH. THIRD TO EIGHTH COLUMNS PRESENT THE RESULTS OF THE SEGMENTATION PROCESS BY USING THE PROPOSED GRAPH-BASED APPROACH AND OTSU'S METHOD, SIDE-BY-SIDE, ORGANIZED BY THREE NOISE LEVELS: $\sigma^2 = 0.02$, $\sigma^2 = 0.10$ AND $\sigma^2 = 0.18$.

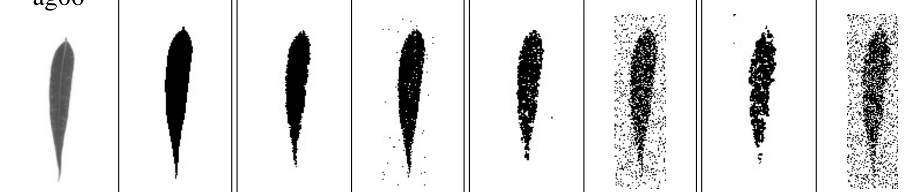
		$\sigma^2 = 0.02$		$\sigma^2 = 0.10$		$\sigma^2 = 0.18$	
Original	Manual	Graph	Otsu	Graph	Otsu	Graph	Otsu
 ag01							
 ag02							
 ag03							
 ag04							
 ag05							

Continuation

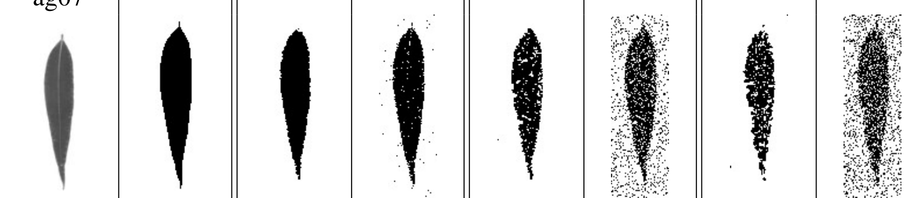
		$\sigma^2 = 0.02$		$\sigma^2 = 0.10$		$\sigma^2 = 0.18$	
Original	Manual	Method	Otsu	Method	Otsu	Method	Otsu



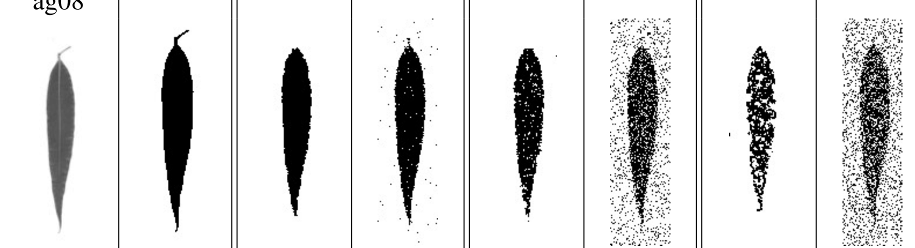
ag06



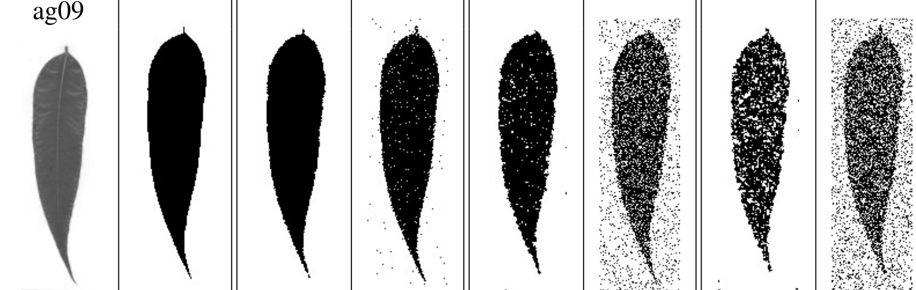
ag07



ag08



ag09



ag10