About the Impact of Pre-processing Tools on Segmentation Methods
Applied for Tree Leaves Extraction

Manuel Grand-Brochier[1], Antoine Vacavant[2], Robin Strand[3], Guillaume Cerutti[1] and Laure Tougne[1]
[1]*LIRIS UMR5205 CNRS, University Lumiere Lyon 2, 5 av. Pierres Mendes France, 69676 Bron, France*
[2]*ISIT UMR6284 CNRS, University d'Auvergne, 28 pl. Henri Dunant, 63001 Clermont-Ferrand, France*
[3]*Centre for Image Analysis, Uppsala University, SE-75105 Uppsala, Sweden*

Keywords: Tree Leaves Segmentation, Comparative Study, Distance Map, Pre-processing Tools.

Abstract: In this paper, we present a comparative study highlighting the improvements provided by pre-processing tools, such as input stroke or use of distance map for segmentation approaches. We propose in particular to highlight new methods for calculating distance map based on the prediction of changes in local color (published by G. Cerutti et al. in *ReVeS Participation - Tree Species Classification Using Random Forests and Botanical Features. CLEF 2012*). We study differents methods using thresholding, clustering, or even active contours, tested for an issue of tree leaves extraction. The observation criteria, such as Dice index, SSIM or MAD for example, allow us to analyze the performance obtained by each approach and in particular those of the GAC method, which are better for this context.

1 CONTEXT AND MOTIVATION

Segmentation tools are increasingly present in many approaches to different areas, ranging from robotics to computer vision or also for medical imaging. The methodological and technological advances (smartphones, multiprocessor, ...) allow scientists and engineers to develop projects/applications focused on different themes such as security, automation or also environment. In this paper we are interested especially in the latter theme and we can cite Leafsnap[1], Pl@ntNet[2] and Folia[3], which develop smartphone applications for analysis and identification of tree leaves. The Folia[3] application presents the advantage of being usuable on natural background. Its first step is based on segmentation tools and takes an important part in the performance of the application. Indeed, the quantity and quality of information directly extracted affect the description and consequently identification. It is therefore essential to optimize and improve existing approaches. We propose a study of the impact of pre-processing tools on segmentation methods. We focus our observations on the extraction of tree leaves and we want to highlight a new approach based on the prediction of changes in local color, proposed by Cerutti (Cerutti et al., 2012).

The literature references many segmentation methods, based on thresholds, non-linear modeling tools or iterative deformations for example. The first edge segmentation methods have appeared in the 70s and they were based on thresholding gradients or histograms (Otsu, 1979; Marr and Hildreth, 1980; Wang and Haralick, 1984; Canny, 1986). Subsequently, Kass (Kass et al., 1987) introduced in 1987 the active contour (or snakes), aimed to deform an initial contour in order to better define the edge of the object to segment. Then, variations have been proposed, based on parametric models (Zimmer et al., 2002; Chan and Vese, 2001) or coupled with tools such as B-splines (Brigger et al., 2000) for example. Other methods are based on clustering of regions, in order to isolate each object in the image. We can cite Split & Merge and MeanShift approaches (Horowitz and Pavlidis, 1974; Cheng, 1995). More recently, various improvements have been proposed (Lynch et al., 2006; Horvath, 2006; Kurtz *at al.*, 2010). In 1989, Greig and al. (Greig et al., 1989) publish a method of image analysis based on the theory of graphcuts. This algorithm was subsequently modified (Boykov and Jolly, 2001; Rother et al., 2004; Felzenszwalb and Huttenlocher, 2004) in view of producing a segmentation based on region growing. By using the analogy between image

[1]http://leafsnap.com/
[2]http://www.plantnet-project.org/papyrus.php
[3]https://itunes.apple.com/fr/app/folia/id547650203?mt=8

Grand-Brochier M., Vacavant A., Strand R., Cerutti G. and Tougne L..
About the Impact of Pre-processing Tools on Segmentation Methods - Applied for Tree Leaves Extraction.
DOI: 10.5220/0004690405070514
In *Proceedings of the 9th International Conference on Computer Vision Theory and Applications* (VISAPP-2014), pages 507-514
ISBN: 978-989-758-003-1

and topographic relief, Beucher et al. (Beucher and Lantujoul, 1979), and more recently Salman (Beucher and Meyer, 1993; Salman, 2006), have proposed approaches based on watershed.

Nowadays, many segmentation methods exist and their optimization is a current challenge. We can mention the orientation of approaches to a specific use, in our case we focus on the segmentation of tree leaves, or adding initialization tools such as an input stroke or a distance map. Concerning the segmentation of tree leaves, research is emerging from the past fifteen years. The existing methods are based either on analysis on white background (Kumar et al., 2012; Valliammal and Geethalakshmi, 2012), or on the use of pairs of images in order to apply a background-extraction process (Neto et al., 2006; Teng et al., 2011). There is therefore, to our knowledge, no method of segmentation of tree leaves, offering analysis on natural background based on a single image. In order to propose an original method, Cerutti introduced in (Cerutti et al., 2011) the guided active contour method (denoted by GAC), dedicated to the segmentation of tree leaves on natural background. Regarding the initialization tools, the use of new technologies (smartphones, touch screen, ...), allows the user to interact with the image to provide additional informations through input stroke. Another optimization is based on the use of color distance map allowing to enhance the contours and identify the various components of the image. The latter can be based on Gaussian, linear regression, geodesic distance or local mean for example. We can also cite an approach based on minimum barrier distance calculation (Karsnas et al., 2012; Strand et al., 2013). Another interactive method for image segmentation is Smart Paint, which has been developed for segmentation of medical images (Malmberg et al., 2012).

After this introduction, we detail the support and the tools used for our comparative study in Section 2. Section 3 is dedicated to the overall results, their interpretations and illustrations. We conclude this paper on the benefits of the pre-processing tools in the context of a tree-leaves segmentation.

2 BENCHMARK

Our comparative study is based on the tree leaves database presented in Grand-Brochier (Grand-Brochier et al., 2013). Illustrated in Figure 1, this database is composed of 232 images (from smartphones) of tree leaves with ground truth. They are simple or palmately lobed leaves on plain or natural background.

Figure 1: Sample images from the database.

To quantify the segmentation (quality, precision, information extracted, ...), we opt for the analysis of six observation criteria: The *Dice index* (or *F-measure*) that characterizes the overall quality of the segmentation area. Based on statistical tests of true or false positives (respectivily denoted by TP and FP) and true or false negatives (respectivily denoted by TN and FN), the *Dice index* is defined by:

$$Dice\ index = 2.0 \times \frac{\frac{TP}{TP+TN} \times \frac{TP}{TP+FN}}{\frac{TP}{TP+TN} + \frac{TP}{TP+FN}} \ ;$$

using these tests, *Manhattan* (or *Matching*) *index* allows to study the similarity rate of the entire image, and is defined by:

$$Manhattan\ index = \frac{TP+FP}{TP+FP+TN+FN} \ .$$

We also study: the *Hamming measure* that calculates the number of disparities between two images; the *Hausdorff distance* which can be defined by the maximum gap (in pixels) between two segmentations; the *mean absolute distance* (denoted by *MAD*) that analyzes contour points therefore the shape of the segmentation; and the *structural similarity* (denoted by *SSIM* (Wang et al., 2004)) for the structural information extracted.

To highlight the influence of pre-processing tools on segmentation methods, we have chosen to compare ten methods, referenced in Table 1. Our study is based on : a method by Thresholding, a Watershed, two Snakes including one using B-Splines, two versions of MeanShift, a Graphcut, a Grabcut, Felzenswalb's and GAC's algorithms. We have chosen two types of improvement: the use of three color distance maps and the manual initialization.

2.1 Color Distance Maps

The use of the color distance map allows the user to enhance the contrast and therefore the contours. This process is based on two assumptions: the object is in the center of the image and the background is in the corners. They are characterized by five seedpoints respectively one for the center and four for the corners.

The principle will be to study the colors and variations around these points. Figure 2 shows three types of distance map: the first based on coupling global distance and local color (Cerutti et al., 2011) (denoted by GD/LC), only using one seedpoint (in the center); the second based on a geodesic distance (denoted by GD), using the five seedpoints; and the last one based on an approach of minimum barrier distance (Karsnas et al., 2012; Strand et al., 2013) (denoted by MBD), using a single seedpoint.

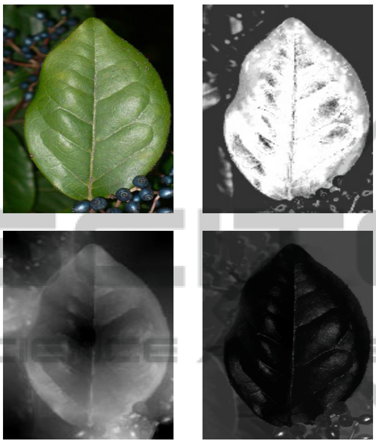


Figure 2: Sample of color distance maps: (top: left to right) initial image, coupling global distance/local color, (bottom: left to right) geodesic distance, minimum barrier distance.

The tool proposed by G. Cerutti (Cerutti et al., 2012) is based on modeling the local color, defined by a distribution of a set of Gaussian. The color distance map is therefore based on a model of global linear regression, on a local adaptative mean color and on an evidence-based combination. The dissimilarity map is defined by the distance of every pixel x in the image to the color model:

$$d_{LinReg}(x) = \|(L_x, a_x, b_x) - (L_x, \hat{a}(L_x), \hat{b}(L_x))\|_2 ,$$

in the L*a*b colorspace. The local adaptative mean color is based on the analysis of the 8 nearest neighbours (denoted by N_8) of pixel x and is defined by:

$$\forall y \in N_8(x), A = \begin{cases} \alpha B + (1-\alpha)C, \text{ if } \|B - C\|_2 < \theta \\ C, \text{ otherwise} \end{cases} ,$$

with $A = (\bar{L_y}, \bar{a_y}, \bar{b_y})$, $B = (L_x, a_x, b_x)$ and $C = (\bar{L_x}, \bar{a_x}, \bar{b_x})$. The final map is based on the combination of the elements detailed above, according to the theory of evidence defined by Shafer (Shaf76).

The two over color distance maps are defined on subsets space of the image points. The principle lies in estimating the shortest distance between a point of the object to be extracted and the background. In (Strand et al., 2013), the barrier cost function of a path is the difference of the maximum and minimum intensity along the path. The minimum barrier distance between two points is defined by the barrier cost of the cheapest path with between the points. In (Karsnas et al., 2012), the *vectorial* minimum barrier distance (MBD) was introduced. This is a method that can be used to compute distance transforms on color images. The cost of a path π is given by a path-cost function $\mathcal{C}(f, \pi)$. Let Π be the set of all paths between p and q in (Z^n, α). The path-cost distance between p and q is

$$\rho_A(p, q) = \min_{\pi \in \Pi} \mathcal{C}(f, \pi) .$$

The minimum barrier distance as defined in (Strand et al., 2013) is obtained by setting

$$\mathcal{C}(f, \pi) = \left(\max_i [f(p_i)] - \min_j [f(p_j)] \right) .$$

With the notation $\vec{f} = (f_1, f_2, f_3)$ for RGB-values, we used the following path-cost function for color images:

$$\mathcal{C}\left(\vec{f}, \pi\right) = \sum_{k=1}^{m} \max_{i,j} \left| f_k(p_i) - f_k(p_j) \right| .$$

Note that this path cost function corresponds to the L_1 diameter in RGB-space of the points in the path. See (Karsnas et al., 2012) for details.

2.2 Input Stroke

For methods permitting it, we propose to add a manual stroke done with the smartphone interaction. This input stroke, illustrated in Figure 3, allows the user to locate the leaf in the image and to extract the local color.

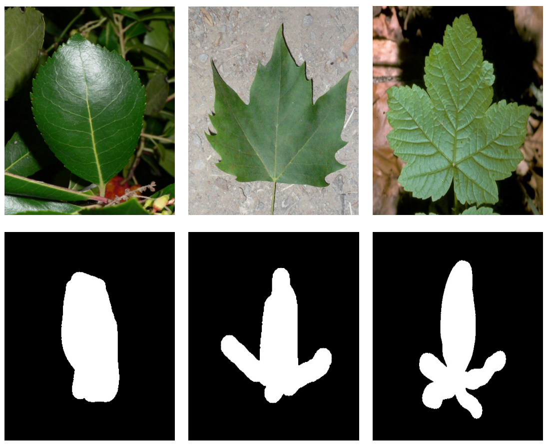


Figure 3: Sample images of tree leaves and their respective input stroke.

Table 1: Average *Dice index*, *Manhattan index*, *Hamming measure*, *Hausdorff distance*, *MAD* and *SSIM* of 232 images. Ten segmentation methods are presented, **with NO input stroke and with NO color distance map**.

	ref.	*Dice*	*Manhattan*	*Hamming*	*Hausdorff*	*MAD*	*SSIM*
Thresholding	(Otsu, 1979)	0.751	81.27%	12969.5	80.15	6.69	0.67
MeanShift	(Cheng, 1995)	0.759	81.23%	12624.8	76.57	6.31	0.70
Pyr. MeanShift	(Cheng, 1995)	0.763	81.05%	13021.5	67.38	5.77	0.73
Graphcut	(Boykov, 2001)	0.727	78.91%	14435.8	81.29	6.81	0.63
Watershed	(Beucher, 1993)	0.749	80.14%	13594.8	74.93	6.13	0.70
Snakes	(Chan, 2001)	0.735	80.43%	13060.2	80.31	5.98	0.66
B-splines Snake	(Brigger, 2000)	0.809	86.70%	8692	34.3	4.20	0.77
Grabcut	(Rother, 2004)	0.876	90.78%	6425.6	41.56	7.16	0.77
Felzenszwalb	(Felzenszwalb, 2004)	0.686	81.80%	12474.4	38.6	4.37	0.77
GAC	(Cerutti, 2011)	**0.881**	**91.78%**	**4215.3**	**15.44**	**2.39**	**0.81**

This mark also allows algorithm to have an *a priori* knowledge on the number of lobes composing the leaf (simple or palmately lobed).

3 RESULTS AND DISCUSSION

In this paper, we propose to study successively the performance of segmentation methods, without preprocessing, then with a distance map, of which we present optimizations, and finally with the addition of a manual initialization. The number of results is quite substancial, so we opt for a comparative analysis based on mean values obtained by each approach on the 232 images. For methods using thresholds or adjustable parameters, we present in this paper the best results obtained after optimization of these approaches with a collection of images.

3.1 With no Initialization and with no Color Distance Map

First, we present in Table 1, the performance obtained by each segmentation methods without preprocessing tools. We see a very clear superiority of the Guided Active Contour approach, for the problem of tree leaves segmentation. Indeed, quality of segmentation (given by the *Dice index*) is increased by 12%. The *Manhattan index*, characterizing the problems of sub- and over-segmentation, is also improved by nearly 8%. The *Hamming measure* confirms the previous observations, since the average number of dissimilarities is divided by 2.5. The *Hausdorff distance* provides precision on dispersion of the segmented regions. Indeed, guided active contour shows an average value equal to 15.44 pixels while the conventional methods get much higher values. The two last criteria (*MAD* and *SSIM*) are used to analyse the shape of the segmentation as well as the quality of information extracted according to the ground truth, through structural analysis. GAC method improves the shape of the segmentation by a factor 3, and the structural aspect is increased by 8% compared to the other approaches.

3.2 With no Initialization and with Color Distance Map

The idea is to replace the original images with more contrast images to facilitate and improve the segmentation. The results presented in Tables 2,3 and 4 are based on three types of color distance maps. The first observation concerns the performance offered by the methods for each of the color distance maps. Indeed, for a problem of segmentation of tree leaves, it appears that the use of a coupling global distance and local color provides the best results. This observation is confirmed by Figure 4, which shows the limits of the other two colors distance map algoritms in the case of natural background. The second observation relates to the improvement in term of performance given to

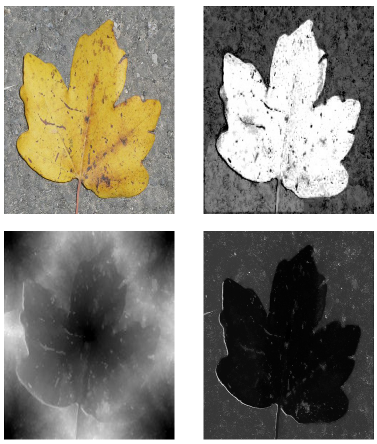


Figure 4: Color distance maps: (top: left to right) initial image, coupling global distance/local color, (bottom: left to right) geodesic distance, minimum barrier distance.

Table 2: Average *Dice index*, *Manhattan index*, *Hamming measure*, *Hausdorff distance*, *MAD* and *SSIM* of 232 images. Ten segmentation methods are presented, **with NO input stroke and with color distance map based on coupling global distance and local color**.

	ref.	*Dice*	*Manhattan*	*Hamming*	*Hausdorff*	*MAD*	*SSIM*
Thresholding	(Otsu, 1979)	0.855	89.51%	7176.8	48.72	5.87	0.78
MeanShift	(Cheng, 1995)	0.816	86.35%	9980.1	61.42	5.56	0.72
Pyr. MeanShift	(Cheng, 1995)	0.846	88.33%	8055.5	51.08	5.11	0.78
Graphcut	(Boykov, 2001)	0.79	85.46%	10220.2	63.13	6.09	0.69
Watershed	(Beucher, 1993)	0.82	84.93%	11624	62.66	5.35	0.76
Snakes	(Chan, 2001)	0.834	87.58%	9251.1	63.57	5.24	0.75
B-splines Snake	(Brigger, 2000)	0.864	90.42%	6432.7	30.9	3.78	0.80
Grabcut	(Rother, 2004)	0.789	83.52%	9397.5	50.08	6.80	0.72
Felzenszwalb	(Felzenszwalb, 2004)	0.793	86.70%	8246.2	34.57	3.81	0.79
GAC	(Cerutti, 2011)	**0.903**	**94.06%**	**3780.9**	**11.56**	**1.56**	**0.86**

Table 3: Average *Dice index*, *Manhattan index*, *Hamming measure*, *Hausdorff distance*, *MAD* and *SSIM* of 232 images. Ten segmentation methods are presented, **with NO input stroke and with color distance map based on geodesic distance**.

	ref.	*Dice*	*Manhattan*	*Hamming*	*Hausdorff*	*MAD*	*SSIM*
Thresholding	(Otsu, 1979)	0.653	78.66%	13465.2	41.90	11.32	0.72
MeanShift	(Cheng, 1995)	0.647	77.49%	13861.4	42.64	10.49	0.72
Pyr. MeanShift	(Cheng, 1995)	0.619	75.19%	14566.1	47.61	11.44	0.71
Graphcut	(Boykov, 2001)	0.621	77.72%	13921.5	40.81	12.30	0.69
Watershed	(Beucher, 1993)	0.655	77.80%	13649.3	42.97	11.94	0.72
Snakes	(Chan, 2001)	0.648	80.07%	12766.1	35.35	13.46	0.73
B-splines Snake	(Brigger, 2000)	0.673	67.23%	21863.4	71.34	7.43	0.73
Grabcut	(Rother, 2004)	0.639	61.08%	22364.0	64.32	6.87	0.61
Felzenszwalb	(Felzenszwalb, 2004)	0.664	64.86%	23621.7	72.55	6.29	0.64
GAC	(Cerutti, 2011)	**0.788**	**84.32%**	**5396.8**	**17.63**	**4.28**	**0.78**

Table 4: Average *Dice index*, *Manhattan index*, *Hamming measure*, *Hausdorff distance*, *MAD* and *SSIM* of 232 images. Ten segmentation methods are presented, **with NO input stroke and with color distance map based on minimum barrier distance**.

	ref.	*Dice*	*Manhattan*	*Hamming*	*Hausdorff*	*MAD*	*SSIM*
Thresholding	(Otsu, 1979)	0.539	55.19%	32052.2	100.36	9.52	0.70
MeanShift	(Cheng, 1995)	0.563	56.59%	30082.2	89.57	8.97	0.68
Pyr. MeanShift	(Cheng, 1995)	0.560	57.55%	28861.3	88.06	8.68	0.65
Graphcut	(Boykov, 2001)	0.54	57.90%	29782.3	96.22	10.34	0.68
Watershed	(Beucher, 1993)	0.541	51.91%	35039.5	101	8.40	0.67
Snakes	(Chan, 2001)	0.59	72.58%	15137.3	31.19	16.3	0.71
B-splines Snake	(Brigger, 2000)	0.561	56.59%	30082.1	89.57	8.97	0.73
Grabcut	(Rother, 2004)	0.592	47.21%	36216.4	88.02	10.84	0.50
Felzenszwalb	(Felzenszwalb, 2004)	0.627	53.61%	34599.1	87.44	9.07	0.57
GAC	(Cerutti, 2011)	**0.728**	**80.44%**	**8245.2**	**23.01**	**6.16**	**0.77**

segmentation approaches. By analyzing Table 2, we can highlight a significant increase in all observation criteria. From a general point of view, the results improved by nearly 10%. In the case of Guided Active Contour method, we notice 2.5% improvement for the *Dice* and *Manhattan index*. The average number of dissimilarities (*Hamming measure*) and *Hausdorff distance* are reduced respectively by 11.5% and 33.6%. The shape of segmentation (*MAD*) and textural information extracted (*SSIM*) were also increased respectively by 53.2% and 6.5%.

To achieve this performance, different tests were applied to determine the best possible color dissimilarity. We proposed a comparative analysis of the distance to the average color based on: a Gaussian, a linear regression, a local mean and a combination

Table 5: Average *Dice index*, *Manhattan index*, *Hamming measure*, *Hausdorff distance*, *MAD* and *SSIM* of 232 images. Four segmentation methods are presented, **with initial trace and with color distance map based on coupling global distance and local color**.

	ref.	*Dice*	*Manhattan*	*Hamming*	*Hausdorff*	*MAD*	*SSIM*
Snakes	(Chan, 2001)	0.872	91.43%	6094.2	40.92	5.12	0.67
B-splines Snake	(Brigger, 2000)	0.861	90.67%	6211.7	29.13	3.45	0.79
Grabcut	(Rother, 2004)	0.898	92.46%	4931.5	35.55	6.44	0.85
GAC	(Cerutti, 2011)	**0.927**	**95.45%**	**2872.7**	**10.82**	**1.06**	**0.87**

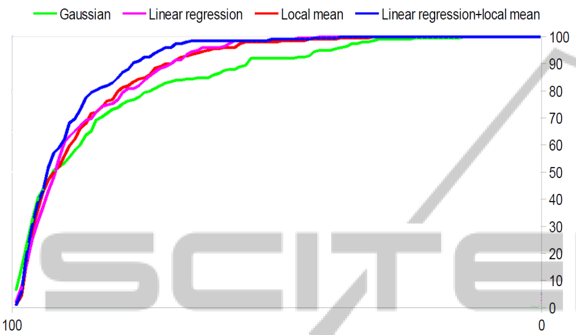


Figure 5: Recovery rate depending on the value of recovery for four color distance estimations.

of linear regression/local mean. Figure 5 shows a plot of recovery rate depending on the value of recovery. Given the results, we therefore opted for color distance maps based on combination of linear regression and local mean for all of our tests presented in this paper.

3.3 With Initialization and with Color Distance Map

The second improvement is based on the interaction between the user (via a smartphone for example) and the algorithm. For methods allowing it (Snakes, B-splines Snake, Grabcut and Guided Active Contour), we integrate an initial trace to locate and retrieve the local color of the leaf. Table 5 presents performances obtained for the four approaches coupled with an initial trace. The best of them, the GAC method, has increased its *Dice index* and *Manhattan index* by 2.5%. It has a *Dice index* greater than 92%, representing therefore a very good result in terms of precision. The quality of the segmentation has been improved through the *Hamming measure* and the *Hausdorff distance*, reduced respectively by 31.6% and 6.8%. The segmentation area is better defined, the *MAD* is increase by 47.1%, thus approaching an average offset of 1 pixel, and the *SSIM* shows that information extracted corresponds more to the ground thruth, with a rate close to 0.9.

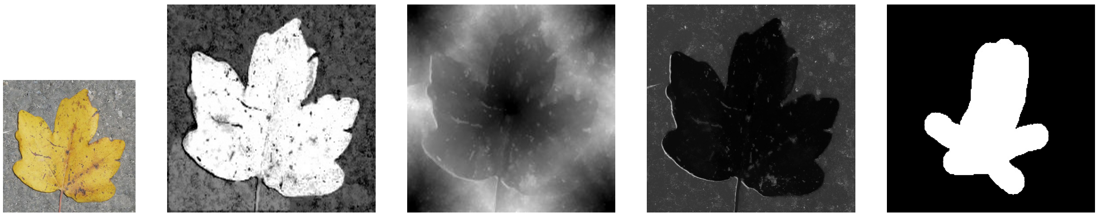
3.4 Illustration

To visualize the different improvements achieved through pre-processing tools, we propose some illustration in Figures 6 and 7. For better clarity, we restrict ourselves to one approach with problem of segmentation and one other approach with the best results. In view of all the results, it appears that the method developed by Cerutti (Cerutti et al., 2011), coupled with a distance map based on the coupling global distance/local color and an initial trace, has the best performance for almost all images of the database.

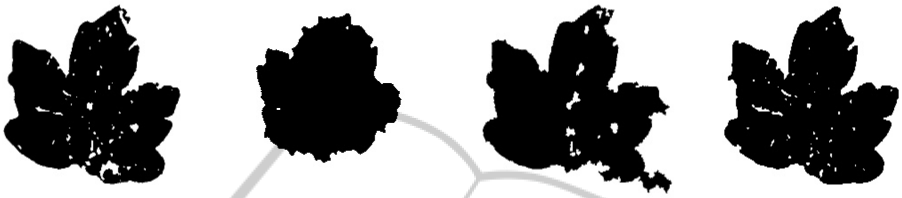
4 CONCLUSIONS

We have presented in this paper a comparative study of the influence of pre-processing tools on segmentation methods. Our analysis focuses on the challenging problems of extracting tree leaves on natural background. We propose at first the use of color distance map, in particular the coupling global distance and local color, to increase significantly the performance of all the tested approaches. Subsequently, we added an initial trace for methods permitting it, relying on technological developments and user needs. Ultimately, these tools have enabled us to improve the precision, shape and quality of the information extracted, in particular for the Guided Active Contour method. This method also provides a more stable segmentation, as we detailed in (Grand-Brochier et al., 2013), through the study of standard deviations, which are lower for all observation criteria. These improvements result in increased computation time, remaining nevertheless acceptable in relation to the proposed performance: around 3.5sec per segmentation against 0.09sec for Thresholding, 1.5sec for Snakes and 60sec for B-spline snake.

In terms of prospects, we are currently studying other tools to reduce potential problems of sub- or over-segmentation. We also wish to study the influence of the pre-processing tools on the description and classification steps. We are also considering the



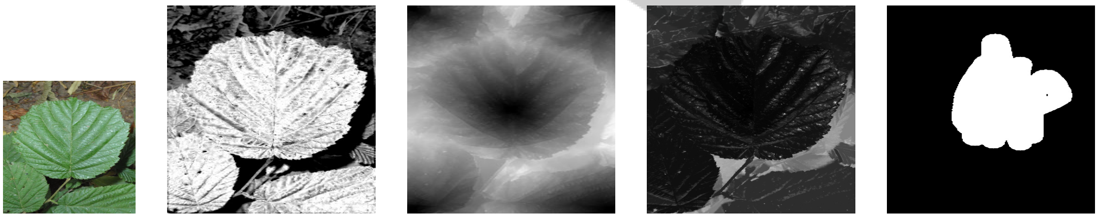
initial image | GD/LC | GD | MBD | stroke + GD/LC



B-splines Snakes approach (*Dice index* (left to right): 0.829, 0.412, 0.618 and 0.871)

Guided Active Contour approach (*Dice index* (left to right): 0.901, 0.855, 0.820 and 0.948)

Figure 6: Segmentation obtained for distance maps based on (left to right) : coupling Global Distance/Local Color, Geodesic Distance, Minimum Barrier Distance, and GD/LC with input stroke, for B-splines Snakes and GAC approaches.



initial image | GD/LC | GD | MBD | stroke + GD/LC

Grabcut approach (*Dice index* (left to right): 0.682, 0.479, 0.623 and 0.704)

Guided Active Contour approach (*Dice index* (left to right): 0.914, 0.813, 0.836 and 0.951)

Figure 7: Segmentation obtained for distance maps based on (left to right) : coupling Global Distance/Local Color, Geodesic Distance, Minimum Barrier Distance, and GD/LC with input stroke, for Grabcut and GAC approaches.

implementation of an application bringing together all this benchmark, in order to use it on any kind of domain (medical imaging, object tracking, or any other). We are currently developing a site for online voting, to test different methods of segmentation with different pre-processing tools and analyze, from a statistical viewpoint, the results through a panel of 24 observation criteria.

REFERENCES

Beucher S. and Lantujoul C. (1979). Use of watersheds in contour detection. *REMD*.

Beucher S. and Meyer F. (1993). The morphological approach to segmentation: the watershed transformation. *MMIP*, p. 433-481.

Boykov Y. and Jolly M. (2001). Interactive graph cuts for optimal boundary and region segmentation. *ICCV*, vol. 1, p. 105-112.

Brigger P. et al. (2000). B-spline snakes: a exible tool for parametric contour detection. *Trans. on Image Processing*, vol. 9(9), p. 1484-1496.

Canny J. (1986). A computational approach to edge detection. *PAMI*, vol. 8(6), p. 679-698.

Cerutti G. et al. (2011). Guiding Active Contours for Tree Leaf Segmentation and Identification. *CLEF*.

Cerutti G. et al. (2012). ReVeS Participation - Tree Species Classification Using Random Forests and Botanical Features. *CLEF*.

Chan T. and Vese L. (2001). Active Contours Without Edges. *Trans. on Image Processing*, vol. 10(2), p. 266-277.

Cheng Y. (1995). Mean Shift, Mode Seeking, and Clustering. *PAMI*, vol. 17(8), p. 790-799.

Felzenszwalb P. and Huttenlocher D. (2004). Efficient Graph-Based Image Segmentation. *IJCV*, vol. 59(2), p. 167-181.

Goëau H. et al.. (2011). The clef 2011 plant images classification task.

Grand-Brochier M. et al. (2013). Comparative Study of Segmentation Methods for Tree Leaves Extraction. *VIGTA*, vol. 7.

Greig D.et al. (1989). Exact maximum a posteriori estimation for binary images. *JRSS*, vol. 51, p. 21-279.

Horowitz S. and Pavlidis T. (1974). Picture segmentation by a directed split and merge procedure. *ICPR*, p. 424-433.

Horvath J. (2006). Image segmentation using fuzzy c-means. *SAMI*.

Karsnas A. et al. (2012). The vectorial Minimum Barrier Distance. *ICPR*, p. 792-795.

Kass M. et al. (1987). Snakes : Active contour model. *IJCV*, p. 321-331.

Kumar N. et al. (2012). Leafsnap: a computer vision system for automatic plant species identification. *ECCV*, 2012, p. 502-516.

Kurtz C. et al. (2010). Multiresolution region-based clustering for urban analysis. *IJRS*, vol. 31(22), p. 5941-5973.

Lynch M. et al. (2006). Automatic segmentation of the left ventricle cavity and myocardium in MRI data. *CBM*, vol. 36(4), p. 389-407.

Malmberg F. et al. (2012). Smart Paint - A New Interactive Segmentation Method Applied to MR Prostate Segmentation. *MICCAI*.

Marr D. and Hildreth E. (1980). Theory of Edge Detection. *Biological Sciences*, vol. 207(1167), p. 187-217.

Neto J. et al. (2006). Individual leaf extractions from young canopy images using Gustafson-Kessel clustering and a genetic algorithm. *CEA*, vol. 51(1), p. 66-85.

Otsu N. (1979). A threshold selection method from gray-level histograms. *TSMC*, vol. 9(1), p. 62-66.

Rother C. et al. (2004). "Grabcut": interactive foreground extraction using iterated graph cuts. *SIGGRAPH*, p. 39-314.

Salman N. (2006). Image segmentation based on watershed and edge detection techniques. *IAJIT*, vol. 3(2), p. 104-110.

Shafer G. (1976). A Mathematical Theory of Evidence. *Princeton University Press*.

Strand R. et al. (2013). The minimum barrier distance. *CVIU*, vol. 117(4), p. 429-437.

Teng C. et al. (2011). Leaf segmentation, classification, and three-dimensional recovery from a few images with close viewpoints. *Opt. Eng.*, vol. 50(3).

Valliammal N. and Geethalakshmi S. (2012). Plant Leaf Segmentation Using Non Linear K means Clustering. *IJCSI*, vol. 9(1), p. 212-218.

Wang S. and Haralick R. (1984). Automatic multithreshold selection. *CVGIP*, vol. 25, p. 46-67.

Wang Z. et al. (2004). Image quality assessment: From error visibility to structural similarity. *TIP*, vol. 13(4), p. 600-612.

Zimm C. et al. (2002). Segmentation and tracking of migrating cells in videomicroscopy with parametric active contours: a toll for cell-base drug testing. *Medical Imaging*, vol. 21(10), p. 1212-1221.