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A Model for Selecting Relevant Elements in Plant Characterization

The Use of Mathematical Morphology in Extraction of Plant Elements in Natural Images

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Abstract- In automatic image analysis, when using natural images, it is important to select the elements in a scene that can lead to correct characterization. Extraneous elements can result in poor values in the parameter evaluation for recognition. Irrelevant elements also increase the processing time, because they can be used incorrectly by the algorithms for characterization or identification. The goal of this paper is to offer identification algorithms and characterizations that will allow effective recognition. We base our procedure on the photographer focus areas to identify those relevant elements in a scene. In this work, we propose a procedure to select the relevant shape from natural images. The treatment uses focal depth with edge detectors. The resulting points are combined with a region partition to obtain relevant shapes.

Keywords- *Mathematical Morphology; Edge Detects; Focal Depth; Image Processing; Computer Vision*

I. INTRODUCTION

Analysis and characterization of natural digital images is a growing topic. The images generally used in automatic identification come from cellular phones or standard digital camera. This diversity excludes use of protocol like the requirement of a uniform background or the central positioning of the captured subject. There are often multiple pieces of information contained in images that are submitted for analysis and characterization. Some are required for characterizing images, others introduce errors. In this work, we propose using the intentions of the photographer to eliminate non-relevant elements. Our hypothesis relies on relevant information, as deemed by the photographer. Automatic identification of images of plant species can be applied in many fields: in agriculture for locating vast fields of weeds or in the field of medicinal herbs used in populations with restricted access to medication.

The process of plant identification from digital images includes the use of subjects like pattern recognition and botanical description. Plant morphology is used to describe plants—this includes part layout and colors that are used for botanical taxonomy. This requires a complete morphological description of all objects included in the scene. One of the steps in treating digitalized image before data exploitation is segmentation. This operation consists of regrouping pixels in between the image of one object or regrouping an image's constitutional elements. In the case of plant digital images elements like leaves, stems, seeds, and petals are gathered in the same object, but such actions don't allow for the automatic analysis of morphology. Therefore, it becomes necessary to split groups of pre-treated objects due to components that appear to be connected from only one part of the plant. In this approach, mathematical and geodesic morphology are applied; this allows constrained operations to be performed, and it preserves the global shape of the treated objects. In the first part of this article we present the context in which the study was performed, and then we introduce the basis of mathematical morphology. Next, we propose algorithms for the separation of constitutional elements that we consider relevant for analysis. Finally, we present the results and the conclusion.

II. CONTEXT

A. Descriptive Botany

Descriptive botany is a part of botany in which the morphology of plants is used for plant characterization and classification [1]. Five parts can be distinguished on plants: the flower, leaf, stem, roots and, when present, the fruit. Each of these elements is described based on its characteristics (color, shape, size of the leaf, the number and position of elements) that allow for plants to be classified into families.

Precise classification of herbs is used in pharmacology, in plant selections and improving cultivation, agriculture, horticulture and forestry.

B. Acquisition System

We used digital photos of plants obtained from large public databases like Flickr and Google. We particularly focused on

those from “TRAditionnal Medicine for the IsLands (TRAMIL)” [2] whose objective is to create a referential interdisciplinary program for the detection, validation and distribution of medicinal herb applications in order to impact public health. Photos were shot by both amateurs and professionals. Therefore, these digital images of plants don't follow a specific acquisition protocol (position of the light source, degree of brightness, distance to the targeted object, etc.). No a priori information on the utilized data was available to the researchers. Our procedure is based on logical criteria like position, space density or non-occlusion of partial objects on image borders.

C. Acquisition Method

The photos were taken by individuals with a range of photographic expertise, which caused a great diversity in digital supports. They haven't been submitted according to any particular method of realization. We started from the hypothesis that a photographer takes photos in a way that the object that caught his attention resides in the focal depth of his objective. Moreover, he arranges the photo to capture details that, according to him, deserve attention. This action can be characterized as the object's space occupation of the scene.

III. RELATIVE WORKS IN PLANTS SEGMENTATION

Informatics in the service of botany is widely used in agriculture, and examples of its application are numerous: it can be used as a guiding system [3-5], to explore plant structures [6], for vegetal cover estimation [7], and weed identification [8]. However, before being able to perform treatments, one important step on the way to automatic exploitation is picture segmentation.

Most of the authors agreed that color is one of the primary characteristics in operationalizing segmenting plant images. The choice of colorimetric space strongly dependent on referred applications, and methods like transformation of colorimetric intervals allow the reappearance of image points showing vegetation [9]. We also distinguish the color image segmentation, a method based on histograms of the pixels proposed by J. Delons [10]. The other method, called the global method, can be found in the example of the 'Mean Shift' [11]; it needs few parameterizations and uses the integrity of pixels of an image before segmenting it. The goal of these procedures is the creation of an image partition segmented by the area of the image, which enables the characterization of plants or vegetal cover [12-14]. Usually, this serves to correct errors produced during segmentation [15], but it also splits the parts of a plant [16], in order to carry out morphological studies on each part of the plant. Most methods depend on objects of identical drafts (in function of the plant or acquisition method) and are very often controlled by empiric parameters or operator intervention.

In this context, the watershed transformation method (WTM), for instance, enables the division of the elements of the scene. This procedure can sometimes change the global structure of elements and lead to the introduction of false positives.

We propose a procedure based on criteria including the exploitation of pixels from an edge map to show only sharp objects and the exploitation of a number of connected components and the number of their pixels, during mathematical morphology operations.

The algorithm that we propose is capable of performing the same operations as WTM, but is more reliable on global morphology of extrapolated objects. Our proposed system is designed to remove elements of doubt around the global structure of a scene element from the analysis. We worked on two maps. The first one represents one segment in the areas of the scene to be processed and the second one is the edge map. These two maps can be provided by any method. The goal of this study was not the segmentation, but treatment of results of the segmentation. We chose to illustrate our procedure with the Mean Shift global method, due to the fact that it uses only one parameter. We detected outlines by the Di-Zenzo [17] edge detector, which is particularly efficient for the detection of edge pixels in digital color photos. The result of segmentation provides pixels, which often represent raw data that have to be treated in order to extract potential characteristics.

IV. ALGORITHM OF PRETREATMENT

A. Segmentation Method

As part of the analysis of natural images to improve the results of identification algorithms, it is necessary to submit the relevant forms of an image. The focal depth of the lens is used to recover the areas of interest. To achieve this, mathematical morphology is evaluated on two types of cards: a region map and contour map.

Color observation is the most appropriate method in the process of plant identification by botanists. This criterion very often proper for designate generally a plant or each part of a flower is therefore criterion we use for the segmentation. However, a color photo is a particular environment point cluster that captures elements like changes in brightness, shadow zones, and overlaps due to other elements present in the scene. These result from the state of the environment and originate from the diversity of colors contained in each element of a digital photo. All captured points belong to the finite set of color classes but are extraordinarily diverse. There are several million possible colors on a digital photo and this multitude of colors makes segmentation complex. To reduce this number, neighboring pixels from the same colorimetric interval in the class are regrouped by applying the Mean Shift method. To create those classes, each pixel is shifted to the closest color class, and

classes are the ones with the highest density level [18, 19]. One of the advantages of Mean Shift is the small number parameters required. Only $\delta r = 6.5$ describes the distance between two colors differentiable to the human eye in the CIELAB interval. In some cases, in the segmentation result, one part of the plant can keep slight colorimetric variations. Classification of pixels can be reinforced by applying fusion methods for instance, those based on Gestalt [20, 21]. The result of this procedure is a cluster of classes that we treat sequentially following their binarization.

For the edge detector, we use Di-Zenzo which is widely explored in the literature for digital color images.

B. Problematic

The first problem is to recover partitions in each color of the image, in the areas focused on by the photographer. The second problem is in a colorimetric partition: there can be several elements that are grouped together (for example, light superposition and contact due to leaves and stem organs). This results in the questions of how to select areas of interest, and, how to recover in these areas of interest forms that allow a morphological characterization as well as descriptive botany.

V. MATHEMATICAL MORPHOLOGY

The segmentation of an image can be found in one connected component of pixels encompassing several parts of a plant, like the leaves and stems. In nature, elements of inflorescence can be superimposed and described by only one connected component. All these objects are separated by mathematical morphology [22] in cases where the objects are slightly superimposed, i.e. where superimposition doesn't denature the proper shapes of each object.

A. Geodesic Distance

d_X is a geodesic conditional distance on X , if X is closed, there exists a geodesic arc for every pair of points X , there is uniqueness if X is simply connected, X convex is equivalent to $d_X = d$, and d is a Euclidean distance.

B. Geodesic Ball

$x \subset X$ and $B(x, \lambda)$ a ball of center x and radius λ , we have a geodesic ball,

$$B_X(x, \lambda) = \{y \in X / d_X(x, y) \leq \lambda\} \quad (1)$$

With: $B_X(x, \lambda) \subseteq B(x, \lambda)$

C. Geodesic Dilatation and Erosion

Y is a set of $Y \subset X$

$$D_{gX}^{\lambda B}(Y) = \{x \in X, \lambda B_x(X, \lambda) \cap Y \neq \emptyset\} \quad (2)$$

$D_{gX}^{\lambda B}(Y)$ is a geodesic dilatation of Y by λB according to X .

$$E_{gX}^{\lambda B}(Y) = \{x \in X, \lambda B_x(X, \lambda) \subset Y\} \quad (3)$$

$E_{gX}^{\lambda B}(Y)$ is a geodesic erosion of Y by λB according to X .

Conditional dilatation is $D_X^B = D^B(Y) \cap X$ where $D_X^B(Y)$ is the dilatation of Y by B according to X .

D. Reconstruction

X is a set of connected components to reconstruct at the end of morphological operations and Y is a set of markers that can intersect X . Under this assumption, we define reconstruction as an infinity dilatation of Y conditionally to X :

$$D_{gX}^{\infty B}(Y) = [D^{1B}(Y) \cap X]^{\infty} \quad (4)$$

E. Ultimate Erosion

This operation consists of successive erosions while retaining the connected components or particles that disappear between two stages of erosion. We define the EU ultimately eroded of the set X by

$$EU(X) = \bigcup_n \{E^{nB}(X) / R[E^{(n+1)B}(X); E^{nB}(X)]\} \quad (5)$$

With $E^{nB}(X)$, the eroded X by an n size structuring element, $R[Y; Z]$, the connected components of Z with a non-empty intersection with Y , all regional maxima of the $d(x, X^C)$ distance function.

VI. ALGORITHMS

A. Observations and Proposition

A plant is, in general, defined by three vegetative organs: the root, stem, and leaves. Fruits, such as inflorescences, can be found on some plants. We are particularly interested in the morphological characteristics, including leaf coloring and structures such as inflorescences, as those are the data that permit identification. To be able to obtain a precise analysis, it is important that each part of the plant is disjointed in the image interspaces. There, we can raise two necessary cases for differentiation:

- Combination of leaf plus stems, with identical colors, where the stem disappears from the first erosion because of the prolonged and delicate form compared to the leaf with a more compact shape. The image used in each figure is clear;
- The superimposition of elements like petals in an inflorescence, where evolution of numerous elements of the same size created during successive erosions, can be observed.

With the aim of acquiring the largest number of elements to analyze, from the two cases above, a number of erosions are chosen that provide most of the connected components at the end of the procedure. After applying the optimal number of erosions to each of the connected components describing the different plant parts, a reconstruction is proceeded keeping in mind the interests of the photographers, based on their position in the focal depth of their objective.

B. Algorithms to Extract Elements Focused of the Scene within an Area

Our algorithm can be divided in two parts. The first part provides rough shapes of scene elements. The second one uses rough elements to reconstruct more details in each element of the scene. To perform this operation, we used results from an edge detector, in a way that reconstruction begins first by the borders of elements then propagates towards their center.

The reconstruction of the focused elements is performed through the function of the pixels resulting from the edge detector. Three cases can be observed:

- an element in the focal depth of the objective will be completely reconstructed because of the strong density of pixels from the edge detector, around this element;
- an element partially in the focal that which will either be or not be reconstructed in function of the proportion of this element in the zone;
- an element out of the focal depth that doesn't contain pixels from the edge detector which will therefore not be reconstructed.

In the case of natural images, the second case is the most predominant, due to the lack of a protocol for photo acquisition.

1) Searching and Labeling Compact Zone

A connected component from one of the clusters, which results from segmentation, can represent several elements of plants and it is imperative to split those elements.

I_M is an image labeling together sets of areas that result from segmentation operations. One part of the plant $e_{k,n}^{I_M}$ is represented by connected components of the label n in the class color k from image I_M . C_I is a map of edges obtained from the original image by color edge detectors, for instance the Di-Zenzo edge detector. During the final operation of erosion on I_M , a function $f(i)$ is created that provides numerous connected components during its iterations i . This graph shows clusters of positions i_c where $i_c = \{i \in \mathbb{N} / f'(i) = 0\}$ (see Fig. 1) indicates the level of iteration where connected components in I_M image, submitted to the further erosion, are of the compact form and are globally homogenous in size. The number of operations of closing under constraints that permit decomposition of connected plant elements on single elements like leaves, petal or fruit, is given by i_{max} of the cluster $\{i_c\}$ which creates most of the connected components in I_E . Finally, C represents the pixels of the contour map C_I which are adjacent to a v distance maximum pixels, of a single connected component of both $e_{k,n}^{I_M}$. Black points are not labeled.

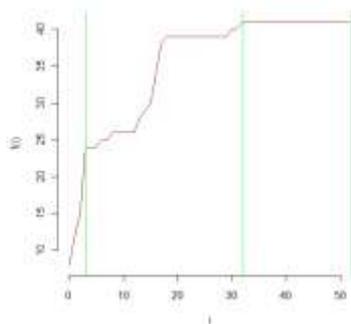


Fig. 1 Evolution of the number of connected components $f(i)$ in a segmented image during the iterations i of erosions in one class color. In green, iterations i_1 , i_2 and i_3 are described in the algorithm1. We are interested in i_2 for it is from here that there are as many connected components, it is also from here that the number of forms of the image remain constant

Algorithms aiming to decompose a plant on unitary elements are written in Fig. 2:

```

For k in color class
  For n in connected components
     $I_{tmp} = e_{k,n}^{I_M}$ 
    Search the ultimate erosion  $EU(I_{tmp})$  and construct  $f$ 
    Search  $i_{max}$  from the rank  $i_1, i_2$  and  $i_3$  are in  $\{i_c\}$  with:
     $i_1 = \text{Min}\{i_c\}$ 
     $i_2 \text{ tq } i_3 > i_2, f(i_2) = f(i_3) \text{ and } i_3 - i_2 = \max(n - p) \text{ with } n, p \in \{i_c\}$ 
     $i_{max} = \text{Max}(f(E^{(i_1+1)B}(I_{tmp})), f(E^{(i_2+1)B}(I_{tmp})))$ 
     $I_E = e_{k,n}^{I_M}$ 
    Compute  $I_E = E^{(i_{max}+1)B}(I_E)$ 
    Compute  $I_E = D_{gI_M}^{(i_{max}+1)B}(I_E)$  with:
     $p \neq q, \text{ let } B(x, 2) \cap e_{k,p}^{I_E} \neq \emptyset, \exists! e_{k,q}^{I_E} \text{ tq } B(x, 2) \cap e_{k,q}^{I_E} \neq \emptyset$ 
    Compute  $I_F = \{y \in C_i \text{ tq } B(y, v) \cap e_{k,p}^{I_E} \neq \emptyset, \exists! e_{k,q}^{I_E} \text{ tq } B(y, v) \cap e_{k,q}^{I_E} \neq \emptyset\}$ 
    Compute  $I_{mask} = I_{mask} + I_E$ 
    Compute  $I_{edge} = I_{edge} + C_i$ 
  EndFor
EndFor
    
```

Fig. 2 Labeling areas of compact design and outline extraction points nearby

2) Construction of Compact Zones

The algorithm defining compact zones reconstruction (pixels in green) is based on three maps: map I_M , the map of edges (pixels in red) I_{edge} , and the map of labels (pixels in yellow) I_{mask} . Finally, an object A indicates whether or not each edge pixel is conserved during the treatment. In the process, each edge pixel is not labeled, rather, each edge takes a label during the procedure in contact with an element in I_{mask} . Fig. 3 presents the results of the evolution of those maps during one treatment of pictures of petals.

- Map C expanded in $e_{k,n}^{I_M}$ to reconstruction, preserves only the part of a plant located in the focal depth;
- The object $A^t(x)$ gives the number of iterations k from which the not-labeled pixel x exists at the instant t in I_{edge} such as: $x \in I_M, A^t(x) > 0$;
- Map I_{mask} permits the identification of connected components with compact shapes.

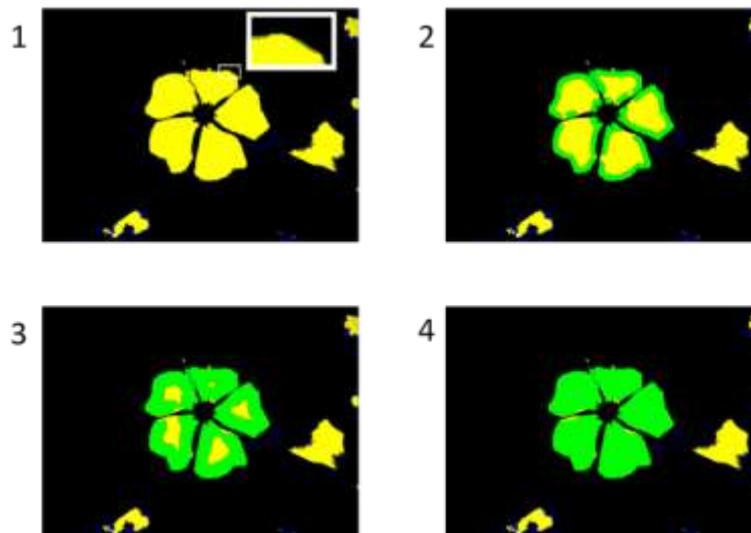


Fig. 3 Some images from the evolution of the proposed algorithm on an image of flower petals. The petals are reconstructed in green during the iterations from the edge pixels. The items that remain in yellow are not built because of the lack of contour points marked in these areas

$NBP(I)$ represents the number of pixels contained in an image I . C^t is the map of edges on iteration t . The variable v represents the number of iterations while one non-labeled pixel exists in C^t . It permits the deletion of elements in C^t , which is not labeled. The algorithm for the construction of zones with compact shapes is given Fig. 4:

```

For k in color class
  For n in connected components
    t = 0
    Ct := ek,nIM ∩ Iedge
    Do
      t := t + 1
      Ct = DgIMIM(Ct-1)
      If Ct ∩ ek,nImask ≠ ∅ then
        For x in Ct
          At(x) := v
        Endif
        For x in Ct
          At(x) := At(x) - 1
          If At(x) < 0 then
            Ct(x) := 0
          Endif
        EndFor
      While Ct-1 ≠ Ct
    EndFor
  EndFor
EndFor

```

Fig. 4 Construction algorithm of connected components of compact forms

3) Selection of Relevant Elements in a Scene

Morphological analysis can be relevant only if it is performed on connected components that describe with accuracy the elements of a scene. The labeling performed in I_{mask} indicates a coarse partition of clusters of pixels to each element of the scene. In further reconstruction, generated pixels cover partitions of I_{mask} and the algorithm preserves only connected components covering coarse forms in a superior percentage to the threshold given by users (95% during our study). Estimation of cover percentage of the connected component e_i is given in Fig. 5:

$$\frac{e_{k,n}^{I_{mask}} \cap e_{k,n}^C}{NBP(e_{k,n}^{I_{mask}})} \quad (6)$$

An application example of these parameters on results of extraction is given in Fig. 5.

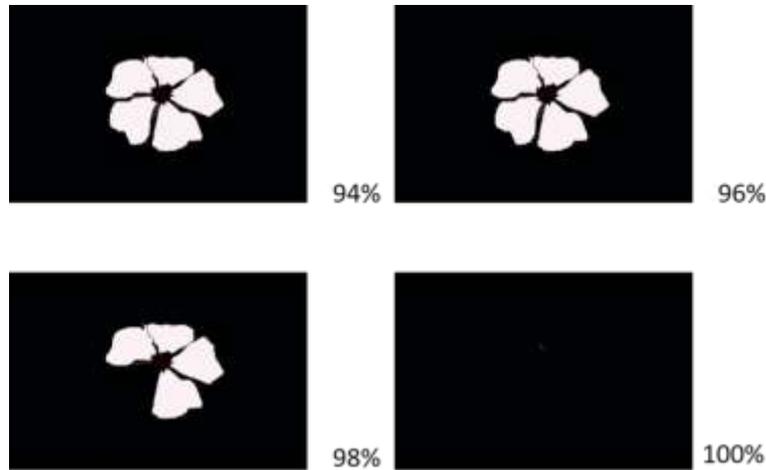


Fig. 5 Illustrations of the result provided by the NM algorithm based on the parameter “recovery rates” on a picture of a flower (black represents the irrelevant areas)

C. Applications

Reconstruction operations of plant parts are presented in Fig. 6. Iteration i_1 indicates the disappearance of extended morphological zones like stems. They have been deleted from the first iterations. For inflorescences, where elements are generally the same size, iteration I_2 is applied, where connected components stay constant during final image erosion. Using points stemming from edge detector Di-Zenzo allows the obtainment of accurate results to the outlines of reconstructed elements, but also suppresses the blurred zones without frontal pixels $x \in I_F$ where $B(x, v) \cap e_i^{I_{mask}} = \emptyset$.

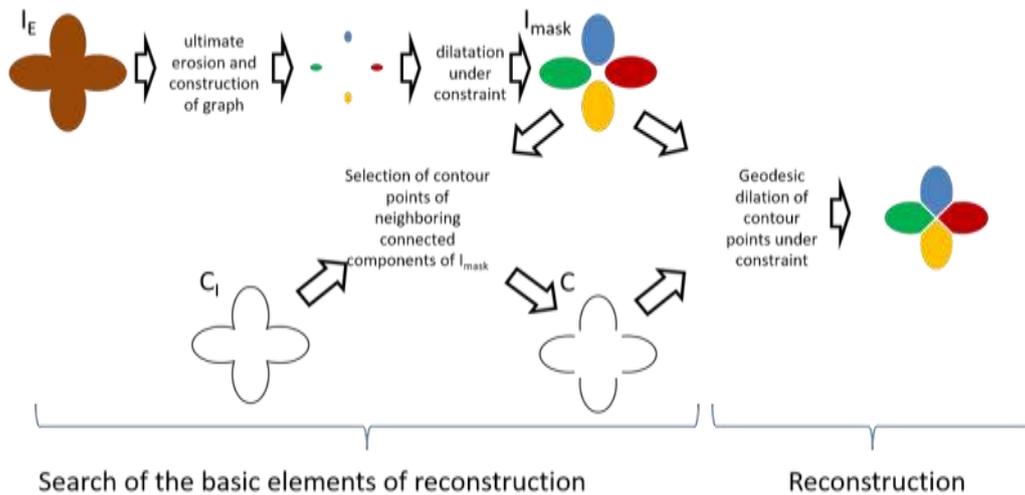


Fig. 6 An image processing plant for the separation of its elementary parts

Fig. 7 gives image processing of plants with the algorithm:

- 1) Original image I .
- 2) Edge detector results from Di-Zenzo on I (threshold 40) give C_I .
- 3) The Mean-Shift procedure on I ($\sigma_r = 6.5$) give I_S .
- 4) The merger using the Gestalt theory I_C .
- 5) I_M that contains $\{e_{k,n}^{I_M}\}$ class color binarized.
- 6) We obtain $I_E := e_{k,n}^{I_M}$ from I_M .
- 7.1) Operation $EU(I_E)$ and search for i_1 .
- 7.2) Operation $EU(I_E)$ and search for i_2 .
- 8) We obtain I_{mask} from a closure operation on I_E according to criteria i_1 and i_2 , we take the row that provides the most connected components.
- 9) We obtain C from C_I and I_{mask} .
- 10) We performed $D_{glE}^{1B}(C)$ as the number of pixels generated during the iterations increases.

On the reconstruction time of one plant part, applying the number of iterations K (allowing for total erosion of connected components in I_M) is not always sufficient to obtain a complete reconstruction of the connected components located around the focal depth. This problem exists given that the number of pixels edging in C_I are not necessarily sufficient in number. Variation in the number of pixels, marked V , created between two iterations of dilatation after passing the rank K , induces three possible cases while the process is still in evolution.

Where $V = NBP(C^{K+t-1}) - NBP(C^{K+t})$, we can observe for one connected component:

- constant evolution $V = 0$ if the dilatation is performed in the form of a 'tube' like a stem;
- increasing evolution $V > 0$ in the cases where edging points are in too small quantity (elements don't appear in the focal depth);
- decreasing evolution $V < 0$ if edging points are in great quantity (element in the focal depth).

From the rank K , the process is stopped while $V > 0$. At the same time, it should be convenient to perform a more accurate study of the model generated by E to improve the obtained results and yield stronger treatments to the small variations. The difference in numbers of the generated pixels in two consecutive iterations doesn't always have to be negative, because the same edge of the connected components is not smooth.

One solution emerges from observation of the number of pixels evolving during iterations. Let $\hat{\partial}$ be a straight line, $y = ax + b$. The variable d is the number of iterations under rank R1 (given maximum pixels generated between two iterations of reconstruction) and rank R2 (representing the maximum number required for the total erosion of a shape). The straight line $\hat{\partial}$ is issued by ACP calculated from the points of cluster G in two dimensions where $G = \{(t - d, NBP(C_F^{t-d})), \dots, (t, NBP(C_F^t))\}$, the first component represents iterations, the second component represents the number of pixels generated between two iterations, and δ is the variance of G in $\hat{\partial}$. The algorithm of reconstruction is written in Fig. 8.

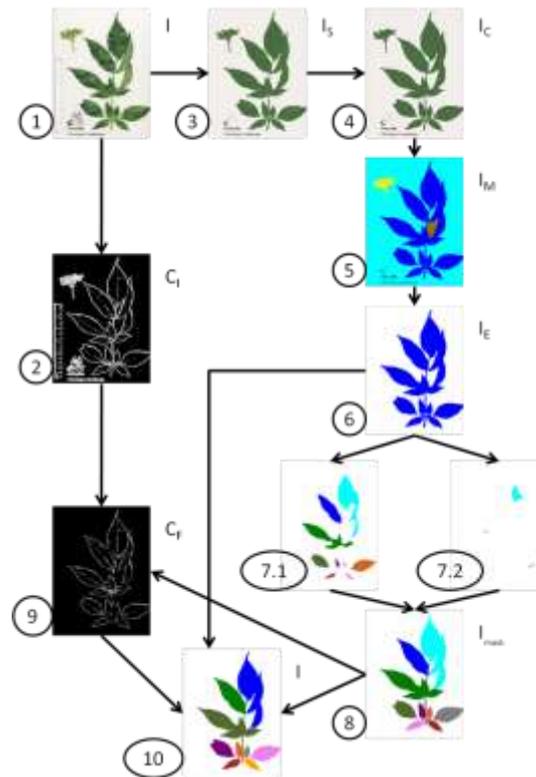


Fig. 7 An image processing plant for the separation of its elementary parts

```

For k in color class
For n in connected components
t = 0
Ct := ek,nIm ∩ Iedge
Do
t := t + 1
Ct = DedgeIm(Ct-1)
If Ct ∩ ek,pImaxk ≠ ∅ then
For x in Ct
At(x) := v
EndFor
EndIf
For x in Ct
At(x) := At(x) - 1
If At(x) < 0 then
Ct(x) := 0
EndIf
EndFor
α := -1
If t > R1 AND t < R2
Put value NBP(Ct) in G
Else
If t >= R2
Delete value NBP(Ct-d) from G
Put value NBP(Ct) in G
Calculate α form ∂ with G
EndIf
EndIf
While (α < 0)
EndFor
EndFor
    
```

Fig. 8 Robust algorithms for connected components construction of compact forms

This algorithm is less sensitive to small variations. Moreover, stopping the process is possible while a number of generated pixels on iterations of reconstruction become globally constant, in the case of stems, or, it increases in the case of propagation towards new forms. The way this functions is demonstrated in Fig. 9. The straight line ∂ is further calculated from iterations starting with new values of cluster G. The slope coefficient value of ∂ controls the algorithms' finalization on the same principle as parameter V .

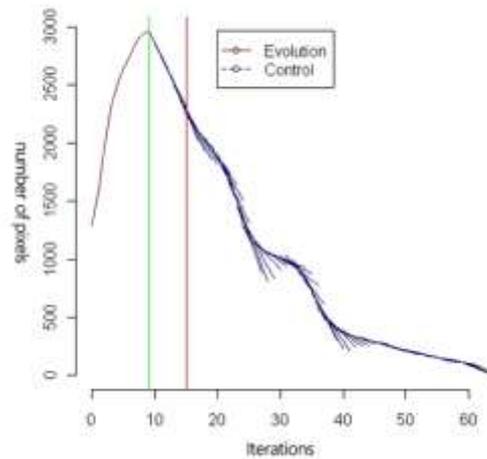


Fig. 9 The number of pixels of a connected component in an image during the dilatation geodesic iterations. Green represents the last decrease in R1 rank of pixels generated at each iteration. In blue is the support ∂ during iterations. And in red is the R2 rank from which the system searches the breakpoint

VII. RESULTS AND DISCUSSION

A. General Cases

Initially we sought to compare our method (OM) with the watershed transformation method (WTM) that is one of the frequently used methods for segmentation of areas. The latter consists of applying a binarization process to the results, then final erosion, and then, with a distance function, borderline building between the obtained residual. These lines consist of pixels that maximize the distance between the connected components of an image. Finally, these pixels are deleted from the binary image.

The experiment was carried out on 400 photos of areas. Each area contained between two and five elements that overlap. We chose disc elements to represent the elements, as it is easy to evaluate them from their perimeter and surface. We studied two parameters: the number of objects extracted per region (marked C_1 , see expression 7) and morphological quality (C_2 , see expression 8) that we evaluated by the density formula. The values of C_1 and C_2 were averaged on 400 images,

$$C_1 = \frac{\text{Minimum}(\text{number}_{\text{expected}}, \text{number}_{\text{obtained}})}{\text{Maximum}(\text{number}_{\text{expected}}, \text{number}_{\text{obtained}})} \tag{7}$$

$$C_2 = \frac{4 \prod \text{Area}(\text{Element})}{\text{Perimeter}^2(\text{Element})} \tag{8}$$

The parameter C_1 gives values in the interval [0; 1], with a value near 1 if the number of extracted elements from one area is close to the expected value. The value given by C_2 is in the interval [0; ∞], and a value close to zero indicates a good morphological presentation of the disc element. The values obtained by parameter C_1 are presented in Table 1 and by C_2 in Table 2.

TABLE 1 RESULTS WITH PARAMETER C_1 FOR METHODS WTM AND OM

Elements by regions	2		3		4		5	
	WTM	OM	WTM	OM	WTM	OM	WTM	OM
Average	1	1	1	1	1	1	1	1
Min	1	1	1	1	1	1	1	1
Max	1	1	1	1	1	1	1	1
Standard derivation	0	0	0	0	0	0	0	0

TABLE 2 RESULTS WITH PARAMETER C_2 FOR METHODS FOR WTM AND OM

Elements by regions	2		3		4		5	
	WTM	OM	WTM	OM	WTM	OM	WTM	OM
Average	0.87	0.8	1.06	0.8	1.08	0.8	1.02	0.8
Min	0.47	0.77	0.49	0.77	0.62	0.77	0.57	0.77
Max	1.24	0.82	1.47	0.82	1.62	0.84	1.55	0.83
Standard derivation	0.13	0.01	0.19	0.01	0.19	0.01	0.21	0.01

The values obtained for parameter C_1 demonstrate that methods OM and WTM are equivalent and are almost always able to extract a good number of elements contained in one area, with results near 1 for all experiments. The values obtained for the

parameter C_2 demonstrate that our method respects the morphology elements of the scene (average value around 0.8). The standard deviation (value 0) shows the stability of OM in faithful morphological restitution of elements of the scene, in 400 treated images. Higher values of parameter C_2 in WTM can be explained by the separation of elements independently from their global morphology. In sum, the results given by parameter C_2 show that OM is more robust than WTM in application where morphological the study of elements is the primary focus.

Segmentation also provides both relevant areas of the image as well as irrelevant ones (in cases of areas with blurred elements). Our algorithm, contrary to WTM, only selects elements of areas in the object's focal depth. In this way, we preserve only clear elements of the image, which are the ones targeted by the photographer. To be able to evaluate the efficiency of our algorithm, we used a new database of 400 images of areas located in focal depth of the object that were able to slightly overlap each other. Each element always represents circles of random radiuses. Belonging to those elements to the focal depth is characterized by providing on the edge maps between 60% and 95% of their contour pixels. Seven areas were randomly generated for which we kept only 50% of their contour pixels on the edge map. In this second experiment, we looked to evaluate the capacity of OM to extract relevant elements of the scene by applying parameter C_1 in relevant areas. The results of this experiment are presented in Table 3.

TABLE 3 RESULTS WITH PARAMETER C_2 FOR METHODS FOR WTM AND OM WHEN THE FOCAL DEPTH MOVE

Elements by regions		2	3	4	5
Edge pixels retained	50%	0.48	0.57	0.54	0.56
	60%	0.90	0.89	0.86	0.84
	70%	0.93	0.91	0.86	0.85
	80%	0.89	0.90	0.84	0.84
	95%	0.84	0.85	0.84	0.87

We noticed that the method provides values closely linked to the percentage of preserved contour pixels and, especially with 50% preserved points, OM algorithm is not able to precisely determine the relevance of an element (value around 0.5). The quantity and distribution of pixels on the edge maps around connected components don't permit a quality reconstruction. On the other hand, with between 60% and 95% of contour pixels detected around connected components, the system provides an acceptable percentage for parameter C_1 placed between 0.8 and 1. A higher quantity of pixels of an element on the edge map allows high quality reconstruction. To summarize a denser quantity of pixels of an element on the edge map, with more homogenous distribution of pixels around the element allows for fast and high quality reconstruction of elements in the picture.

On Table 4 emphasize the capacity of OM algorithms not considering elements outside the focal depth. For this we applied Eq. (9),

$$C_3 = \frac{\text{number}_{error}}{\text{number}_{total}} \quad (9)$$

This consists of a number of bad extractions of connected components on the total number of extracted connected components by OM algorithms. Parameter C_3 is in the interval [0; 1] and the smaller its value is, the better the algorithm efficiency is. We always varied the number of edge pixels located around the relevant elements, to show that the algorithm remains efficient if the number stays high. On each picture there are always seven areas located outside the focal depth. The number of relevant objects is therefore highly superior to those of interest on the scene. The results of this experiment are found in Table 4.

TABLE 4 RESULTS OBTAINED USING C_3

Elements by regions		2	3	4	5
Edge pixels retained	60%	0.13	0.35	0.42	0.08
	70%	0.34	0.18	0.09	0.37
	80%	0.15	0.25	0.39	0.16
	95%	0.16	0.36	0.28	0.36

Values obtained for parameter C_3 are less than 0.5 and in general are near zero. OM algorithm, which uses results from the edge detector for extracting shapes, resulting from segmentation, is specific for selecting a majority of relevant shapes in the scene.

B. Application on Plants

We illustrate the results obtained with our algorithm with a plant database [23]. The task is based on the Pl@ntLeaves dataset which focuses on 71 tree species from the French Mediterranean area. It contains around 5436 pictures subdivided into 3 different kinds of pictures: scans (3070), scan-like photos (897) and free natural photos (2469).

We used the test dataset results. There are 1882 images (741 scans, 211 scan-like photos, 480 natural photos). An illustration of the results of images is presented as follows in Fig. 10.

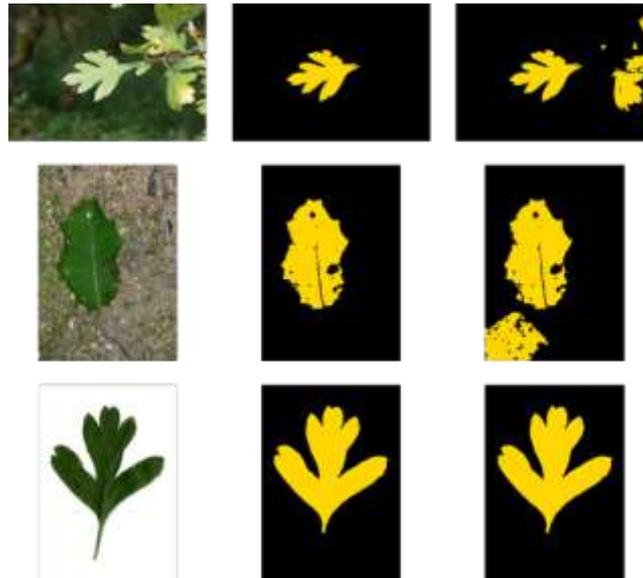


Fig. 10 Left, original image, center, the result of human selection of relevant areas and right the result of the selection of relevant areas by the algorithm (in yellow). The first line represents a free natural photo, the second line represents a scan-like photo and the third is a scan

To determine if the automatic selection of relevant forms is equivalent to human selection, we relied on the classification into 4 groups of selected pixels (see Table 5 for results):

TABLE 5 RESULTS OF COMPARISONS OF RELEVANT PIXELS OBTAINED WITH HUMAN SELECTION COMPARED AGAINST OUR ALGORITHM

Automatic selection	(Average of 140498,7248 pixels in 1882 images)			
	TP	FP	TN	FN
Average	38599.38098	591.2773645	96866.33741	4441.729012
Standard derivation	23263.23575	2258.885339	25368.84034	10399.0618
Percentage	27%	0.42%	68.94%	3.16%

True Positive (TP): the pixels are turned on both in the human result and the automatic result.

False Positive (FP): the pixels are not lit in the human results but are turned on in the automatic result.

True Negative (TN): the pixels are turned off in both the human result and the automatic result.

False Negative (FN): the pixels are turned on in the human and are not turned on in the automatic result.



Fig. 11 Left, original image, center, the result of the pre-segmentation and right, the result produced by the algorithms based on geodesic morphology

The highest rates were obtained for the True Positives and True Negatives demonstrating the ability of the algorithm to detect many relevant areas and eliminate those parts of the photos that have little interest. The True Negatives occupy 68% of the pixels, because this is the background. Finally, there are few errors that are shown by a False Positive and False Negative rates are quite low at 0.42% and 3.16% respectively.

In Fig. 11 we present some images where we moved connected components, issued from the algorithms, with the produced breaks. We have an illustration of the separation of different elements contained in the same connected component.

C. Application in Industry

Capacity of rebuilding relevant forms of our procedures can be exploited in many areas where criteria are focused on the analysis of the shape. We can take the example of the food industry. The food sector is expanding rapidly and tools for analyzing the quality of products are essential nowadays. To survey product chains, cameras pointed towards conveyor belts transporting products are used. In an example of cordon-bleu production analysis, shapes and number of products are counted (Fig. 12). To perform those operations, at the start binarization is applied, so the cordon-bleu is transformed in white on a background in black. A cordon-bleu is visible as half a circle with two set parameters, perimeter and surface. Morphological quality is analyzed by formula number 10 that gives values $V \in [0; \infty]$. This formula was obtained by connecting radius variable from formulas calculating half perimeter and circle surface.

$$V = \left| \frac{Perimeter}{(2 + \pi)} - \sqrt{\frac{2Surface}{\pi}} \right| \quad (10)$$

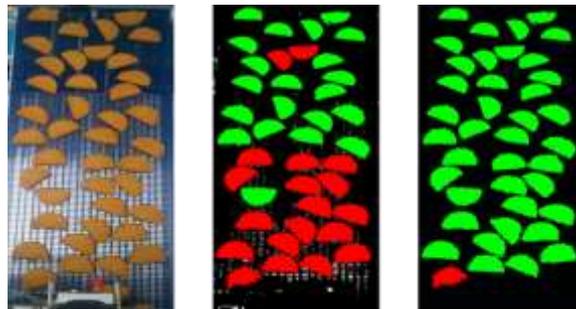


Fig. 12 Original image (left) of a treadmill cordon bleu, the result of binarization (center) after a segmentation operation, and our algorithm result (right) as a result of binarization. In green are shown the elements recognized as food by the formula and red, the other elements of the scene

Conventionally we distributed values of V in two classes, the first one in interval $[0; 30]$ designated to a cordon-bleu (presented in green on the picture of results), the second belongs to the interval $[30; \infty]$ for all other elements of the scene (presented in red). Algorithm restores the best results, as the elements are separated, in respecting their global morphology from the beginning. Extracted combinations (perimeter, surface) reflect well scene elements. The use of binarization gives connected elements that make morphological development difficult.

VIII. CONCLUSIONS

In this work we proposed a method of plant characterization based on mathematical morphology that allows for the division of connected components by segmenting them and the creation of more precise relations between connected components and elements of a plant like inflorescences, leaves, fruits. The method preserves the forms found in the focal depth of the photographer. Such a process is based on results from the most suitable edge detector for a treated image. The reconstruction consists of diffusing pixels of the edge map within connected components extracted by applying our algorithms. The proposed reconstruction algorithm uses as controls the number of points generated after each geodesic dilation operation. This method ensures the complete reconstruction of a form. We have shown that the use of the number of erosions, which is necessary for deleting a form, does not allow enough time to complete reconstruction.

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