Flower image segmentation based on color analysis and a supervised evaluation

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***Abstract*—We propose a flower segmentation schema which overcomes some limits of previous works. Indeed, it does not involve any interaction with the user, or make assumptions based on the domain knowledge. To achieve segmentation, we used OTSU thresholding on Lab color space. The thresholding was performed, separately, on the three component L, a and b, and the best result is selected relatively to the ground truth. The experimentation of the proposed method, performed using the dataset from the Oxford flower collection, make better the results, while consuming less CPU time, than the method proposed by Nilsback and Zisserman[5].**

(a) Green flower (b) Brown flower

Fig. 1. Example of brown and green flowers.

I. Introduction

With the development of computer science, image processing techniques can be used to assist botanist in the plant image analysis. Precisely, indexing the content of these images should allow the automatic classification and recognition of plant according to their visual appearance [11, 14, 15]. Some works are focused on plant leafs, for instance Chia-Ling Lee and Shu-Yuan Chen in [12] invoked the problem of leaf classification and used a region based feature to propose a new method. Those features include aspect ratio, compactness, centroid and horizontal/vertical projections. In [13], authors are interested on leaf image retrieval. To build their system, they have considered shape and venation features.

In our case, we are interested in flower image segmentation which is an important component in plant analysis process because it allows the extraction of the flower region. Consequently, the accuracy of the segmentation result will contribute to the pertinence of the output of such system regardless its goal: identification, classification or retrieval. In literature, there was some previous work on flower image segmentation. We present some of them in the next paragraph.

In [1], the authors proposed a segmentation algorithm based on color classification and the domain knowledge. In fact, they supposed that flowers are rarely green, black, gray or brown and the background usually occupies the border of the image. In [2], the segmentation has been developed using an iterative algorithm-driven by domain knowledge. A relevance feedback schema was used to correct the segmentation in the case of false assumption. For the flower region extraction, the RGB color space is quantified and then converted to a color names space.

To extract the general structure of plants, the segmentation algorithm used in [4] is a graph-based method where the nodes present the pixels of the image and the arcs correspond to the neighborhood relations between pixels. The technique of maximum flow / minimum cut is then applied to separate the plant and the background. This algorithm requires a manual selection of seeds presenting the plant and the background.

In [5], the authors proposed a flower segmentation algorithm based on the minimization of Markov Random Fields (MRF) using graph-cuts. First, a general color distribution is computed using the ground truth. Then, a specific distribution to each image is adjusted iteratively through a learning process. The authors also proposed a model for the description of the petals structure. This model is tolerant to viewpoint changes and petal deformations and it is applicable to many flowers classes.

Although, cited works give good results, they have some shortcomings. Some works are based on the domain knowledge [1,2]. In this case, generated hypothesis can be wrong and affect the result (Fig 1). Other works are based on the interactivity with the user [2,4] or exploit the ground truth to initialize the segmentation process[5].

Our contribution consists in the proposition of a flower segmentation schema to overcome the above drawbacks. Indeed, our algorithm minimizes the independence toward the use of a ground truth, doesn't involve the user to initialize the segmentation algorithm and it is not based on the domain knowledge. Then, we compared our results to Nilsback and Zisserman results[5]. Their approch is based on a learning process and it fails if a ground truth is unavailable or if the number of flower by class is low. Four classes have been discarded because they don't contain enough images

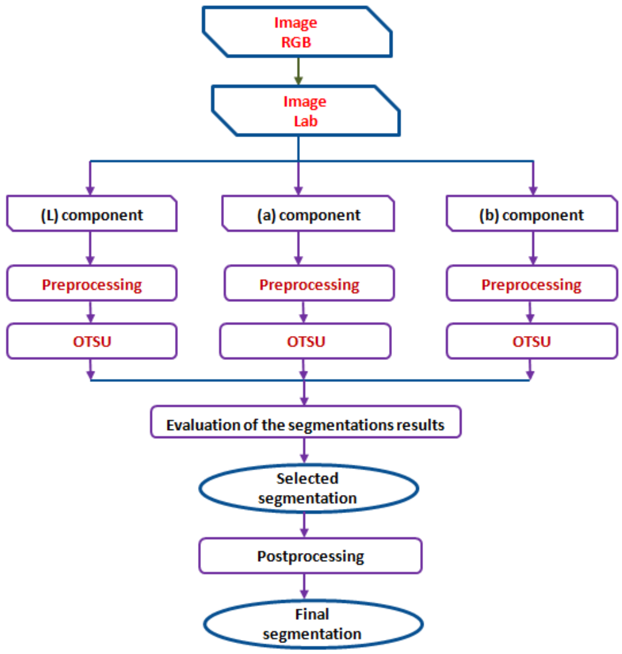


Fig. 2. Different steps of the proposed method.

(snowdrops, lily of the valleys, cowslips and bluebells). The presented process is also computationally expensive.
This paper is organized as follows: in section 2, the proposed method for image segmentation is described. Experiments and evaluation results are presented in sections 3. Finally, some conclusions and perspectives of this work are given.

II. The Proposed Segmentation Schema

Usually, flower images contain a large green area due to the presence of leafs surrounding the flowers. The remained area is occupied by the flower region which can be also characterized by its color. The region homogeneity can be expressed using color and/or texture features. In our case, color is discriminative and can be used as homogeneity criterion in order to perform foreground/background segmentation. Fig. 1 shows the different steps of the proposed method. First, we transform the image to the Lab color space. Then, we apply the OTSU thresholding algorithm on each Lab component, independently. Finally, in order to choose the best result, we used a supervised measure for segmentation results evaluation. The last step is performed because no prior information about the flower image is available. Thus, we don't know which one of the color components encloses the pertinent information that is the best representation of the flower color.

A. RGB to Lab transformation

Color is thereby represented in many different color systems. The choice of the color space can be a very important decision which can influence the segmentation result. We study several color spaces in order to select the appropriate one. To achieve segmentation, the color space to use has to be perceptually uniform so it can be used to express regions homogeneity into a given image. Perceptually uniform means that a change of the same amount in a color value should produce a change of about the same visual importance.This study revealed that the RGB color space has some drawbacks: in particular, the strong correlation between the three components R, G, B and the redundancies of many colors. The study showed also that in the HSV and HSL color spaces, when the luminance and/or saturation tend to 0, the value of the component "Hue" loses its importance. These spaces do not correct the lack of homogeneity of the RGB color space and are dependent on the system that produces color. In the other hand, Lab and Luv color spaces, proposed by the CIE (the lnternational Commission on Illumination - abbreviated as CIE from its French title Commission lnternationale de I'Eclairage) are known as a perceptually uniform color spaces. The main difference between the two color spaces is in the implemented chromatic adaptation model. The Lab colour space normalizes its values by the division with the white point while the Luv color space normalizes its values by the subtraction of the white point.
Based on the previous study on color spaces, we opted for the CIE-LAB color space. In Lab color space, the (L) component represents the luminance; (a) component presents the colors between the red and the green; (b) component presents the colors between the yellow and the bleu.

B. Localization of the color information

In order to identify the color component which encloses the most pertinent information, we treat them independently. This procedure has several advantages. It allows the distinction between the chrominance and the luminance layers which can be beneficial in two cases: first, when the image presents white flowers. In fact, the white color can be seen as an equal presence of all chrominances. In this case, the (L) component includes the most pertinent information. Consequently, the segmentation using the (L) component gives the best results. Second, the removal of luminance layer is useful to eliminate the effect of the color degradation due to textured pattern into the flower surface or to acquisition condition. In this case, we obtain more homogeneous regions and the thresholding algorithm using (a) or (b) components performs well.

C. OTSU thresholding

We used the OTSU thresholding technique [8] to perform segmentation. This algorithm tries to find an optimal separation between classes by computing a global threshold for an image. The best threshold t^* is selected if it minimizes the within-class variance, which is equivalent to the maximization of the between-class variance (1).

$$t^* = \underset{1\leq t\leq L}{\operatorname{Arg\,Max}} \{\omega_0(\mu_0-\mu_T)^2+\omega_1(\mu_0-\mu_T)^2\} \qquad (1)$$

In (1), ω_0 and ω_1 denote the probabilities of the background and foreground classes, μ_0 and μ_1 represent the mean of the two classes and μ_T is the mean of the whole image.
Previous works showed that OTSU's algorithm is an effective technique [6,7,9]. It is widely used in image processing

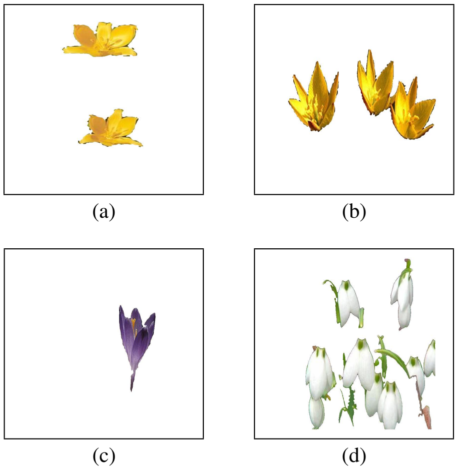


Fig. 3. Examples of segmentation results. (a,b) Two disconnected regions. (c) Region having a negligible size. (d) Many regions.

because he gives a good segmentation results and it is easy to implement.
In our work, instead of applying the OTSU thresholding algorithm on the color image defined on the Lab color space, we separated the three color components (L), (a) and (b) and we segmented, independently, each color component.

D. Evaluation of the segmentation results

After the segmentation step, we need to decide which of the three segmentation results, obtained using each of the three components, gives the best result. So, we compared those results to the ground truth and we choose the nearest one. The comparison is performed considering an evaluation measure. Several assumptions have to be made in order to choose the appropriate evaluation measure: First, the measure must be independent of the number, the size and the position of the flower region into the image. Indeed, we can have more than one flower in the same image and the size of a flower can be not significant compared to the entire image (Fig. 3). Considering those assumptions, we opted to the measure proposed by Shufelt in [3], taking into account the number of true positives (TP), false positives (FP) and false negatives (FN). This measure presents the quality percentage given by (2).

$$Quality\ percentage = \frac{100.TP}{TP + FP + FN} \tag{2}$$

E. Preprocessing and Postprocessing steps

In the preprocessing step, we applied first, a median filter using a 5x5 neighborhood to eliminate the noise and then we expanded the dynamic of the histogram to produce an image with better contrast.
After we obtained the segmentation result and in order to clean it, we added a postprocessing step. So we removed all small regions into the background (having a size inferior to a fixed threshold) and then we filled all the holes into the foreground.

TABLE I
COMPUTATIONAL COMPLEXITY.

	Complexity	CPU time
Our method	$O(s)$	$\leq$ 20 s
Nilsback method	$nbr \times O(l \times s^2 \times \|c\|)$	$\geq$ 5 min

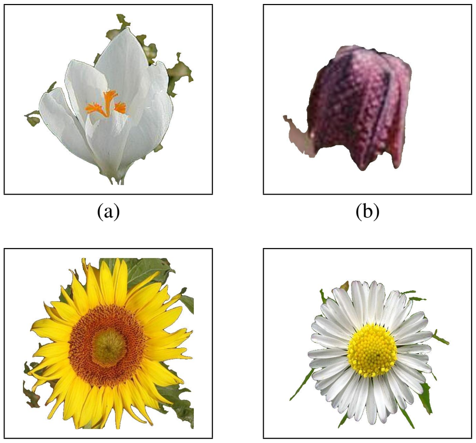
III. Experimental results

The evaluation was performed using a flower dataset provided by Oxford University and used to achieve the work of Maria-Elena Nilsback and Andrew Zisserman[5]. There were 17 classes in this dataset and 80 images in each class. The dataset is available on [10].
We compared our work to the segmentation scheme proposed by Nilsback and Zisserman [5]. Despite the proposed method in [5] gives good segmentation results in most cases, it is time-consuming which is a big shortcoming especially for a real-time applications. Indeed, due to the fact that every image is represented by a graph, the segmentation process can exceed 5 minutes on one image and the complexity of this algorithm is $nbr \times O(l \times s^2 \times |c|)$ where nbr is the number of iteration required until convergence of the algorithm, s is the number of nodes within the graph which is equal to the image size, l is the number of edges on the graph and $|c|$ represents the cost of the minimum cut. The experiments show that our proposed algorithm is much faster than [5]. In fact, the complexity of the algorithm is $O(s)$ with $s = m \times n$ where n and m denotes, respectively, the width and de height of the image. In practice, the segmentation doesn't take more than 20 s, in the worst cases. Those results are illustrated in Table1.
For the quantitative performance evaluation, we used an overlap score (OS), between the ground truth segmentation and the segmentation obtained by our algorithm. OS is computed as indicated in the equation (3).

$$OS = \frac{true\ foreground \cap segmented\ foreground}{true\ foreground \cup segmented\ foreground} \tag{3}$$

If we consider the mean overlap score, we can conclude that our method has comparable result to Nilsback method. Indeed, our method gives an average OS equal to 84% whereas the average OS for Nilsbacks method is about 93%. As it can be noticed, the gain on time was joined with a drop of the overall accuracy (Fig. 4) which is due to the fact that some background pixels are similar to foreground pixels so they had been considered as part of the flower region. However, those results are good and can be used in flower recognition process. As Fig. 5 indicates, the mean overlap score (OS) for each class can reach 90% and is never below 70%. Furthermore, 81% of image has an overlap score over 80%.

Our work overcomes another limit of Nilsback algorithm. In fact, the last one needs classes with a heigh number of images and not including flower fields. Therefore, 4 classes has been discarded which are snowdrops, lily of the valleys, cowslips and bluebells. In the other hand, our algorithm can



(a) (b)

(c) (d)

Fig. 4. Examples of inaccurate segmentation results given by our method.

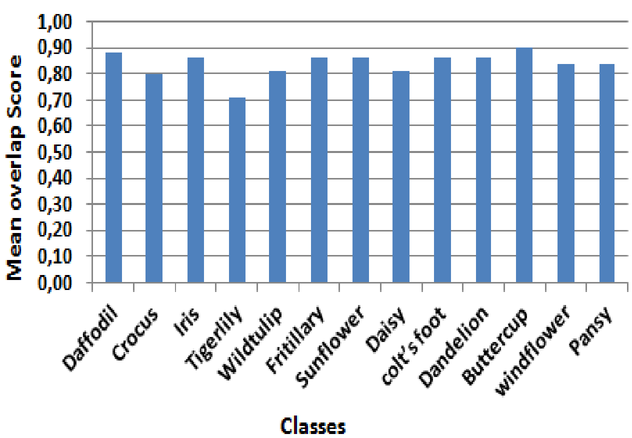
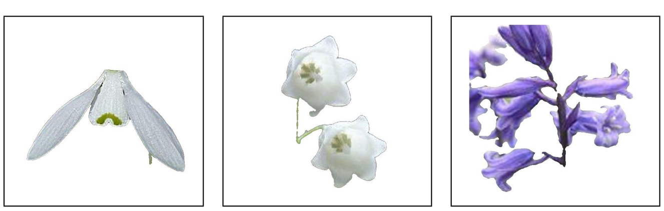


Fig. 5. Mean Overlap score per class.

br applayed in all cases. Fig. 6 shows a segmentation result of some of those flowers.

In Fig. 7, we illustrate some segmentation results of some flower images. We can see that our algorithm (middle column) can perform better than Nilsback's (last column).

We used the ground truth only in the evaluation phase to compute the supervised metric. Our ongoing works are about founding an unsupervised metric that replace the supervised one in order to ensure a full independency to the use of the ground truth. This will cope with another limit of Nilsback's work.



(a) snowdrops (b) lily of the valley's (c) blubells

Fig. 6. Examples of segmentation results on images discarded by Nilsback algorithm.

Fig. 7. Examples of the segmentation results: First column: Original Image. The middle column: Nilsback segmentation results. The last column: Our segmentation results.

IV. Conclusion

In this work, we proposed a fast flower image segmentation schema based on OTSU thresholding technique and Lab color space. The experimental results proved that we can obtain good results within short execution-time. In fact, even some results are not accurate, they still exploitable. This inaccuracy is due to the failure of the OTSU algorithm in some cases: for instance when the image histogram is unimodal or when the foreground and background have very different sizes. This shortcoming can be easily surmounted by using an improved OTSU algorithm. This will be the first perspective of this work. As second perspective, we will change the supervised evaluation measure used in the comparison of the segmentation results to an unsupervised one in order to guaranty a full independency to the use of the ground truth.

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