# 레벨셋 기반 꽃 분할을 위한 노이즈 제거

(Noise Removal for Level Set based Flower Segmentation)

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## 요 약

본 연구에서는 노이즈를 제거하고 자연 영상에서 자동으로 꽃을 분할하는 후처리방법을 제시한다. 레벨 셋 알고리즘을 이용한 자연영상 꽃 분할에서는 레벨 셋이 색과 에지 정보에만 의존하기 때문에 기대하지 않았던 분리된 노이즈들이 발생한다. 실험 결과는 제안 방법이 꽃 영역과 배경 영역의 많은 노이즈를 성공적으로 제거하였음을 보여준다.

■ 중심어 : | 꽃 분할 | 가우시안 혼합 모델 | 레벨 셋 알고리즘 | 스마트 폰 영상 |

## Abstract

In this paper, post-processing step is presented to remove noises and develop a fully automated scheme to segment flowers in natural scene images. The scheme to segment flowers using a level set algorithm in the natural scene images produced unexpected and isolated noises because the level set relies only on the color and edge information. The experimental results shows that the proposed method successfully removes noises in the foreground and background.

■ keywords : | flower segmentation | Gaussian mixture model | level set algorithm | smart phone images |

## Ⅰ. INTRODUCTION

High resolution phone cameras have been developed and are widely used in the smart phones to get better image quality. As increase of using those cameras, applications running in the smart phones get also varied. For instance, blooming flowers often attract our attention but we rarely know their names. Thus, the applications are able to provide the users with the name and the properties of flowers taken by smart phones in any places using automated flower recognition scheme.

Image segmentation is an initial but essential stage of image recognition scheme to distinguish objects from background. Also, the technology to extract plants from natural scene images is useful and marketable for portable devices like mobile phones or smart phones. Over the past years, thus, a considerable number of studies have been made on plants extraction in natural scene images to utilize its applications such as image-based information search, image-based plants indexing, and so on [1-4]. However, it is still challenge task to automatically segment flower area in the images because of a large percentage of color distortion in the flower images, close-up photography [2].

In flower segmentation, various image data are mainly used to get color features, shape features and size features as well as texture features (leaf glossiness). For these kinds of feature, the most important rose organs are petals, flowers and leaves [5]. In our previous study [6], we developed a new scheme to segment flowers using a level set algorithm based on color and edge information in the natural scene images taken by mobile phones. For the accurate segmentation results and effective computational efficiency, a GMM(Gaussian Mixture Model) algorithm was applied to find very close initial contour to the flower area for the level set. However, the scheme provided the segmentation results with isolated noises because the level set relied only on the color and edge information. Thus, we

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propose a fully automated scheme to segment flowers in natural scene images after taking out noises using simple post-processing steps.

The remainder of this paper is organized as follows. Section 2 describes the proposed methods including a GMM to define the initial contour of the level set algorithm which is formulated in the next subsection and post-processing steps. Section 3 provides experimental results and discussion with the unique characteristics and limitations of this study. Finally, the conclusions as well as a future work are followed.

## II. METHODS

Proposed method consists of initial segmentation, refined segmentation stage, and post-processing (Fig. 1). Initial segmentation stage includes $k$-means clustering and a GMM algorithm. In the refined segmentation, a level set is applied based on the initial contour indicated by the GMM in RGB color space. Finally, noises are taken out in the post-processing step to get the flower area.

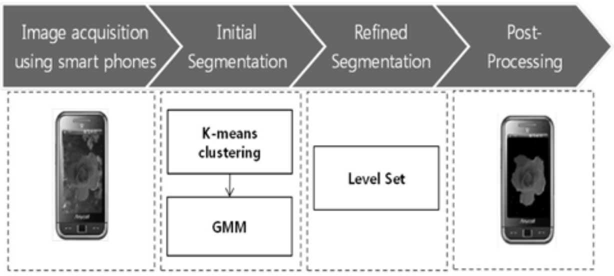


Fig. 1. Proposed system to segment flower area with three steps

### 1. Initial Segmentation

In order to initially segment flower area, we use a GMM algorithm. GMM is a parametric probability density function represented as a weighted sum of Gaussian component densities. They can be employed to model the color distributions of an interesting object and background in digital images. Especially, GMM parameters are estimated from training data using the iterative Expectation-Maximization (EM) algorithm.

A GMM is a weighted sum of M component Gaussian densities as given by the equation,

$$p(x|\lambda) = \sum_{i=1}^{M} w_i g(x|u_{i,} \sum_i) \qquad (1)$$

where $x$ is a d-dimensional continuous-valued data vector, $w_i, i=1,\cdots,M,$ are the mixture weights and, $g(x|u_{i,}\sum_i)$ $,i=1,\cdots,M,$ are the component Gaussian densities.

In our previous study [6], we apply a $k$-means clustering algorithm to create initial parameters for a GMM. Then, a GMM algorithm is followed with two Gaussians; one represents foreground (flower) while the other indicates background. Especially, flower area has lower variation in the pixel location than background area, because flower area is generally located at the middle in the image by the users during image acquisition. Therefore, to discriminate which class presents the flower area we compare location variations between flower area and background area. Then the area with smaller location variation is considered as the flower area.

### 2. Refined segmentation

Recently, level set algorithm was introduced as an image segmentation tool using an energy minimizing method. The algorithm is guided by speed functions that pull it toward features such as lines and edges. The level set provides a unified account of a number of visual problems, including detection of edges, and subjective contours. However, it is difficult for the algorithm to automatically make initial contour and segment flowers in natural scene images because of their complex shapes and multi-channel characteristic of images. Especially, it takes too long for the algorithms to find the objects in the images because of their iterative execution.

In this stage, we use a level set algorithm to refine the segmentation of flower area based on the initial segmentation results by a GMM algorithm [6]. The level set method specifies a deformable curve or surface as a zero level set of a scalar signed distance functions, $\phi: U \rightarrow R$, where we can think of $\phi(s,t)$ as the dynamic volumetric function changing in time $t$ [5, 2]. Thus, a curve C can be expressed as the following set: $C=(x,y) \in R^2 | \phi(s,t)=0$. This deformable model separates the inside and the outside of some object; it is, therefore, often referred to as the interface. Thus, the curve or interface is given by the zero level set of the time-dependent level set function $\phi$ at any time $t$.

Here, the geometric curve evolution equation is assumed to be given by $C_t = \frac{\partial C}{\partial t} = Fn$, where $F$ is any speed quantity that does not depend on a specific choice of parameterization. Then, its implicit level set evolution equation that tracks the evolving contour is given by

$$\phi_t = \frac{\partial \phi}{\partial t} = F|\nabla \phi| \tag{2}$$

This relation is easily proven by applying the chain rule, and using the fact that the normal of any level set is given by the gradient,

$$\begin{aligned} \phi_t &= < \nabla\phi, C_t > \\ &= < \nabla\phi, Fn > \\ &= F < \nabla\phi, \frac{\nabla\phi}{|\nabla\phi|} > \\ &= F\ |\nabla\phi| \end{aligned} \tag{3}$$

This formulation enables us to implement curve evolution on the x, y coordinate system. It automatically handles topological changes of the evolving curve.

Here, we are going to think about solving the level set equation. Let $\phi(s,t^n)$ represents the current values of $\phi$ at some grid point s and time $t^n$. Updating in time consists of finding new values of $\phi$ at every grid point after some time increment Δt. A rather simple first-order accurate method for the time discrimination of equation (2) is the forward Euler method given by

$$\phi_t = \frac{\phi(s,t^{n+1}) - \phi(s,t^n)}{\Delta t} = F|\nabla \phi| \tag{4}$$

So along the time axis, solutions of level set equation are obtained using finite forward differences, beginning with an initial model and stepping sequentially through a series of discrete time steps. Thus the update equation is given by the following solution:

$$\phi(s,t^{n+1}) = \phi(s,t^n) + \Delta t F|\nabla\phi|, \tag{5}$$

where $F$ is a user-defined speed term which generally depends on a set of order n derivatives of $\phi$ as well as other functions of $s$.

As the first issue to choose properly the speed function, we may consider the image regularization problem which removes the noise or spot. In general, we need techniques that can remove noise without too much blurring. The speed function in level set equation is chosen as the smoothing term using mean curvature [7, 8]. As an example, we consider the explicit curve evolution as the geodesic active contour term, given by

$$C_t = (g(c)k - < \nabla g, n >)n \tag{6}$$

The corresponding level set evolution is

$$\phi_t = (g(c)\frac{\nabla\phi}{|\nabla\phi|}|\nabla\phi|$$

Here if we take the function g(·) with one, then the speed function in the corresponding level set equation becomes the mean curvature of the level set S in the direction of the curve normal n :

$$F_s = \alpha k_i (\nabla \cdot \frac{\nabla\phi}{|\nabla\phi|}). \tag{7}$$

Here this speed function is weighted by factor α, allowing the user to control the amount of smoothing, and is tuned for each dataset. And a multiplicative stopping term $k_i$ slows down the deformable curve near the boundary and stops it at the boundary or edge of object. This is given as

$$k_i = \frac{1}{1 + |\nabla(G^* I)|} \tag{8}$$

Second, we can also consider another speed term. This term can lead the deformable curve toward the edges in the input data. It attracts the curve models to certain intensity or color features in the input data. The idea using this measure is that in many cases, the gradient direction is a good estimator for the orientation of the edge contour. We note that this measure gets a high value if the curve normal has a same direction of the image gradient. As an example, we also consider the explicit curve evolution as the robust alignment term and the threshold term [9, 10]. The first variation as a gradient descent process is

$$C_t = \beta\, sign(<\nabla I, n>)\Delta I + \gamma(c_2 - c_1)(I - (c_1 + c_2)/2)n,$$

where $c_1 = \frac{1}{|\Omega_c|}\iint_{\Omega c} I(x,y)dxdy$ and

$$c_2 = \frac{1}{|\Omega/\Omega_c|}\iint_{\Omega/\Omega c} I(x,y)dxdy.$$

The corresponding level set evolution is

$$\phi_t = \beta\, sign(<\nabla I, n>)\Delta I + \gamma(c_2 - c_1)(I - (c_1 + c_2)/2)|\nabla\phi| \quad (9)$$

Finally, by combining two kinds of terms derived until now, we can obtain the final level set evolution equation:

$$\phi_t = \phi_{t-1} + \Delta t \cdot \begin{Bmatrix} (\alpha k_i(\nabla \cdot \frac{\nabla\phi}{\nabla\phi}) \\ + \beta\, sign(<\nabla I, \nabla\phi>)\Delta I \\ + \gamma(c_2 - c_1)(I - (c_1 + c_2)/2) \end{Bmatrix} |\nabla\phi| \quad (10)$$

### 3. Post Processing

After applying the level algorithm where the propagation depends on color and edge in images, lots of isolated noises in the foreground (flower area) and background appear. So, we apply a simple method to remove the noises. Especially, the users locate the flowers in the center of the scene as the biggest object when taking the pictures using mobile phones because the flowers are the main attracting objects. From the observation, we first remove all isolated foreground blobs smaller than the biggest one. Then, we also take out any blobs smaller than the biggest background.

## III. RESULTS AND DISCUSSIONS

To test the performance of the proposed method to segment flower area using the level set, whose initial contour is defined by a GMM with two Gaussians, and post-processing, we applied it to the images taken by mobile phones outdoors. A GMM clustering algorithm roughly defined the initial boundary of the flower area in Fig. 2. Then, the level set tracked the shape of the flower area while its curve or interface was given by the zero level set of the time-dependent level set function at any time. The iteration of the level set stopped when the difference of the level set function between two adjacent times was less than the predefined value.

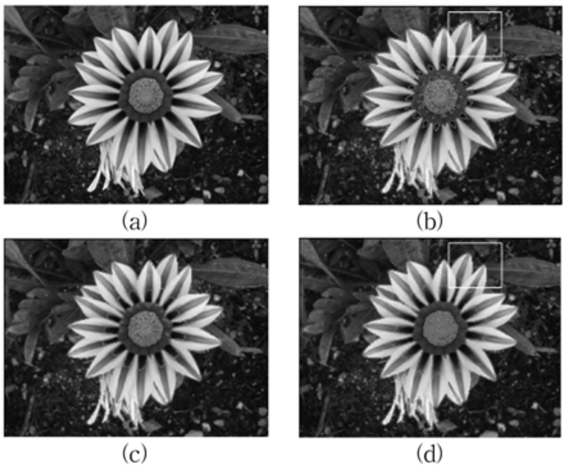


Fig. 2. Example of the segmentation results using the proposed method: (a) original input image (b) initial contour of the level set defined a GMM (c) intermediate result of a level set after 10 iterations (d) final result at 45th iteration of the level set

A GMM is well known algorithm to segment interesting objects in the images. However, because of the complicated background and the homogeneous color information, it often fails in accurately segmenting objects as shown in Fig. 3(a). However, it may be used as an initial segmentation result for the more sophisticated method such as a level set. Also, level set may have a good guide to help it forward to optimal boundaries of the flower area based on the initial contour provided by a GMM as depicted in Fig. 3(b).

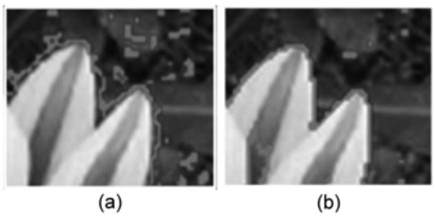


Fig. 3. Flower segmentation results: (a) by a GMM and (b) by the level set algorithm

Especially, complicated background with similar color or intensity to the interesting flower area induced lots of noises in the foreground area as well as background area as shown Fig. 4. Our proposed simple post-processing steps only rely on the size of the objects obtained by the level set. However, they successfully removed all isolated foreground and background noises from the level set-based segmentation results.

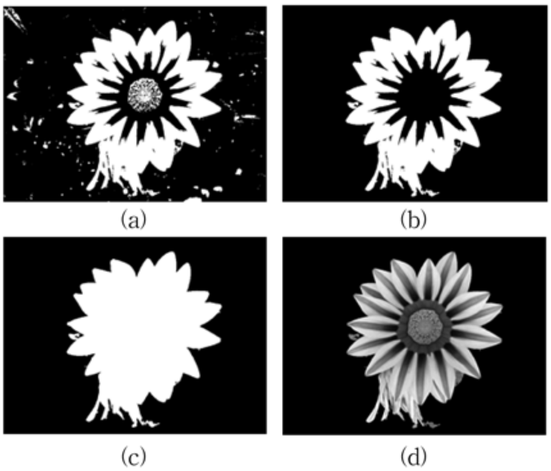

Fig. 4. Intermediate results of the post-processing: (a) binary image acquired by the level set algorithm where white and black means flower area (foreground) and background, respectively (b) and (c) result after removing isolated foreground noises and after taking out isolated background noises (d) final flower segmentation result by the proposed method

Our method was able to segment various flowers regardless of their colors (Fig. 5). However, the proposed method still has a limitation such as that it tends to wrongly segment some backgrounds around edge between foreground and background as flower area. In addition, the precise extraction of an object of interest from the background consisting of various objects is an essential step for recognition [3]. Therefore, we will consider more complicated information such as combination of color and edge to identify noises in both foreground and background as a future work.

Fig. 5. Segmentation results by the proposed method where the first row depicts input images and the second row shows their segmentation results

## IV. CONCLUSIONS

Previously, we proposed a method to segment flower area using combination of two algorithms including a GMM and a level set to reduce computational efficiency and increase segmentation accuracy. First, GMM was applied to the input image to cluster or segment flower area to set the initial contour of the level set. Then, level set deformed the contour to the optimal solution. However, lots of noises in both foreground and background appear while preventing the user from satisfying the segmentation results. In this study, we add post-processing steps into the previous work to remove those noises. The experiment results have shown that the proposed method successfully removes lots of noises. However, the method tends to fail in segmenting some segments into the other side. Therefore, we will study on developing a robust method using various color information and edge in post-processing steps as a future work to tackle this limitation.

## REFERENCES


[1] J.X. Du, X.F. Wang, and G.J. Zhang, "Leaf shape based plant species recognition," *Applied Mathematics and Computation*, vol. 185, pp.883-893, 2007.

[2] D.C. Cho, H.C. Kim, J.A. Lee and W.Y. Kim, "An Auto White Balance Restricting a Target Region of Grey World Method," *The Korea Institute of Signal Processing and Systems*, 2007.

[3] T. Saitoh, K. Aoki, T. Kaneko, "Automatic Recognition of Blooming Flowers," *IEEE ICPR*, vol. 1, pp.27-30, 2004.

[4] J. Zou and G. Nagy, "Evaluation of Model-Based Interactive Flower Recognition," *IEEE ICPR*, vol. 2, pp.311-314, 2004.

[5] Z. Miao, M.H. Gandelin, and B. Yuan, "A new image shape analysis approach and its application to flower shape analysis," *Image and Vision Computing*, vol. 24, pp.1115-1122, 2006.

[6] Sang Cheol Park, Soo Hyung Kim, Guee Sang Lee, Chil Woo Lee, In Seop Na, Ha Le, and Do Yen, "Flower Area Segmentation by a Level Set based on GMM Initialization," *Proc. KSII 3rd Int. Conf. Internet (ICONI)*, pp. 17-21, Sepang, Malaysia, Dec. 2011.

[7] R. Malladi, J.A. Setian, and B.C. Vemuri, "Shape Modeling with Front Propagation: A level Set Approach," *IEEE Transaction on PAMI*, Vol. 17, pp 158-175, 1995

[8] D.L. Pham, C. Xu, and J.L. Prince, "A survey of current methods in medical image segmentation," *Technical Report JHU/ECE 99-01*, The Johns Hopkins University, 1998

[9] J.A. Sethian, "*Level Set Methods and Fast Marching Methods*," Cambridge university press, 2005.

[10] M. Sonka, and J.M. Fitzpatick, "*Handbook of Medical imaging: vol.2 Medical ImageProcessing and Analysis*," SPIE Press, 2000.

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