

Pre-informed Level Set for Flower Image Segmentation

Syed Inthiyaz, P.V.V. Kishore and B.T.P. Madhav

Abstract This work proposes a pre-informed Chan–Vese (CV) based level sets algorithm. Pre-information includes objects colour, texture and shape fused features. The aim is to use this algorithm to segment flower images and extract meaningful features that will help in classification of floral content. Shape pre-information modelling is handled manually using advance image processing tools. Local binary patterns (LBP) features makeup texture pre-information and RGB colour channels of the object provide colour pre-information. All pre-defined object information is fused together to form high dimension subspace defining object characteristics. Testing of the algorithm on flower images datasets shows a jump in information content in the resulting segmentation output compared to other models in the category. Segmentation of flowers is important for recognition, classification and quality assessment to ever-increasing volumes in floral markets.

1 Introduction

Flowers induce instantaneous and elongated effects on emotions, mood, behaviours and memory of both males and females [1]. The authors studied extensively about the reactions flowers cause during their contact with humans in three different ways and concluded that human happiness is directly linked to flowers. This is the reason for a 30% increase in world floriculture market every year and a 25% in India per annum [2]. The other side of the story is the losses incurred as they do not last long

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after they are cut from the plant. The storage, temperature, sorting, packaging and transportation are some of the causes for a market loss of nearly 25% every year [3].

Computer vision based algorithms are capable of determining the quality of flower during its journey from blossoming to final consumer market. In this work we limit ourselves to the first stage of development of a complete floral quality tester using computer vision models. The first and most complicated task is to extract the flower to lower dimensional subspace for classification. The binary segmentation of the flower is performed by using a higher dimensional feature subspace comprising colour, texture and shape characteristics of the image objects. The proposed method is evaluated on flower database available at oxford [4].

In [5], the authors use an image-specific colour distribution which detects the shape of the flowers in the image automatically. The algorithm starts with colour descriptor and transforms into a foreground/background segmentation initializing a generic shape model. The generic shape model is applicable across multiple classes and viewpoints. Previously Das et al. [6] used colour of the flowers as domain knowledge for segmentation. The algorithm also learns image background model from the periphery of the image. This model works well when the flower in the image is different from background by over 50%.

But the oxford database which is being used in our work does not follow this rule and the creators of the database propose the algorithm in [7]. Here the authors develop a visual vocabulary of flowers based on colour, texture and shape information. This model overcomes the ambiguities that arise during flower classifications due to ambient lighting variations, petals shape deformations, colour changes and occlusion during image capture. Our work in this paper is also focused on pre knowledge of shape, colour and texture of the flower.

In this work we introduce a mixed feature as pre-information for the level set function. The mixed feature is made up of shape, texture and colour. For colour RGB planes are featured. Shapes are hand modelled from the original images of flowers. For texture we use Local Binary Patterns (LBP) features instead of GLCM or Gabor features. The mixed feature image of a flower from the dataset is shown in Fig. 1.

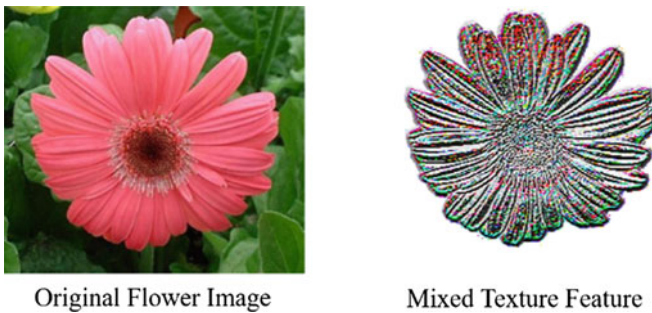


Fig. 1 Mixed feature using colour, texture and shape (CTS) images

The pre-information related to flower in CTS form is provided as constraints in the formulation of level sets. Level sets were first introduced by Osher and Fedkiw [8] and later popularized by Vese and Chan [9]. A number of versions of level sets with shape [10] and texture priors [11] were very popular with the image processing research community. A combination of colour, texture and shape features are used exclusively by computer vision researchers for complex image segmentation.

2 Multi Feature Level Set Formulation

Colour, texture and shape features form a knowledge base for the level set function to operate on the image plane. Previous algorithms used three different functions for level set formulation from these features. In this work we propose to use a single term for all these features to be incorporated in a level set. A brief review of the level sets and feature extraction models make up this section.

2.1 Colour Feature and Texture Features

Previous works extracted Red, Green and Blue (RGB) vectors from the image plane to construct a size $(\text{RGB}) \times 3$ vector feature subspace. Other methods involve converting RGB space to Lab or HIS or HSV colour spaces and extracting them as colour features. The novel model proposed in this work saves computing power initially by avoiding this step. The idea is to use each of the R, G and B planes separately during contour propagation. The level set is formulated on these three sub-planes, which will be elaborated in the level sets section.

Nature creates different varieties of flowers based on colours and textures. Quite a few models in texture extraction were ideated for flower segmentation. They are Grey-Level Covariance Matrix (GLCM), Gabor Filters, wavelet filters and Local Binary Patterns (LBP). Results of our analysis in Figs. 1 and 2 show that LBP features in RGB plane provide us with good texture of the flower compared to the other three.

LBP compares each pixel in a pre-defined neighbourhood to summarize the local structure of the image. For an image pixel $I(x, y) \in \mathbb{R}^+$, where (x, y) gives the pixel position in the intensity image. The RGB image is $I(x, y, N) \in \mathbb{R}^+$, where N represents RGB colour planes. The neighbourhoods of a pixel can vary from 3 pixels with radius $r = 1$ or a neighbourhood of 12 pixels with $r = 2.5$. The value of pixels using LBP code for a centre pixel (x_c, y_c, N) is given by

$$\mathbf{LBP}(x_c, y_c, N) = \sum_{i=1}^N \sum_{j=1}^P s(g_p - g_c) 2^p \quad (1)$$

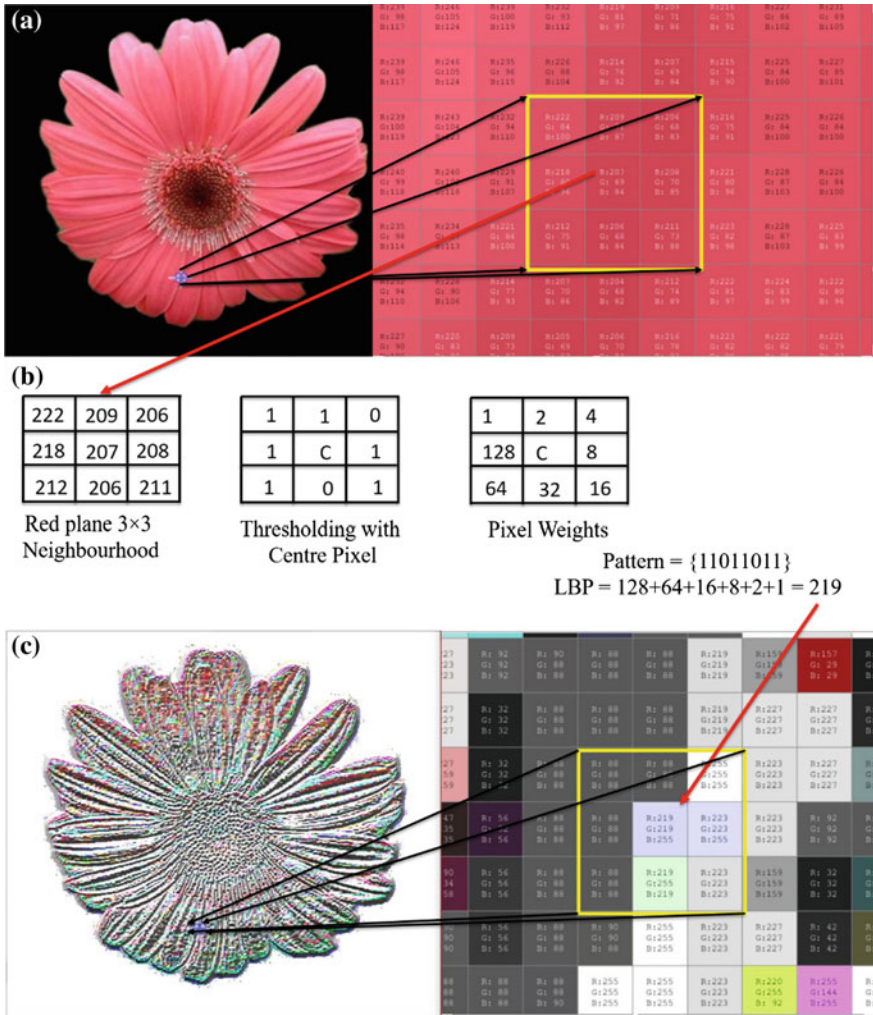


Fig. 2 **a** Original flower image. **b** LBP process for 3 × 3 window and **c** the resultant local binary patterns resulting in a colour texture image

$$s(x) = \begin{cases} 1 & \forall x \geq 0 \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

where g_c is intensity grey value of centre pixel at (x_c, y_c) and g_p is grey value around the neighbourhood of g_c . The value of N represents colour plane and P gives the number pixels in the neighbourhood of g_c . Figure 2 gives the LBP calculations on the flower image in Fig. 1.

The LBP texture features are invariant to monotonic grey-level changes that are predominant in flower images. Computational simplicity makes the LBP ideal for this work as the next stage involves more computationally intensive algorithm in the form of level sets. This colour texture flower data forms the pre-information to the level set function.

2.2 Level Set Formulation

The level set model introduced by Osher and Fedkiw [8] and few others is an image segmentation model based on a closed contour spreading in the image plane adhering to object edges. An implicitly defined contour of arbitrary shape Θ in the image plane O : $\{\phi(\mathbf{x}, \mathbf{y}) \in \mathbb{R}^2\}$ as the zero-level set of an embedding function $\phi : O \rightarrow \mathbb{R}$:

$$\Theta = \{\mathbf{x}, \mathbf{y} \in O | \phi(\mathbf{x}, \mathbf{y}) = 0\} \quad (3)$$

Level set function ϕ evolves instead of contour Θ itself giving advantages in the form of no marker control and immune to topological deformations of the active contour in the image plane. Here we focus on Chan Vese (CV) [9] level set functional formulated from [10] in the image plane $I : \Theta \rightarrow \mathbb{R}^+$ as

$$E^{Cv}(\phi) = \int_{\Theta} (I(\mathbf{x}) - C^+)^2 H(\phi(\mathbf{x})) d\mathbf{x} + \int_{\Theta} (I(\mathbf{x}) - C^-)^2 (1 - H(\phi(\mathbf{x}))) d\mathbf{x} + \lambda \int_{\Theta} |\nabla H(\phi(\mathbf{x}))| d\mathbf{x} \quad (4)$$

$I(\mathbf{x}, \mathbf{y})$ is a 2D image plane represented as $I(\mathbf{x})$. Here $H(\phi(\mathbf{x}))$ is a Heaviside step function. C^+ represents average intensity of pixels considered constant in positive ϕ region and C^- represents negative ϕ region constant. The last term in Eq. (4) tries to keep a smoothing contour during evolution and λ is proportionality constant deciding on the minimum amount of separation needed between boundaries. The first two parts constitute external energy representing error between the image and piecewise constant approximations of the evolving level set functional. Gradient descent minimization of the level set ϕ gives a curve evolution expression

$$\frac{\partial \phi}{\partial t} = -\frac{\partial E^{Cv}}{\partial \phi} = \delta(\phi) \left[\lambda \left(\nabla \cdot \left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right) - (I(\mathbf{x}) - C^+)^2 + (I(\mathbf{x}) - C^-)^2 \right] \quad (5)$$

CV model proposed the $\delta(\phi)$ term which helps level set detect even the internal edges.

A shape and texture prior model for level set as a learning basis will focus on segmenting the flower in RGB sub-planes which is useful in post processing

recognition. To establish a unique relationship between its surrounding level set ϕ and a pre-defined shape, texture, colour (STC) model ϕ^{STC} , it will be assumed that $\phi < 0$, inside ϕ^{STC} , $\phi > 0$, outside ϕ^{STC} and $|\phi| = 1$ everywhere else. The model ϕ^{STC} is defined as a combination of shape and texture models taken across RGB colour planes. The colour model in this case is user dependent and can be either HSV or lab colour space. The combination level set function is

$$\phi^{\text{STC}} = \sum_{N=3} \phi^{\text{S}} + \phi^{\text{T}} \quad (6)$$

There are many ways to define this signed distance functions out of which we use the most widely applied with constrains towards scaling, rotation and translational properties. In this work we propose to use initial contour ϕ and shape prior ϕ^{STC} contour to compute level set area difference:

$$d^2(\phi, \phi^{\text{STC}}) = \sum_{i=1}^N \int_{\Theta} (\mathbf{H}(\phi(x)) - \mathbf{H}(\phi^{\text{STC}}(x)))^2 d\mathbf{x} \quad (7)$$

where N is the number of colour sub-planes the image is defined. The defined distance function is image size independent, nonnegative, symmetrical and satisfies the triangle inequality. Local energy minimization between $(\phi_0, \phi^{\text{STC}})$ maximizes the possibility of finding correct shape in the cluttered backgrounds. The affine transformations are defined by current STC ϕ_0 . The curve evolution expression is obtained by applying Euler–Lagrange equation on (7) as

$$\frac{\partial \phi_0}{\partial t} = \sum_{i=1}^N 2\delta(\phi_0) \times (\mathbf{H}(\phi^{\text{STC}}) - \mathbf{H}(\phi_0)) \quad (8)$$

where $\delta(\cdot)$ is delta function and t is artificial time step. Finally combining STC prior energy term in (7) and CV level set function in (2), we get the total energy function of the level set as

$$\mathbf{E}^T = \sum_{i=1}^N \zeta \mathbf{E}^C + (1 - \zeta) \mathbf{E}^{\text{STC}} \quad (9)$$

Here ζ controls the effect of STC prior energy on the image energy. For single shape priors the energy functional used for algorithm development is derived from evolution equations in (5) and (8) is

$$\frac{\partial \phi}{\partial t} = \sum_{i=1}^N \zeta \delta(\phi) \left[\lambda \left(\nabla \cdot \left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right) - (\mathbf{I}(\mathbf{x}) - \mathbf{C}^+)^2 + (\mathbf{I}(\mathbf{x}) - \mathbf{C}^-)^2 \right] + 2(1 - \zeta) \times (\mathbf{H}(\phi^{\text{STC}}) - \mathbf{H}(\phi)) \quad (10)$$

where C^+ and C^- are updated iteratively in each discrete time step using the expressions

$$C^+ = \sum_{i=1}^N \frac{\int_{\Theta} I(H(\phi)) \mathbf{d}x}{\int_{\Theta} (H(\phi)) \mathbf{d}x} \quad (11)$$

$$C^- = \sum_{i=1}^N \frac{\int_{\Theta} I \times (1 - H(\phi)) \mathbf{d}x}{\int_{\Theta} (1 - H(\phi)) \mathbf{d}x} \quad (12)$$

The following proposed level set model is tested for different flower images in the dataset [4].

3 Results and Discussion

The following parameters of the proposed level set functional needs adjustments during the simulation trials. The shape, texture, colour (STC) effect term ζ is set based on the complexity in the image planes. This term controls the contour movement distributions on the sub-planes related to shape and texture. The ζ is around 0.634 for images captured under lesser ambient lighting or with dominating backgrounds compared to flower foregrounds. For high-quality images this value is kept very low around 0.12. In this work the value of ζ ranges from 0.1 to 0.7.

The level set stopping criteria is set using the gradient descent algorithm. Contour evolution stops when the error between the current iteration and previous iteration reaches a pre-defined threshold. The error value is set 0.0001. The performance of the proposed method is estimated using Structural Similarity Index (SSIM) against the other methods such as Gabor Texture Prior (GTP) and Grey-Level Covariance Matrix Texture Priors (GLCMTP).

The segmentation results for various flower images in the dataset are presented in Fig. 3 along with their shape and texture priors. Local binary pattern based texture is used in all the simulations. Figure 3 shows initial contour in yellow and final contour in green. Both the contours are projected on to the image under IC heading. The final iteration count for each flower image is different, even though the images collected in Fig. 3 are shown for common iteration count. The last column shows the binary segmented flower image that can be used for classification process. Visual analysis of the segmented flower indicates the quality of the proposed method. A very clear picture is obtained about the flower showing internal texture and its shape. The internal stem of the flower in Anthurium is fully extracted under the cluttering influence of the flower texture. This near perfect segmentation can achieve good classification rates. Figure 4 shows more test results on flower images from the dataset in [4].

Figure 4 gives the performance of the algorithm when tested on images of different colour, shape and texture. The resulting flower images can be presented to

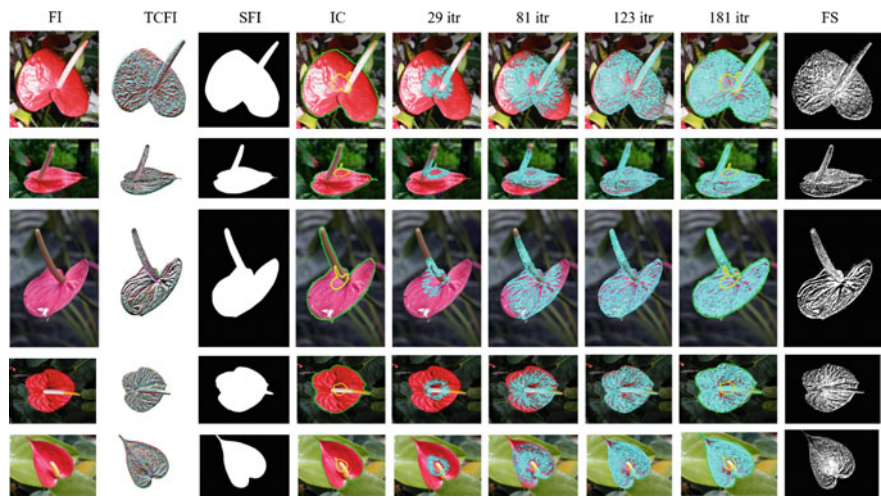


Fig. 3 Flower segmentation process, *FI* flower image, *TCFI* texture colour FI, *SFI* shape flower image, *IC* initial contour, *29 itr* 29th iteration captured, *81 itr* 81th iteration captured, *181 itr* 181th iteration captured, *FS* segmented flower



Fig. 4 Segmentation results of the proposed algorithm on flowers of different sizes, shapes, textures and colours

a classifier for classification. For qualitative performance measurement we use structural similarity index as a measure between the segmented output and the hand segmented ground truth. The ground truth is extracted using expert craftsman in Photoshop.

Superiority of the proposed Local Binary Pattern Texture (LBPT) segmentation is established by comparing its performance with Gabor Texture Prior (GTP) and Grey-Level Covariance Matrix Texture Priors (GLCMTP). The performance indicators are SSIM and number of iterations. SSIM measures the local and global similarity between pixels between images. We use reference image as the hand segmented image and the test image is represented by segmented flower.

Table 1 gives global SSIM values for flowers in the database between LBPT, GTP and GLCMTP. SSIM values are in the range of [0, 1]. Is SSIM score is '0' indicates no match and '1' indicates a perfect match.

The average SSIM value for all the images in the dataset from the proposed algorithm (LBPT-LS) is around 0.9282 and the average number of iterations is 189. The average SSIM values for GTP-LS and GLCMTP-LS are 0.7798 and 0.7801 respectively. Similarly, the average iteration count is 221 and 228 for GTP and LCMTP. Further these values can be improved using a combination of these methods and more complicated flower image structures.

Table 1 Performance indicators for the flower segmentation algorithms using level sets

Flower name	No. of images/flower	LBPT-LS		GTP-LS		GLCMTP-LS	
		Avg. SSIM	Avg. Itr.	Avg. SSIM	Avg. Itr.	Avg. SSIM	Avg. Itr.
Anthurium	10	0.923	181	0.785	220	0.786	222
Barbeton daisy	10	0.918	186	0.776	236	0.778	226
Bishopof llandaff	10	0.935	192	0.753	242	0.751	232
Californian Poppy	10	0.952	188	0.802	224	0.800	234
Frangipani	10	0.920	184	0.786	229	0.789	219
Hibiscus	10	0.872	177	0.742	211	0.748	221
Lotus	10	0.942	187	0.795	236	0.791	226
Rose	10	0.852	171	0.736	209	0.730	219
Thorn apple	10	0.892	179	0.761	219	0.760	229
Tree mallow	10	0.865	173	0.750	213	0.752	223

4 Conclusion

A novel method for flower image segmentation is attempted in this work. Flower images are the most complicated structures nature creates for humans which are difficult to understand. The task is accomplished using level sets that are pre-informed about the colour, shape and texture related to the flower. Local binary patterns make texture information related to the flower. Shape is hand segmented and the level set is evolved in the RGB colour plane using the shape and texture information. SSIM and number of iterations are used as a performance measure for comparing the proposed level set with Gabor texture filter based level set and grey covariance matrix based level sets. The proposed method using LBP textures outperforms the other two texture models for flower classification.

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