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Color Image Segmentation Using Binary Level-set Partitioning Approach

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Abstract: In this study, we introduce a novel level set method for color image segmentation. It is based on the Binary Space Partitioning (BSP) tree technique developed by Pei and Cheng and the multiphase level-set framework developed by T. Chan and L. Vese. We present a new variational formulation for geometric contours that divides the image region in a binary fashion using binary quaternion moment preserving thresholding technique and therefore completely eliminates the need of the costly re-initialization and calculation of number of regions procedure. The sum of square error value determines the required homogeneity of the color in the region and inturn decides the number of regions in the image. Our variational formulation consists of an internal energy term that penalizes the deviation of the level set function from a signed distance function and quaternion moment based external energy term that drives the motion of the zero level set rapidly and discontinuously toward the color boundaries in an image. The resulting evolution of the level set function is the gradient flow that minimizes the overall energy functional. The proposed algorithm has been applied to both synthetic and natural color images with promising results.

Key words: Segmentation, color, level sets, binary space partitioning tree, energy minimization

INTRODUCTION

Color image segmentation has been and still is, the subject of active research in computer vision and image analysis. Applications such as satellite, natural and medical image analysis and remote sensing, express the images as multi-dimensional data. By now, a large number of algorithms have been developed for processing multi-dimensional data. Binary Space Partitioning (BSP) tree method (Qiu and Sudirman, 2001) is one of the segmentation techniques, which uses binary quaternion moment preserving thresholding technique (Pei and Cheng, 1999), that treats the input data as a point in a multi-dimensional space. The drawback of this method is the use of straight lines for segmenting the image. To overcome this problem we combine the level set approach with the BSP tree method.

Level set methods (Osher and Sethian, 1988), were first introduced for capturing moving fronts. Active contours were introduced (Kass *et al*., 1987) for segmenting objects in images using dynamic curves. The existing active contour models can be broadly classified as either parametric active contour models or geometric active contour models according to their representation and implementation. In particular, the parametric active contours (Xu and Prince, 1998) are represented explicitly as parameterized curves in a Lagrangian framework, while the geometric active contours (Caselles *et al*., 1993; Caselles *et al*., 1997; Malladi *et al*., 1995), are represented implicitly as level sets of a two-dimensional function that evolves in an Eulerian framework.

Geometric active contours models are based on curve evolution theory (Kimia *et al*., 1995) and level set method (Osher and Fedkiw, 2002). The basic idea is to represent contours as the zero level set of an implicit function defined in a higher dimension, usually referred as the level set function and to evolve the level set function according to a Partial Differential Equation (PDE).

Chan and Vese (2001) proposed an active contour model using a variational level set formulation. By incorporating region-based information into their energy functional as an additional constraint, their model has much larger convergence range and flexible initialization. Vemuri and Chen (2003) proposed another variational level set formulation. By incorporating shape-prior information, their model is able to perform joint image registration and segmentation.

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Li *et al.* (2005) proposed a new variational formulation for geometric active contours that forces the level set function to be close to a signed distance function and therefore completely eliminates the need of the costly re-initialization procedure. Li *et al.* (2007) also, introduced local binary fitting energy with a kernel function in the variational level set formulation to extract the local image information. However, their application is limited to bimodal image segmentation (an object lying on a background). A multi-phase approach has been proposed to multi-valued image segmentation (Chan and Vese, 2001; Luminita *et al.*, 2002). However, the number of regions is restricted to be a power of two. Generally, 2 issues arise when extending variational segmentation to an arbitrary number of regions. First, the complexity of the algorithms increases with the number of regions. Second, the segmentation requires a careful manual initialization in order to avoid converging to undesirable local minima (Yezzi *et al.*, 2002). Recently, Allili and Ziou (2007), proposed an approach based on active contours for automatic segmentation of color images with an arbitrary number of regions, using region and boundary information. But the computation time is very large.

In this study, we present a new multi-level, geometric contour using the key idea of binary space partitioning tree to overcome the above issues. The method segments the images with an arbitrary number of regions without using any prior knowledge concerning the number of regions or their statistics. The segmentation is steered by region information, where the region information is based on quaternion moments. To perform the segmentation in a fully automatic fashion, the approach uses binary quaternion moment preserving thresholding technique that initializes automatically two phases by creating the binary image. Each phases are divided into 2 phases recursively in hierarchical manner following binary space partitioning tree technique (Sudirman and Qiu, 2000).

MATERIALS AND METHODS

Consider a given vector valued image I: $\Omega \rightarrow \Re^d$, where, $\Omega \subset \Re^n$ is the image domain and $d \geq 1$ is the dimension of the vector I(x). For gray level images, d = 1, for color images, d = 3, for multispectral images d = 3. Let, C be a contour in the image domain Ω. We define the initial contour by creating a binary image for a given color image using Binary quaternion moment preserving thresholding technique. Since, we follow the idea of BSP tree, we always divide the region in a binary fashion.

Binary level set formulation: A given curve C (the boundary of an open set $\omega \in \Omega$, i.e., $C = \partial\omega$) is represented implicitly, as the zero level set of a scalar Lipschitz continuous function $\phi: \Omega \rightarrow \Re$ (called level set function), such that:

$$\begin{aligned} &\phi(x,y) > 0 \text{ in } \omega \\ &\phi(x,y) < 0 \text{ in } \Omega \setminus \omega \\ &\phi(x,y) = 0 \text{ on } \partial\omega \end{aligned} \tag{1}$$

A typical example of level-set function is given by the signed distance function to the curve. Using this representation, geometrical quantities, properties and motions can be expressed. Initially we propose 2 level-set functions ϕ_1 and ϕ_2, where:

$$\begin{aligned} &\phi_1(x,y) > 0 \text{ in } \omega, \\ &\phi_1(x,y) < 0 \text{ in } \Omega \setminus \omega \text{ and} \\ &\phi_1(x,y) = 0 \text{ on } \partial\omega \end{aligned} \tag{2}$$

$$\begin{aligned} &\phi_2(x,y) < 0 \text{ in } \omega, \\ &\phi_2(x,y) > 0 \text{ in } \Omega \setminus \omega \text{ and} \\ &\phi_2(x,y) = 0 \text{ on } \partial\omega \end{aligned} \tag{3}$$

We define for each point $x \in \Omega$, the following energies to update the level sets ϕ_1 and ϕ_2.

$$\varepsilon_x^{BLP}(C,BI) = \rho_1 \int_{in(C)} BIdy + \rho_2 \int_{out(C)} BIdy \tag{4}$$

$$\varepsilon_x^{BLP}(C,NBI) = \rho_1 \int_{in(C)} NBIdy + \rho_2 \int_{out(C)} NBIdy \tag{5}$$

ε_x^{BLP} (C, BI) is used to update ϕ_1 and ε_x^{BLP} (C, NBI) s used to update ϕ_2. BI is the binary image obtained after applying BQMP thresholding technique to the given region. NBI is the complement of BI. Since the contribution of second term in Eq. (4) and (5) is very less we eliminate it in the further equations. However, the above energies ε_x^{BLP} are defined locally for a point $x \in \Omega$. To find the entire object boundary, we must minimize ε_x^{BLP} for all the points in the image domain Ω. So, we define the following energy functionals:

$$\varepsilon(C,BI) = \int_\Omega \varepsilon_x^{BLP}(C,BI)dx \tag{6}$$

$$\varepsilon(C,NBI) = \int_\Omega \varepsilon_x^{BLP}(C,NBI)dx \tag{7}$$

Indeed, using the Heaviside function H(z), equal with 1 if $z \geq 0$ and with 0 if $z < 0$, the length of C $L(\phi)$ and the area of C ε_x^{BLP} (ϕ, BI) ε_x^{BLP} (ϕ, NBI) are defined as follows:

$$L(\phi) = \int_\Omega \delta(\phi(x))\left|\Delta\phi(x)\right|dx \tag{8}$$

$$\varepsilon_x^{BLP}(\phi,BI) = \rho\int BI(x)H(\phi(y))dy \tag{9}$$

$$\varepsilon_x^{BLP}(\phi, NBI) = \rho\int NBI(x)H(\phi(y))dy \quad (10)$$

where, H is the Heaviside function. BLP stands for Binary Level-set Partitioning method and δ is the univariate dirac function or we can say it is the derivative of heaviside function. The length of the zero level curve of ϕ is needed to regularize the zero level contour of ϕ. Thus, the partitioning energies $\varepsilon^{BLP}(\phi, BI)$ and $\varepsilon^{BLP}(\phi, NBI)$ in Eq. (6) and (7) can be written as:

$$\varepsilon^{BLP}(\phi,BI) = \int_\Omega \varepsilon_x^{BLP}(\phi,BI)dx$$

$$= \rho\int_\Omega [\int BI(x)H(\phi(y))dy]dx \quad (11)$$

$$\varepsilon^{BLP}(\phi,NBI) = \int_\Omega \varepsilon_x^{BLP}(\phi,NBI)dx$$

$$= \rho\int_\Omega [\int NBI(x)H(\phi(y))dy]dx \quad (12)$$

In order to ensure stable evolution of the level set function ϕ, we add the distance regularizing term in Li *et al.* (2005, 2007) variational level set formulation to penalize the deviation of the level set function ϕ from a signed distance function. The deviation of the level set function ϕ from a signed distance function is characterized by the following integral:

$$P(\phi) = \int_\Omega \frac{1}{2}(|\Delta\phi(x)| - 1)^2 dx \quad (13)$$

Now, we define the entire energy functional

$$\phi_1 = \phi + \kappa(\varepsilon^{BLP}(\phi,BI) + \mu P(\phi) + \eta L(\phi)) \quad (14)$$

$$\phi_2 = \phi + \kappa(\varepsilon^{BLP}(\phi,NBI) + \mu P(\phi) + \eta L(\phi)) \quad (15)$$

where, μ and η are nonnegative constants.

In practice, the Heaviside function H in Eq. (9) and (10) are approximated by a smooth function H_ε defined by:

$$H_\varepsilon(x) = \frac{1}{2}[1 + \frac{2}{\pi}\arctan(\frac{x}{\varepsilon})] \quad (16)$$

The univariate dirac function δ_ε is calculated as follows:

$$\delta_\varepsilon(x) = H_\varepsilon^{'}(x) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + x^2} \quad (17)$$

By replacing H and δ in Eq. (11, 12) and (14) with H_ε and δ_ε the energy functionals ε^{BLP} and L are regularized as $\varepsilon^{BLP}{}_\varepsilon$ and L_ε. As in (Li *et al.*, 2007), we choose $\varepsilon = 1$ for good approximation of H and δ by H_ε and δ_ε. Thus, the energy functionals ϕ_1 and ϕ_2 in Eq. (15) and (16) are approximated by:

$$\phi_1 = \varepsilon_\varepsilon^{BLP}(\phi,BI) + \mu P(\phi) + \eta L_\varepsilon(\phi) \quad (18)$$

$$\phi_2 = \varepsilon_\varepsilon^{BLP}(\phi,NBI) + \mu P(\phi) + \eta L_\varepsilon(\phi) \quad (19)$$

These are the energy functionals we will minimize to find the multivalued region boundaries.

Multi level formulation: The multi-level formulation of the proposed level-set segmentation of color images involves three main stages.

- Creating binary image for a given image or its subregion using Binary quaternion moment preserving thresholding technique (Pei and Cheng, 1999)
- Termination criteria testing stage. Sum of square error calculated for each color channel is used as the termination criteria
- Segment the region using vector level set function and vector heaviside function

The first stage determines how an image or subregion will be partitioned, whereas the second one decides if a particular image or sub regions are required to be partitioned and the third one determines how the subregion is represented and stored.

The proposed multi-level, binary level set segmentation algorithm is given:

SEGMENTATION ALGORITHM

Input: Color Image to be segmented.

Output: Set of contours.

- Apply Gaussian filter for smoothening the given image
- Let, the zero level set function ϕ_0 be ones matrix in size of the given image
- Initialize the image queue (imq) with the given image
- Initialize the ϕ queue (ϕq) with the zero level set function
- Fix the sum of square error threshold SST (stopping criteria)

- While, the queue imq is not empty
- [im1, im2, ϕ_1, ϕ_2, flag] = BLP (imq(front), ϕq (front), SST)
- If (flag==1)
- Insert im1 and ϕ_1 into imq and ϕq queues, respectively
- Insert im2 and ϕ_2 into imq and ϕq queues, respectively
- Else
- Display the contour of ϕq(front) since it is one of the final segments
- End if
- Delete imq(front) and ϕq (front)
- End while.

BLP algorithm
Input: Image or sub region, corresponding level set function, sum of square error threshold.

Output: Two segments of the given region, their level set functions, flag to indicate whether the given region is the final segment or it is partitioned into 2 segments.

- Apply BQMP thresholding technique
- Calculate Sum of Square Error (SSE)
- If SSE < SST
- Flag = 0
- Else
- Flag = 1
- Compute ε^{BLP} (ϕ, BI) and ε^{BLP} (ϕ, NBI)
- Compute penalizing term P(ϕ)
- Compute Length term L(ϕ)
- Compute ϕ_1 and ϕ_2 using Eq. (14) and (15), respectively.
- Let, h_1 and h_2 be the heaviside (ϕ_1) and heaviside (ϕ_2), respectively.
- Compute im_1 where, $im_1 = h_1 \bullet im$
- Compute im_2 where, $im_2 = h_2 \bullet im$
- Return im_1, im_2, ϕ_1, ϕ^2 and flag

Representation of the subregion: Initially we start with given image of size mxn and ϕ_0, which is 2 dimensional ones matrix of size mxn. In every iteration, the given image or region and the level set functions are divided into two. The segmented image regions can be represented by either 1D or 2D vector. We use 2D matrix of size mxn where, the elements of segmented region are the intensity values and the others zero. Similarly, every level set function is divided into ϕ_1 and ϕ_2, where, $\phi_2 = \sim\phi_1$ in that region and $\phi_2 = \phi_1$ in other region, using the following Lagrange equations, obtained by minimizing the energy functionals Eq. (18) and (19) and a multi-level tree structure is generated.

To minimize the energy functional ϕ_{2i} with respect to ϕ_i, we derive the gradient descent flow:

$$\frac{\phi_{2i}-\phi_i}{\tau} = -\delta_\varepsilon(\phi_i)(\rho BI) + \eta\delta_\varepsilon(\phi_i)\operatorname{div}\left(\frac{\nabla\phi_i}{|\nabla\phi_i|}\right) + \mu\left(\nabla^2\phi_i - \operatorname{div}\left(\frac{\nabla\phi_i}{|\nabla\phi_i|}\right)\right) \quad (20)$$

where, δ_ε is the smooth Dirac function given by Eq. (17) and BI is the binary image obtained by applying BQMP thresholding technique.

$$\frac{\phi_{2i+1}-\phi_i}{\tau} = -\delta_\varepsilon(\phi_i)(\rho NBI) + \eta\delta_\varepsilon(\phi_i)\operatorname{div}\left(\frac{\nabla\phi_i}{|\nabla\phi_i|}\right) + \mu\left(\nabla^2\phi_i - \operatorname{div}\left(\frac{\nabla\phi_i}{|\nabla\phi_i|}\right)\right) \quad (21)$$

Where: NBI =~ BI

The above Eq. (20) and (21) are the proposed multi-level active contour model in this study. ϕ_{2i} and ϕ_{2i+1} are the 2 children of the functional node ϕ_i. The phases are numbered as a binary tree.

Advantages of our model: The significant limitation of Binary space partitioning tree is, splitting the region of an image using straight lines with minimum number of orientations. There was a tradeoff between the accuracy and computation time. In contrast to Binary space partitioning tree method, our model didn't use straight lines to partition the region. Instead, a curvature model is defined to represent the partitioning region. Hence, robust and accurate segmentation based on color moments is acquired.

Another advantage of our model is that no initialization and reinitialization is necessary in our method, due to BQMP thresholding and regularizing term Eq. (13), respectively. Moreover, our method starts with All-ones level set function and it is splitted into two level set functions automatically in every iteration based on our multi-level curvature model. In particular, we can simply initialize ϕ_0 as unary function, which takes a constant value.

Automatic re-initialization of level set function: Here, we propose the functionals ϕ_1 and ϕ_2 as the level set functions in every iteration. Let, Ω_1 and Ω_2 are 2 disjoint subsets in the image domain Ω, where, Ω_1 = ones (BI) and Ω_2 = zeros (BI) (BI is the binary image generated by applying binary quaternion moment preserving thresholding technique to the image domain Ω) and $\partial\Omega_1$ and $\partial\Omega_2$ are all the points on the boundaries of Ω_1 and Ω_2, respectively, which can be efficiently identified by some simple morphological operations. Then, the functions ϕ_1 and ϕ_2 at level 1 are defined as:

$$\phi_1(x,y) = \begin{cases} -\rho \mid (x,y) \in \Omega_1 - \partial\Omega_1 \\ 0 \mid (x,y) \in \partial\Omega_1 \\ \rho \mid (x,y) \in \Omega_2 \end{cases} \tag{34}$$

$$\phi_2(x,y) = \begin{cases} -\rho \mid (x,y) \in \Omega_2 - \partial\Omega_2 \\ 0 \mid (x,y) \in \partial\Omega_2 \\ \rho \mid (x,y) \in \Omega_1 \end{cases} \tag{35}$$

where, $\rho > 0$ is a constant. As suggested by Chunming Li in Eq. (15) we choose ρ larger than 2ε, where ε is the width in the definition of the regularized Dirac function δ_ε in Eq. (17).

Traditional level set methods use signed distance functions computed from a contour or level set functions computed from arbitrary region, as initial level set functions. Unlike traditional methods, the proposed level set functions at level 1 are computed from the binary image computed by applying BQMP thresholding technique. Such region-based initialization of level set function is not only computationally efficient, but also allows for automatic segmentation. The thresholding scheme identify 2 clusters such that range of positions in the 3 dimensional RGB cube are exactly divided in the middle by the hyperplane.

RESULTS AND DISCUSSION

We experiment the proposed multi-level, multiphase segmentation method using binary quaternion moment preserving and level set approach.

As most common methods, level-set functions are chosen to be the signed Euclidean distance to their zero level sets. They are updated using gradient minimization

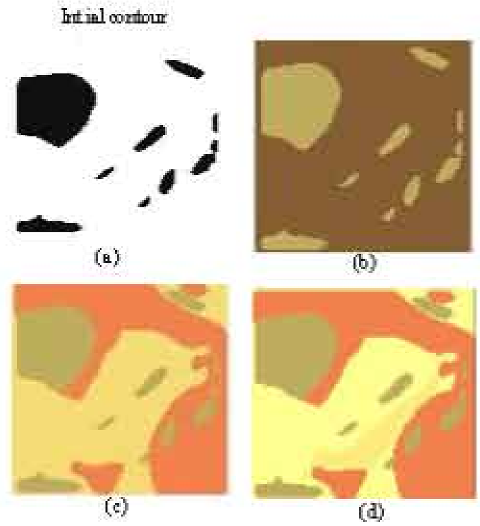

Fig. 1: Segmentation of pepper image, a) Binary image obtained by the application of BQMP thresholding technique, b) segments at level 1, c) Segments at level 2, d) Segments at level 3, In a), b) and c) The obtained 4 segments are colored their mean color

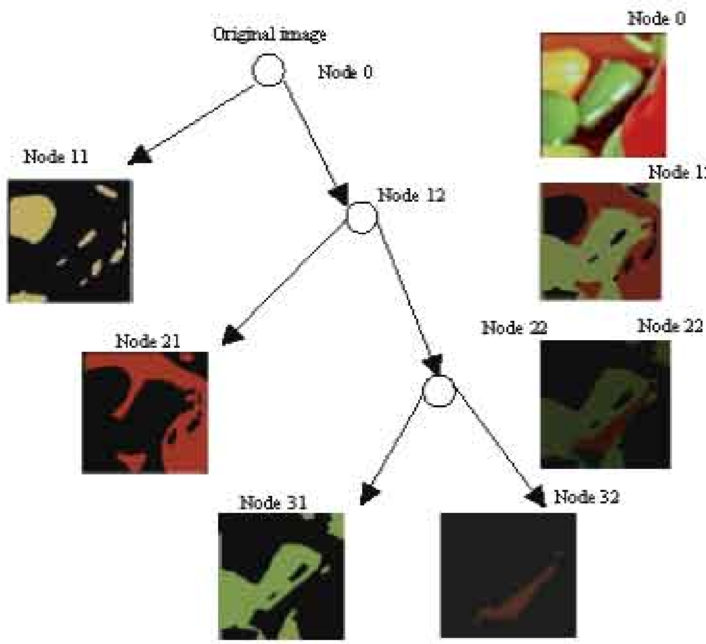

Fig. 2: Multi-level tree structure of the pepper image segmentation using the proposed algorithm

techniques and re-segmented using multi-level binary space partitioning tree method and sum of square error criterion is used for deciding the number of segments. Hence, the proposed method is called as binary level-set partitioning approach for color image segmentation. Figure 1 presents the segmentation of a pepper image. The proposed method divides the pepper image into four segments, where, the SST $=11\times10^6$, $\varepsilon = 1.0$, $\kappa = 20$, $\rho = 4$, $\mu = 0.01$ and $\eta = 1$. Figure 2 shows its multi-level tree structure and Fig. 3 displays the contours of all the segments collectively. Figure 4 shows them, separately. Figure 5 shows how the proposed algorithm segments the object from the background. Figure 6 shows the contours of a natural image. The parameters used for this segmentation are SST $= 20\times10^6$, $\varepsilon = 1.0$, $\kappa = 5$, $\rho = 4$, $\mu = 0.04$ and $\eta = 0.8$. The number of segments obtained for these parameter values is nine. Figure 6a displays the

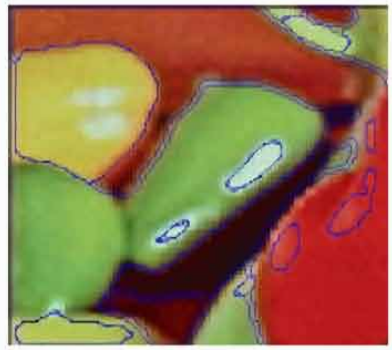

Fig. 3: Contours of all segments

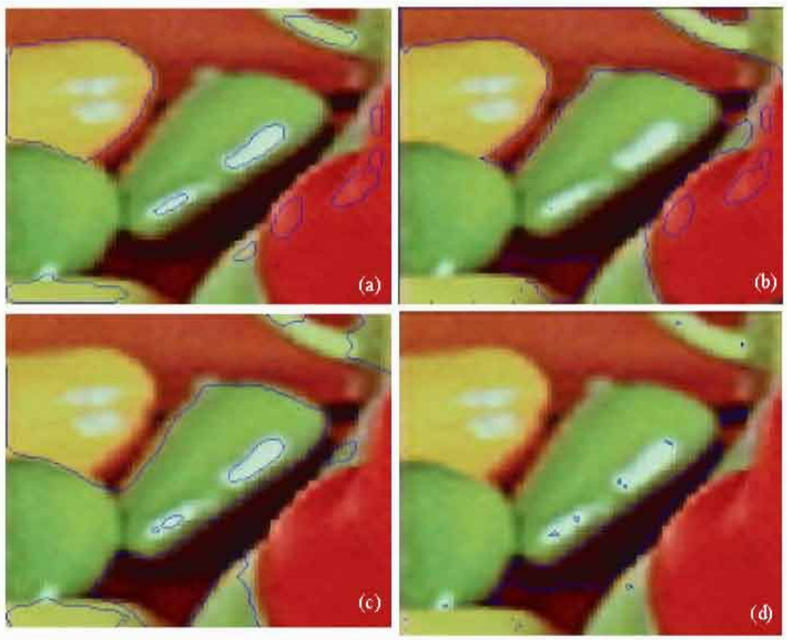

Fig. 4: Contours of each segment of pepper image

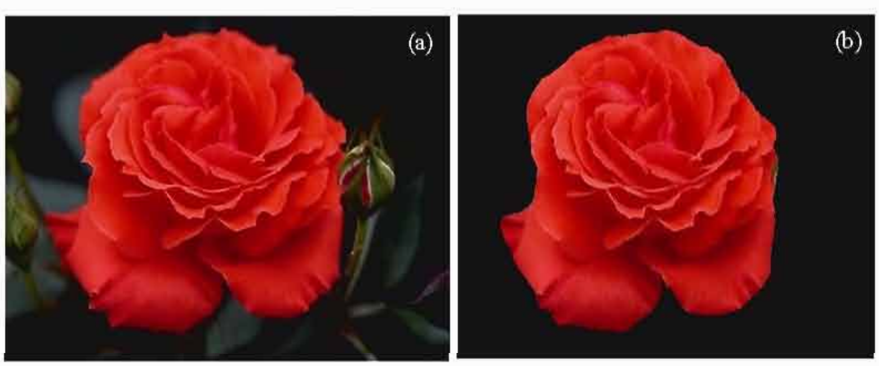

Fig. 5: The proposed method segments the flower from the background a) original image b) flower segment

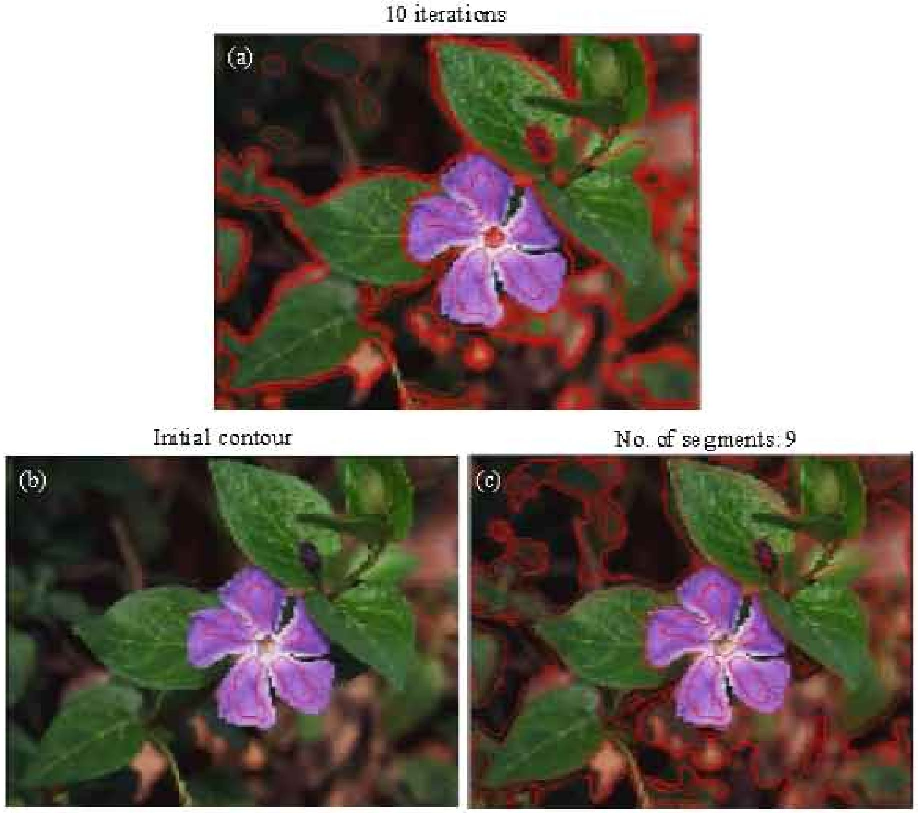

Fig. 6: a) Contours of segments at all levels, b) initial contour, c) contours of segments at leaf level

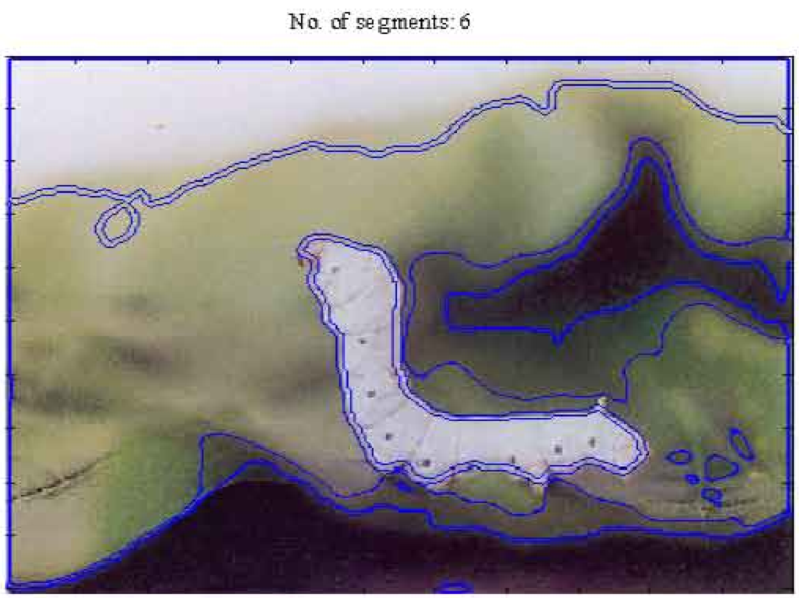

Fig. 7: Result of applying our algorithm to an agricultural image for segmenting the silkworm from a mulberry leaf

contours generated at all iterations. Figure 6 b shows the contour at level 1. Figure 6c shows the contours of the final segments (Fig. 7). We applied our algorithm to an agricultural image to segment the silkworm from a mulberry leaf. Silkworm was successfully segmented and it was used to measure the length and area of the silkworm. Figure 8 shows the contours of each segment when the SST = 15×10^{6}.

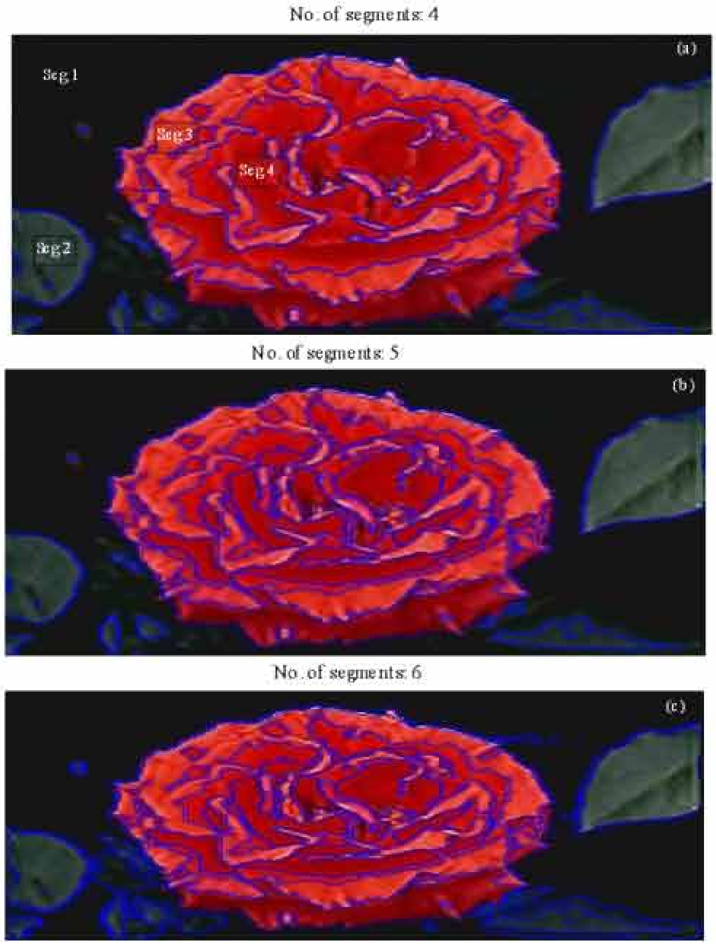

Fig. 8: Different number of segments obtained for different SST

CONCLUSION

In this study, we propose a novel region-based multiphase, multi-level active contour model for color image segmentation. The proposed method combines the Binary space partitioning tree and level set framework and efficiently utilizes the color information, therefore is robust, fast and is able to segment color images with same color and different intensity. The selection of sum of square error threshold plays a major role in our algorithm. Different number of segments are obtained by fixing different thresholds. We obtain 4 segments for the SST = 22×10^6, 5 segments for the SST = 16×10^6 and 6 segments for the SST = 11×10^6. To overcome the above problem some statistical image features can be used to fix the threshold.

Future research: Our future research will concentrate on adding the texture information in to the proposed model, so that it may be used for color texture segmentation. Also, like BSP tree method, the proposed algorithm can be used for color image compression and retrieval.

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