

Hybrid Image Segmentation Technique

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Abstract: *This paper deals with phase of designing a new approach of segmentation Global Region-based Model and Local Region-based Model. The brief description of proposed scheme is presented, followed by the design. The chapter begins with the introduction followed by discussion of experimental results. The proposed segmentation approach is detailed and followed by its evaluation and comparisons with some existing methods.*

Keywords: Hybrid Image Segmentation

I. INTRODUCTION

The approach used in this segmentation involves partitioning an image based on abrupt changes in intensity, such as edges. Edges in an image are assumed to represent object boundaries, and used to identify objects. Usually edges occur at the point of intersection of two regions with intensities which are varying. The traditional edge detection methods usually use Sobel, Robert and Prewitt edge detectors.

Another discontinuity-based approach involves use of deformable model. The curves or surfaces that deform under the influence of internal and external forces to delineate object boundary are deformable models. The internal forces preserve the shape smoothness and the external forces drive the model toward the desired region boundaries.

Some of the traditional edge detection methods are described in section 4.2 and deformable model based methods are described in section 4.3.

1.1 Traditional Edge Detection Method

Edge is a crucial part of an image matrix. Common types of edges in image are lines, steps and junctions. The edge, within a neighborhood of a grayscale image, splits up two regions with the gray level that is more or less uniform with different values on the two sides of the edge. It is considered as a local feature. 1D continuous domain edges include ramp, step, line and roof [Podder et. al., 2018]. There are many edge detection techniques such as Sobel, Canny and Prewitt etc. These edge detection methods as described in next section.

1.2 Sobel Edge Detection

An estimation of the image intensity function's gradient is used in Sobel operator to find the edge. Using the points with maximum derivative of the image intensity function, edges could be found easily. This operator is inexpensive in terms of computations because it is centered on the principle of image convolution with a separable and integer valued filter in both horizontal and vertical direction (Figure.4.1).

To magnify the differences among the points on the opposite side of a boundary and eliminate the smooth gray level changes in the pixels located on the same sides of a boundary, a 3×3 mask is used. The Sobel masks which magnify horizontal and vertical edges are G_x and G_y respectively.

$$\nabla f \equiv \text{grad}(f) = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

Magnitude of vector is given by following equation,

$$M(x, y) = \text{mag}(\nabla f) = \sqrt{G_x^2 + G_y^2}$$

The gradient vector directions are given by,

$$\alpha(x, y) = \tan^{-1} \left[\frac{G_y}{G_x} \right]$$

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * A; G_y = \begin{bmatrix} +1 & 2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * A$$

where * indicates the convolution symbol.

Step-1: Read the input image.

Step-2: The image matrix is converted to double.

Step-3: S_H mask in x direction and S_V mask in y direction are applied to compute $\nabla I(x, y)$.

$$\text{Mask Matrix are } S_H = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}; S_V = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

Step-4: $\text{mag}(\nabla I(x, y))$ is calculated.

Step-5: Without considering the border pixels, the edge detection procedure starts from the pixel (2, 2).

$$\text{Magnitude of vector, } I(p+1, q+1) = \sqrt{G_x^2 + G_y^2}$$

The Image I pixel position will be $I(2, 2)$ for $p=q=1$. Thus the borders are not considered. For $p = 1: \text{size}(A, 1) - 2$ and for $q = 1: \text{size}(A, 1) - 2$

The filter mask is 3×3 , so pixel matrix will be $I(3, 3)$. And normally it will be $I = (\text{size}(A, 1) - 2, \text{size}(A, 2) - 2)$. As a result, the borders are left.

Step-6: The Threshold value of image I has been calculated.

Step-7: The Sobel Edge detected image has been obtained.

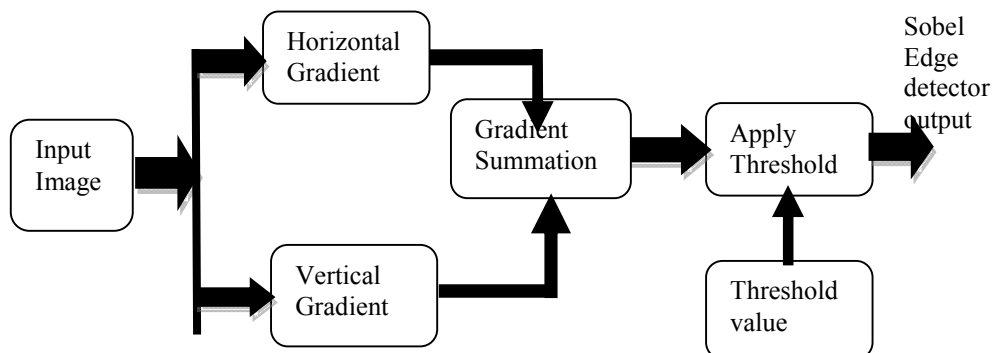


Figure: Sobel Edge Detection System

II. CANNY EDGE DETECTION

A directional alteration in the image intensity or corresponding color is an image gradient. The algorithm runs in different phases. Initially Gaussian filter is applied in order to eradicate noise. Gaussian filtering operators blur the image. In smoothing step, the fresh image is convolved with the filter function. After that the maximum magnitude value of image gradient is computed using step operator and the edges are marked. The operator simply searches for local maxima and indicates it as edges in non-maximum suppression phase. Then the double threshold system with hysteresis is applied to conclude potential edge. At the end of process, a black and white image is acquired where each pixel is indicated as either an edge pixel or a non-edge pixel.

1. Reading of the input image.
2. Input image is converted to gray scale.
3. Noise removal is done.
4. Gradient magnitude and angle are computed.
5. Performing Non-Maximum Suppression.

6. Applying Hysteresis Thresholding.
7. If t_{low} is higher than gradient magnitude value of the pixel (x, y) then the edge has to be discarded (Black Region).
8. If t_{low} is less than gradient magnitude value of the pixel (x, y) then the edge should be kept. (White Region)
9. If pixel (x, y) has gradient magnitude between lower and higher threshold & any of its neighbors situated in a 3×3 region have gradient magnitudes greater than higher threshold, the edge has to be kept (write out white).
10. If at least one neighboring pixel (x, y) having high gradient magnitudes falls between lower and higher threshold, the 5×5 region must be searched to see if any of these pixels have a magnitude greater than higher threshold value. If so, the edge has to be kept (write out white) else, the edge has to be discarded (write out black).

III. PREWITT EDGE DETECTION

It is a discontinuous differentiation operator which computes an approximation of the image intensity gradient function. The outcome of the Prewitt operator is the corresponding gradient vector or the normalization of this vector at each point in the grayscale image.

Prewitt operator uses two 3×3 kernels (Small convolution matrix). These kernels convolve with the original image to calculate estimates of the derivatives for horizontal and vertical direction changes. Consider input image I and H_x and H_y are two images which at each point contain the horizontal and vertical derivative approximations. The computations are as follows:

$$H_x = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} * I; H_y = \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} * I$$

Prewitt operator works satisfactorily with Poisson noise distorted digital image and have low computational cost whereas its performance decreases with other type of noise.

Result from the edge detection method cannot be used as a result of segmentation. All the edges are detected by these edge detectors. So, it is very difficult to find the relation between the edges and the region of interest. Edges are required to be merged into edge chains to improve borders in the image. These techniques work very well only on images with high-quality disparity between different regions. In addition, these methods are noise sensitive [Podder et. al., 2018].

3.1 Deformable Model

It is another discontinuity-based approach. The ability to directly generate closed parametric curves or surfaces from images and incorporation of a smoothness constraint providing robustness to noise and spurious edges, are the main advantages of these models. Two general classes of deformable models depending on way of evolution are (1) the parametric deformable models or active contours or snakes, and (2) the geometric or implicit models or level set. The parametric model uses explicit representation based on Lagrange formulation. The geometric deformable model represents the contour implicitly and evolves according to the Euler formulation based on the theory of surface evolution and geometric flows [Wang et. al., 2010].

Parameterized models are based on assumption that the prior object boundary information is available, which is not true in reality. So, these models are initialization sensitive and fail to converge to concavities. In Non-parameterized models, object boundary detection is based on image gradient and is affected by noise and weak edges. Initialization sensitivity of these models is less compared to parametric ones.

The active contour models can be categorized into edge-based and region-based models. Edge-based active contour models rely on the local edge information for curve evolution whereas region-based active contour models rely on statistical information of region.

The segmentation precision of edge-based methods is often higher than that of region-based methods since it allows the user to mark the boundary directly.

Region-based active contours model relies on an energy minimization approach to stop the evolution of the curve rather than using an edge-stopping function. Region-based models typically aim to identify region of interest by using a region

descriptor, such as intensity, color, texture or motion, to guide the motion of the contour instead of utilizing an image gradient. So performance of region-based models is better in the presence of image noise and weak object boundaries than edge-based model.

Edge-based active contour models utilize image gradients in order to identify object boundaries and are usually sensitive to noise and weak edges. Region-based ACMs have many advantages over edge-based ones. Initially, region-based models utilize the statistical information inside and outside the contour to control the evolution. These models are less sensitive to noise and location of initial contour, further more they can efficiently detect the exterior and interior boundaries simultaneously [Reddy et. al., 2011].

3.2 Active Contour/Snakes

It is a top-down approach. An early implementation of active contours is called Snakes. Active contour methods allow iterative deformation of contour to partition an image into various regions. In active contour models, prior knowledge such as shape and intensity distribution can be easily incorporated for robust image segmentation. They can be readily used for shape analysis, recognition applications, regional tracking, edge detection, object classification and motion tracking since they provide smooth and closed contours as segmentation results. They reduce human intervention in the task of segmentation. Energy functional F which is associated with closed contour curve is minimized to evolve curve toward the object boundary [Tong-yao, 2011].

They are visually represented as closed contours (like an irregular balloon or bubble). We may have open (like a length of string) snakes. Here, energy is dependent upon contours shape and location within an image. Local energy minima represent the corresponding image properties [Fan et. al., 2012].

Snake model shows improved reliability and accuracy of contour extraction compared to conventional moving target detection algorithm. It uses local and global information to achieve the objectives of the exact location of the border.

A traditional parametric active contour (or snake) is a curve $P(s) = [x(s), y(s)]$, $s \in [0, 1]$, which moves through the spatial domain of an image to minimize the energy functional [Chen et. al., 2010]. In this method, the boundary of an object in an image is surrounded by closed curve which deforms under the influence of internal forces, external constraint forces. The energy function of snakes is:

$$E_{\text{snake}} = \int_0^1 E_{\text{snake}}(P_s) ds = \int_0^1 E_{\text{int}}(P_s) + E_{\text{ext}}(P_s) ds$$

Internal energy is expressed as:

$$E_{\text{int}} = \frac{1}{2} (\alpha_s |P'(s)|^2 + \beta |P''(s)|^2)$$

$P'(s)$ and $P''(s)$ express the first and second derivatives about P_s ; α, β respectively express the elastic force and bending forces weights, they determine degree of extension and bending.

The external energy E_{ext} is derived from the image data such as boundaries. The external energy component attaches the curve to edges, lines. The external force for gray-value image I is $E_{\text{ext}} = -| \nabla G_{\sigma} \otimes I |$ where G_{σ} is the Gaussian kernel of standard deviation σ and \otimes denotes convolution.

Snakes are not capable of handling topological changes. Also, they have small capture range because of quick reduction in external forces during evolution. Snakes are sensitive to noise. In snakes, initial contour must be specified before the curve evolution can begin, and the resulting boundary is dependent on this selection. So to overcome these drawbacks, variations of the parametric active contour method by using edge-based or region-based external forces to handle topological changes or shape-based prior knowledge to avoid spurious edges have been proposed [Goceri et. al., 2012].

An effective external force for active contours is Gradient vector flow (GVF), but its isotropic nature handicaps its performance. NGVF model is anisotropic but is sensitive to noise and could erase weak boundaries. A novel external force called adaptively normal biased gradient vector flow (ANBGVF) for active contours can preserve weak edges and smooth out noise while maintaining other desirable properties of GVF and NBGVF, such as enlarged capture range, initialization insensitivity and good convergence at concavities [Zhao and Liu, 2011].

Gradient vector flow snakes, geodesic active contours improve robustness and stability of snakes but these methods still have the problem of converging at local minima [Artan et. al., 2011].

IV. IMPLEMENTATION SCREENSHOTS

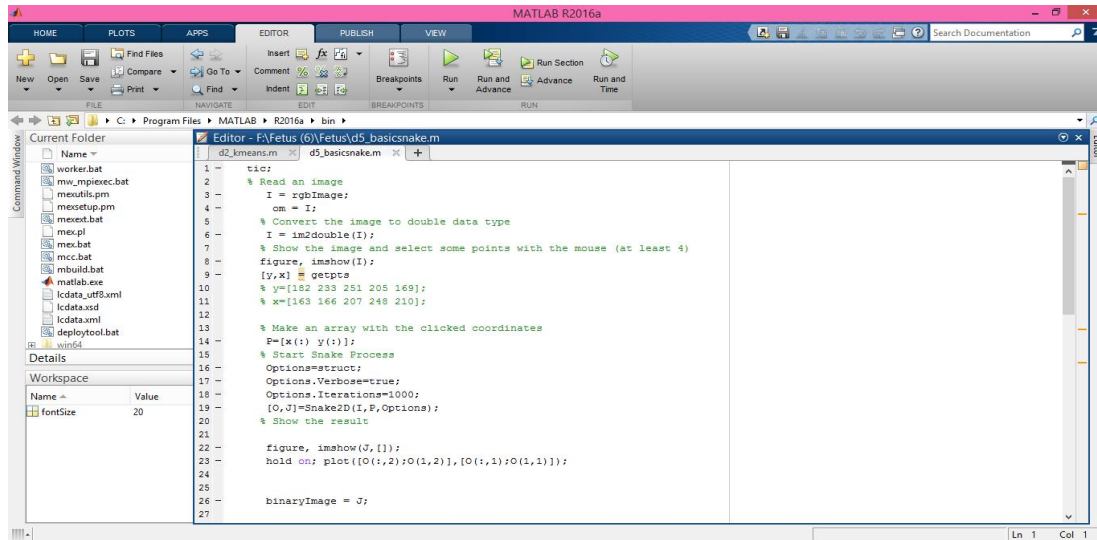


Figure: Screenshot for Module Implementation of Basic Snake

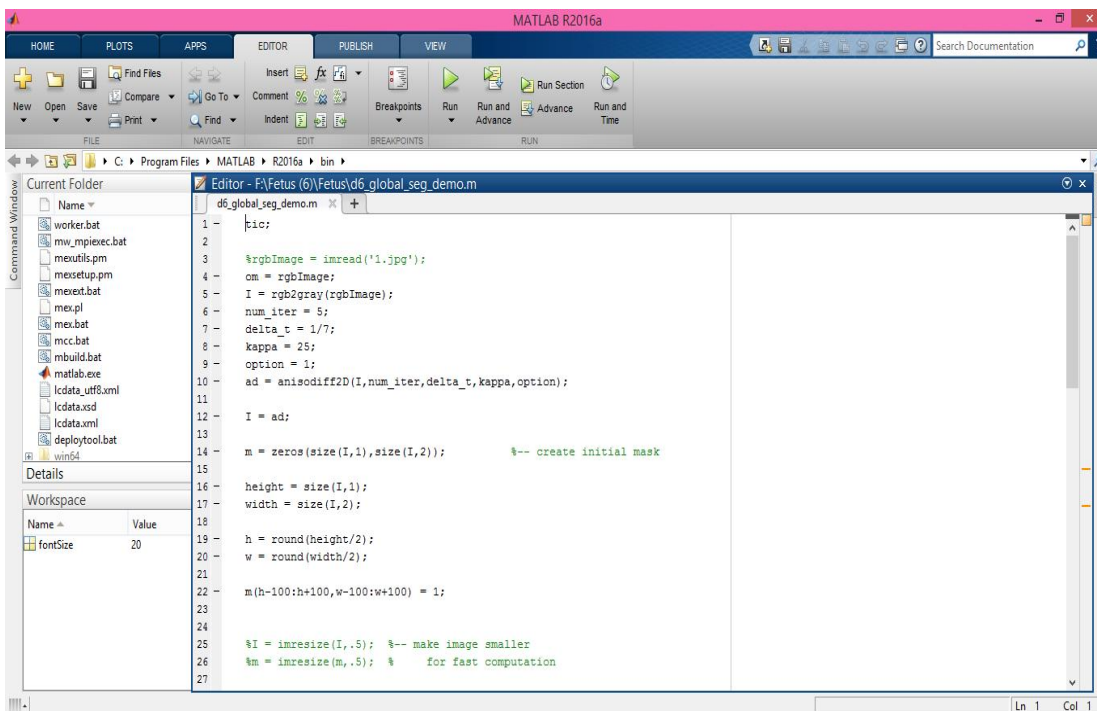


Figure: Screenshot for Module Implementation of Existing Global Method

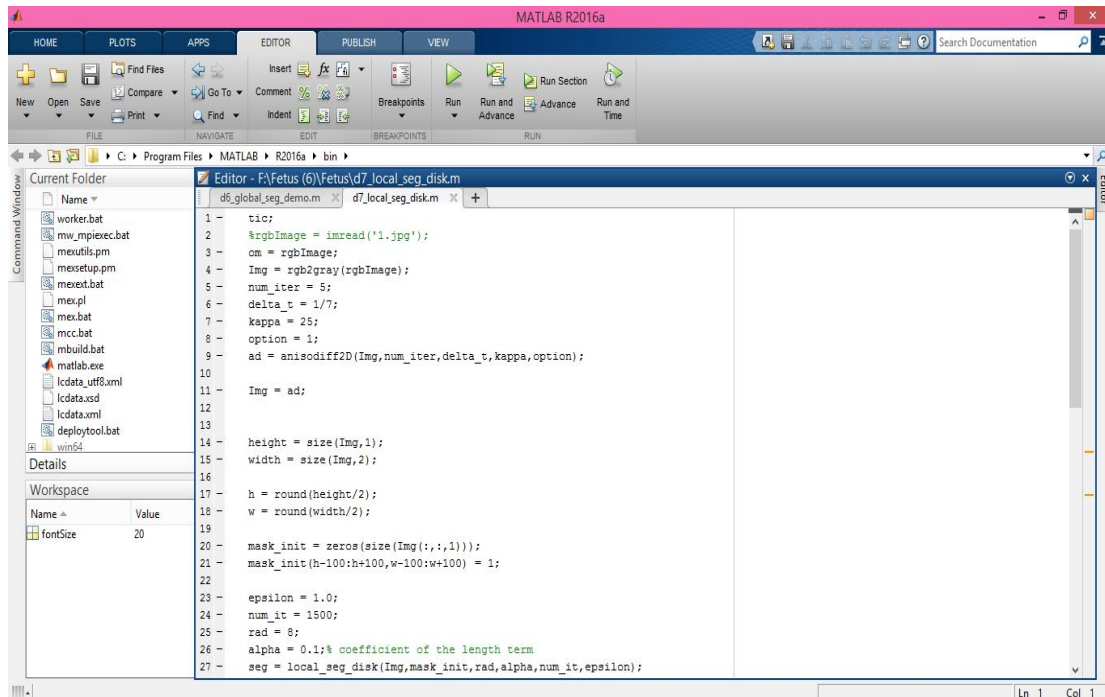


Figure: Screenshot for Module Implementation of Existing Local Method

V. SUMMARY AND DISCUSSION

The proposed algorithm for global region-based and local region-based approach are described and concluded as:

- Testing results for existing and proposed global region-based and local region-based algorithms will be calculated and compared.
- Testing results shows that proposed global region-based and local region-based algorithms performs well on different images.
- Evaluated values of Structural Similarity, Correlation, Mean Square Error, Peak Signal to Noise Ratio, Dice Similarity Coefficient and Jaccard Similarity Coefficient are compared for different images and found to be related with improved accuracy for existing and proposed methods.
- Detailed analysis is done on different images to find out how proposed technique worked to produce optimal results.

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