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Segmentation of Satellite and Medical Imagery using Homomorphic Filtering based Level Set Evolution

Kama Ramudu[1], Azmeera Srinivas[2] and Tummala Ranga Babu[1]

[1]Department of Electronics and Communication Engineering, Acharya Nagarjuna University, Guntur – 522510, India; ramudukama@gmail.com, drtrb@rediffmail.com
[2]Kakatiya Institute of Technology and Science, Warangal – 506015, India; srinivas_azmeera@yahoo.com

Abstract

Objectives: The objective of this paper is to detection of the tissues and tumors, from medical images and oil spill regions and cloud regions from SAR Images respectively. **Methods/Statistical Analysis:** A novel region- based segmentation method for satellite and medical imagery using Homomorphic Filtering based Level Set Evolution (HLSE) approach. In real world images intensity inhomogeneity occurs, Segmentation of such images is a considerable challenge in image processing. Region based segmentation algorithms are widely used for intensity homogeneity of the Region of Interest (ROI). These images are still a tedious task and cumbersome due to weak contrast and poor resolution of images etc. The automatic segmentation of such images is very difficult. The main reason is a large amount of inhomogeneity present in the background and foreground of real world image. The conventional methods like C-V model and Distance Regularized Level Set (DRLS) method lead to getting improper segmentation with unconvinced results. **Finding:** We proposed an efficient segmentation method on satellite and medical using Homomorphic Filtering based Level Set Evolution (HLSE) approach. In the pre-processing step, we extract the illumination and reflectance components from the original image with the help of homomorphic decomposition process. Later, in the post- processing step, the illumination and reflectance images are applied to the level set model for accurate and robust segmentation. **Improvements/Applications:** The proposed segmentation results are effectiveness, superior and accurate compared to conventional methods. This new approach is very helpful for detection of the white matter and gray matter, cancerous cells in brain and bone in medical images. Similarly for SAR images detection of the oil slick, cloud regions etc.

Keywords: Biomedical Images, K-means Clustering, Level Sets and Image Segmentation, SAR Images

1. Introduction

Medical and satellite imaging are one of the fields in applied science. In medical image processing, there are a number of challenging problems such as image restoration and enhancement, accurate and automatic segmentation of a region of interest; image features classifications, quantitative measurement of image features, in clinical sector development of integrated systems[1,2]. NASA developed a long-term earth observatory for observing environment changes in land surfaces, atmosphere, biosphere, water bodies and ocean of the earth. The cyclone, oil spills, fire etc are the earth observation images. Each image shows the details of the area affected or covered under it. The Study and analysis of such images are tedious tasks including the Image enhancement, segmentation, description, and image representation etc. In this paper, our work is mainly focusing on oil spills segmentation of ocean SAR images. Image segmentation based on Level set algorithms can be classified into two categories. The First category based on edge-based segmentation and the second category is the segmentation based on regions in the images called region segmentation. In the first category mostly preferred, edge detection method is Geodesic Active Contour (GAC) model for efficient detection of edges in the image. The GAC method extracts edges in

**Author for correspondence*

the image, the contour locks around the boundaries of the object by utilizing the gradient operator to obtain the of Edge Stopping Function (ESF)[3-5].

The proposed method is a region-based segmentation implementing in two steps: Fist step it utilizes the homomorphic filtering in the preprocessing. This filter is to separate the illumination component and reflectance components from the original image. All the real world images like medical and satellite images suffer from low or poor resolution, low contrast, and large inhomogeneities in the image. Illumination and reflectance of the object vary based on the different environment conditions. It is not possible to segment the regions of objects in the presence of inhomogeneity intensities. So we need to cluster the inhomogeneities into homogeneous intensity regions based on the clustering techniques. The Second step in the post- processing of our model is to derive the energy formulation based on illumination and reflectance components. Finally, the segmentation results are obtained by minimizing the above -said energy formulation in the presence of illumination and reflectance components respectively.

This paper is organized as follows. In Section 2 is described the homomorphic filtering process. The brief explanation of the proposed levels set model in Section 3. Similarly in Section 4 and 5 are the Experimental results with discussions on biomedical and satellite images and conclusion respectively.

2. Homomorphic Filtering Process

The light from a source illuminates the object and its reflections from the object are captured by sensors to form an image. Thus the image I(x,y) is considered as the product of the illumination component A(x,y) and Reflection component R(x,y). The low-frequency component in the image represents the illumination and the high-frequency components associated with the reflection of the object.

The purpose of the homomorphic filtering process is to decompose the quantities of illumination and reflection components. More control the above components apply two different transfer functions. Suppose to enhance the high- frequency components of the original image simultaneously to reduce the low-frequency components associated with the illumination component. The original image I(x,y) can be represented in terms of illumination component A(x,y) and Reflection component R(x,y) as follows

$$I(x,y) = A(x,y)XR(x,y) \qquad (1)$$

Now the problem is to separate these two components with the help of Fourier transform. The problem with the Fourier transform is that

FT (XxY) ≠FT(X) +FT(Y) (2)

Here FT stands for Fourier Transform.

However

FT(X+Y) = FT(X) + FT(Y) (3)

So we make the multiplication into addition with the help of logarithmic transform on both sides of equation (5).

The procedure of the homomorphic filtering process is to separate the illumination and reflectance components as follows.

Step 1: Take the original Image I(x,y)

Step 2: Apply log transformation on both sides of the equation (1).

These results in

$$\ln(I(x,y) = \ln(A(x,y)) + \ln(R(x,y)) \qquad (4)$$

Step 3: Taking Fourier transform of equation (4)

Step4: Design filters separately for the illumination component and reflectance component. The transfer functions of the filters can be different for the two components.

Step 5: Apply inverse Fourier transforms to get the filtered image.

Step 6: apply an anti-log function to get the original image.

3. Proposed Method

In this section, we implementing the homomorphic filtering process with level set model for accurate and faster segmentation results. This proposed algorithm demonstrated on biomedical and satellite images. The proposed homomorphic filtering using level set model is described in the following steps:

3.1 Implementing Homomorphic Filtering using Level Set Model

3.1.1 Energy Formulation based on Homogeneous Intensity Clustering

Each region to be segmented based on the region of interest, the widely used method for segmenting the regions in the image based on region-based segmentation method. The intensities in the regions to be segmented with Gaussian distribution or intensity mean. The intensity mean calculations are difficult for ROI in the intensity inhomogeneities. The intensity inhomogeneities are overlapped the intensities present in the regions. Based on the nonuniform pixel intensities, it is impossible to segmentation of these regions directly. The properties of the homogeneous intensities are very simple. Image segmentation of our proposed level set model effectively utilizes the property of local intensity clustering with illumination and reflectance components.

The intensities in the neighborhood N can be classified into C clusters with K_i centers, i=1,2……C based on the Homogeneous Intensity clustering property. The homogeneous intensity clustering utilizes the standard K-Means clustering. To minimize the clustering criterion, the K-means clustering can be written as

$$F = \sum_{i=1}^{C} \int_{N} \left| A(x,y) - K_i \right|^2 u_i(x) dx \tag{5}$$

Where C is the clusters, A(x,y) is the illumination image, K_i is the cluster center for ith cluster and u_i is the Membership Function (MF) in the region Ω_i. The region to determine based on the property of membership function i.e $u_i(x) = 1$ for X∊ Ω_i and $u_i(x) = 0$ for otherwise. Equation (5) can be rewritten as after satisfying the property of membership function is

$$F = \sum_{i=1}^{C} \int_{\Omega i \cap N} \left| A(x,y) - K_i \right|^2 dx \tag{6}$$

Classifying the intensities, we defined the clustering criterion in equation (5) as follows

$$E_y = \sum_{i=1}^{C} \int_{\Omega i \cap N} K(y-x) \left| A(x,y) - K_i \right|^2 dx \tag{7}$$

Here introduce $K(y-x)$ in the clustering criterion as nonnegative Gaussian function called kernel function. This function holds the two properties $K(y-x)$ =0 for $x \notin N$

With the Gaussian window function in equation (16) can be rewritten as the clustering criterion as follows

$$E_y = \sum_{i=1}^{C} \int_{\Omega i} K(y-x) \left| A(x,y) - K_i \right|^2 dx \tag{8}$$

This clustering criterion is for homogeneous intensities as a basic element in energy formulation of our proposed level set model.

We need to minimize the equation (8) by considering the integration with respect to 'y' of E_y in the image domain Ω. We define the energy function after minimizing as follows

$$E = \int \left(\sum_{i=1}^{C} \int_{\Omega i} K(y-x) \left| A(x,y) - K_i \right|^2 dx \right) dy. \tag{9}$$

The kernel function K can be considered as the uniform function, it can be defined as K(x) = a for $|x| \le \rho$ and K(x) =0 for otherwise. 'a' is a positive constant, in this paper we considered the uniform Gaussian function, it is defined as

$$K(x) = \begin{cases} \frac{1}{a} e^{\frac{-|x|^2}{2\sigma^2}}, for |x| \le \rho \\ 0, otherwise \end{cases} \tag{10}$$

3.1.2 Energy Minimization using Level Set Evolution

In equation (13), we proposed the energy term for the homogeneous intensity clustering is in terms of the regions $\Omega_{1,} .... \Omega_C$. From equation (13) it is very difficult to get the solution to the energy minimization problem. So we considered in this section, the energy formulation derived in equation (13) is converted into a level set formulation. Which has the regions are disjoint with a number of level set functions. This LSF utilizes the regularization term; with the help of well-known variational level set models for minimizing the energy function[6-8.]

An LSF can be extracted from the level set methods, which has taken the positive and negative signs. These are used to represent two disjoint regions $\Omega_{1,}$ and $\Omega_{2,}$ in the image domain. Let $\phi : \Omega \to R$ be a LSF, the signs of the LSF can be defined as two disjoint regions as follows.

$\Omega_1 = \{u : \phi(u) > 0\}$ And $\Omega_2 = \{u : \phi(u) < 0\}$ (11)

Suppose for the C>2, we consider two or more LSF's to represent C regions $\Omega_{1,} .... \Omega_C$ .In the case of C=2 in the energy formulation in the Level Set Function (LSF) is called Two-Phase Level Set Model (TLSE). Similarly, if C>2 are called Multiphase Level Set Model (MLSE)[9,10.]

In this paper, we implementing two-phase level set evolution in the presence of illumination component and reflectance component. In equation (15) Level Set Function (LSF) ϕ is to represent two disjoint regions $\Omega_{1,}$ and $\Omega_{2,}$. The membership functions can be defined in the two-phase level set model for the two disjoint regions $\Omega_{1,}$ and $\Omega_{2,}$ are $z_1(\phi) = H(\phi)$ and $z_2(\phi) = (1 - H(\phi))$ respectively. Where 'H' is the Heaviside function. So finally, the energy formulation in equation (18) can be converted into the level set formulation with C=2 as following

$$E = \int (\sum_{i=1}^{C} \int_{\Omega i} K(y-x)\left|A(x,y) - K_i\right|^2 z_i(\phi(x))dx)dy \quad (12)$$

Equation (12) can be rewritten as by changing the order of integration as following

$$E = \int (\sum_{i=1}^{C} (\int_{\Omega i} K(y-x)\left|A(x,y) - K_i\right|^2 dy) z_i(\phi(x))dx \quad (13)$$

Equation (13) is final Energy level set formulation, which is in terms of ϕ and K can be denoted as E(ϕ ,K). From equation (13), we can rewrite the energy formula of LSF in the following formula

$$E(\phi, K) = \int \sum_{i=1}^{C} E_i(x) z_i(\phi(x))dx \quad (14)$$

Where $E_i(x)$ is the function denoted by the following Energy formulation of illumination component is

$$E_i(x) = \int K(y-x)\left|A(x,y) - K_i\right|^2 dy \quad (15)$$

Similarly, the energy formulation of the reflectance component is as following

$$E_i(x) = \int K(y-x)\left|R(x,y) - K_i\right|^2 dy \quad (16)$$

The proposed LSE model utilized the Equation (14) as the data term. The new energy formulation of the proposed model as

$$F(\phi, K) = E(\phi, K) + vL(\phi) + \mu R(\phi) \quad (17)$$

Here $L(\phi)$ and $R(\phi)$ are regularization terms in the final level set function can be defined as

$$L(\phi) = \int \left|\nabla H(\phi)\right| dx \quad (18)$$

The regularization term $L(\phi)$ is used to compute the arc length of the zero level contour of ϕ .it serves as smooth the contour.

Theothertermisdefinedasthe $R_p(\phi) = \int p(\left|\nabla(\phi)\right|)dx$ with energy density function $p:[0,\infty) \to R$ such that p(s)≥p(1) for all 's' i.e S=1 is the minimum value of 'P'. The energy density function 'p', the energy regularized term $R_p(\phi)$ is minimized by satisfying the property $\left|\nabla\phi\right| = 1$, this property called signed distance property and the energy term is called distance regularization term. This term is introduced by the chuming Li, more general variational LSE is called Distance Regularized LSE (DRLSE)[11].

We obtain the segmentation results by the level set evolution by minimizing the equation (20). Finally equation (20) can be minimized with respect to ϕ . The standard gradient descent model is called Gradient Vector Flow (GVF) is used to minimize the above energy function with respect to ϕ is as follows

$$\frac{\partial\phi}{\partial t} = -\frac{\partial F}{\partial\phi} \quad (19)$$

After simplified the above equation using equation (15&16), the final corresponding GVF equation is called final level equation in the presence of illumination component as following

$$\frac{\partial\phi}{\partial t} = -\delta(\phi)(E_1 - E_2) + v\delta(\phi) div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) + \mu\, div(d_p(|\nabla\phi|)\nabla\phi) \quad (20)$$

Here ∇ is the gradient operator, div (.) is the divergence operator and the function d_p is defined as

$$d_p = \frac{p'(s)}{s}$$

4. Simulation Results and Discussion

Implementation of suggested algorithm is performed on four unique medical and satellite images for segmenting of bone tissues and oil spills regions respectively. The proposed results are analyzed and compared with the C-V[12] active contour model and DRLS as shown in

Figures 1, 2, 3 and 4. The proposed segmentation results are accurate and faster based on the following parameters i.e tuning parameter, iterations and CPU time.

Our proposed level set method segmenting these regions accurately and effectively when compared with conventional methods as shown in Figures 1, 2, 3 and 4. The database of medical images are taken from web simulated database[13] and SAR oil spill images taken from the NASA database. These images were rescaled to 256x256 for contour evolution of the both proposed and conventional methods for preprocessed images.

In Figures 1, 2, 3 and 4 are the experimental results of proposed as well as the conventional methods. In Figure 1a, 2a, 3a and 4a are original medical and SAR images respectively. In Figures 1b, 2b, 3b and 4b are the illumination image. Figures 1c, 2c, 3c, and 4c are the reflectance estimated images and 1d, e, 2d, e, 3d, e and 4d, e are segmentation results with C-V and DRLSE model respectively. These models fail to detect the proper edges, regions and boundaries of images for the evolution of the level set contour C. Because these models, the contour curve evolution is a one-way approach with inherent limitations of edge based model and it is sensitive to the level curve. In Figures, 1f, g, 2f, g, 3f, g and 4f, g are the proposed level set segmentation based on the illumination and reflectance images respectively and 1h, 2h, 3h and 4h depicts the final segmentation regions respectively.

In Table 1 and 2, the proposed model is faster, accurate and superior for detection of tissues and oil spills in medical and SAR images respectively. All the experimentation is done on MATLAB R2014a 32b in Windows 10 OS with Intel(R) dual Core(TM) 32bit processor, CPU @ 1.80 GHz, 2 GB RAM. The CPU time is recorded for all the algorithms are tabulated in Table 2 and 3.

4.1 Setting Parameters

In our experiment, for best results we assumed the following parameters: In C-V model we consider the time step $\Delta t = 4$, controlling parameters $\mu = 0.2$, $v = 0$, and $\lambda 1 = \lambda 2 = 1$. For DRLSE model, the time step $\Delta t = 5$, penalty term coefficient $\mu = 0.04$, contour length coefficient $\lambda = 5$, and $\alpha = -3$ and The proposed level set model utilized the following parameters i.e $\Delta t = 0.1$, sigma=1and mue=0.5 respectively.

We use the level set contour of positive values and negative values of zero level curves are inside and outside the contour respectively for CV and the proposed model, In DRLSE model, the signs of the level set curves are negative inside and positive outside the zero level contour and sensitive to noise. Denoising process is not performed in proposed and CV models and these are robust to noise

Table 1. Comparative analysis of conventional methods

Images C-V model DRLSE model			
iterations	**evolution time (s)**	**iterations**	**evolution time (s)**
Image1 100	52.3142s	200	65.2067s
Image2 100	47.2987s	200	63.1065s
Image3 100	50.4006s	200	76.2006s
Image4 100	45.2067s	200	55.5609s

Table 2. Comparative statement for CPU time and number of iterations of proposed level set model

Images Proposed Homomorphic filtering based Level Set Model

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iterations evolution time

Illumination Reflectance Illumination Reflectance

Image1 50 25 43.9576s 31.0981s

Image2 35 30 38.9860s 37.3065s

Image3 25 30 42.3904s 31.8299s

Image4 26 26 34.0006s 32.2890s

Table 1 and 2 are the performance analysis of conventional and proposed methods in terms of the number of iterations and CPU respectively. Table 2 values shoes proposed LSF evolution with less number of iterations over the conventional models values shows in table 1. It means that proposed model accurately segments regions of tissues and oil spills in medical and satellite images respectively.

The conventional models are C-V and DRLSE, these models takes a longer time to segment the regions but it fails to detect the boundaries and edges in the image and the proposed level set model in the presence of illumina-

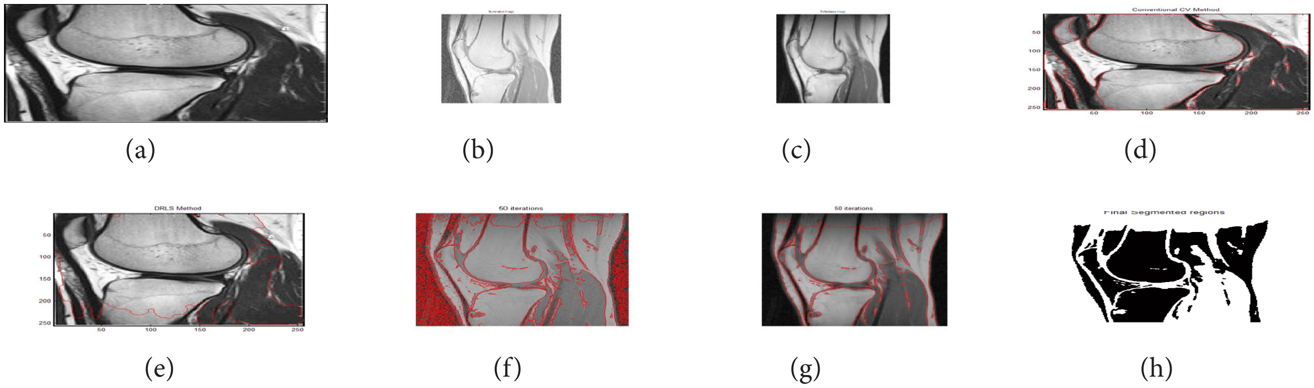


Figure 1. Experimental results with conventional methods and proposed algorithms: (a) is the original knee image with 256x256 (b) is the illumination estimated image, (c) is the reflectance image, (d) represents the segmentation results using conventional C-V[12] model, (e) is the segmentation results with DRLS model[11], (f) and (g) are the proposed level segmentation results in the presence of illumination and reflectance component respectively, (h) depicts the final segmented regions with proposed level set method.

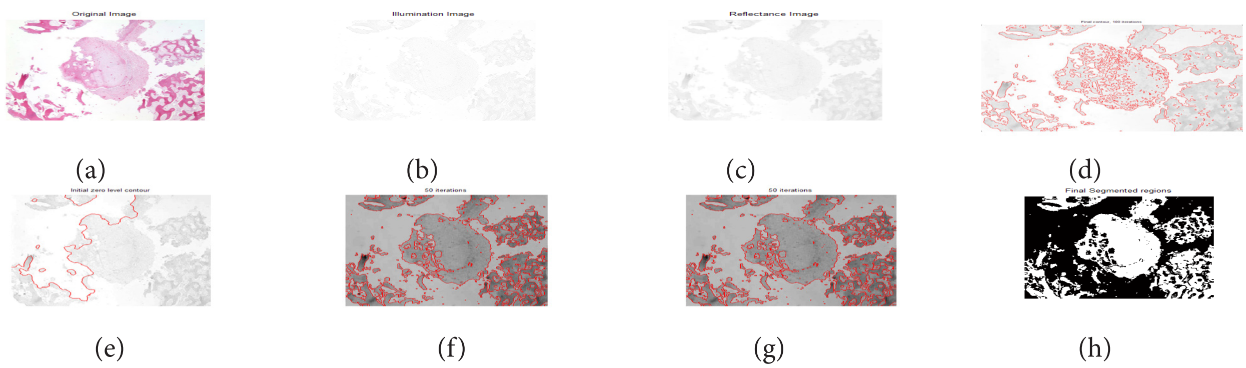


Figure 2. Experimental results with conventional methods and proposed algorithms: (a) is the original Bone sarcoma tissue image with 256x256 (b) is the illumination estimated image, (c) is the reflectance image, (d) represents the segmentation results using conventional C-V[12] model, (e) is the segmentation results with DRLS model[11], (f) and (g) are the proposed level segmentation results in the presence of illumination and reflectance component respectively, (h) depicts the final segmented regions with proposed level set method.

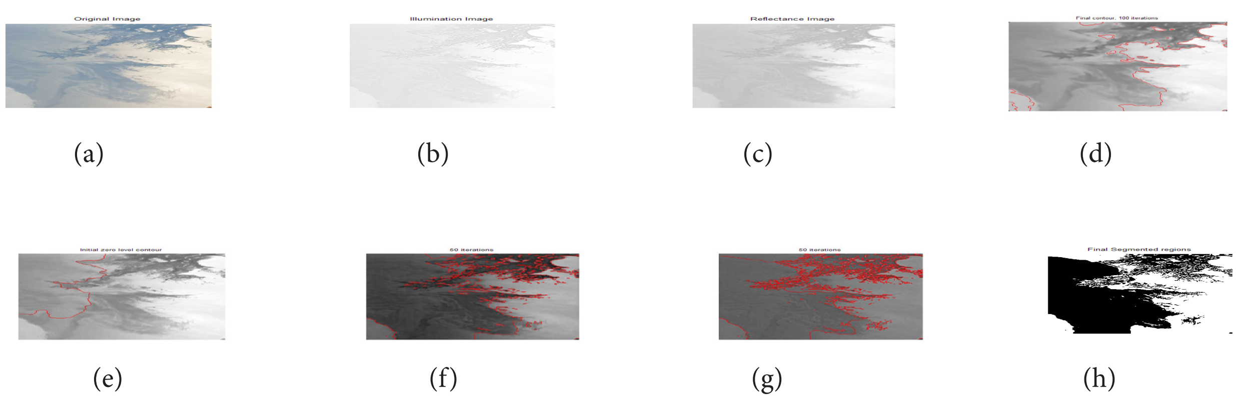
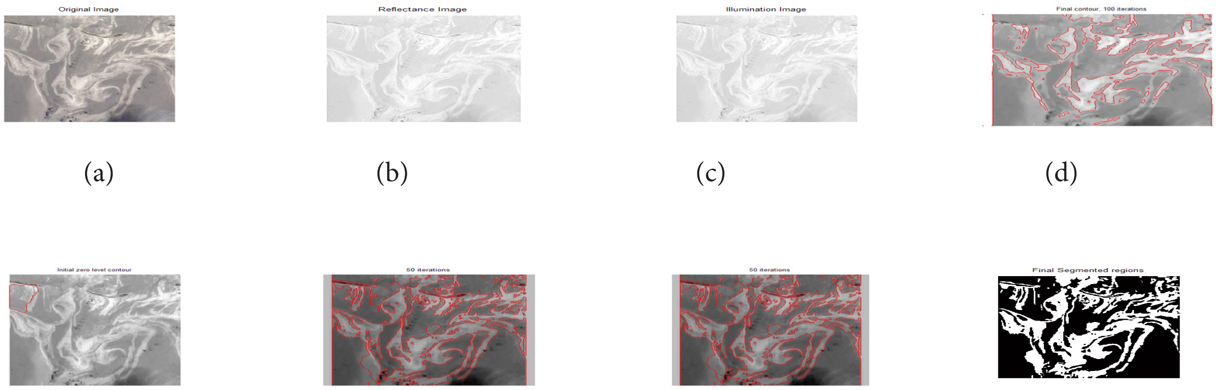


Figure 3. Experimental results with conventional methods and proposed algorithms: (a) is the original Cloud image with 256x256 (b) is the illumination estimated image, (c) is the reflectance image, (d) represents the segmentation results using conventional C-V[12] model, (e) is the segmentation results with DRLS model[11], (f) and (g) are the proposed level segmentation results in the presence of illumination and reflectance component respectively, (h) depicts the final segmented regions with proposed level set method.



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 4. Experimental results with conventional methods and proposed algorithms: (a) is the original oil spill SAR image with 256x256 (b) is the illumination estimated image, (c) is the reflectance image, (d) represents the segmentation results using conventional C-V[12] model, (e) is the segmentation results with DRLS model[11], (f) and (g) are the proposed level segmentation results in the presence of illumination and reflectance component respectively, (h) depicts the final segmented regions with proposed level set method.

tion. The proposed model requires the small amount of time to detect the regions compared with other models.

5. Conclusion

We presented an improved level set segmentation algorithm based on homomorphic filtering process. The proposed Homomorphic Filtering with Level Set Evolution (HLSE) done in two steps: the first step is homomorphic filtering is to separate the illumination and reflectance with the help of log and fourier transforms. Due to the intensity inhomogeneities present in the real time images are medical and SAR images. It is impossible to detect the regions in the inhomogenetics. In this paper, we proposed homogeneous intensity clustering approach for homogeneous regions. The second step, we implementing the energy formulation derived inhomogeneous intensity clustering is converted into the energy formulation in variational LSE with the help of gradient vector flow equation in the presence of illumination and reflectance. The derived level set energy function is minimized with respect to level set function. This algorithm was tested on real world biomedical and SAR images for detection tissues and oil spills in sea waves. The experimental results of our proposed model are faster, accurate and superior to the conventional methods.

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