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A Region Based Method for Bias Correction of Images in Relating to Intensity Inhomogeneity in MRI

Padmavathi C

Assistant Professor,
Electronics and communication Department, SALITER, Ahmedabad
Padmavathi_c87@yahoo.com

Abstract— **Intensity irregularity may be a sizeable challenge in image segmentation. The foremost wide used image segmentation algorithms are square measure region-based and usually deem the homogeneity of the image intensities within the regions of interest, which frequently fail to supply correct segmentation results thanks to the intensity irregularity. This paper proposes a completely unique region-based technique for image segmentation that is ready to affect intensity in homogeneities within the segmentation. First, supported the model of pictures with intensity in homogeneities, we have a tendency to derive an area intensity agglomeration property of the image intensities, and outline an area agglomeration criterion perform for the image intensities in an exceedingly neighborhood of every purpose. Snake rule is meant to be interactive, therein it detects on wherever regarding the boundaries square measure, so snake's square measure want to minimize the energy and then trace the contour or boundary. Therefore, by minimizing this energy, snake rule is ready to at the same time phase the image and estimate the bias field, and therefore the calculable bias field will be used for intensity irregularity correction or Bias correction. Our technique has been valid on artificial pictures and real pictures of varied modalities, with fascinating performance in presence of intensity in homogeneities.**

Keywords-Image segmentation, snake rule, bias correction, intensity irregularity, MRI.

I. Introduction

Diagnostic imaging is a useful tool in medication nowadays. Resonance imaging (MRI), computerized axial tomography (CT), digital diagnostic procedure, and alternative imaging modalities offer an efficient means that for noninvasively mapping the anatomy of a subject matter. These technologies have greatly hyperbolic information of traditional and pathologic anatomy for medical analysis and square measure a important element in designation and treatment designing. With the increasing size and variety of medical pictures, the employment of computers in facilitating their process and analysis has become necessary. The image segmentation algorithms, play an important role in various medical specialty imaging applications like the quantification of tissue volumes, diagnosis, localization of pathology, study of body part, treatment designing, partial volume correction of useful imaging information and laptop integrated surgery.

Intensity irregularity happens in real-world pictures attributable to varied factors, like spacial variations in illumination and imperfections of imaging devices that complicates several issues in image process and laptop vision. Particularly, image segmentation is also significantly troublesome for pictures with intensity in homogeneities attributable to the overlaps between the ranges of the intensities within the divided regions. This makes it not possible to spot these regions supported the pel intensity. the most objective of the paper is to over return the intensity irregularity mistreatment the mix of level set methodology and snake algorithmic program, which is able to intern pave the thanks to correct analysis of pictures obtained in scanning.

II. Existing System

The wide used image segmentation algorithms sometimes have faith in intensity homogeneity, and so aren't applicable to photographs with intensity inhomogeneities. In general, they're below 2 categories - Region primarily {based} models and edge based models. one in every of the foremost wide used strategies of segmentation is represented below:

A. *Water Shed remodel method*

The watershed remodel projected by Vincent and Soille4 may be a acknowledge segmentation technique, that relies on immersion simulation, Associate in Nursing permits the generation of an initial image partition into regions and consequently, alternative region-based techniques are often employed in order to supply closed, one pixel-wide contours or surfaces. The technique relies on the belief that image contours correspond to the crest lines of the gradient magnitude image which may be detected via watershed tracing. The Watershed remodel, additionally known as the watershed methodology, is a picture segmentation approach supported grey scale mathematical morphology, to the case of color or, additional typically speaking, multi element pictures. Totally different ways square measure conferred and a special attention is paid to the "bit compounding approach".

The principle is shortly represented as following: Let *I* be a grayscale digital image, the gradient image ||Ñ*I*|| is computed; for every object of interest, an enclosed particle is detected (either interactively or automatically); flood waves are propagated from the set of markers and flood the geographic surface ||Ñ*I*||. Watersheds square measure outlined the lines separating the so-called suppose structure basins, those belong to different minima.. The geographic region can flow all the way down to the minimum M. once the water reaches the grayest worth, the perimeters of the union of all dams' kind the watershed segmentation. The strength of watershed segmentation is that it produces a novel answer for a specific image, and it is simply tailored to any quite digital grid and extended to n-dimensional pictures and graphs. However, the noise within the image leads to over segmentation. Another disadvantage of watershed segmentation, once more associated with the image noise and also the image's separate nature, is that the ultimate boundaries of the metameric region area unit lack of smoothness. Thus it's not AN economical plan to treat the watershed segmentation because the final segmentation

B. Mean Shift Method

MS is a data-clustering method that searches for the native peak density points and then groups all the data to the clusters defined by these peak density points. When used for image segmentation, each pixel **x**i, i=1,…,n, in the image is treated as an input data, and the density at point **x** is estimated by

$$f(x) = \frac{c}{nh^d} \sum_{i=1}^{n} K\left(\left\| \frac{\mathrm{x} - \mathrm{x}_i}{h} \right\|^2 \right)$$

Where *h* refers to bandwidth measuring parameter, *d* is the information spatiality, *c* is a normalization constant, and **K (-)** is the density estimation kernel. In the implementation of the mean-shift technique, the uniform kernel is employed. To find a neighborhood maximum of the density, an initial point **y1** is selected and then successively updated by

$$\mathrm{y}_{j+1} = \frac{\sum_{i=1}^{n} \mathrm{x}_i K\left(\left\| \frac{\mathrm{y}_j - \mathrm{x}_i}{h} \right\|^2 \right)}{\sum_{i=1}^{n} K\left(\left\| \frac{\mathrm{y}_j - \mathrm{x}_i}{h} \right\|^2 \right)}$$

Until convergence. With these native peak density points, the image is segmented into regions by grouping each pixel to its corresponding native peak-density point.
In the adopted implementation, there are mainly three essential parameters: the spatial bandwidth measuring parameter Hs, the range bandwidth measuring parameter Hr, and the minimum phase space S that has the similar meaning assuming to one in EG. Since the entire test images in our benchmark are gray level images, the range bandwidth Hr, which is mainly related to the color channels, is mounted to its default value. The bandwidth parameter Hs determines the resolution in choosing the native peak-density points. In alternative words, Hs control the number of resulting segments.

C. Thresholding

Thresholding is a straightforward simple type of segmentation. A threshold is outlined, and then every pixel in a picture is compared with this threshold. If the pixel lies on top of the edge i.e above the threshold it will be marked as foreground, and if it is below the threshold as background. The threshold will most frequently be intensity or colour value. Other types of thresholding exist wherever the edge is allowed to vary across the image; however thresholding is a basic technique, and can solely work for very simple straight forward segmentation tasks.

Most graphics packages exist with some variety of thresholding segmentation. "Magic Wand" is such a tool, and is enclosed in Adobe Photoshop seven. With this tool the user will choose a seed or multiple seed pixels and can set some value of tolerance level. The segmentation is then performed by testing all pixels against the set tolerance level (INCORP, 2002). This technique is easy to use, but the results are most often unsatisfactory and finding the correct tolerance level can be cumbersome, and sometimes even impossible (Rother et al., 2004).

III. A NOVEL EFFICIENT METHOD FOR IMAGES WITH INTENSITY INHOMOGENEITY

The new method uses level set method and snake algorithm to overcome the existing difficulties. The image obtained using watershed method doesn't segment the image perfectly. The proposed method helps in segmenting the images accurately. This is often used for clinical analysis.

We see that it is generally easy to work with a shape through its level set function than with the shape directly, where it is required to watch all the possible deformations the shape might undergo.

A. Snake Algorithm

Snakes are energy minimizing splines that are guided by external constraints and internal constraints, and are influenced by image forces that pull them towards features like lines and edges. They are active in that they lock onto nearby edges. Snakes are thus known as due to the twisting motion they endure when they are minimizing their energy functions. Snakes work on the assumption that edges are found not solely by gazing at the native local gradient, but also at the long vary distribution of the gradient. This is often done by exploiting curvature constraints along with continuity constraints. Snakes have an enclosed energy function that determines their snap elasticity and rigidity, and also has an external energy function supported with an image information and user interaction.

B. The Combination of Level Set Method & Snake Algorithm

In the initial step, the noise corrupting the image is reduced by noise reduction technique. This noise suppression permits a additional correct calculation of the image gradient and reduction of the quantity of the detected false edges. Aside from the preprocessing stage, our segmentation strategy can consist in exploiting snake transform as a pre-segmentation tool, and then refine the segmentation result with the level set technique. This approach combines the benefits of each method: the snake rework pre-segmentation is rough but quick, and the level set needs only a few iterations to produce the final, fast, highly accurate, and smooth segmentation.

The decision of selecting the snake segmentation because the initialization of the subsequent level set methodology is in keeping with the subsequent reasons. The primary reason is, that it is possible that the real blindness of segmentation is reduced, and the accuracy of segmentation is improved. The second reason is for increasing the computation speed. It is not necessary for the pc to know about the arrival time of the inside point of the sub-regions, so the boundary of interesting objects is overlapping with the result of snake transform, it will have narrow band decision, and therefore the whole computation cost will be reduced.

The snake algorithm is applied to the gradient magnitude of the original image data set. Among the existing snake algorithms, a 3D analogy of the immersion-based approach of Vincent and Soille's snake algorithm4 was used because of its accuracy and speed of computation. The output of the snake algorithm is a partitioning of the input data in volume regions of which the interior does not contain any sharp gray value transitions. As we know, the algorithm leads inevitably to an over segmentation of the data because all the crest lines of the data set are detected. Therefore, the noise filtering preprocessing need to be applied to the image data first. After the initial segmentation based on snake transform, the final segmentation is accomplished based on level set method. By combining snake transform and level sets, this method is able to produce highly accurate segmentations of topologically and geometrically complex structures in much less time than where level sets alone.

IV. MAGNETIC RESONANCE IMAGING

The segmentation of the cerebral cortex in 3D brain MR images is the subject of this work. This section provides an overview of the functioning of MRI and highlights the properties of the obtained images. Of course there are other suitable imaging techniques that allow for 3D brain representations. Two important ones are computed tomography (CT) and 3D medical sonography.

A. Functioning of Magnetic Resonance Imaging

MRI creates 3D images, which are composed of several non-overlapping plane images. It measures the existing magnetization in every volume element at a given measuring time and the signal differences are visualized on a gray scale.

During image acquisition, the object of interest is placed in an external magnetic field and the protons start to process around the direction of that field. They are now in a state of higher energy and process in phase. This leads to the creation of a transversal field, perpendicular to the external field. When the external field is released, the protons move back into their position of equilibrium and induce a longitudinal magnetization, parallel to the external field. This phenomenon is called T1 relaxation. Furthermore, the transversal field disappears because the protons loose phase coherence. This is called T2 relaxation.

After activation, these magnetic fields are measured at a certain point in time. Because different tissue types possess distinct relaxation times, one can derive the type of tissue from the measured signal intensity. The sequence of activation and measurement is repeated several times to obtain the final MR image. This procedure increases the contrast. Tissue exhibiting a short T1 relaxation time appears with high intensities in the image and those having a long T1 relaxation time get low intensity values assigned. The intensity distribution precedes contraries for the T2 modality because the transversal magnetic field does disappear instead of originating.

B. Properties of MR Images

MRI is a non-contact procedure and emits no dangerous radiation. The properties of the MR images exhibit

- a high signal-to-noise ratio,
- a high soft tissue contrast and
- a high resolution.

Unfortunately there are two disadvantageous phenomena that MR images are subject to. These are the occurrence of intensity inhomogeneity and the partial volume effect (PVE).

Images obtained from MRI acquisition systems, exhibit intensity inhomogeneities that are unrelated to the underlying anatomy. They appear for different reasons. One source of error are spatial variations in the magnetic fields during the measurement. Another are the regional differences in the magnetic properties of the biological materials. They can cause the effective magnetic field to become non uniform. Next to such technical reasons, intensity inhomogeneities are introduced through unavoidable movement of the person during the scanning procedure. The below Fig. indicates the visual impact of intensity inhomogeneity.

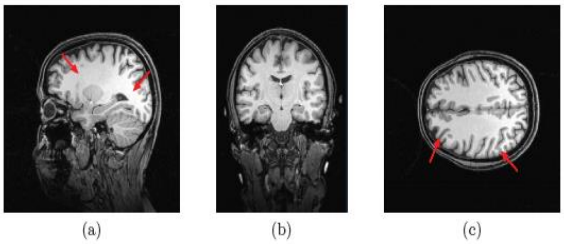


Fig. 1. Illustrating intensity inhomogeneity in MR images

These are the sagittal (a), coronal (b) and axial (c) orientation. The impact of intensity inhomogeneity can be studied in (a). The two arrows point in areas of different mean intensity values within the white matter. The partial volume effect primarily occurs in thin folding of the cortex. The arrows indicate exemplary regions in (c).

V. VARIATIONAL FRAMEWORK FOR IMAGE SEGMENTATION AND BIAS ESTIMATION

The level set framework adds dynamics to interfaces represented by implicit surfaces.Implicit surface representation and the approach to add movement is highlighted first.The realization using partial differential equations (PDEs) is consecutively derived and numerical solutions to solve them are shortly addressed. Finally important notes on the utilization of level set methods are presented.

A. Implicit Surface Representation

The implicit surface representation shall now be pointed out. The two-dimensional example of the unit circle is presented in Fig. 2. Its surface is described by the curve x2 +y2 = 1. The implicit representation defines the interface by some function whose argument is a point p.

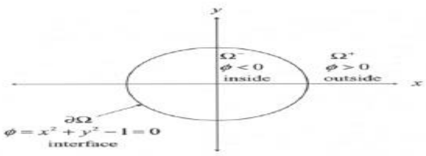


Fig.2. Implicit representation of unit circle

This is defined over the whole domain, not just on the boundary. All points with the same value form interfaces. This is discretized on a mesh to represent it in a finite form. Here usually Cartesian grids are used. Their spatial subintervals are equal in size. This situation is presented in Fig. 3

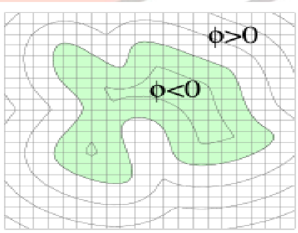


Fig.3. Visualization of the implicit function on a Cartesian grid

Level set methods work on such implicitly defined interfaces but take signed distance functions for their representation. Signed distance functions are a subset of implicit functions defined by

$$\phi(p) = \pm d(p)$$

With the distance function d being

$$d(p) = \min(|\ p - p_I\ |) \text{ for all } p_I \in \partial\Omega.$$

Thus, level set methods use implicit functions _ that define the shortest Euclidean distance from p to the interface. The domain of any point can still be directly deduced. In addition, it holds the extra property. This is of importance for numerical accuracy.

B. Level Set Equations

The evolution of the surfaces is described by partial differential equations that are an initial value formulation of the problem. This is required as the surface can move in all spatial directions and thus may cross a certain point several times. The previous section mentioned motion in normal direction only. However, the level set framework commonly defines three kinds of motion. These are the motion in an externally generated velocity field, the normal direction and involving mean curvature. All motions can be derived from one fundamental level set equation ([Str07]). It is given by

$$\phi_t + \vec{V} \cdot \nabla\phi = 0,$$

Where _t is the partial derivative in time, r_ denotes the divergence and ~V quantifies an external velocity field. The fundamental level set equation is already exactly the equation for motion in an externally generated velocity field.

Defining $\vec{V} = V_n\vec{N}$ to be an internally generated velocity,

$$\phi_t + V_n\vec{N} \cdot \nabla\phi = 0.$$

N is the outward unit normal vector to the interface. It is directly computable from $\vec{N} = \frac{\nabla\phi}{|\nabla\phi|}$. Using

$$\vec{N} \cdot \nabla\phi = \frac{\nabla\phi}{|\nabla\phi|} \cdot \nabla\phi = \frac{|\nabla\phi|^2}{|\nabla\phi|} = |\nabla\phi|,$$

The above Eq. can be rewritten to

$$\phi_t + V_n |\nabla\phi| = 0.$$

This is the level set equation for motion in normal direction. Depending on the sign of Vn, the interface moves inward or outward in normal direction.

Finally motion involving mean curvature is presented. Again a normal directed velocity field $\vec{V} = V_n\vec{N}$ that depends directly. This time Vn is characterized by $V_n = -b\kappa$ where b is a constant and k is the mean curvature. Using the same intermediate step as for motion in normal direction, Eq. above becomes

$$\phi_t + b\kappa |\nabla\phi| = 0.$$

The mean curvature quantifies the rate of change in direction on the interface. It can be directly computed, as the divergence of the normal vector

$$\kappa = \nabla \cdot \left(\frac{\nabla\phi}{|\nabla\phi|}\right).$$

It holds that k> 0 for convex regions, k< 0 for concave regions and k = 0 for planar regions. This is illustrated in Fig.

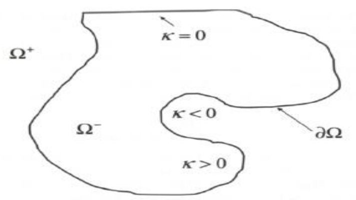


Fig. 5. Interpretation of the mean curvature

An adequate modelling usually involves several types of motion. The example of a moving waterfront clarifies this aspect. The spreading of a waterfront depends on the substratum lying in its way. Furthermore, wind might influence its propagation and a real waterfront exhibits surface tension. This behavior can be simulated using a spatially varying force in normal direction, an external velocity field and motion involving mean curvature, respectively. Due to the fact that all motions act on _ as vector fields, their influences can be overlaid, leading to

$$\phi_t + \vec{V} \cdot \nabla\phi + V_n |\nabla\phi| + b\kappa |\nabla\phi| = 0.$$

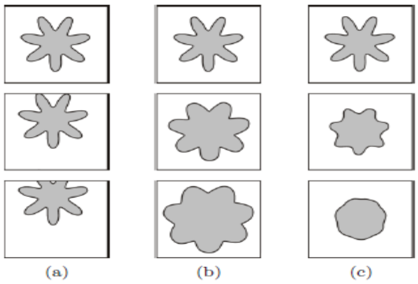


Fig.6. Evolution of a star-shaped interface for each of the three different types of motion. Motion in an externally generated velocity field (a) dislocates the whole interface whereas motion in normal direction (b) evolves the interface normal to itself. Motion involving mean curvature (c) attends the interface.

C. Notes on Utilisation of Level Sets

This section presents important aspects for the application of level set methods. These are the preservation of the signed distance, the extrapolation of velocities to the whole domain and an efficient implementation scheme.

Reconstruction of the Signed Distance Due to numerical errors during the evolution, ϕ generally does not remain a signed distance function. Instead the level sets approach or separate from each other and develop noisy features. These effects lead to changes in the local gradients that appear as perturbations in the interface. In order to reduce this misbehavior, ϕ has to be reinitialized in regular intervals. This requires finding a new ϕ that has the same zero level set as before but again the property of $|\nabla\phi| = 1$. Sussmann et al. propose the following reinitialization equation

$$\phi_t + S(\phi_0)(|\nabla\phi| - 1) = 0,$$

Where $S(\phi_0)$ is a sign function returning Ω^+, -1 in Ω^- and 0 on the interface. This equation Reaches its steady state for $|\nabla\phi| = 1$ and it can be solved using methods immanent to the level set framework. According to this the surface propagation can be formulated as a boundary value problem.

$$|\nabla T| F = 1, T = 0 \text{ on } \Gamma.$$

Here Γ denotes the initial location of the interface and T(p) is an arrival function. The front propagates with velocity F and above eqn. computes the arrival time for any grid point. The arrival times are proportional to the distance to the interface because F is constant for all grid points. Choosing F = 1 this formulation results in the signed distance function.

Even though fast schemes exist, periodical reconstruction of the distance function is a laborious solution and only a compromise between performance and accuracy. There are alternatives to the Hamilton-Jacobi approach of Osher and Sethian. PDEs that always remain distance functions by construction are proposed by Gomes and Faugeras. A solution that is inherent to the level set framework is given by

$$V_t + \vec{N} \cdot \nabla V = 0.$$

It is a Hamilton-Jacobi equation that extrapolates the values of V from the interface to the image domain. The propagation reaches steady state when the values of V are constant on rays normal to the interface. Hence all level sets are subject to the same velocity field strengths and the signed distance is maintained. Again, the extrapolation of the velocities can be implemented more efficiently, using an extended version of the fast marching method.

D. Application to Image Segmentation

Due to the context of this paper, general concepts regarding their application in image segmentation shall be pointed out. Image segmentation has already been introduced as partitioning an image into meaningful regions. Therefore usually two model assumptions are made: firstly, the features within an object are assumed to be similar while those between different regions shall differ and secondly, the contour of a segment should be as compact as possible. Mumford and Shah proposed a mathematical formulation of these assumptions in terms of energy minimization.

$$E(u,\Gamma) = \int_\Omega (u-I)^2 dx + \lambda \int_{\Omega-\Gamma} |\nabla u|^2 dx + \nu \int_\Gamma ds.$$

Here Γ denotes boundaries separating different regions, u are features that characterize the image I and λ and ν are weighting parameters. The elementary principle of all approaches is the aim to express image or model information by means of the velocity fields. They propagate the zero level set towards the boundary of the required object. This has led to the segmentation model of implicit active contours.

VI. LEVEL SET FORMULATION AND ENERGY MINIMISATION USING SNAKE ALGORITHM

The level set component is designed as a stack of classes. Each class adds further functionality. In the following, the functionality of each class is described. This is accompanied by remarks on the implementation. C LevelSet Abstraction encapsulates the required C function calls of LSMLIB. It is intended as the C++ abstraction layer to the underlying library. It provides the numerical kernels that are the core components of most level set applications. Basically, this includes routines for: computation of spatial derivatives, first-order accurate time integration and reconstruction of the distance function as well as extrapolation of velocities using the fast marching method. Implicit functions are represented on regular grids. The required data structures are defined in this class. The implicit function is realized as a contiguous linear sequence of elements of data type double.

This is a very basic type but it allows the representation of one or higher dimensional arrays. The same data type is used to store the spatial derivatives and its values during intermediate processing. Parameters defining the geometric dimensions and the index space are also provided. CLevelSetCore provides the basic functionality that any level set application requires. It already presents a working level set implementation, including:

- the creation of initial surfaces,
- the evolution influenced by all three types of motion,
- the computation of stable time steps and a narrow band implementation.

This implementation employs the following numerical schemes. First-order accurate Euler steps are used for time integration, whereas the spatial discretization involves second-order accurate schemes. This includes the application of upwind differencing for motion in an external velocity field, Godunov's scheme for motion in normal direction and central definite differences for motion involving mean curvature. The selection of low-order accurate schemes is reasonable in respect of the performance. Numerical stability is guaranteed as long as the distance function is reconstructed in regular intervals. Second-order accurate schemes are assumed to be a sufficient choice for the spatial discretization. The involvement of a larger neighbourhood seems to be unreasonable due to the highly convoluted nature of the cortical surface.

A. Implementation of level set component

The numerical solution is less sensitive to temporal truncation errors than to spatial errors ([OF03]). This justifies the use of only first-order accurate steps. The narrow band implementation limits the computation to a small band along the zero level set. The included voxels are determined from the distance function. Their geometric coordinates are stored in a linear array and the corresponding indices are used to restrict the computation to the narrow band. Voxels representing the outer layers of the narrow band are stored in a separate array. A sign change , at these locations, indicates that the zero level set has reached the boundary of the narrow band. In this case the narrow band is redetermined. The computational costs for reconstruction of the signed distance as well as the extrapolation of velocities are also decreased by this implementation. However, these computations have to be carried out beyond the boundary of the narrow band because its correct determination depends on an accurate signed distance function. CLevelSetSubdivision provides the parcelling of the level set domain. It contains functions for region assignment and the computation of proximity relationships. The required coordinates are provided by the shared CLS Subdivision class. CLevelSetImageProcessing connects the image domain with the level set domain. External knowledge, derived from the image data, is incorporated in the propagation of the level sets. This includes intensity, gradient and statistical information. The CLS Image class maintains this information at a shared location. So a waste of memory for redundant storage of the image data is avoided. The computation of the propagation fields is already accomplished in this layer. The related computations have been described in detail and the required intensity probability distributions for the inner and outer domain of the level set are provided by CLS Image.

C LevelSet Coupling covers functions that compute the coupling constraints for the evolution of the level sets. The coupling is carried out using the rule-based system described. The distance is computed using the level set function of the opposite surface, which is represented by another instance of the current class. Each narrow band has to be sufficiently wide to cover the zero level set of the oth.er level set instance. The current realization employs a size of 8mm

The coupling creates additional dependency on the correctness of the signed distance function that represents the opposite surface. The fast marching method computes the extrapolation of the propagation fields along with the reconstruction of the signed distance. In case the evolution is constrained by constant image information only this is required for every level set instance once. However, the signed distance function needs to be reconstructed before it is usable for the opposite surface. Consequently, the computational costs for the maintenance of both level set functions increase by 50%.

B. Description of Snake Algorithm

1. *Greedy Snake Theory*
   - Points are moved through an Iterative Process
   - Energy Function for each point in the Local Neighbourhood is calculated
   - Move to point with lowest Energy Function
   - Repeat for every point

- Iterate until Termination Condition met
- Defined number of iterations
- Stability of the position of the points

2. *Energy Function*
   - Three Components
   - Continuity
   - Curvature
   - Image (Gradient)
   - Each Weighted by Specified Parameter
   - Total Energy = $\alpha \cdot$ Continuity + $\beta \cdot$ Curvature + $\gamma \cdot$ Image
3. *Continuity*
   - Abs(avg_dist_btw_nodes – dist(V(i),V(i-1))
   - Value = Smaller Distance between Points
   - The higher α, the more important the distance between points is minimized.
4. *Curvature*
   - $\mathrm{Norm}(V(i-1) - 2\cdot V(i) + V(i+1))^2$
   - Normalised by greatest value in neighbourhood.
   - The higher β, the more important that angles are maximized
5. *Image Gradient*
   - Img_grad (V(i))
   - High Image Gradient = Low Energy value
   - The higher γ, the more important image edges are.
6. *Drawing Corners*
   - For each Snake Point take Curvature Value
   - IF Greater than other points
   - AND specified Angular Threshold
   - AND Image Gradient high enough
   - THEN set β for that Snake point to 0, allowing a Corner
7. *Varying α β γ*
   - Choose different values dependent on Feature to extract
   - Set α high if there is a deceptive Image Gradient
   - Set β high if smooth edged Feature, low if sharp edges
   - Set γ high if contrast between Background and Feature is low

VII. DISADVANTAGES OF WATERSHED TRANSFORM METHOD

Disadvantages of the single-watershed method include less precision, a more complex analysis, and a longer calibration period. However, there are several advantages which may more than offset the disadvantages. Single-watershed calibration can be used on almost any watershed. It need not conform to the rigid requirements for pairing. The method can be adapted to evaluate treatment effects on a disturbed watershed. For example, the effects of reforestation and erosion control on the hydrology of Pine Tree Branch Watershed have been evaluated by the single-watershed method.

VIII. ADVANTAGES OF PROPOSED SYSTEM

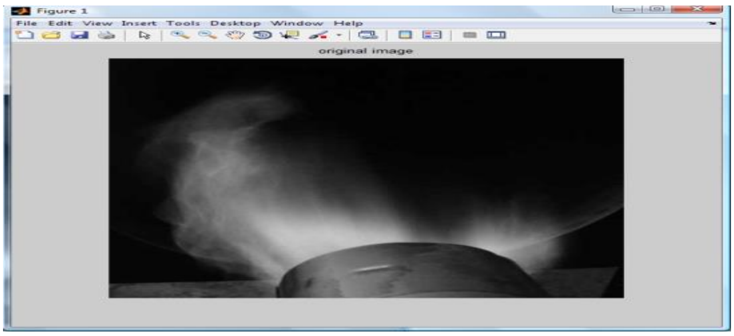
Level set methods have been shown to be versatile, robust, accurate, and efficient techniques for a wide class of problems in etching, d level set of a higher dimensional function, whose equation of motion resembles a Hamilton-Jacobi equation.

The resulting techniques are able to handle sharp corners and cusps in the propagating solution, as well as topological changes, and three-dimensional effects. The computational labor is the same as other methods, with the advantages of increased accuracy and robust modeling.

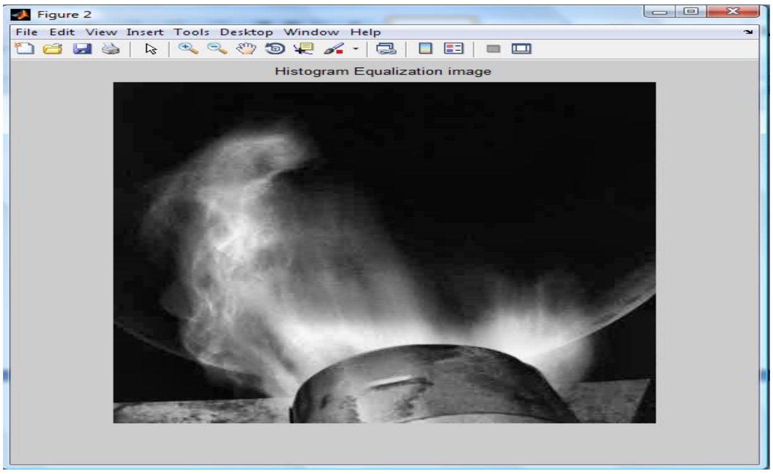
IX. SIMULATION RESULTS

1. Existing System (watershed transform method)

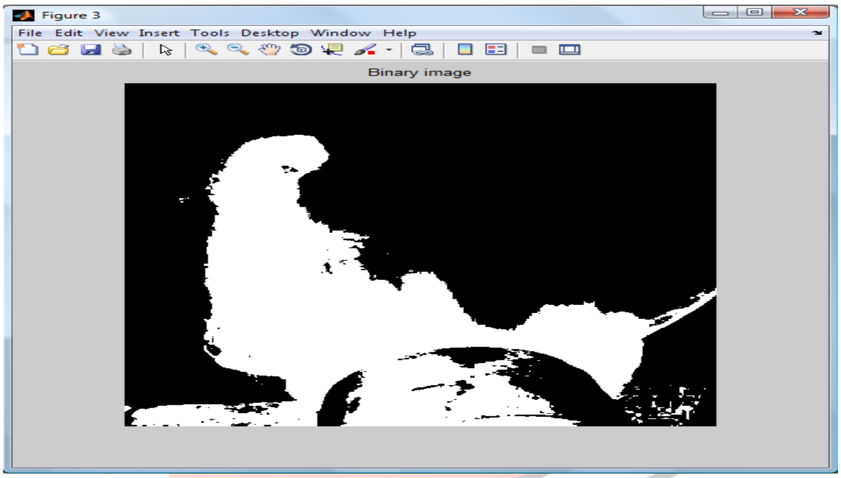
1. *Original Image:*



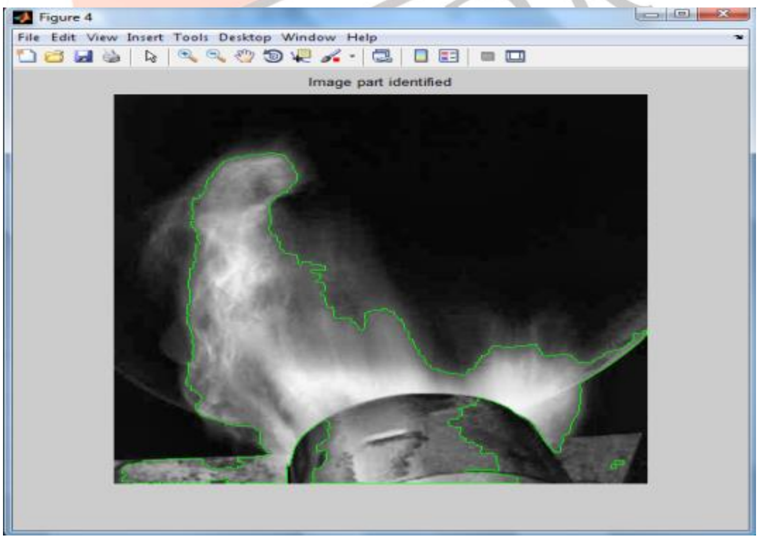
2. *Histogram Equalization image:*



3. *Binary Image:*

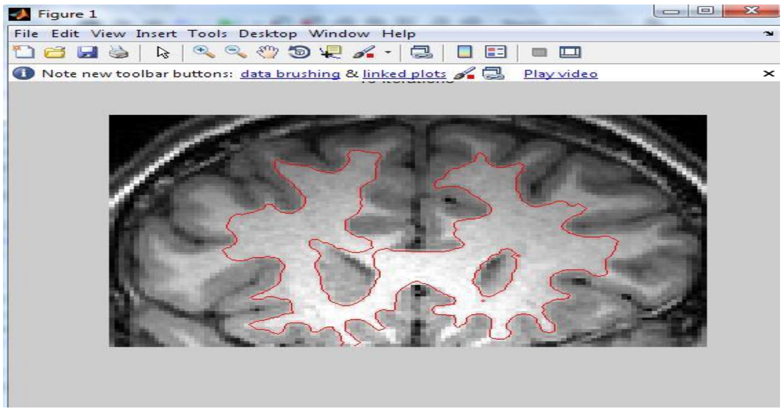


4. *Final Segmented Image:*

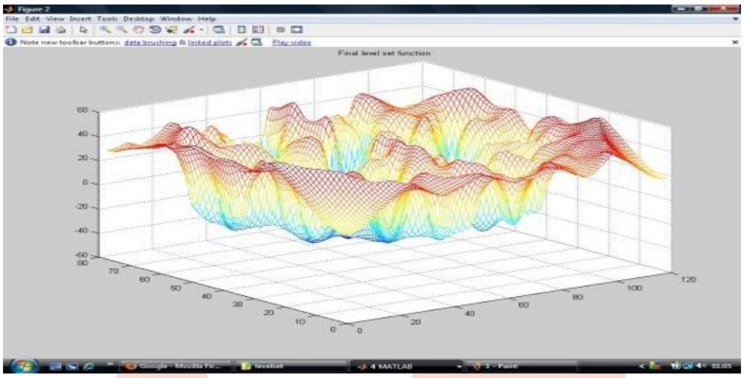


B. Output UsingLevel Set Method & Snake Algorithm:

1. *Input Brain Image to be analyzed*



2. *Final Level Set Function Obtained*



X. CONCLUSION

The method allows the segmentation in 3 Tesla MR Images that are subject to considerable magnitude of intensity unregularity. The segmentation results fulfill the requirements that emerge from the intended application. The statistical significance of MRI measurements can be further increased as a result of the satisfying delineation of the cortical surface. Moreover, the algorithm performs in a highly automatic fashion and the degree of automation can be further increased due to its robustness regarding to the initialization. Another advantage is the fact that the method depends only on few tunable parameters. Extensive tuning should be unnecessary when being applied to MR images recorded with different scanners.

OUR method has also been tested on 7T MR IMAGES with promising results. At 7 t significant gains in image resolution can be obtained due to increase in snr. However susceptibility induced gradients scale with the main field, while the image gradients are currently limited to essentially the same strengths as used at lower field strengths .this is highly localized and strong bias which is traditional methods for bias correction. our method can be used to achieve the same. It is very difficult to define a region descriptor for images with image with intensity inhomogeneity, these methods are computationally too expensive and are quite sensitive to the initialization of the contour which limits their utilities and some of them suffer from serious boundary leakage problems in images with weak object boundaries and are sensitive to initial conditions. More robust to initialization faster and more accurate.

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