ISSN: 2278-4632
Vol-11 Issue-01 2021

MAMMOGRAM IMAGE ENHANCEMENT USING SNAKE MODEL WITH IMAGE SEGMANTATION

BODDU RAJA SRINIVASA REDDY
Professor, Department of CSE , Sri Vasavi Institute of Engineering And Technology, Nandamaru, Pedana Mandal, Krishna dist, A.P., India.

Abstract:

In this paper the internal structures of human body obtained from various modalities of CT and MRI are used for diagnosis purpose. Using MRI the tumor parts can be seen very clearly, however they cannot provide actual dimensions of tumor size so as to give a better treatment. For such situations whole brain atlas (WBA) needs to be drawn using different methods available at hands. Sometimes these are used to be drawn by hand with experts in olden days. However the present method proposed in this research using the level set method where accurate boundaries are captured with respect to the tumor area in 2D MRI images. The other reason for using segmentation is to identify the error areas of liver in detail as this method will allow us understand the problem area very clearly at each pixel level. The usage if edge detection method, deformation models, contour models are simple to use. However, in these models the training of set needs to be done carefully after analyzing large quantity of data. In snakes method the explicit parametric form is used and the curve will be almost like a snake. However, this method is having problems when it has to undergo splitting and merging while defining the shape. To solve these kinds of problems implicit active contour approach is used instead of explicitly following original interface and embeds in higher dimension scalar function.

Keywords:-Spatial information; Image segmentation, Denoising, Snake algorithm

1. INTRODUCTION

Ultrasound imaging is a key modality in medical diagnosis. The accurate targets' detection provides precise clinical information for diagnosis. However, compared with other medical imaging modalities, ultrasound images suffer heavily from speckle noise. The speckle noise can be modeled as multiplicative noise, and logarithmic transformation converts it to an additive noise model [1]. The lower quality of ultrasound images results in weak and uncompleted boundaries [2].Image denoising is to produce a good estimate of the original image from a noisy observation, and is a basic preprocessing stage for image segmentation, especially for ultrasound images. Tremendous approaches have been proposed to reduce additive noise, and wavelets shrinkage technique [3] maybe one of the most famous algorithms and has been widely applied in ultrasound image denoising [4]. However, due to the isotropic characteristics, this technique yields overly smoothed estimate results for anisotropic features, edges for example. A new multiscale geometric analysis technique named the curvelet transform localizes along curves within images [5]. Though it is still under development, it has shown successful results in denoising applications due to its anisotropic nature. However, for isotropic parts of images, curvelets denoising does not work well. Consequently, a means to take advantage of both techniques may achieve better performance.
The snakes [6] have attracted many researchers attention in the field of ultrasonic image segmentation [7]. A snake curve is an energy-minimizing contour guided by external image and internal spline forces. GVF snake [8] keeps the internal force of the traditional snake model and

 DOI : 10.36893.DRSR.2021.V11I01.1054-1061

ISSN: 2278-4632
Vol-11 Issue-01 2021

creates the GVF force as the external force which results in its insensitivity to initialization and enables boundary concavities detection. Unfortunately, the utility is limited in noisy images and the selection of parameters is almost empirical.

The purpose of this paper is to outline the algorithm to segment noisy ultrasound images. A new denoising scheme based on wavelets and curvelets is presented Edges' information which is wrongly discarded by wavelet shrinkage is picked up by curvelets from the residue image to

improve the performance. A parameter-varying snake model is introduced, incorporating prior knowledge on the contours' shape and similar degree based on Fourier descriptors of snakes. It addresses the problem of varying parameters during snake method. we qualify the performance and present results for real ultrasound images.

2. Segmentation techniques

These techniques are classified briefly in two ways: contextual segmentation and non – contextual segmentation. In the later case, it ignores the relation between the properties of an image and pixels are simply grouped at one place based on some global attributes like gray levels and etc. In this case the pixels are assigned for a particular region based on their gray values by applying intensity – based thresholding. However, in contextual technique added exploitation will be done among the relationships between image features. In this case thresholding is one the mostly used segmentation technique that also used for MRI brain tumor segmentation [32]. Based on the intensity or brightness, that contains solid objects in the background with dissimilar forms but with uniform brightness. Every pixel in this case is compared with the threshold value. In case of higher value compared to the threshold value is termed as foreground threshold and with lower or equal value to threshold value is considered to be the background threshold and is generally set to black color [1]. According to the discussions of Chowdhury *et al.* proposed a new method of thresholding, which is based on divergence function. The objectives function is developed by using divergence function among different classes, objects and background of the images in this method. Needed threshold will be identified at the places where divergence function represents global minimum. However, in another method proposed by Lefohn et at in is based on contour based method. In this method a semiautomatic method was introduced for the segmentation of tumors using Level sets. The users can select the tumor region in this method for the initialization of first segmentation. Based on the visual inspection from the results the Level set parameters are tuned and repetition of segmentation process continues.

There are wide range of segmentation techniques used in the market based on the merits and demerits of the method. Generally used segmentation methods are GVF Snake model, thresholding, Rough set method, Water Shed method, Level set method and Fuzzy C means algorithm. The first two methods are considered to be parametric active contours, in which, they are defined as curves within the image domains that move with the influence of inter forces that comes from the curve itself. Generally in this method the external forces are calculated from the data of image. However, Level set is considered to be with the category of Geometric active contours where, this method is evolves contours in two dimensions or with a surface in 3 dimension by simply manipulating the functions of higher dimensions.

2.1 GVF Snake

Gradient Vector Flow (GVF) is considered to be dense vector fields that are generally derived from images by reducing the energy functionalities in a varied frame work. In simple, according to Shivakumar in a GVF field is an external potential force field that is obtained by using the gradient of an image for different tasks. Generally the minimization can be achieved by solving pairs of decoupled linear partial differential equations that diffuses gradient vectors of gray – level or binary edge maps that are computed from images. The active contours that use GVF Fields as their external

 DOI : 10.36893.DRSR.2021.V11I01.1054-1061

ISSN: 2278-4632
Vol-11 Issue-01 2021

forces are called as GVF Snakes. The major advantage of it is to provide the insensitivity for the initialization and it capacity for moving into concave boundary regions.

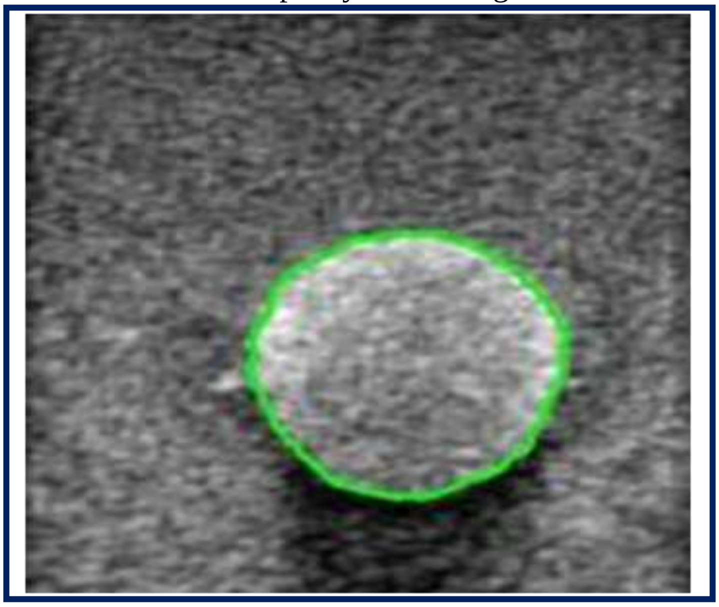

Figure – 1: Example for GVF Snake model

Kass in the year 1987 suggested the method of using GVF force field to follow the edges in an image by a curve of an image. In this the curve will move itself for a suitable shape and position [7]. These curves will be having physical properties as elasticity and rigidity. These curves are also attracted by image edges and are called as active contours or snakes. These concepts become more popular for the analysis of medical images. But two key problems were seen using active contour algorithms. In the first problem, the initial contour must be close to the actual boundary or else it converges with wrong results. In the second case, the active contours face problem for progressing in the boundary concavities [7].

Though many methods proposed for solving the above problems could not satisfy the requirements of health care units due to the evolution of a new problems from the side effects from the presented solutions. These methods include resolution method, control point method, pressure forces and directional attraction according to Xu. Xu also used GVF fields as snake external force as they are derived from dense vectors from the images. Sometimes the images were identified as corrupted due to noise and sampling artefacts. These situations increase the difficulties for partitioning the liver from noises using common methods. As it is discussed in earlier topics GVF is having larger capture range while comparing with traditional snake method and GVF also push the active contours in the boundary concavities. However, the liver shape considered having complex parameters and they tend to have deep concavities in some of the CT images. On the other hand the GVF snake does not communicate correctness of the images if shape of initial contour is not in real shape. To solve this problem one can use maximum force angle map for evaluating variability of directions of GVF forces. This will help for finding appropriate initial contour and using Gaussian function one can generate the edge map that always considered to be as a problem in real time. Considering an example with higher value of sigma there will be a kind of blur in the boundary of the liver and hence the GVF snake will be having an error by crossing the liver and sometimes it might even reach the heart as well. For this reason Canny in his research recommended the edge detector for best results.

2.1.1. Gradient vector flow field

Xu and Prince developed this method to solve most of the segmentation problems in the year 1997. GVF is computed as the diffusion of gradient vectors of gray level or binary edge map that is derived from an image. The resultant field will be having larger capture range and hence the active contour

 DOI : 10.36893.DRSR.2021.V11I01.1054-1061

will be initialized at the far end of a desired boundary. The GVF field force the active contours into boundary concavities at a place where the traditional snake methods have poor convergence [7]. An example shown in figure – 1 with a U – Shaped object with potential force field within boundary concavity is shown. A clear observation of this image reveals that at the concavity the distance potential points are horizontally but in opposite direction. Hence they are preventing the contour from convergence into boundary concavity. For solving these problems Xu and prince addressed vector diffusion, that diffuses gradient of an edge map at distant regions of the boundary. The amount of diffusion will be based on the strength of the edges for avoiding distorting objects boundary [8] .

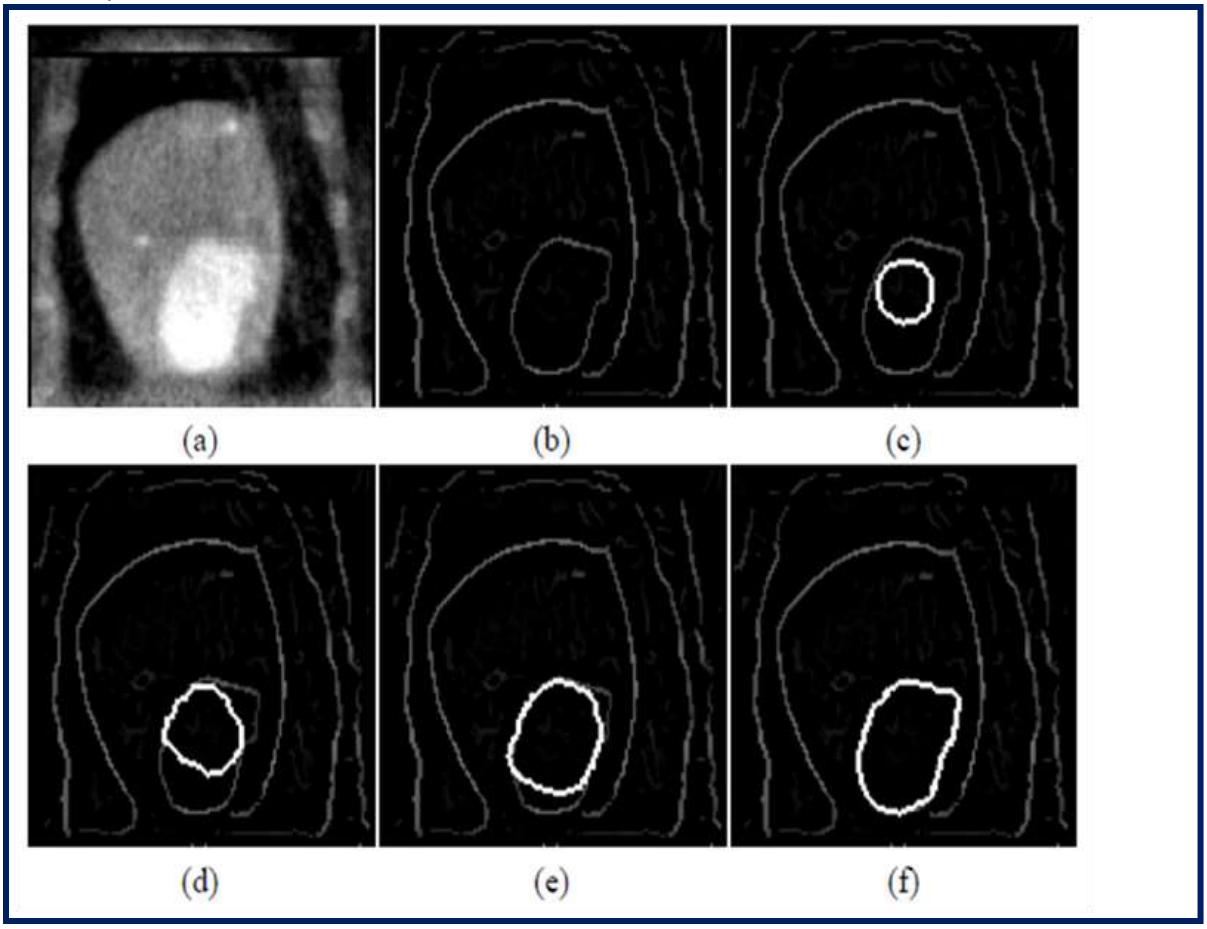

Figure – 2: Example for pressure forces driven deformable contours (a) Intensity CT image slice of the left ventricle. (b) Edge detected image. (c) Initial deformable contour. (d) - (f) Deformable contour moving toward the left ventricle boundary, driven by inflating pressure force [9].

A vector partial differential equation of a GVF field is given in equation1.

$$\frac{\partial v}{\partial t} = g(|\nabla f|)\nabla^2 v - h(|\nabla f|)(v - \nabla f,) \text{ ...... } 1$$

Where $v(x, y, 0) = \nabla f, \partial v/\partial t$ represents partial derivative of $v(x, y, t)$with respect to *t;*

∇^2 – Laplacian operator; and

f – it is the edge map with higher value for the desired object boundary and it can be derived by an edge detector.

 DOI : 10.36893.DRSR.2021.V11I01.1054-1061

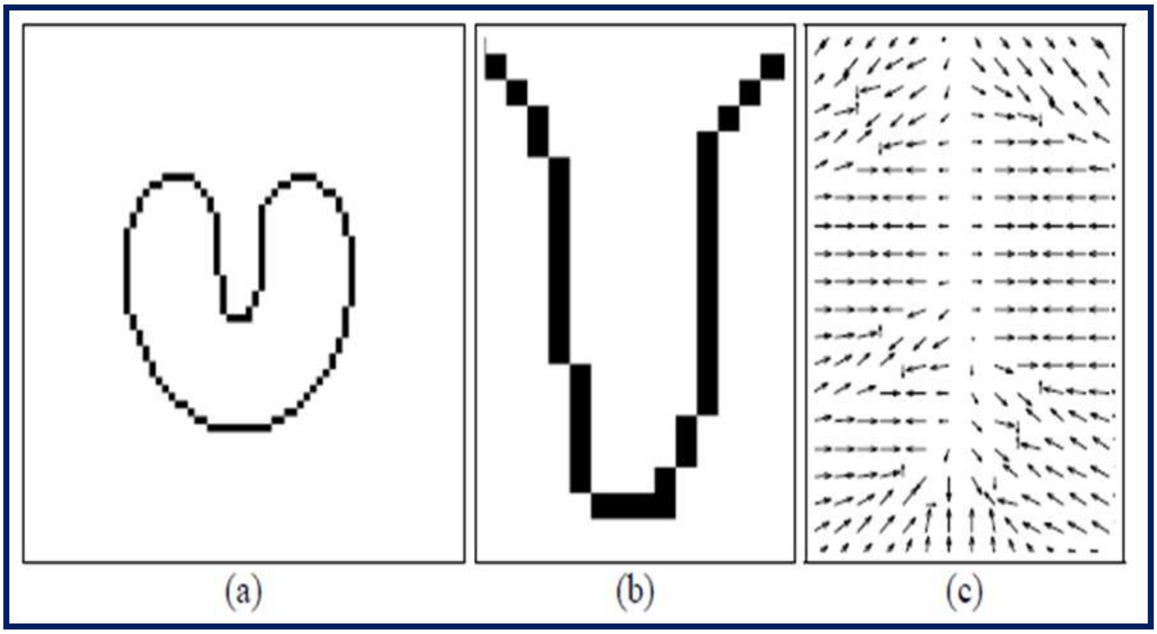

Figure – 3: Distance potential force (DPF) field example (a) close-up of a U-shaped object (b) with boundary concavity, and (c) DPF within concavity [8].

The GVF field definition can be applicable for all kinds of dimensions. The two examples of $g(r)$and $h(r)$are given by following equations :

$g(r) = \exp\{-(r/k^2)\}$ 2

$h(r) = 1 - g(r)$ ...... …………………3

Where *k* is the scalar and *r* is the dummy variable, or
$g(r) = \mu$ ...... …………………………4

$h(r) = r^2$ ...... ……………………………5

Where, μ is a positive is a scalar.

It is seen that GVF is having large range and an improved convergence can be noticed for deforming contours for most of the boundary concavities.

2.2. Generalized Force Balance Equations of GVF

The solutions shown in figure – 3(a) and 3(b) satisfy the Euler equations with respective energy models. The poor configurations are attributed to converge to local minimum of objective function. Previous research reports provided a solution for this problem by formulating deformable contours directly from the following equation in which the standard external force $F_{ext}^{(p)}$ is replaced by general external force $F_{ext}^{(g)}$as follows [9]

$F_{int} + F_{ext}^{(g)} = 0$ ...... ………………………………..6

$F_{ext}^{(g)}$ will be having a deep impact on implementation and behaviour of the deformable contour. In

 DOI : 10.36893.DRSR.2021.V11I01.1054-1061

ISSN: 2278-4632
Vol-11 Issue-01 2021

detail, external forces $F_{ext}^{(g)}$ are divided into two classes: Static and Dynamic forces. Static forces compute the image data and do not change like deformable contour progress. Dynamic forces are bound to change with respect to the deformable contour deforms. For improving the standard deformable contour forces many authors introduced wide range of dynamic external forces. As an example of multi resolution deformable contours are considered and the forces used in this and pressure forces that are used in ballons are in fact dynamic external forces. But these two methods include lots of complexity for the implementation and probability of having more unpredictability is more . In another case the pressure force need to be initialized either by push out or by push in. Sometimes it may even overwhelm weak boundaries in case they are acting very strongly. So that they may not be able to move into boundary concavities in case of wrong pushing direction or sometimes it may possible that they act too week.

For such situations a new method of statistical external forces was introduced in which, the forces don't change with respect to time and it only depend on position of deformable contour. This method is evolved from Helmholtz theorem, considers most general static vector field that is divided into two components. They are irrotational (curl free) component and Solenoid (Divergence free) component. The external force that is generated by variational formulae of traditional deformable contour will enter the force balance equation as static irrotational field due to its nature of gradient potential function. Hence general static field $F_{ext}^{(g)}$can be observed by allowing possibilities which includes both irrotational components and solenoid component. A separate solenoid field from an image can also be constructed which later can be used as a standard irrotational field.

3. Modified snake model

3.1. Snake model

Snakes are curves defined within an image domain, which move under the influence of internal forces within the curve itself and external forces derived from the image to minimize the energy function *E*=

*E*int+ *E*ext. *E*int characterizes the contour, and the relative weights α and β govern the snake's tension and rigidity, respectively. *E*ext denotes the external energy which leads the snake towards edges, and γ indicates its weight [6]. Traditional snakes often converge to the local minimum of the energyfunctional, and in addition the capture range is quite small which result in the convergence contour sensitive to the initialization. Another problem is that traditional snakes have difficulties inprogressing into boundary concavities. The GVF snake resolves these problems by GVF force.

However, if desired edges are weak in very noisy images such as in ultrasound images, noise need to be removed by some effective approaches instead of the Gaussian filter.

3.2. Shape similarity metric

Fourier Descriptor is a feature for the distribution description of image pixels on image contour, and we follow it to represent the shape of discrete snake contours *S*(*n*):

$$Shape(s,u) = normalize\{|\frac{1}{N}\sum_{n=0}^{N-1} ZeroMean(s(n))e^{-j2\pi un/N}|\}$$

Therefore, a shape similarity metric between snake *S* and expected snake *S*Expected is equal to <*Shape*(*S*), *Shape*(*S*Expected)> .

3.3. Segmentation scheme

 DOI : 10.36893.DRSR.2021.V11I01.1054-1061

ISSN: 2278-4632
Vol-11 Issue-01 2021

A parameter-varying snake model is introduced incorporating prior knowledge on the contours' shape and shape similarity metric. In practice, parameters of snakes affect the segmentation results to a great
extent. Intuitively, the external energy should govern the minimization procedure when the segmentation is started, in order to force the initial contour to evolve close to boundaries. For the later stages, the shape prior becomes a more important feature for segmentation.

In this scheme, we address the problem of choosing parameters. The segmentation process by snake model starts from a smaller α, β and a larger γ until it reaches its convergence. Then the shape similarity metric between the snake curve and the expected shape is computed. If these two shapes differ a lot, these parameters are changed and snake algorithm is restarted in which the last snake is taken as an initial snake. This procedure will last until the shape similarity is satisfied.

4. Experiments and results

The test image for denoising is a noisy Lena image. The PSNR of denoising result by wavelet shrinkage is 28.2. The residue image is figure 1(a). This image contains a lot of image details which should not be discarded. Figure 1 (b) shows the denoising result by our proposed denoising algorithm and PSNR =30.2. Results show that the proposed algorithm performs well. Experiments for the segmentation scheme are shown in figure 4. α =0.1, β =0 and γ=1 at starting, and for the second stage α =1,β=1 and γ=0.2. Snake of figure 4(b) is better than that of figure 4(a). The segmentation results prove that this scheme is successful and effective.

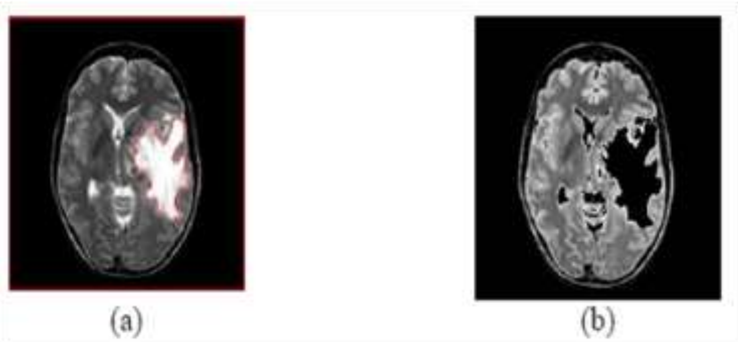

Figure 4. Segmentation result (a) of the first ; (b) of the second.

5. Conclusion

This work can be further extended for different medical images like MR brain images, Knee images. The proposed method proves to be good in extracting the liver regions this idea can be applied for the extraction of deformable masses in MR brain images. It is expected that the future research will focus on building robust statistical segmentation models.

A novel segmentation scheme for noisy images is presented in this paper, which consists of a new denoising method and a parameter-varying snake model. Various experimental results show that this scheme is promising[10].

References

[1] Vinayak Dutt and James Greenleaf 1996 Adaptive speckle reduction filter for log-compressedB-scan images *IEEE Trans. Medial Imaging* **15** 802-813

[2] Jun Xie, Yifeng Jiang and Hung-tat Tsui 2005 Segmentation of kidney from ultrasound imagesbased on texture and shape priors *IEEE Trans. Medical Imaging* **24** 45-57
371

[3] David L Donoho 1994 Ideal spatial adaptation by wavelet shrinkage *Biometrika* **14** 425-455

 DOI : 10.36893.DRSR.2021.V11I01.1054-1061

ISSN: 2278-4632
Vol-11 Issue-01 2021

[4] David L Donoho 1995 De-noising by soft-thresholding *IEEE Trans. Info. Theory* **41** 613-627
[5] Jean-Luc Starck, Emmanuel J Candes and David L Donoho 2002 The curvelet transform forimage denoising *IEEE Trans. Image Processing* **11** 670-684
[6] Kass M, Witkin A and Terzopoulos D 1987 Snakes: active contours models *Int. J. of Comput.Vis.* **1** 321-331
[7] Cvancarova M, Albregtsenb F, Brabrandd K and Samset E 2005 Segmentation of ultrasound images of liver tumors applying snake algorithms and GVF *Int. Congress Series* **1281** 218–223
[8] Chenyang Xu and Jerry L Prince 1998 Snakes, Shapes, and Gradient Vector Flow *IEEE Trans.image processing* **7** 359-369

[9]Ashburner, John, and Karl J. Friston. "Image segmentation." *Human Brain Function*, (2003): 695-706.

[10] Dass, R., Devi, S., & Priyanka, P. (2012). Effect of Wiener-Helstrom Filtering Cascaded with Bacterial Foraging Optimization to Despeckle the Ultrasound Images. *International Journal of Computer Science Issues(IJCSI),*

 DOI : 10.36893.DRSR.2021.V11I01.1054-1061