

Detection of Masses in Mammogram Based on Non-Linear Filtering Techniques

B. Sridhar

Department of ECE, Lendi Institute of Engineering & Technology, Vizianagaram, India
Email: srib105@gmail.com

K. V. V. S. Reddy

Department of ECE, Andhra University, Visakhapatnam, India
Email: kvvsreddy@gmail.com

A. M. Prasad

Department of ECE, JNT University, Kakinada, India
Email: amprasad@gmail.com

Abstract—The present method proposed for cancer detection in mammograms. To extract various intensity regions is a difficult task in mammograms. It has low intensity values and noise impose at low frequencies. A nonlinear filter is more suitable to extract the types of noise and enhance sharpness of edges. The characteristic shows the adaptive bilateral filter is a nonlinear filter. Now a day's Adaptive bilateral filters (ABF) is showing optimum results to remove the noises and enhance the edges of objects in the image sharply. A gradient operator with adaptive controlled parameter can efficiently highlight and segmented the edges. The proposed method is a combination of an ABF and morphological gradient operator is applied for masses detection. The method is experimented on MIAS database mammograms and ground truth is calculated. The method is validated with performance metrics.

Index Terms—non-linear filters, adaptive bilateral filters, morphological gradient, cancer detection, mammograms

I. INTRODUCTION

Medical image analysis research is to be growing by efficiently using advanced operators and algorithms. These operators are much effective to extract the features. Mammogram image analysis is used to detect the cancer in the breast of suspicious women. It can produce an in depth structures of breast tissues. The incidence of breast cancer is rising in every country of the world especially in developing countries such as India [1]. Number women in India are beginning to work outside their homes which allow the various risk factors of breast cancer to come into play. These include late age at first childbirth, fewer children and shorter duration of breast-feeding. The incidence varies between urban and rural women; the incidence in Mumbai is about 27 new cases per 100,000 women per year while in rural Maharashtra it is only 8 per 100,000. The chances of cure in women who develop the disease are related to early

diagnosis. There are 3 methods for early detection of breast cancer [2]. In mammograms, the objects of clustered masses or lesions, micro-calcifications, distortion are appear in breast architecture. CAD system is developing since last decade to improve the accuracy in detection of cancer. CAD is able to identify the Regions of Suspicion part (ROS); it can make a decision whether a ROS is benign or malignant. The general process of CAD for mammograms refers to image pre-processing, defining ROI, extracting features and classifying a ROI into benign, malignant or the appearances of micro calcifications are small bright arbitrarily shaped regions. The appearances of mass lesions are dense regions of different size and properties, which can further described by circumscribed, speculated or ill-defined. Screening mammography is performed at various intervals dependent on age of the patient and the standards of screening in a country. Mammograms can be used to check for breast cancer in women who have no signs or symptoms of the disease. This type of mammogram is called a screening mammogram. Screening mammograms usually involve two x-ray pictures, or images, of each breast [3]. The x-ray images make it possible to detect tumours that cannot be felt. Screening mammograms can also find micro calcifications (tiny deposits of calcium) that sometimes indicate the presence of breast cancer. However, mammography is expensive, technology driven and requires stringent quality control and extensive experience on the part of technicians and doctors involved. If these are not available, mammography can do more harm than good by falsely diagnosing cancer or missing it when it is actually present [4], [5].

In order to identify these structures the radiological studies have chosen only mammograms than other modalities images. Therefore, a new developments on a computer aided Design (CAD) systems by using these operators such as nonlinear filters algorithms, mathematical morphological operators etc are still in practise to achieve a precise results. Breast contains the

abnormalities can be identified by x-rays photography is called mammograms shown in Fig 1. These abnormalities are also called masses or lesions [5]. The masses are classified in three types; those are benign, partial malignant, malignant. The mammogram consists a benign gives no cancer, which appears a regular circular shape with centre. Partial malignant does not follow the circular shapes with multi centres, which gives the result that the women have chances to get a cancer in few couple of years. A malignant mass is tense to be a cancer, which follows no regular shape and seem to be clusters. Buyue Zhang et.al [7] was proposed the adaptive bilateral filter (ABF) than the ordinary form of the bilateral filters.

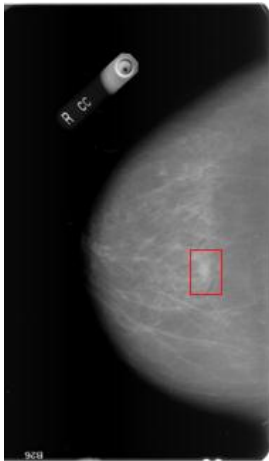


Figure 1. Mammogram marked with masses.

Alexander Wong [7] introduced a different perceptually based process for noise removal of image signals represented by low signal to noise ratios. Results are shown that the process is effective at removing signal noise, while enhancing both qualitatively and quantitatively. Hyung W et.al [8] were developed a new bilateral filter method to reduce speckle noise reduction in ultrasound images for the purpose of segmentation and Measurement.

II. BACK GROUND

A. Mathematical Morphology (MM) Operations

The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the *structuring element* used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image. The rule used to process the pixels defines the operation as dilation or erosion [11].

B. Understanding Structuring Elements (SE)

An essential part of the dilation and erosion operations is the structuring element used to probe the input image. A structuring element is a matrix consisting of only 0's

and 1's that can have any arbitrary shape and size. The pixels with values of 1 define the neighborhood. Two-dimensional, or *flat*, structuring elements are typically much smaller than the image being processed. The center pixel of the structuring element, called the *origin*, identifies the pixel of interest or the pixel being processed. The pixels in the structuring element containing 1's define the *neighborhood* of the structuring element. These pixels are also considered in dilation or erosion processing. The two basic morphological operations, dilation and erosion with a structuring element B, are defined for a grey-scale image $f \in L \alpha (\mathbb{R}^2)$ by [1]

$$\text{Dilation: } (f \oplus B)(x) = \sup\{f(x-y), y \in B\} \quad (1a)$$

$$\text{Erosion: } (f \ominus B)(x) = \inf\{f(x+y), y \in B\} \quad (1b)$$

The names can be easily motivated when considering a shape in a binary image and a disc shaped structuring element. In this case dilation blows up its boundaries, while erosion shrinks them. Dilation and erosion form the basis for constructing other types of morphological processes, for instance opening and closing:

$$\text{Opening: } (f \circ B)(x) = ((f \ominus B) \oplus B)(x) \quad (2)$$

$$\text{Closing: } (f \bullet B)(x) = ((f \oplus B) \ominus B)(x) \quad (3)$$

In the preceding shape interpretation opening smoothes the shape by breaking narrow region and eliminating small islands, while closing smoothes by eliminating small holes

C. Selection of Structure Elements

Structure elements are classified in to Omni directional and multi scaled elements is one way to plot the square windows [19]. In general consider α is the angle of rotation. Let us consider N is a value then order of the SE is $(2N+1) \times (2N+1)$. Then the equation of the structure element is represented as

$$W = \left\{ \frac{s(n_1+s_1n_2+s_2)}{\theta_s} = s\alpha - N \leq s_1, s_2 \ll N \right. \quad (4)$$

For all $s=0, 1 \dots 4N-1$ and α is the angle of the rotation expressed as $\alpha = 180^\circ / 4N$. Suppose $N=2$ then dimension of the SE is 5×5 , the angle value is obtained as $\alpha=0, 22.5, 45, 135, 157.5$

Consider the structure element sequence have same shape in common and size increased follow the accretion of I. then defining to different features from the various values of image, the size of the structure must be adjusted [24]. In general, select basic structure element shape and the number of structure elements of the order $(2i+1) \times (2i+1)$.

Opening is applied to highlight or remove the regional maxima's in the gray scale image. Here the structure element is selected a 'disc' shape have dimensions $3 \times 3, 5 \times 5, 7 \times 7$ etc. The best result is obtain at lower dimensions, however the simulation time is increased. The main disadvantage of the opening operation, it may not remove the regions whose dimensions greater than or equal to structural element dimensions. This problem can be solved by using opening by reconstruction [9]. Maker

image is produced by subtracting an input image from low constant gray value. After reconstruction the image is marked with regional and appears with the similar intensity. Opening is erosion followed by dilation, while opening-by-reconstruction is erosion followed by a morphological reconstruction. The opening with a closing can remove the dark spots and stem marks in the gray scale image. Then the reconstruction-based opening and closing are more effective than standard opening and closing at removing small blemishes without affecting the overall shapes of the objects. Calculate the regional maxima of dilated image to obtain good foreground markers.

D. Adaptive Bilateral Filtering

Bilateral filtering smoothes images while preserving edges, by means of a nonlinear combination of nearby image values. The method is non-iterative, local, and

$$r(m_0, n_0) = \sum_{m=m_0-N}^{m_0+N} \sum_{n=n_0-N}^{n_0+N} e^{\left(\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^2}\right)} \cdot e^{-\frac{1}{2}\left(\frac{g[m,n]-g[m_0,n_0]-w[m_0,n_0]}{\sigma_r[m_0,n_0]}\right)^2} \tag{6}$$

$$h[m, n; m_0, n_0] = I(\Omega_{m_0, n_0}) r_{m_0, n_0}^{-1} e^{\left(\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^2}\right)} \cdot e^{-\frac{1}{2}\left(\frac{g[m,n]-g[m_0,n_0]-w[m_0,n_0]}{\sigma_r[m_0,n_0]}\right)^2} \tag{7}$$

$r(m_0, n_0)$ is a normalization factor that assures that the filter preserves average gray value in constant areas of the image.

A Gaussian filter is filtering the low frequency noise and restores the edges. Combinations of domain and range Gaussian filters are applied to give maximum weight pixels, which is near to centre value. A combined operations of domain and range filter along with the bilateral filter at nearer to edge pixel gray level values is become stretched out, Gaussian filter is slopping around the edge. It gives a guarantee to take an average of adjacent pixel values and minimizes the gradient direction. Thus, the bilateral filter greatly smooth's the noise and restoring edge formations.

The ABF maintains the actual form of bilateral filter, in addition two significant modifications is included. As shown in the equation 6 & 7 is consists a two exponential functions one is the operator of range filters and second the domain filter functions. The range filters is included an offset (w) function and width is introduced in domain filters. Those function turns the bilateral filter is spatially adaptive. If the offset value is zero and width is constant the ABF is acts as an ordinary bilateral filter. The variation of these two values or either one is fixed the filters shows an effective performance to restores the image and edges are sharpen. It is concentrated on edges at maximum level and improves the slope.

In ABF the pixel gray level variation plays an important role during the training of filter. Here we make the difference of the centre pixel value with mean of the local widow to be chosen. Its response is more effects on the strength of edges, separates the regions and reduces the robustness to the noise. So apply a Laplacian of Gaussian to the image before undergone for filtering process

III. METHODOLOGY

simple. Its combine gray levels or colors based on both their geometric closeness and their photometric similarity, and prefers near values to distant values in both domain and range. The bilateral filter proposed by Tomasi and Manduchi in 1998 is a nonlinear filter that smoothes the noise while preserving edge structures [10]. Bilateral filter are a spatial domain filter, the response of the filter is given in the equation (5)

$$y(m, n) = \sum_k \sum_l h[m, n; k, l] x[k, l] \tag{5}$$

$Y(m, n)$ is the noise removed image.

$h[m_0, n_0; k, l]$ is the response at $[m, n]$ to an impulse $I[k, l]$ and $x[m, n]$ is the degraded image.

Where (m_0, n_0) is the center pixel of the window Ω_{m_0, n_0} . σ_d and σ_r are the standard deviations of the domain and range Gaussian filters, respectively

To detect lesions for various mammograms are extracted using a nonlinear filtering processing with morphological gradient operator. Adaptive bilateral filter is nonlinear filter. Bilateral filter has two important changes. One, an offset value is included along with range filter. Next both width and range of the adaptive filters are included with respective output value. The output of the edge preserved with Laplacian of Gaussian (LOG) operation is improved the sharpness[6]. The quality of the image purely depends on the image structure. The shift-variant filtering operation of the bilateral filter is given by,

$$y(m, n) = \sum_k \sum_l h[m, n; k, l] x[k, l] \tag{8}$$

$y(m, n)$ is the noise removed image.

$h[m, n; k, l]$ is the response at $[m, n]$ to an impulse $I[k, l]$ and $x[m, n]$ is the degraded image.

Where $[m_0, n_0]$ is the centre pixel of the window. σ_d and σ_r are the standard deviations of the domain and range Gaussian filters, respectively a normalization factor that assures that the filter preserves average gray value in constant areas of the image. To mark the dynamic changing of the intensity levels the mathematical morphology is used [5]. Gradient morphology will show a very good efficiency to marks intensity

$$\begin{aligned} Ge(x) &= x - (x \ominus B) \\ Gd(x) &= (x \oplus B) - x \\ G(x) &= (x \oplus B) - (x \ominus B) \end{aligned} \tag{9}$$

Region is given in equation 9. B is the structure element, $Ge(x)$ is gradient erosion, $Gd(x)$ gradient dilation and $G(x)$ is morphological gradient.

If B is chosen as the rod structure element with flat top, whose domain is the origin and its 4-neighbor, then gradient by erosion and dilation are also called erosion residue edge detector and dilation residue edge detector respectively [9]. Here extracted masses obtained with the $G(x)$. A series of operations are applied with adaptive

bilateral filters along morphological gradients to train the algorithm and generate optimum results.

IV. RESULTS AND DISCUSSIONS

The Proposed algorithm is simulated in MATLAB 7.8 and experimented with 10 datasets of ROI of mammogram are taken MIAS data base [10]. The results are observed as shown in Fig. 2A is the input image 2b is the segmented area by using adaptive bilateral filters. 2c) segmented by morphological gradient operation along with filters. Here it gives two features of the masses. One is the size of the mammogram and it shapes. Fig. 2 & Fig. 3 appears to be nearly circles then the observe masses is a benign. In Fig. 4 show the results a partial malignant. Fig. 5 show cluster types of segmentation have the shape is irregular. It can be considered a malignant. The results are compared with ground truth values. And also calculated proposed method average metrics specificity is 84.24% sensitivity is 96.71%.

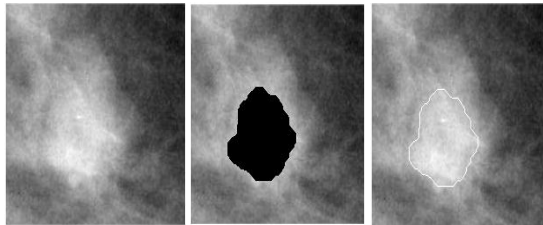


Figure. 2 A.input masses B.Segmented output C.Segmented with boundary

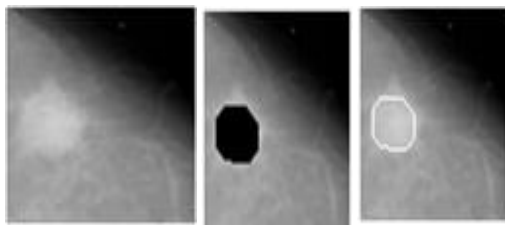


Figure. 3A benign input masses B.Segmentedoutput C.Segmented with boundary

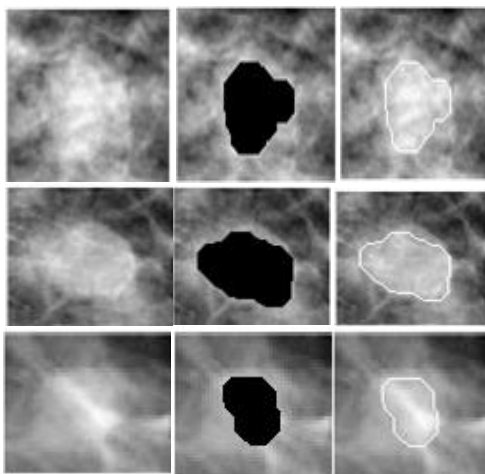


Figure. 4 A partial malignant input masses B.Segmentedoutput C.Segmented with boundary

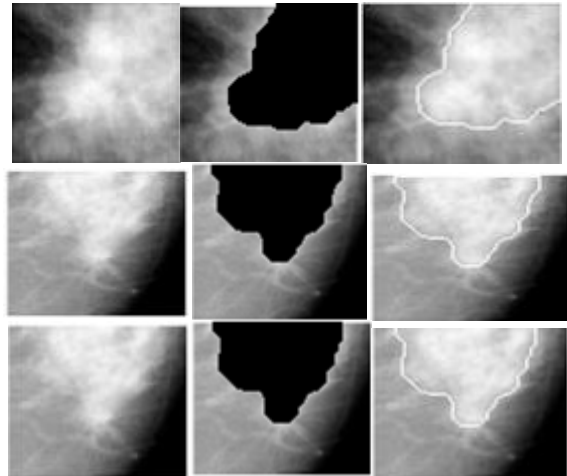


Figure. 5 A malignant input masses B.Segmentedoutput C.Segmented with boundary

The proposed method evaluated with comparison of ground truth is given by the experts. The algorithm is evaluated with four parameters are sensitivity, specificity, Jacard index and Dice coefficient [7]. Let us consider a segmented image. The output correctly segmented or not is defined TP or TF.

True Positive (TP) = an abnormal classified as abnormal, True Negative (TN) = A normal classified as normal, True Positive Fraction (TPF) also called Sensitivity defined as

Number of abnormal classified as abnormal divided by with total number of abnormal.

True Negative Fraction (TNF) also called Specificity defined Number of normal classified as normal divided by with total number of normal.

$$\text{Jaccard Index (JI)} = \frac{Rgt \cap Rcs}{Rgt \cup Rcs} \quad (10)$$

$$\text{Dice coefficient (DC)} = 2 * \frac{Rgt \cap Rcs}{Rgt + Rcs} \quad (11)$$

where Rgt is manually segmented by the expert in radiology with ground truth of the mammogram. Rcs is the detection of cancer by proposed method. Jaccard is the statistical measure fundamental measure of the sample sets, It is defined as principally of their intersection divided by the principally of their union. Dice coefficient is defined as It is defined as principally of their intersection divided by the principally of their sum. The calculated values for all mammograms are shown in graphs the values show the proposed algorithm is accurate and it is comparable to the existence method [11].

The simulated results of the 10 datasets are evaluated by sensitivity, specificity, JI, DC are calculated and average value of the each dataset is tabulated in Table I

The proposed method detected of masses in the mammogram of the area 0.6 to 2.2cm and also shape of the mass is efficiently measured. The Fig. 6 show a graph is depicted between these sensitivity, specificity and mammogram data sets. The specificity of the range 68% to 85%, sensitivity varies in the 91.4 to 98.21%.

TABLE I SENSITIVITY(%), SPECIFICITY(%), JI AND DC

Image Number	Sensitivity (%)	Specificity (%)	JI	DC
1	98.21	76.42	0.8	0.81
2	98	81.44	0.75	0.78
3	95.01	76.12	0.7	0.78
4	97.5	85.52	0.81	0.85
5	94.88	77.76	0.68	0.72
6.	91	68	0.67	0.72
7	97.1	71	0.71	0.85
8	91.4	71.67	0.69	0.7
9	98	72	0.75	0.86
10	92.10	69.11	0.67	0.71

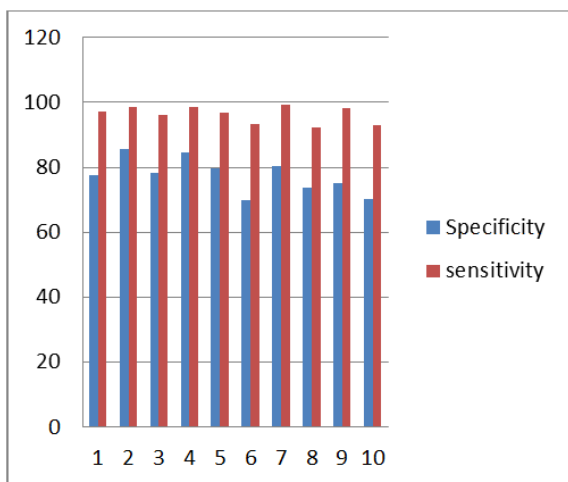


Figure.6 performance analysis through sensitivity, specificity Vs image data sets

Fig. 7 show the stem graph is drawn in between the JI, DC and mammogram data sets. JI is calculated, varies between 0.67 to 0.81 and DC is calculated, varies between 0.7 to 0.86. This proposed method shows efficient results, which is comparable with expert method.

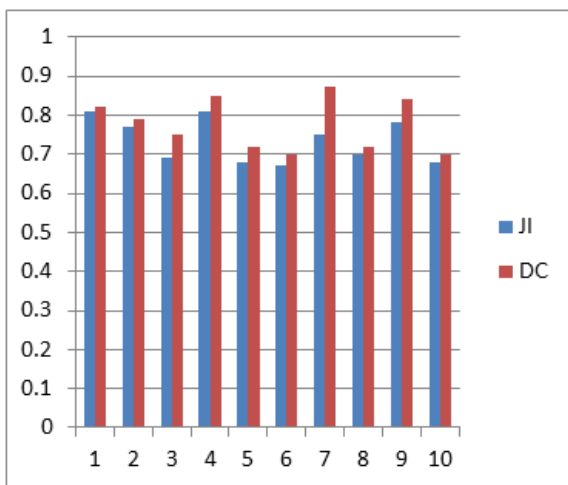


Figure. 7 performance analysis through Jacard index, Dice coefficient Vs image data sets

V. CONCLUSIONS

The Proposed method is based on the detection of cancer using non linear filters. This method chosen an adaptive bilateral filter as a non-linear filter, along with mathematical gradient operators. The proposed algorithm is experimented on ten types of data sets mammograms total 231 ROI mammograms, out that 123 malignants, 70 benign are observed. The experimental results shown methods is much efficient qne compared existed methods [1]. Hence, this method can be preferable for diagnosis of early detection malignancy as second reader in mammogram image analysis. This method some time gives more number of false positives, if low quality digital mammogram is chosen. In Future work the micro calcifications accuracy will be improved by representing segmented image in three dimensional, and evaluation process also to be improved by using artificial neural network methods.

ACKNOWLEDGEMENTS

This research work is supported by our institutions. The authors show the gratitude to the institutions, Head of the institutions, Co Faculty, Scholars. The authors are thankful to the Local government Hospital near to our institutions to support their clinical suggestions to progress of this work.

REFERENCES

- [1] N. Riyahi Alam, F. Younesi, and M. S. Riyahi Alam, "Computer-aided mass detection on digitized mammograms using a novel hybrid segmentation system," *International Journal of Biology and Biomedical Engineering*, vol. 3, no. 4, 2009.
- [2] B. Sridhar and K. V. V. S. Reddy, Efficient Computer Aided System based on Mathematical Morphology and Higher Order Partial Differential Equations for Breast Cancer Detection CNC, 2013, pp. 234-239.
- [3] J. Bozek, K. Delac, and M. Grgic, "Computer-aided detection and diagnosis of breast abnormalities in digital mammography," in *Proc. 50th International Symposium ELMAR-2008*, Zadar, Croatia, 10-12 September 2008.
- [4] T. Matsubara, T. Ichikawa, T. Harab, H. Fujitab, *et al.*, "Automated detection methods for architectural distortions around skinline and within mammary gland on mammograms," *International Congress Series*, vol. 1256, pp. 950-955, 2003.
- [5] J. Tang and M. Ragaraj, "Rangayan computer aided detection and diagnosis of breast cancer with mammograph: Recent advances," *IEEE Trans on Information Technology in Biomedicine*, vol. 13, no. 2, March 2009.
- [6] B. Zhang and J. P. Allebach, "Adaptive bilateral filter for sharpness enhancement and noise removal," *IEEE Transactions on Image Processing*, vol. 17, no. 5, May 2008.
- [7] A. Wong, "Adaptive bilateral filtering of image signals using local phase characteristics," *Elsevier Signal Processing*, vol. 88, pp. 1615-1619, 2008.
- [8] H. W. Kang, C. K. Chui, and U. K. Chakraborty, "A unified scheme for adaptive stroke-based rendering," *Visual Computer*, vol. 22, no. 9-11, pp. 814-824, 2006.
- [9] R. C. Gonzalez, R. E. Woods, and S. L. Eddins, *Digital Image Processing using MATLAB*, Upper Saddle River, N. J: Pearson Prentice Hall, 2004.
- [10] S. Meenalosini and E. Kannan, "Malignancy detection in mammogram using gray level gradient buffering method," *International Journal of Cancer Research*, vol. 47, no. 1, pp. 1110-1118, 2012.
- [11] H. S. Bhadauria and M. L. Dewal, "Intracranial haemorrhage detection using spatial fuzzy c-mean and region-based active contour on brain CT imaging," *Signal, Image and Video*

Processing, Springer-Verlag London Limited, vol. 8, no. 2, pp. 357-364, 2014.

B. Sridhar, male, is a Faculty at the Lendi Institute of Engineering Technology. He is currently working towards the Ph.D. degree in the department of Electronics and Communications Engineering, JNTU, Kakinada. His research interests include computer vision, digital image processing and Software Development. His teaching interests are digital image processing, Signal processing, and Optical communications & networks.

Dr. K. V. V. S. Reddy, male, He was a Professor in the Department of Electronics and Communications Engineering, Andhra University. His areas of research interest are signal & image processing.

Dr. A. M. Prasad, male, is presently working as a Professor in the department of Electronics and Communications Engineering, J.N.T. University, Kakinada. His research interests include Antenna wave propagation, computer vision, digital image processing and Wireless communications.