Bias Correction and Segmentation of Images with Intensity Inhomogeneity

[1]G. Swapna, [2]G. Chenchu Krishnaiah

[1]PG Scholar, Department of ECE, Gokula Krishna College of Engineering, Sullurpet, India
[2]Professor & Dean, Department of ECE, Gokula Krishna College of Engineering, Sullurpet, India

Abstract: Intensity non-uniformity or intensity inhomogeneity usually occurs in Real world Images, those images cannot be segmented by using image segmentation. The most commonly used algorithms in image segmentation are region based and depends on the homogeneity of the image intensities which usually fails to produce accurate segmentation results due to the intensity non-uniformity. In this paper we proposed a novel region based method for image segmentation which can be able to discuss with intensity non-uniformities in image segmentation. First according to the image models with intensity non-uniformities we define a local clustering criterion function for the intensities in the image neighborhood of each part. The local clustering criterion function is then integrated with respect to the neighborhood center to give a global criterion of image segmentation. In a level set formulation this criterion defines an energy in terms of level set functions that represents the partition of image domain and a bias field that corresponds to the intensity non-uniformity of the image. Therefore, by minimizing the energy we can able to segment the image simultaneously and estimate the bias field can be used for the intensity non-uniformity correction. This method is applied on MRI images and real world images of various modalities with desirable performance in the presence of intensity non-uniformities. The experiment results show that the method is stronger, faster and more accurate than the well-known piecewise smooth model and gives promising results. As an application this method is used for segmentation and bias correction of real world images and MRI images with better results.

***Index Terms* - Bias field, Energy minimization, Image segmentation, Intensity non-uniformity, Level set method.**

I. INTRODUCTION

Intensity non-uniformity frequently occurs in real world images due to the various factors such as imperfections of the imaging devices which correspond to many problems in image processing and computer vision [1]. Image segmentation may be mainly difficult for the images with intensity non-uniformities due to the overlap between the ranges of the intensity in the regions to be segmented. This makes it impossible to categorize these regions based on the pixel intensity. Those extensively used image segmentation algorithms depends on intensity homogeneity and hence not applicable to images with intensity non-uniformities .In general, intensity non-uniformity has been an interesting problem in image segmentation.

The level set method is used as a statistical technique for tracking the interfaces and shapes that has been progressively applied to image segmentation in the past years. In the level set methods surfaces are represented to the zero level set of higher dimensional function called as level set function. With level set illustration the image segmentation problem can be formulated and solved by using mathematical theories and including the partial differential equations [2]-[4].

The advantage of level set method is that numerical computations involves curves and surfaces which can be performed on fixed Cartesian grid without having no constraints. Existing level set methods for image segmentation can be resolute into two classes; they are Region-based models and Edge-based models. Region-based models are used to categorize each region by using a certain region descriptors to guide the motion of the active contours. It is very difficult to define a region descriptor for images with non-uniformities. Most of the region based models are based on the assumption of intensity homogeneity. A typical example is piecewise constant models and level set methods are proposed based on general piecewise smooth formulation proposed by Mumford and shah. These methods are able to segment the images with intensity non-uniformities however these methods are worked out to be too expensive and are quite sensitive to the initialization of the contour. Edge-based models use edge information for image segmentation; those models do not assume homogeneity of image intensities and thus can be applied to images with intensity non-uniformities [5]-[7].

These methods are quite sensitive to initial conditions and frequently suffer from serious boundary leakage problems in images with weak object boundaries. A novel region based method for image segmentation is proposed. A local intensity clustering property and local intensity clustering criterion function for the intensities in a neighbourhood of each point is defined in this paper. This local clustering criterion is integrated over the neighbourhood center to define energy functional, which is converted to a level set formulation minimization of this energy is achieved by an interleaved process of level set evolution and estimation of bias field. This method is applicable to the segmentation and bias correction of MR images [8]-[11].

II. MODELLING OF INTENSITY INHOMOGENEITY

Images with intensity inhomogeneity was represented using the following notation.

$$I = bJ + n \quad (1)$$

where I is the read image, b is the spatially varying bias field, J is original image which is to be estimated, n is zero-mean finite variance Gaussian noise. Hence the image intensity can directly be estimated to be a Gaussian distribution with mean bJ and variance σ^2, by assuming that the variance of n is σ^2. But the statistical characteristics of the intensity of the image cannot be completely described by the Gaussian model alone. To have a better introspection each domain should be indorsed to a Gaussian model. The intensity conforming to the domain μ_i is modeled as

$$p(I(y)\,|\,\beta_i) = \frac{1}{\sqrt{2\pi}\sigma_i}\exp\left(-\frac{\left(I(y)-b(x)c_i\right)^2}{2\sigma_i^2}\right), y \in \mu_i \quad (2)$$

where β_i takes on different values from {b, c_i, σ_i}, σ_i is a constant with respect to the standard deviation of image intensity ad $b(x)c_i$ is spatially varying local mean. A circular neighborhood center is considered for each point x in the image domain μ. The circular neighborhood is represented by

$$O_x = \{ y \mid \| y - x \| \le \rho \} \tag{3}$$

Here ρ is the radius of neighborhood region O_x. Now a different domain is defined with the following mapping from the original image domain to the new domain.

$$M : I(x \mid \beta_i) \rightarrow \bar{I}(x \mid \beta_i) \tag{4}$$

Now the original image domain may be represented by D(M) and new domain by R(M). The mapping is formally defined as follows.

$$\bar{I}(x \mid \beta_i) = \frac{1}{m_i(x)} \sum_{y \in \mu_i \cap O_x} I(y \mid \beta_i) \tag{5}$$

where $m_i(x) = \|\mu_i \cap O_x\|$.

As the intensity of pixel 'y' can be independently distributed [4], the newly defined domain can be treated as normal distributed with a non-zero mean of bc_i and variance $\frac{\sigma_i^2}{m_i(x)}$. The overlap that exists between adjacent regions can always be suppressed. As the inhomogeneity changes so smoothly throughout the image, an approximation can be made as follow.

$$I(y \mid \beta_i) = I(x \mid \beta_i), \forall y \in \mu_i \cap O_x \tag{6}$$

Also, because of the peculiar property of Gaussian density functions, i.e. the product of two Gaussian density functions is also a Gaussian, the following can be arrived.

$$\prod_{y \in \mu_i \cap O_x} p\big(I(y \mid \beta_i)\big) = p\big(I(x \mid \beta_i)\big)^{m_i(x)} \propto N\left(bc_i, \frac{\sigma_i^2}{m_i(x)} \right) \tag{7}$$

Now use the notation $D = \{ \bar{I}(x \mid \beta_i), i = 1, \ldots, N \}$. Then the likelihood function is defined as

$$p(D \mid \beta) = \prod_{i=1}^{N} p\big(\bar{I}(x \mid \beta_i)\big) \propto \prod_{i=1}^{N} \prod_{y \in \mu_i \cap O_x} p\big(I(y \mid \beta_i)\big) \tag{8}$$

where $\beta = \{ \beta_i, i = 1, \ldots, N \}$.

The energy functional is defined as follows.

$$E(\beta) = -\int_{\mu} \log p(D \mid \beta)\, dx = L - \sum_{i=1}^{N} \int_{\mu} \int_{\mu_i \cap O_x} \log\Big(p\big(I(y \mid \beta_i)\big)\Big) dy\, dx \tag{9}$$

Here L is a constant. Let $K_\rho(x,y)$ be function that characterizes the region O_x

$$K_\rho(x,y) = \begin{cases} 1, & \| y - x \| \le \rho \\ 0, & else \end{cases} \tag{10}$$

Now E(β) can be written as

$$E(\beta) = \sum_{i=0}^{N} \int_{\mu} \int_{\mu_i} K_\rho(x,y) \left(\log\left(\sqrt{2\pi}\sigma_i\right) + \frac{\big(I(y) - b(x)c_i\big)^2}{2\sigma_i^2} \right) dy\, dx \tag{11}$$

In [12], C. Li R. Huang et al. presented a level set method with weighted K-means (WKLS). The energy functional of this method is given below.

$$E_\beta = \sum_{i=1}^{N} \int_{\mu} \int_{\mu_i} G_\rho(x,y) \big(I(y) - b(x)c_i \big)^2 dy\, dx \tag{12}$$

where $\beta = \{ b, c_i, i = 1, \ldots N \}$ and $G_\rho(x,y)$ is curtailed Gaussian kernel. This method is very close to the one presented earlier except few considerations. They are K_ρ to be Gaussian and σ_i to be $1/\sqrt{2\pi}$ and E(β) and E_β are similar. But the model presented in this paper considers the variations of variance among different tissues. This result in a better accuracy than WKLS.

III. Local Intensity Clustering Property

Region based image segmentation method typically depend on a specific region descriptor of the intensities of in each region to be segmented [13]. For example consider the seeded region based model, in this set of seeds as input along with the image. The seeds mark each of objects to be segmented. But this method is difficult to give such type of region descriptor for images with intensity non-uniformities. The overlap between the distributions of the intensities in the regions $\Psi_1 \ldots\ldots\ldots \Psi_N$ with the presence of intensity that's why it is impossible to segment these regions directly based on the pixel intensities. The property of local intensities is simple, which can be effectively exploited in the formulation of our method for image segmentation with simultaneous estimation of the bias field. Based on the observed image and assumptions we are able to derive a useful property of local intensities, which is referred to as a local intensity clustering property. Consider a circular neighborhood with a radius ρ centered at each point y ϵ Ψ that is

$$O_Y \overset{\Delta}{=} \{ x : | x - y | \le \rho \}. \tag{13}$$

The partition region $\overset{N}{\underset{i=1}{\Psi_i}}$ of the entire domain Ψ induces a partition of the neighborhood of the O_Y, i.e., $\{O_Y \overset{N}{\underset{i=1}{\cap}} \Psi_i\}$ forms a partition of O_Y.

For a slowly varying bias field b_f, the values $b_f(x)$ for all x in the circular neighborhood O_Y are close to $b_f(y)$.

$b_f(x) \approx b_f(y)$ for $x \in O_y$ (14)

Where $b_f(x)$ is the bias field with the function of x, $b_f(y)$ is the bias field with the function of y. Thus, the intensities $b_f(x)T(x)$ in each sub-region $O_Y \cap \Psi_i$ are close to the constant $b_f(y)$ that is

$b_f(x)T(x) \approx b_f(y)c_i$ for $x \in O_y \cap \Psi_i$ (15)

where $b_f(y)\, c_i$ is the constant, $b_f(y)$ is the bias field with the function of y, $b_f(x)$ is the bias field with the function of x, and T(x) is the real image with the function of x. substitute above equation in the observed image equation then we get

$I(x) \approx b_f(y)\, c_i + N_a(x)$ for $x \in O_y \cap \Psi_i$ (16)

In the above equation $N_a(x)$ is the additive zero mean Gaussian noise. That is the intensities in the set $\overset{i}{\underset{Y}{I}} = \{I(x): x \in O_y \cap \Psi_i\}$ forms a cluster with center $m_i \approx b_f(y)c_i$, which can be considered as samples drawn from a Gaussian distribution with mean m_i.

IV. Formulation of Level Set

To represent each of the regions $\{\mu_i, i = 1,..., N\}$ with N as a power of 2, multiple level set functions $\{\phi_i, i = 1,..., n\}$. Let $M_i(\Phi_N(.))$ be the function that characterizes the complete region μ_i. $\Phi_N(.)$ is basically a function of set $\{\phi_i, i = 1,..., n\}$. The energy functional which is already given can now be written as follows.

$$E^{SMLS}_{\Phi_N,\beta} = \sum_{i=1}^{N} \int_\mu d_i(y) M_i(\Phi_N(y))\, dy \tag{17}$$

here $d_i(y)$ is defined as follows.

$$d_i(y) = \int_\mu K_\rho(x,y) \left(\log\left(\sqrt{2\pi}\sigma_i\right) + \frac{(I(y) - b(x)c_i)^2}{2\sigma_i^2} \right) dx \tag{18}$$

M_i is defined as follows for i = 1,2,3 and 4, which is four – phase case, by using which any other phase can be extended.

$$\begin{cases} M_1 = H(\phi_1)H(\phi_2), M_2 = H(\phi_1)(1 - H(\phi_2)) \\ M_3 = (1 - H(\phi_1))H(\phi_2), M_4 = (1 - H(\phi_1))(1 - H(\phi_2)) \end{cases} \tag{19}$$

Here H(*Φ*) is Heaviside function and is given by $H_\varepsilon(\phi) = \frac{1}{2}\left[1 + \frac{2}{\pi}\tan^{-1}\left(\frac{\phi}{\varepsilon}\right)\right]$. (20)

The minimization of $E^{SMLS}_{\Phi_4,\beta}$ with respect to each variable is obtained by setting the remaining variables. The variables c, b and σ takes the following expressions for minimizing $E^{SMLS}_{\Phi_4,\beta}$ in each case.

$$c_i = \frac{\int (K_\rho * b) I M_i(\Phi_4) dy)}{\int (K_\rho * b^2) M_i(\Phi_4) dy)} \tag{21}$$

$$b = \frac{\sum_{i=1}^{4} K_\rho * (I M_i(\Phi_4)) \frac{c_i}{\sigma_i^2}}{\sum_{i=1}^{4} K_\rho * (M_i(\Phi_4)) \frac{c_i}{\sigma_i^2}} \tag{22}$$

$$\sigma_i = \sqrt{\frac{\int\int K\rho(y,x)(I(y) - b(x)c_i)^2 M_i(\Phi_4(y))\, dy\, dx}{\int\int K\rho(y,x) M_i(\Phi_4(y))\, dy\, dx}} \tag{23}$$

The smoothness of the bias is guaranteed by the normalized convolution [14]. The energy functional can also be minimized with respect to the level set functions. The respective gradient descent is given below.

$$\frac{\partial \phi_1}{\partial t} = -[(d_1 - d_2 - d_3 + d_4)H(\phi_2) + d_2 - d_4]\delta(\phi_1) \tag{24}$$

$$\frac{\partial \phi_2}{\partial t} = -[(d_1 - d_2 - d_3 + d_4)H(\phi_1) + d_3 - d_4]\delta(\phi_2) \tag{25}$$

Here $\delta(\phi)$ is the delta function and the regularized form of this function is $\delta_\varepsilon(\phi) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + \phi^2}$.

V. RESULTS AND DISCUSSION

We first demonstrate our method in the two phase case (i.e. N=2). Unless otherwise specified, the parameter σ is set to 4 for the experiments in this section. All the other parameters are set to the default values. Fig. 1 shows the results for MRI images. The curve evolution processes are depicted by showing the initial contours (in the left column), bias field (in the middle column).

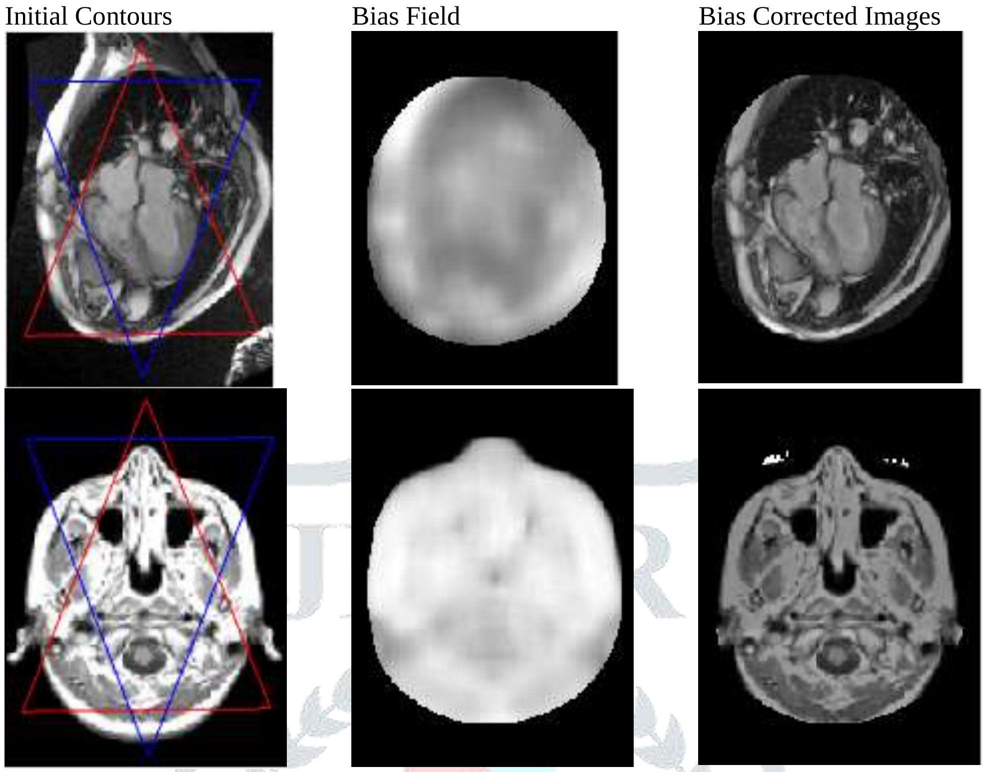

Fig. 1 Bias correction

Intensity non-uniformities can be clearly seen in these two images. Our method is able to provide a desirable segmentation result for such images. The estimated bias field by our method can be used for intensity non-uniformity correction (or bias correction). Given the estimated bias field, the bias corrected image is computed as the quotient $I/\hat{b}_f$. To demonstrate the effectiveness of our method in simultaneous segmentation and bias field estimation, we applied it to medical images with intensity non-uniformities. These images exhibit clear intensity non-uniformities. The initial contour is plotted on the original image in Column 1 of Fig.2. The corresponding results of bias field estimation, segmentation, and bias correction are shown in Columns 2, 3 and 4, respectively. These results demonstrate desirable performance of our method in segmentation and bias correction. We first display the results for MR images in the first column of Fig. 2. These images exhibit obvious intensity non-uniformities. The segmentation results, computed bias fields, bias corrected images, are shown in the second, third, and fourth column respectively. It can be seen that the intensities within each tissue become quite homogeneous in the bias corrected images. The improvement of the image quality in terms of intensity homogeneity can be also demonstrated by comparing the histograms of the original images and the bias corrected images.

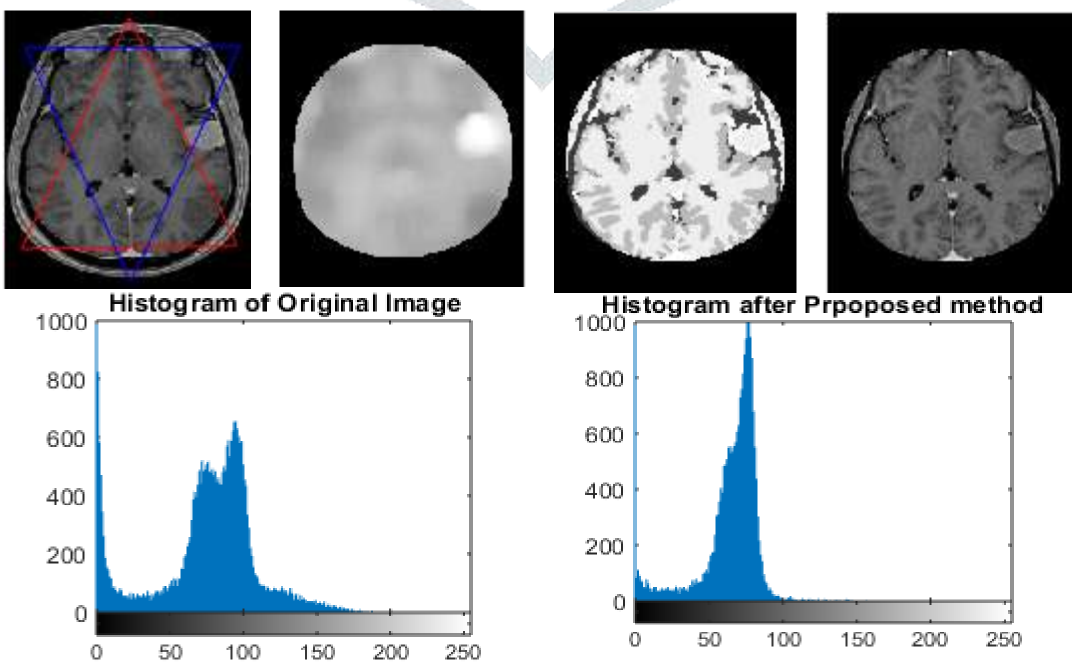

Fig. 2: Simulation Results with MR images as input

The histograms of the original images (left) and the bias corrected images (right) are plotted in the next row. The results of the real world images are given in Fig. 3. The first column shows the initial contours, second column shows the bias field, third column shows the segmentation results and fourth column shows the bias corrected image.

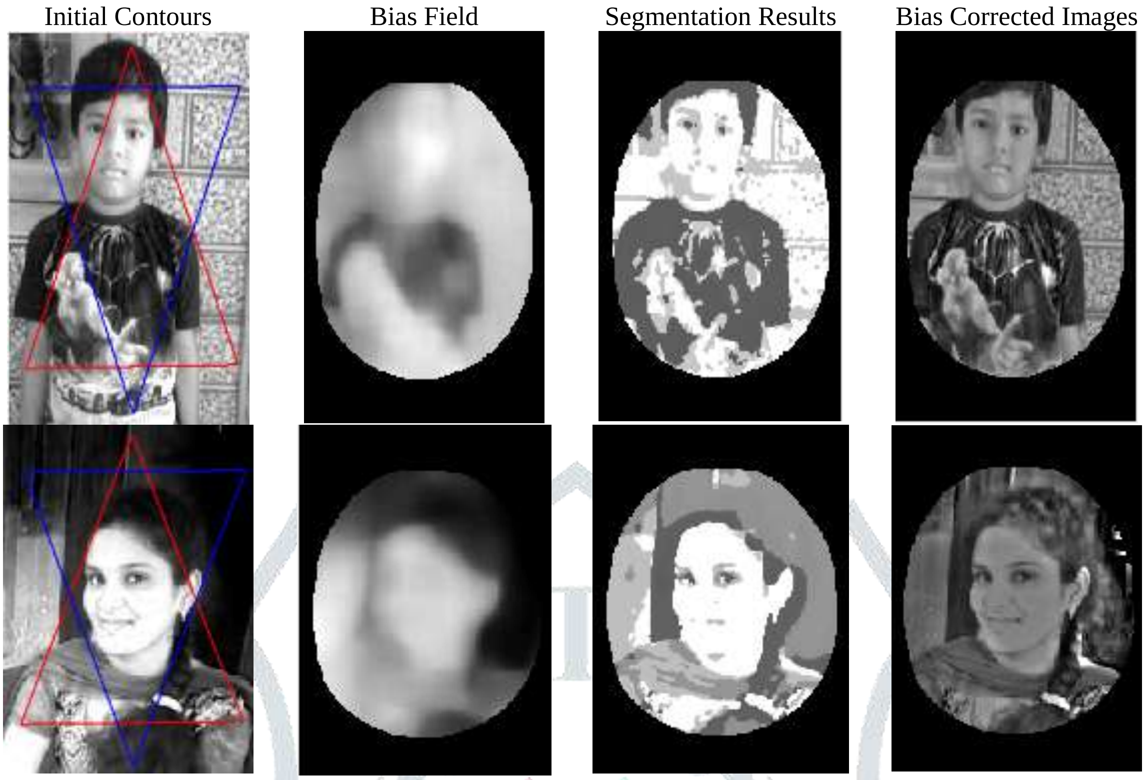

Fig. 3: Simulation Results with Natural Images as input

The present work can be extended by considering a specialized database or set of images of different categories. Also by considering rectangular neighborhood rather than circular neighborhood the overlapping of intensity regions can be avoided well.

VI. Conclusion

A variation level set framework was presented for segmentation and bias correction of images with intensity non-uniformities. Based on a generally accepted model of images with intensity non-uniformities and a derived local intensity clustering property, we define energy of the level set functions that represent a partition of the image domain and a bias field that accounts for the intensity non-uniformity. Segmentation and bias field estimation are therefore jointly performed by minimizing the proposed energy functional. The slowly varying property of the bias field derived from the proposed energy is naturally ensured by the data terminal our variation framework, without the need to execute a clear smoothing term on the bias field. Our method is much more robust to initialization than the piecewise smooth model. Experimental results have demonstrated superior performance of our method in terms of accuracy, efficiency, and robustness. As an application, our method has been applied to MR image segmentation and bias correction with promising results.

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G. Swapna received B.Tech in Electronics and Communication Engineering from Gokula Krishna College of Engineering, Sullurpet affiliated to JNTUA, Ananthapuramu in 2016. Currently she is doing her post-graduation in Digital Electronics and Communication Systems in Gokula Krishna College of Engineering, Sullurpet. Her research interests include Signal and Image Processing, Communication systems.

Dr. G. Chenchu Krishnaiah, obtained his B.Tech degree in Electronics and Communication Engineering from KSRM College of Engineering, Kadapa, A.P India and Master of Engineering (ME) degree in Applied Electronics (AE) from Sathyabhama University, Chennai, India. He earned his Ph.D. degree (Wavelet based image compression) in ECE Department from JNT University, Anantapur, A.P, India. He is having 19 years of experience in teaching and in various positions. Presently he is working as Professor & Dean at Gokula Krishna College of Engineering, Sullurpet - 524121, SPSR Nellore (Dist), A.P, India. His area of research interest includes wavelet Transforms, Digital Image Processing, Image compression and Denoising algorithms Digital Signal Processing, Embedded Systems, VLSI Design and VHDL Coding. He is a life member of ISTE (India).