A Novel Method For Generation Of Random Fields For Boundary Detection And Classification Of Images

C. NagaRaju *
Professor& Head of CSE,
VRS&YRN College of Engg. & Tech.
Chirala-523155.

Dr.P.S.V.Srinivasa Rao**
Professor Head of CSE
Rao & Naidu Engg.College
Ongole-523 001

G.Girija Rani***
Asst.Professor in CSE
RGM College of Engg.& Tech.
Nandyal-518 502

ABSTRACT:
Markov random field(MRF) theory has been widely applied to the challenging problem of Image Segmentation. Image segmentation is a task that classifies pixels of an Image using different labels so that the Image is partitioned into non-overlapping labeled regions. Image segmentation is one of the most difficult problems that researchers are facing because most of the real objects have complex shapes, boundaries and morphology, and true images are often corrupted by noise that cannot be ignored. To tackle the difficult problem of image segmentation, researchers have proposed a variety of methods. In this paper, a new texture segmentation method using compound MRFs is proposed, in which the label MRF and boundary MRF are coupled with gray level watershed method to help improve the segmentation performance. The boundary model is relatively general and does not need prior training on boundary patterns. Unlike some existing related work, the proposed method offers a more compact interaction between label, boundary MRFs with gray level water shed method. It is experimentally shown that proposed method can segment objects with complex boundaries and at the same time s able to work under noise corruption. The new method has been applied to medical image segmentation. Experiments on synthetic images and real clinical datasets show that the proposed method is able to produce more accurate segmentation results and satisfactorily keep the delicate boundary. It is also less sensitive to noise in both high and low signal-to-noise rati regions than some of the existing models in common use.

Key words:
Boundary model, Markov random fields (MRFs), image segmentation, gray level watershed, Markovianity and frequency of gray levels.

INTRODUCTION:

Segmentation using the Markov random field (MRF) modeling is characterized by probability distributions of site-interacting properties and neighboring restriction [1]. The most notable property of the MRF model is that the conditional probability of one site over all the others is only dependent on the relation of the site over its neighbors. This property, called Markovianity, which embodies the spatial interactions of adjacent sites and offers a way to incorporate prior information into the MRF models [9,5]. The advantages of MRF modeling are as follows. It has a relatively simple and effective architecture for embedding the prior and likelihood probabilities. It also takes into consideration the contextual constraints while maintaining the complexity at a tractable level by keeping the size of the neighborhood system relatively small.In order to introduce boundary information in the image model, a new kind of random field has been proposed. This random field not only describes the behaviour of a given texture or zone of the image, but it represents the whole image. This global characterization is achieved by using a model with two different levels, hierarchically distributed. The model assumes that an image is composed of a set of regions, each one characterized by an independent random field. The union of these random fields forms the observed image, named the upper level of the model. The location of these random fields within the image (position and shape of the regions) is governed by an underlying random field, named the lower level of the model. This kind of models is called hierarchical models [6,7] or Compound Random Fields (CRFs) [8,10].

DEFINITION:

A Compound random field (Q, X) = $\{Q_{ij}, X_{ij}\}$ defined on a lattice δ is formed by a lower level Q and a upper level X. The lower level is a discrete valued random field where each Qij can take values from the set {1, ..., M}. The upper level is a random field where each X_{ij} can take values from a set of M independent random fields $\{ X^K\}$, with k = 1, ..., M, following

$$Xij\,(.)=\boldsymbol{X}_{ij}^{K}\,(.) \text{ if } Q_{ij}\,(.)= K \text{ for } \quad k=1,\ldots\ldots M \tag{1}$$

Processes Q and $\{X^K\}$ are mutually independent random fields. Note that each realization **q** of the process Q performs a partition of the lattice δ into M region types. Therefore, in the case of segmented images, a realization Q = **q** can be seen as an image of labels, relating each point to a region, and each one of the random fields X^K as the model for the texture of region k. The usual procedure for dealing with this kind of models in the image processing framework is by assuming that the image to be

Manuscript received May 5, 2008
Manuscript revised May 20, 2008

processed is a realization of the upper random field (X = x). Thus, the objective is to determine the realization of the lower random field (Q = **q**) that has given rise to x. This objective can be achieved by a maximum a posteriori (MAP) estimation; that is, maximizing the a posteriori distribution P (Q = q / X = x) for a given x [9]. Using Baye's rule

$$P(Q=q/X=x)=(P(X=x/Q=q)P(Q=q))/ P(X=x); \quad (2)$$

Where P (X = x) does not affect the maximization procedure. Therefore, instead of maximizing P (Q = q / X = x), since

$$P(Q = q,X = x)=P(X = x/Q = q)P(Q = q), \quad (3)$$

The joint distribution P (Q, X) can be maximized, yielding the same result. Nevertheless, functions representing these joint probabilities are very complicated, usually non-linear and multimodal. In this paper, a novel method is proposed by combining coupled MRF with gray level water shed method.

Related work:

The coupled MRF model that is formulated in a probabilistic framework based on the Bayesian theory is introduced. The elements of the framework are given and details on the boundary model and the coupling of two MRFs (label and boundary MRFs) are discussed and proposed new method. Let S = {1,. .. ,n} index n sites in an image lattice, supposing that the image of interest has n pixels. $X = \{x_i | i \in S)$ and $D = \{d_i | I \in S\}$ are two MRFs representing label tag and boundary tag, respectively. x_i is assigned one of the labels in $L_l= \{0, 1, .. . , m - 1\}$ where m represents the number of possible classes. d_i belongs to one of the binary tags in L2 = {0, 1} where 0 and 1 represent non-boundary and boundary sites, respectively. The observed field is denoted by $Y = \{y_i | i \in S\}$, where y_i is the known image intensity. Let $\Omega_X = L1 \ x\ldots xL_l=L_l^n$ and $\Omega_D = L2 \ x\ldots \ x = L_2^n$ be the configuration spaces of the label MRF X and boundary MRF D, respectively. Advocated by Geman and Geman [1] and others, the maximum a posteriori (MAP) approach is commonly used to estimate the optimal solution of MRF models. This MAP-MRF framework allows us to develop algorithms systematically based on the Bayesian decision and estimation theory. The posterior probability P(X, D/Y) in our model represents the joint probability of label and boundary MRFs, X and D, given the observed intensity field Y and can be estimated using the Baye's theorem

$$P(X,D/Y)=P(YIX,D)P(X,D)/P(Y) \quad (4)$$

where P(YIX, D) reflects the likelihood of the observed intensity values given the information of labels and boundaries in an image; P(X, D) embodies the joint prior knowledge of the label MRF X and boundary MRF D; and P(Y) is the likelihood of the observed intensity values. Since the observed intensity values are known and unchanged, P(Y) is thought to be constant so that (1) further leads to P(X, DIY) α P(YIX,D)P(X, D). The MAP estimation for the optimal solution is then estimated by

$$(X\hat{}, D\hat{}) = \operatorname{argmax}_{X\in \Omega x,\, D\in\Omega D} P(Y/X,D)\, P(X,D) \quad (5)$$

where X^ is the final segmented image that we target. By virtue of the Markovianity of MRF theory, interactions between sites in S are constrained in a neighborhood system $N=\{N_i \, i\in S\}$, where N_i and S denotes a set of sites in the vicinity of site i. According to the Hammersley-Clifford theorem, X is an MRF with respect to N if and only if P(X) is a Gibbs distribution with respect to N. A Gibbs distribution of X is given by

$$P(X) = (1/Z)\, e^{-U(X)/T} \quad (6)$$

Where T is a temperature constant, U(X) is an energy function and Z is a normalizing constant. Supposing that the likelihood function can be expressed in Gibbs distribution, the MAP estimation becomes

$$(X\hat{}, D\hat{}) = \operatorname{argmax}_{X\in \Omega x,D\in\Omega D}\ 1/Z\, e^{-(U(Y/X,D)+U(X,D))/T} \quad (7)$$

where U(Y/X, D) and U(X, D) are the likelihood and prior energy functions, respectively. This further leads to an energy minimization problem, i.e.,

$$(X\hat{}, D\hat{}) = \operatorname{argmin}_{X\in \Omega x,D\in\Omega D} U(Y/X,D)+U(X,D) \quad (8)$$

Where, X^ is the solution of the segmentation problem. We assume that the intensity field Y and the boundary MRF D are independent of each other because the observed image intensity is not affected whether the site is on the region boundary or inside the region. Therefore, the likelihood energy becomes

$$U(Y/X,D) = U(YIX) \quad (9)$$

Assuming that each region is without texture and nearly homogeneous before it is corrupted by a Gaussian noise with zero mean and standard deviation σ, we can formulate the likelihood energy as

$$U(YIX)= U(Y/X)= \Sigma_{i\in S} (Y_i-\mu_{xi})^2/2\sigma^2 \qquad (10)$$

where μ_j represents the mean intensity of region j (j Є L1). The standard deviation (SD) σ can also be dependent on region class. In that case, only a small change is needed to make in (7), and we should use m different SDs. σ_j,j=0,... m-1 for each region j. However, in this paper, since we assume that an image is corrupted by independent and identically distributed noise, we use a uniform noise SD for the whole image.

The prior energy U(X, D) defines the interactions between the label MRF X and boundary MRF D and is the major contribution of this paper. Here, we adopt a general mode that does not need prior training about the boundary patterns. We assume that a boundary is part of a region and an edge is located between two regions (boundaries). If all the first-order neighbors of a pixel and the pixel itself belong to the same region, we regard this pixel as inside one region and not a boundary point. Otherwise, it is located on the boundary of its region. An edge belongs to no region and actually is on the dual lattice of the image. We systematically study the situations when a single edge passes through a 3 x 3 window to see what the likely configurations of the two MRFs, X and D are. On the assumption that the boundary of the object of interest is linked and continuous, we select a number of preferable cases from all the possible combinations of X and D configurations in N and penalize the other cases. In the energy minimization framework, as stated in (5), preferred cases should make the energy U(X, D) low and the penalized ones should make the energy value high. For instance, the case where site i and all its first-order neighbors j Є N_i are labeled as the same class and there is no boundary site in N_iU{i} is preferable so we assign a low energy value to it. The case can be formulated as an energy function by

$$\gamma.\ \delta (d_i) (\Sigma_{j\in Ni}\ x_i \text{ XOR } x_j + \Sigma_{j\in Ni} d_j), \gamma>0 \qquad (11)$$

Where if x=0, δ (x) = 1; else δ (x) = 0. The sign XOR represents the "exclusive or" operation and 'y is the penalty if the configuration does not belong to this case. For another example, we also prefer the case where there is a straight edge passing through the 3 x 3 window. This case can be formulated by

$$\gamma.\ \delta (d_i -1) (|\Sigma_{j\in Ni}\ x_i \text{ XOR } x_j -1|+| \Sigma_{j\in Ni} d_j -3|), \gamma>0 \qquad (12)$$

$$\Sigma_{i\in S}\ \gamma.[\delta (d_i)t_1(i)+ \delta (d_i -1)t_2(i)] , \gamma>0$$

$$t_1(i)= \Sigma_{j\in Ni}\ x_i \text{ XOR } x_j + \Sigma_{j\in Ni} d_j \quad t_2(i)= |\Sigma_{j\in Ni}\ x_i \text{ XOR } x_j -1|+| \Sigma_{j\in Ni}d_j -3| \qquad (13)$$

Equation (13) is actually a combination of (11) and (12). We explore all the possible scenarios of a single edge passing through a 3 x 3 window. In this paper, we mainly focus on the single edge scenarios to simplify the problem. Once we know which configurations of label MRF X and boundary MRF D should be chosen and how they should be matched, it is not difficult to count the number of labels different from the center pixel .x_i using $\Sigma_{j\in Ni}$ x_i XOR x_j and count the number of the neighboring boundary pixels using $\Sigma_{j\in Ni} d_j$. These are essential for the energy function construction

$$U(X,D)= \Sigma_{i\in S}\ \gamma.[\delta (d_i)T_1(i)+ \delta (d_i -1)T_2(i)] , \gamma>0$$

$$T_1(i)= \Sigma_{j\in Ni}\ x_i \text{ XOR } x_j .(|\Sigma_{j\in Ni} x_i \text{ XOR } x_j -1| +|\Sigma_{j\in Ni} d_j -4|)$$

$$T_2(i)= (|\Sigma_{j\in Ni}\ x_i \text{ XOR } x_j -1|+\Pi_{k=1..4}| \Sigma_{j\in Ni} d_j -k |)$$

$$(|\Sigma_{j\in Ni}\ x_i \text{ XOR } x_j -2|+\Pi_{k=2..4}| \Sigma_{j\in Ni} d_j -k |)$$

$$(|\Sigma_{j\in Ni} (x_i \text{ XOR } x_j -3)|+\Pi_{k=3..4}| \Sigma_{j\in Ni} (d_j -k) |) \qquad (14)$$

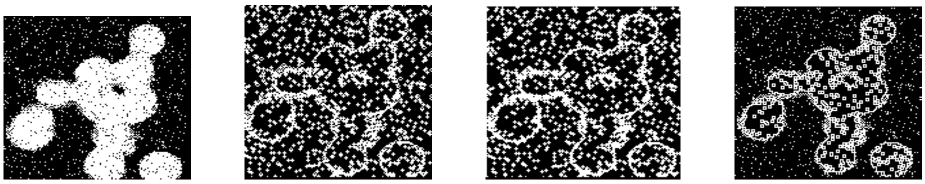
Where XOR represents the "exclusive or" operation and γ is the penalty. Terms T_1 and T_2 account for nonboundary (d_i =0) and boundary (d_i =1) situations, respectively. The motivation to use this model is that a true boundary or edge without noise should be continuous at least in a small window, like a 3 x 3 neighborhood. If one site is corrupted by noise and regarded as a boundary, probably the neighborhood would not conform to the true pattern of a reasonable boundary because of the randomness of noise. Then, due to the penalty given by the prior energy term, this case would most likely be discarded. Moreover, this model is capable of keeping complex boundary information because it is tolerant of all kinds of boundary shapes of true objects.

Novel MRF method:

Coupling label MRF with boundary MRF boundary detection method produces fine edges for non-textured image classification. This method is not suitable for textured images that have small features because it eliminates small features in the Image. Due to this reason this method may not suitable for document images, satellite and textured images. To overcome these drawbacks this method is combined with gray level watershed method and proposed new method. This method produces better results than previously defined boundary MRF method.

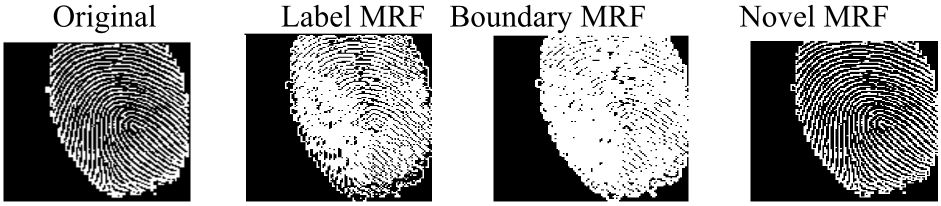
Boundary MRF method work on small neighborhoods only, if neighborhood size is increased it may not produce better results in noise images. But small size masks are not suggestible for noise images. To overcome the drawbacks in Boundary MRF method, here we are proposing a new method by applying 5 × 5 mask. This method has two steps first, consider 5 × 5 mask and decompose it into 9 masks each of size 3 × 3. Then apply gray level watershed method which is specified in chapter5 on each 3 × 3 mask and store the result in vector. Second, apply Boundary MRF method on resultant vector of gray level watershed method and produces the result. This new method produces better result for noisy images because larger no. of neighborhood pixels is used to estimate the character of resultant pixel. This method produces better results for both textured and non-textured images. The proposed method describes a textured and non-texture segmentation model using compound MRFs based on a boundary model. The main target of this approach is to enhance the performance of segmentation by emphasizing the interactions between boundary MRFs with gray level water shed method. The comparisons with existing boundary MRF models show that the proposed model can give more accurate segmentation results in both high and low noise level regions while preserving subtle boundary information with high accuracy. However, it is more complex and time consuming method.

EXPERIMENTAL RESULTS:

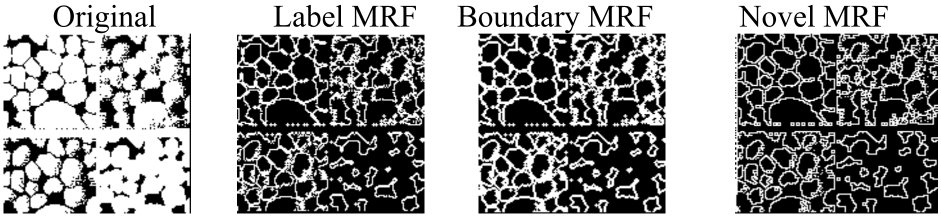


Original(cells) Label MRF Boundary MRF Novel MRF

Original Label MRF Boundary MRF Novel MRF

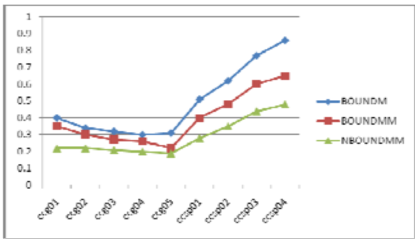


Original Label MRF Boundary MRF Novel MRF



Original Label MRF Boundary MRF Novel MRF

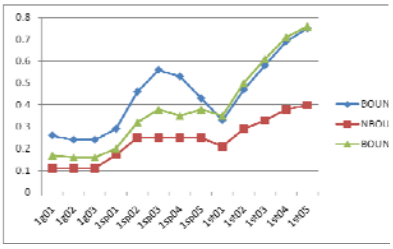
IMAGES	line	bound	Novel
ccg01	0.4	0.35	0.22
ccg02	0.34	0.3	0.22
ccg03	0.32	0.27	0.21
ccg04	0.3	0.26	0.2
ccg05	0.31	0.22	0.19
ccsp01	0.51	0.4	0.28
ccsp02	0.62	0.48	0.35
ccsp03	0.77	0.6	0.44
ccsp04	0.86	0.65	0.48



Graph 1

Table 1: Texture Images with 10%to50% of Gaussian, Speckle and Standard Deviation Noises

IMAGES	line	novel	bound
1g01	0.26	0.11	0.17
1g02	0.24	0.11	0.16
1g03	0.24	0.11	0.16
1sp01	0.29	0.17	0.2
1sp02	0.46	0.25	0.32
1sp03	0.56	0.25	0.38
1sp04	0.53	0.25	0.35
1sp05	0.43	0.25	0.38
1st01	0.33	0.21	0.35
1st02	0.47	0.29	0.5
1st03	0.58	0.33	0.61
1st04	0.69	0.38	0.71
1st05	0.75	0.4	0.76



Graph 2

Table 2: Cell Images with 10% to 50% of Gaussian, Speckle and Standard Deviation Noises

CONCLUSIONS:

There are a few parameters related to the proposed method needed to be estimated before we perform segmentation. These parameters are the mean intensity μj for every region j [in (7)]. the standard deviation σ of the noise [in (7)], the threshold for the gradient map ,the weight, γ, of the prior energy [in (11)] and frequency of gray level in watershed method[11].

A new proposed method is shown through experiments that it can outperform the conventional MRF based segmentation methods. Using the boundary MRF D, this model has the advantage of directly taking into account the discontinuity between different regions while a single MRF does not have this advantage [8]. If constructed properly, the coupled boundary MRF D would probably help the label MRF X to improve its segmentation performance because more information, in particular boundary information, is incorporated extensively in the segmentation process. The line process was introduced because researchers intended to solve the problem related to discontinuities. This allows and models interactions between the boundary field and the label field but works in a less effective way than the proposed method. The interaction between boundary sites in our model is far more sophisticated than those proposed by Gernan and Geman [1] (LP1) and Geiger and Girosi [3, 4] (LP2). We study all the possible scenarios of single edge occurring in neighborhood window, and the corresponding configurations of label and boundary MRFs. Moreover, we couple the two MRFs, D and X, more compactly than LP2. The work in LPI only studied six cases of edge configurations. This seems to be insufficient to tackle complicated boundaries. The boundaries found by the proposed model preserve better shapes than the LP1 and LP2 models. Owing to the consideration of discontinuity, the LP models often find boundaries closer to the ground truth than conventional methods. The contribution of this paper lies in a new formulation of MRF model, but the final result of MRF model will also depend on the MRF solver. However, it is known to the sensitive to initialization. This is the reason why we need to obtain a relatively good starting condition in the initialization. Another limitation of this method is that it can only change one label at one time and this may be the reason why the proposed model has moderate improvement over the control models, Another reason for the moderate improvement is that boundary is not the majority part of the whole image and the improvement on boundary may not be accompanied by significant improvement of overall segmentation accuracy. To overcome these draw backs here a new method is proposed. This new method produces better result for noisy images because larger no. of neighborhood pixels is used to estimate the character of resultant pixel. This method produces better results for both textured and non-textured images. The proposed method describes a textured and non-texture segmentation model using compound MRFs based on a boundary model with gray level watershed. The main target of this approach is to enhance the performance of segmentation by emphasizing the interactions between label and boundary MRFs with gray level water shed method. This method has been tested on images with Gaussian noise of 10% to 50% (1g01 to 1g05), on speckle noise of 10% to 50% (1sp01 to1sp05) and standard deviation noise of 10% to 50%(1^{st}01 to 1^{st}05). The comparisons with existing boundary MRF models show that the proposed model can give more accurate segmentation results in both high and low noise level regions while preserving subtle boundary information with high accuracy. However, it is more complex and time consuming method.

REFERENCES:

[1] T.R.ohlfing,R.Brandt,R.Menzel and C.R.Maurer,jr.," Evaluation of atlas selection strategies for atlas based image segmentation with application to confocal microscopy images bee brains,“ Neuro image vol.21,no.4,pp.1428-1442,2004

[2] T.R.ohlfing,D.B.Russakoff,and C.R.Maurer,jr.," performance based classifier combination in atlas based image segmentation using expectation-maximisation parameter estimation, “IEEE Trans.Med.imag.,vol23.no.8,pp.983-994,aug.2004

[3] T.R.ohlfing C.R.Maurer and jr."Multi classifier framework for atlas based image segmentation,"PatternRecognit.Lett.,vol.26,no.13,pp. 2070-2079,2005

[4] L.Xu,A.Krzyak, and C.Y.Suen ,“methods of combining multiple classifiers and their applications to handwriting recognition," IEEE Trans.Syst.ManCybern.,vol.22,no.3,pp.418-435,mar.1992.

[5] J.Kittler, M.Hatef, R.D.W.Duin, and J.Matas, “on combining classifiers,"IEEE Trans.Pattern Anal.Mach. Intel.vol.20.no.3pp.,226-239,mar.1998

[6] S.k.Warfield,K.H.Zou,andW.M.Wells,"Simultaneous truth and performance level estimation(STAPLE);An algorithm for the validation of Image Segmentation",IEEETrans.Med.Imag.vol 23,no 7,pp.903-921,july 2004.

[7] S.P.Raya and J.K.Udupa,"Shape-Based Interpolation of Multidimensional object",IEEE Trans.Med.Imag. vol.9 no1 pp.32-42,jan.1990.

[8] G.J.Grevera and J.K.Udupa,"Shape Based Interpolation of multidimensional Gray-level images," IEEE Trans.Med.Imag. vol.15 no1 pp.881-892,mar.1996.

[9] -,"An objective comparision of 3-D Image Interpolation methods", IEEE Trans.Med.Imag. vol.17 no14 pp.642-652 ,aug.1998.

[10] G.Borgefors,"Distance Transforms in digital Images,"Comput. Vis. Graph.Imageprocess., vol.34 no 3.pp.344-371,1986.

[11] T.Saito and J. –I.Toriwaki,"New Algorithms for Euclidean distance transformation of n-Dimensional Digitized picture with applications" Pattern Recognit. Vol.27 no.11 pp.1551-1565, 1994.

About authors:

C.NagaRaju received his B.Tech degree in Computer Science from J.N.T.University Anantapur, M.Tech degree in Computer Science from J.N.T.University Hyderabad and pursuing his Ph.D in digital Image processing from J.N.T.University Hyderabad. Currently, he is working as a professor and HOD in the Department of Computer Science & Engineering in VRS&YRN College of Engineering& Technology, Chirala. He has got 13 years of teaching experience .He has published five research papers in various national and inter national journals and about twenty four research papers in various national and international conferences. He has attended twenty seminars and workshops. He is member of various professional societies like IEEE, ISTE and CSI

Dr.P.S.V.Srinivasa Rao received his B.Tech degree in Computer Science from Bangalore University, Bangalore, M.Tech degree in Computer Science from J.N.T.University Hyderabad and **Ph.D** Computer Science & Engineering in Image Processing from Magadh University, Bodhgaya, Bihar. Currently, he is working as a professor and HOD in the Department of Computer Science & Engineering in Rao& Naidu Engineering College, Ongole. He has got 15 years of teaching experience .He has published three research papers in various national and inter national journals and about five research papers in various national and international conferences. He has attended ten seminars and workshops. He has published text book on C&Data Structure. He is member of various professional societies like ISTE and CSI.

G.Girija Rani received her B.Tech. Degree in Computer Science from Bhoj Reddy College of Engineering& Technology Hyderabad and M.Tech degree in Computer Science from RGM College of Engineering & Technology Nandyal. She is working as Asst.Professor in the Department of Computer Science & Engineering in RGM College of Engineering& Technology, Nandyal. She has got 6 years of teaching experience. She has attended five seminars and workshops. She is member of various professional societies like ISTE and CSI.