

Texture Classification Based on Random Threshold Vector Technique

B.V. Ramana Reddy¹, M.Radhika Mani², B.Sujatha³, and Dr.V.Vijaya Kumar⁴

¹Associate Professor, Dept. of CSE, KSRM COE, Kadapa, A.P., India

²Assistant Professor, Dept. of CSE, GIET, Rajahmundry, A.P., India

³Associate Professor, Dept. of CSE, GIET, Rajahmundry, A.P., India

⁴Dean and Professor, Dept. of CSE and IT, GIET, Rajahmundry, A.P., India

busireddy100@gmail.com¹ radhika_madireddy@yahoo.com²

sujatha_sujathab@yahoo.co.in³ vakulabharanam@hotmail.com⁴

Abstract

A new feature set derived from the fractal geometry, called the random threshold vector (RTV) is proposed for texture analysis. The RTV is computed for different run length entropy dimensions. The run length entropy dimensions are calculated based on different thresholds. To test the rotationally invariant feature, the run length entropies are calculated in different directions. The experimental results show that the RTV contains great discriminatory information needed for a successful classification.

Keywords: *Rotation invariant, Feature set, Threshold, Binary image, Fractal geometry, Run length, Entropy dimensions.*

I. Introduction

Different image objects are best characterized by different texture methods. The texture classification methods which attained success in their operation are found in industrial, bio medical, remote sensing areas and target recognition [1]. For content based information retrieval [2] texture said to be an important feature. As there are lot of variations apparent in natural textures, different features should be selected according to the characteristics of texture images, to achieve the best performance for texture classification. Over the years, a good number of texture classification methods are proposed which can capture different texture properties of the image. The methods of texture classification can be broadly categorized as statistical processing, geometrical processing, model based processing and signal processing. The analysis of statistical properties of texture that deals with the spatial distribution of grey values is the basis for every work in the early period. Some of the adapted statistical methods are co-occurrence matrix [4,5] and auto correlation function [6]. When coming to geometrical methods textures are treated to be the composition of texture primitives that are extracted and analyzed [7] different stochastic models are here with proposed for both texture modeling and classification such as Gaussian Markov Random Fields [8, 9, 10] and spatial autocorrelation function model [11]. To analyze the frequency contents either in spatial domain [12, 13] or in frequency domain, the signal processing techniques, based on texture filtering is recommended. However to measure the characteristics of the images, more powerful texture feature extraction methods are needed for some applications.

This paper proposes a novel method to classify textures. The distribution of properties of pixel with grey levels greater than or equal to some threshold evaluates the texture. A set of points on a two dimensional plane is considered to be the pixel. The set of points is considered as a fractal set such that it can be characterized by the dimension it has. The famous and recommendable measures are Hausdroff dimension [15], mass dimension and Entropy dimension [16]. Though these are useful for characterization sometimes it is difficult to evaluate. The dimension which requires easy computation can be an alternative. This paper proposes a new dimension called run length entropy. The thresholding of the image is done for a number of thresholds, based on which several set of points will be obtained and each set has its own run length entropy dimension. The random threshold vector which is useful for texture classification and can be achieved through run length entropy. The organization of the paper is as follows. Section 2 deals with the methodology of texture classification by Random Threshold Vector (RTV), the results and discussions are presented in section 3 and last section deals with conclusions.

2. Methodology

A binary image is obtained from a grey level image based on some threshold. That is N number of different binary images can be obtained from a grey level image. Where 'N' is the number of different grey levels of the image. The thresholded binary image of a grey level image I at threshold (th) is defined by the equation (1)

$$I(x, y) = \begin{cases} 1 & \text{if } I(x, y) \geq th \\ 0 & \text{if } I(x, y) < th \end{cases} \quad (1)$$

Therefore a binary image is considered as a realization or outcome of a random closed set. A grey scale image is reduced to several binary images and, from a stochastic point of view, is a realization of a multivariate random closed set. In the present method binary images are obtained on the random threshold of a grey level image as stated in equation (2) where μ and σ^2 be the grey level mean and variance of an image I respectively and for some integers of k and i.

$$th = \mu + (i/n)k\sigma \quad (2)$$

As per the observations that, in a coarse texture, relatively long grey level runs would occur more often and that a fine texture should contain primarily short runs. Galloway proposed the use of a run length matrix for texture feature extraction [17]. For a given image, the proposed method defines a run-length matrix RLM (i,j) as number of runs starting from location (i,j) of the original image in the predefined direction. For a given binary image of the dimension N×N the present paper generates two different RLM's called as Zero RLM (ZRLM) and One RLM (ORLM). The ZRLM contains the run length values for zero and ORLM contains the run length values for one of the given binary image respectively. For a given binary image I(x,y) with a value of zero at location (x,y), the ZRLM(x,y) will be having any value between 1 to N and ORLM(x,y) will be having a value of zero always in this case and for the I(x,y) with a value of one, the ORLM(x,y) will be having any value between 1 to N and ZRLM(x,y) will be having always a value of zero. The Figure1, 2 and 3 explains the proposed method of generating ZRLM and ORLM for a given binary image of 4×4.

0	0	1	1
0	0	0	0
1	0	0	1
1	1	1	1

Figure 1. Original Image

2	1	0	0
4	3	2	1
0	2	1	0
0	0	0	0

Figure 2. ZRLM for Figure 1

0	0	2	1
0	0	0	0
1	0	0	1
4	3	2	1

Figure 3. ORLM for Figure 1

Based on RLM's the present paper evaluates the run length entropy dimension (RLED). The RLED of the image is calculated by the equations (3)-(7)

$$H_R = \frac{E_0 + E_1}{L_0 + L_1} \quad (3)$$

Where

$$E_0 = \sum_{i=1}^n \sum_{j=1}^n ZRLM_k(i, j) \times \log(ZRLM(i, j)) \quad (4)$$

$$E_1 = \sum_{i=1}^n \sum_{j=1}^n ORLM_k(i, j) \times \log(ORLM(i, j)) \quad (5)$$

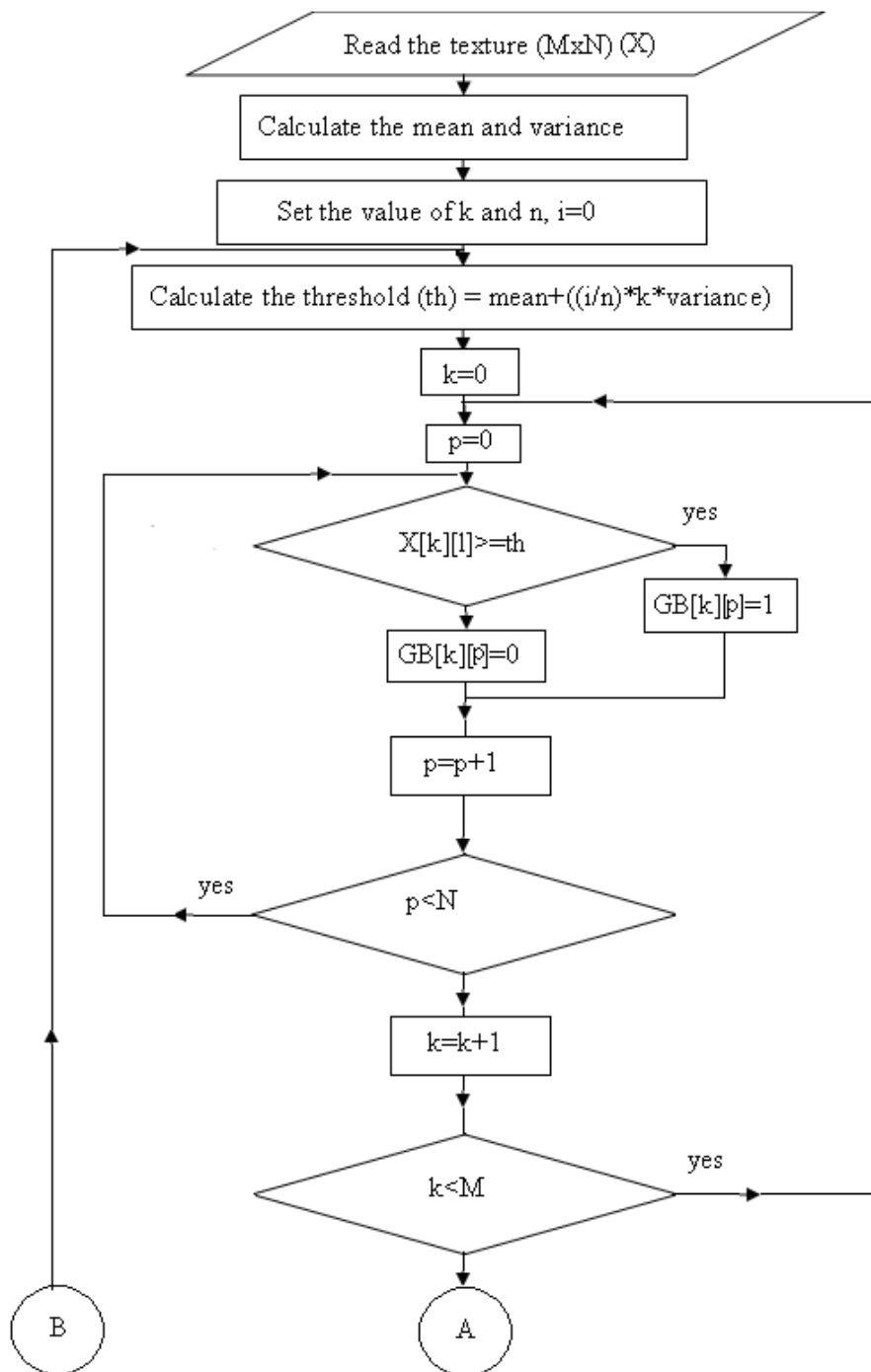
$$L_0 = \frac{1}{N \times N} \sum_{i=1}^n \sum_{j=1}^n ZRLM(i, j) \quad (6)$$

$$L_1 = \frac{1}{N \times N} \sum_{i=1}^n \sum_{j=1}^n ORLM(i, j) \quad (7)$$

Then the proposed RTV of an image I is defined by the equation (8)

$$RTV = (H_0, H_1, \dots, H_n) \quad (8)$$

where the H_i is the RLED of the thresholded image, the entire process of RTV is shown in the form of flowchart in figure 4. The present method obtains RTV in four different directions i.e. 0° , 45° , 90° and 135° .



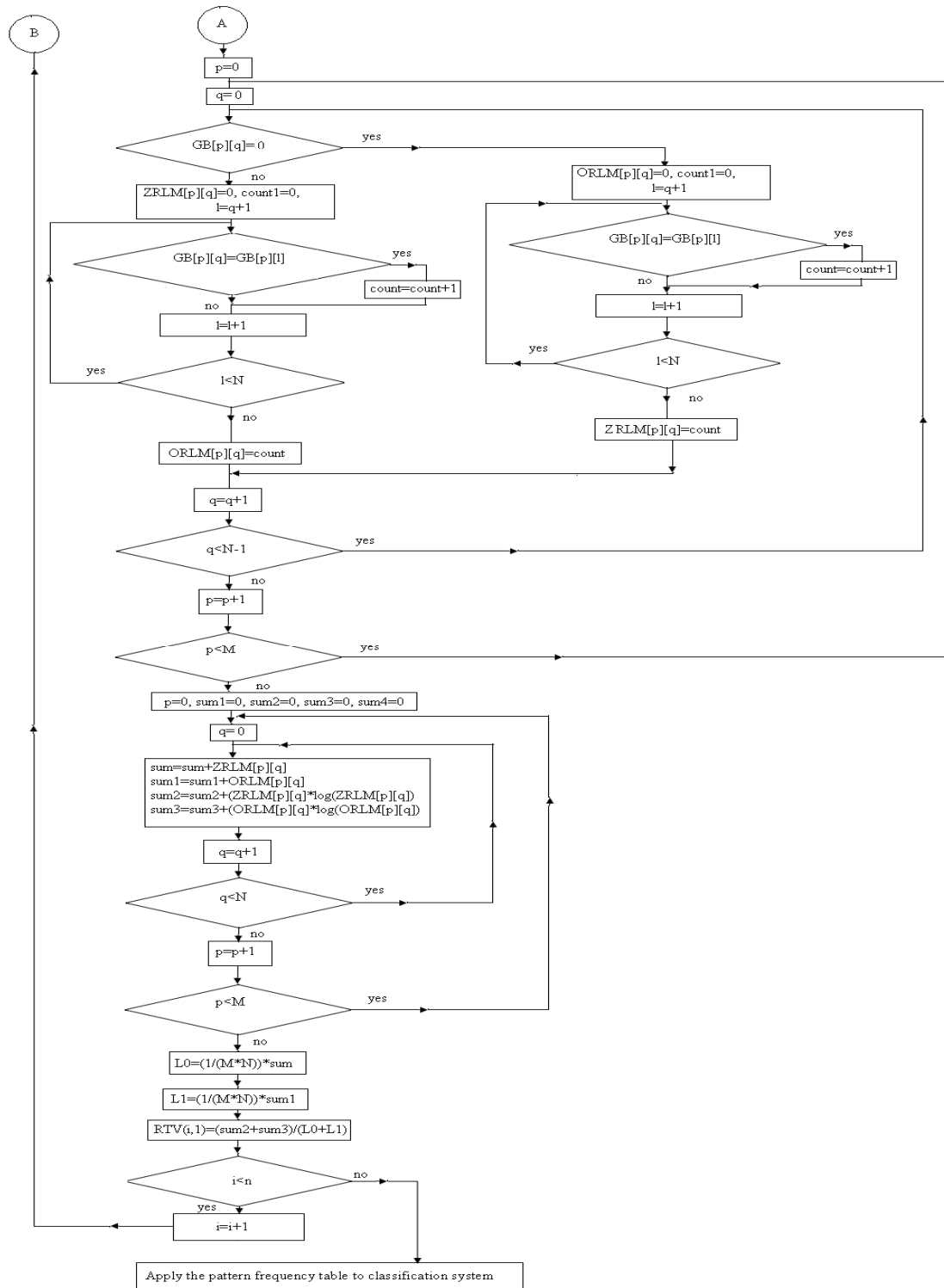


Figure 4. Methodology for texture classification system by RTV.

3. Results and Discussions

The present paper has considered 48 textures from VisiTex album, 8 granite textures and 8 marble textures from [18]. This results a total of 64 textures with a resolution of 256×256.

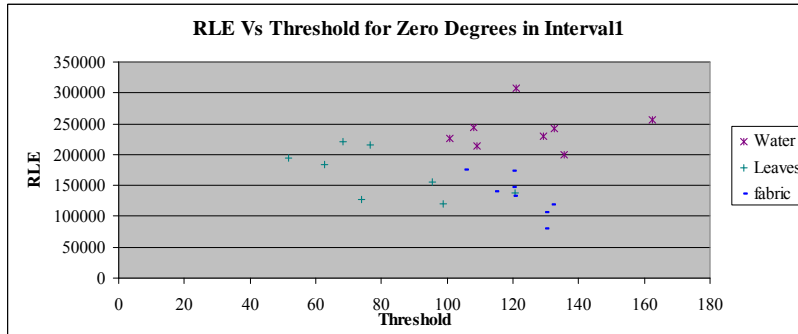


Figure 5. Classification graph for Water, Leaves and Fabric Textures in Interval 1

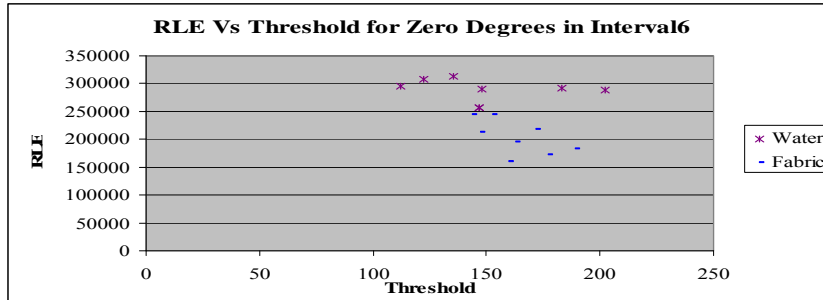


Figure 6. Classification graph for Water and Fabric Textures in Interval 6

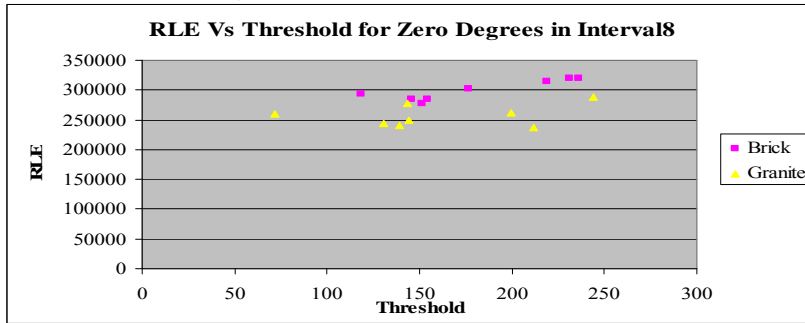


Figure 7. Classification graph for Brick and Granite Textures in Interval 8

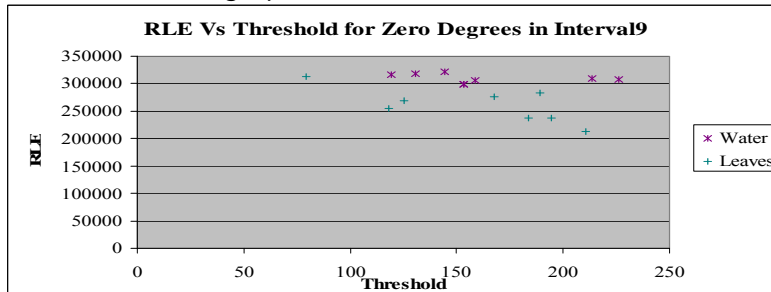


Figure 8. Classification graph for Water and leaves Textures in Interval 9

Table 1. RTV for Interval 1 of 45 degrees

		Bark				Brick	
Tex. No	Th	RLE	Tex. No	Th	RLE	Tex. No	RLE
Bark.0000	101.07	235630.00	Brick.0000	96.63	154020.00		
Bark.0001	111.40	186020.00	Brick.0002	161.12	166270.00		
Bark.0003	75.54	168250.00	Brick.0003	148.63	214040.00		
Bark.0004	69.37	144400.00	Brick.0004	122.80	135460.00		
Bark.0005	48.20	212990.00	Brick.0005	109.11	172890.00		
Bark.0006	52.32	159320.00	Brick.0006	158.38	240900.00		
Bark.0007	75.71	240970.00	Brick.0007	75.63	197370.00		
Bark.0009	113.32	195060.00	Brick.0008	87.20	234410.00		
		Water				Food	
Tex. No	Th	RLE	Tex. No	Th	RLE	Tex. No	RLE
Water.0000	132.52	151440.00	Food.0000	123.86	118160.00		
Water.0001	120.98	251170.00	Food.0001	114.93	164270.00		
Water.0002	129.28	131950.00	Food.0002	127.93	116300.00		
Water.0003	107.98	160660.00	Food.0003	106.48	154130.00		
Water.0004	109.21	142110.00	Food.0005	109.31	82556.00		
Water.0005	135.68	106060.00	Food.0006	115.70	155430.00		
Water.0006	100.73	150100.00	Food.0010	67.82	254690.00		
Water.0007	162.57	195190.00	Food.0011	63.48	230050.00		
		Granite				Marble	
Tex. No	Th	RLE	Tex. No	Th	RLE	Tex. No	RLE
Granite.0000	50.83	154580.00	Marble.0000	103.43	115500.00		
Granite.0001	133.86	170750.00	Marble.0001	160.04	127260.00		
Granite.0002	172.57	159670.00	Marble.0002	142.07	167080.00		
Granite.0003	109.86	137410.00	Marble.0003	137.80	161430.00		
Granite.0004	220.75	155770.00	Marble.0004	49.22	240260.00		
Granite.0005	116.70	101420.00	Marble.0005	55.58	222640.00		
Granite.0006	102.44	135630.00	Marble.0006	86.32	229130.00		
Granite.0007	106.53	193720.00	Marble.0007	227.98	236940.00		
		Leaves				Fabric	
Tex. No	Th	RLE	Tex. No	Th	RLE	Tex. No	RLE
Leaves.0000	62.68	206740.00	Fabric.0000	119.92	141260.00		
Leaves.0001	51.63	192050.00	Fabric.0004	105.58	141050.00		
Leaves.0002	73.98	220540.00	Fabric.0007	129.80	95721.00		
Leaves.0003	98.82	116940.00	Fabric.0008	120.26	154000.00		
Leaves.0005	76.46	211700.00	Fabric.0011	131.93	109770.00		
Leaves.0006	68.27	192050.00	Fabric.0013	120.16	157100.00		
Leaves.0010	120.74	142890.00	Fabric.0015	114.82	152520.00		
Leaves.0011	95.56	154450.00	Fabric.0018	130.10	77465.00		

The experiments are carried out on all these 64 textures, but it becomes laborious to provide results for this large set of textures at each stage of discussion. On each texture, the run length entropy is calculated in four directions with k as 2 and n as 10. For each texture, the RTV is calculated for 11 intervals in four angles. Due to lack of space only one table i.e.

Table 1 is given for RTV at interval 1 of 45° for all textures. Only few graphs of Figure 5, 6, 7 and 8 shows the classification of various texture sets called water, leaves, fabric, brick and granite. By these figures it is clearly evident that good classification of textures are resulted at various intervals of zero degrees. And the same is true for all sets of textures at different intervals and at different angles.

4. Conclusions

A new set of texture features called “Run Length Entropy” is proposed and based on this feature set, RTV is proposed for texture classification. The RTV is constructed by using the run length entropy through four different orientations. The results clearly indicate the rotationally and randomly invariant nature of the present method. The proposed RLD technique precisely classified the textures.

Acknowledgements

The authors would like to express their cordial thanks to K.V.V. Satya Narayana Raju, Chairman, Chaitanya Institutions and K. Sashi Kiran Varma, Secretary, GIET, Rajahmundry for providing Research facilities. Authors would like to thank Dr. G.V.S. Anantha Lakshmi for her invaluable suggestions and constant encouragement that led to improvise the presentation quality of the paper and Authors would like to thank U.S.N. Raju for his invaluable suggestions.

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Authors



B.V.Ramana Reddy received the B.Tech degree from S.V.University in 1991. He completed M.Tech in Computer Science from JNT University, Masab Tank, Hyderabad, India in 2002. He is having nearly 15 years of teaching and industrial experience. He is currently working as Associate Professor, Dept of C.S.E, KSRM College of Engineering, Kadapa, Andhrapradesh, India. He is a member of Srinivasa Ramanujan Research Forum (SRRF), Godavari Institute of Engineering and Technology (GIET), Rajahmundry. He is pursuing his Ph.D from JNT University, Anantapur in Computer Science under the guidance of Dr. V. Vijaya Kumar. He is a life member of Indian Science Congress Association. He published 5 papers in various conferences and journals.



M. Radhika Mani received the B.Tech (CSE) degree from Sir C.R. Reddy College of Engineering, Andhra University in 2005 and received her M. Tech. (Software Engineering) from Godavari Institute of Engineering and Technology (GIET), JNT University in 2008. Presently she is working as an Assistant Professor in GIET, Rajahmundry. She is pursuing her Ph.D. from JNT University, Kakinada in Computer Science under the guidance of Dr. V. Vijaya Kumar. She is a member of SRRF-GIET, Rajahmundry. She has published more than 10 research publications in various National, Inter National conferences, proceedings and Journals.



B.Sujatha received the B.Tech. degree from JNT University, Kakinada in 1997 and received her M. Tech. (Computer Science & Engineering) from Andhra University in 2002. She is having 10 years of teaching experience. Presently she is working as an Assoc. Professor in GIET, Rajahmundry. She has published 1 research publications in Inter National Journal. She is a member of SRRF-GIET, Rajahmundry. She is pursuing her Ph.D from Mysore University in Computer Science under the guidance of Dr. V.Vijaya Kumar. Her research interest includes Image Processing and Pattern Recognition. She is a Life member of ISCA.



Vakulabharanam Vijaya Kumar received integrated M.S. Engg, degree from Tashkent Polytechnic Institute (USSR) in 1989. He received his Ph.D. degree in Computer Science from Jawaharlal Nehru Technological University (JNTU) in 1998. He has served the JNT University for 13 years as Assistant Professor and Associate Professor and taught courses for M.Tech students. He has been working as Dean for Dept of CSE and IT at GIET, Rajahmundry and Head SRRF-GIET, Affiliated to JNT University, Kakinada. His research interests include Image Processing, Pattern Recognition, Network Security, Steganography, Digital Watermarking, and Image retrieval. He is a life member for CSI, ISTE, IE, IRS, ACS and CS. He has published more than 100 research publications in various National, Inter National conferences, proceedings and Journals.