Efficient Region of Interest Extraction Methods for Multiple Medical Images

B. P. Santosh Kumar, K. Venkata Ramanaiah

Abstract: Medical images do contain important and unimportant spatial regions. Compression methods which are capable of reconstructing the image with high quality are required to compress the medical images. For these images, only a portion of it is useful for diagnosis hence a region based coding techniques are significant for compressing and transmission. Extracting a significant region is of great demand since a slighter mistake may leads to wrong diagnosis. This paper is focused on investigating multiple image processing algorithms for medical images. All the images may not contain the same region of interest, so different approaches are supposed to apply for different images. In this three types of medical images were considered like magnetic resonance (MR) brain images, computer tomography (CT) abdomen images and X-ray lung images. In this paper three automatic region of interest extraction algorithms were proposed for different types of images.

Keywords: Medical image compression, Region of interest, CT, MRI, abdominal image compression

I. INTRODUCTION

Medical images are acquired in multiple forms like computer tomography (CT), Ultra sound (US), Magnetic resonance imaging (MRI), positron emission tomography (PET), Single photon emission computed tomography (SPECT) and others that generate image data which require huge storage space. These images are stored in Hospital information system (HIS) or picture archiving and communication systems (PACS) and it was observed that a semi demanding hospital may produce a data around 10~15GB per on average per day which becomes critical demand for them store such a huge data [16] [5]. On other hand, to transmit this huge data for telemedicine applications require a dedicated high end network involving huge cost of maintenance [9].

There are various issues involved in transmission of the image data to rural areas, according to survey conducted by a French agency it was mentioned that only 25 % of the doctors' conduct practice in rural areas where the major portion of the people reside [25].

So exchange of information to these rural destinations requires dedicated networks which are practically cumbersome. One of the alternate is to suppress the data without losing the meaningful information in it and transmitting them though low speed networks.

Medical image compression is one of the solutions for reducing the storage space and handles the transmission bandwidth requirements [20] Image compression methods are broadly categorized into lossy and lossless methods. For medical images, a lossy compression with 10 % compression is not acceptable as they distort the texture content in the images leading to the improper location and orientation of abnormality.

Storage of these medical images is too problematic for instance a 3D MRI contains a stack slices (images) that usually requires a huge space for storage. To overcome such limitations a region of interest (ROI) based compression is introduced that intends to preserve the quality of certain important regions while compression others. In image processing it can be termed as hybrid mechanism of integrating both lossy and lossless compression methods for single image

A. ROI image Compression

The concept of ROI based image compression is introduced to overcome the limitation of Lossy and Lossless compression modes. In Lossy mode, higher compression ratios can be achieved but it may lead to the loss of important clinical information on other hand in lossless mode the data is not compressed largely thereby occupies a large storage space and bandwidth. So there is a need for hybrid ROI image compression method that aims to compress for higher ratios and also preserve the important information [8].

The figure 1 depicts the compression spectrum from which it can be observed that in lossy mode the image can be compressed up to 85 % retaining 15-40% of the original file size. In loss less mode it can retain 80% of the original size, compressing only up to 20 %, the intermediate ROI based compression can compress up to 65 %, hence it can be concluded that ROI based image compression is more suitable for medical images.

B. P. Santosh Kumar*, Department of Electronics and Communication Engineering, YSR Engineering College of Yogi Vemana University, Proddatur, India, Email: santoshyvuce@gmail.com

Dr. K. Venkata Ramanaiah, Department of Electronics and Communication Engineering, YSR Engineering College of Yogi Vemana University, Proddatur, India.

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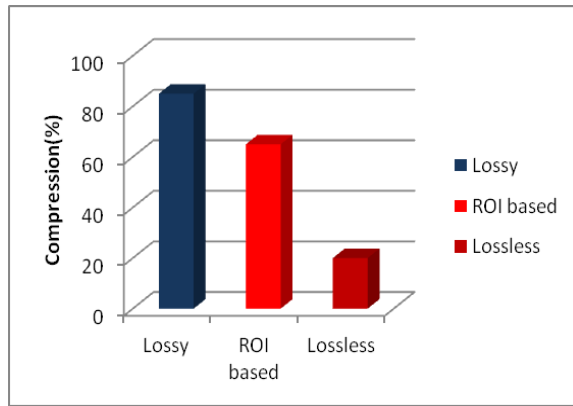# Efficient Region of Interest Extraction Methods for Multiple Medical Images

Fig 1: Compression mode spectrum

In general, different medical images have different important regions and a single extraction approach is not suitable for all the images. So there is a need to develop multiple extraction algorithms which are suitable for particular images. Most of the researchers proposed ROI based compression for MR or CT brain images which is not sufficient and may not work with other parts of human body. Many researchers have focused on extracting the abnormality region and treating the region as ROI and the rest others as Non ROI but the method fails to apply compression when there is no presence of abnormality. This paper concentrates on proposing extraction approach for MR brain image, CT abdomen image and Lung images.

II. LITERATURE REVIEW

In order to extract a particular ROI from medical image four main methods are been proposed so far [1]. The first, is the segmentation that aims to partition into multiple segments for easier analysis of every region. But manual segmentation is time consuming and tedious process and hugely depends upon the user experience [2]. Second is the mathematical approach where three points from left, right and top are selected to form a sector of circle. These points are interpolated to form a contour for ROI. Third is interactive segmentation approach that requires annotations from the user to detect the ROI. Fourth is the mask based approach, in which a binary mask is generated using image processing methods that indicate the ROI.

Several methods were proposed so far which fall into one of the category, Canadian radiologists (CAR,2011) found that K-means clustering could able to produce a size reduction of 21%~22 % when compared with respect to original image. Another algorithm names as Chan vase method could achieve average reduction of 23%~24%. Vikas and Manpreet in [10] performed fractal lossy compression for non ROI and also introduced an approach for removing noise. Liu and others in [27], proposed a lossy to loss-less ROI compression scheme, this scheme relies on SPIHT and EBCOT coding where the images are partitioned into foreground and background. To code the ROI information a chain code is used. As it involves complex algorithms, this method consumes more time for processing. Ravi kiran et.al, in [18] [19], proposed a block based PCA algorithm for implementing lossy and lossless compression for non ROI and ROI. This method uses canny edge operator for extraction of mask region which produces segmentation blobs and fails to neglect the skull region specifically for MR brain images. Most of the methods

concentrate on a single medical image and in particular MR brain, which brings the scope for new methods to be proposed for images projecting different parts of human body

III. PROPOSED METHODOLOGY

The block diagram of the ROI based image compression is depicted in figure 3, the input image is first processed for ROI localization which is a crucial step in ROI based image compression. In this work three types of medical images were considered as shown in figure 3.

For every type of medical image that represent a certain organ in human body has different region of interest and a single approach cannot be used to extract it.
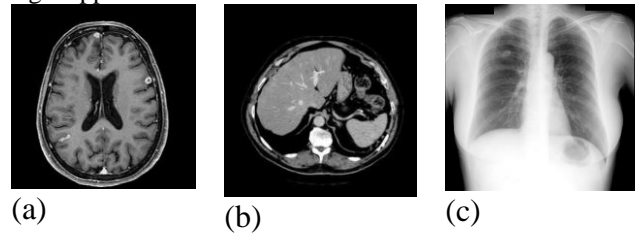

(a)   (b)   (c)

Fig 2: Samples of different types of medical images that wereused in this work

A. ROI Extraction for MR brain Image

In general, a brain image consists of white matter, Gray matter, skull and background regions [28]. The important clinical information required for diagnosis is usually not relied in skull and background region, so appropriate techniques may be incorporated to remove these regions. The ROI and NROI regions which are considered in this work are shown in figure 4. In this work a sequence of morphological operations was applied to remove the non ROI from MR brain image.
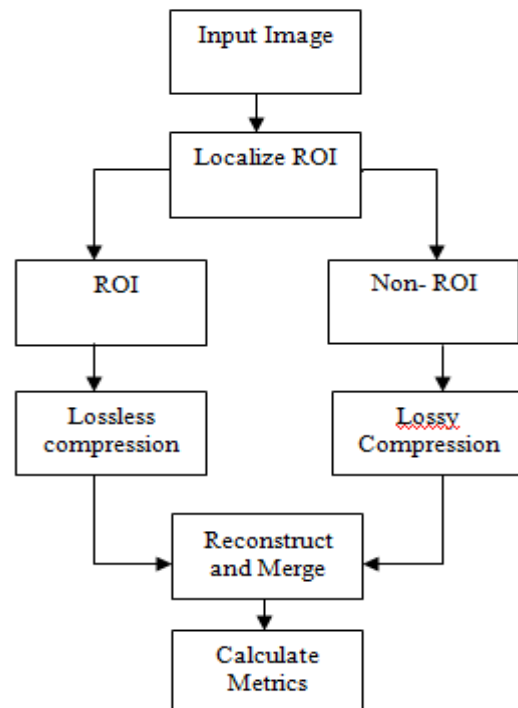

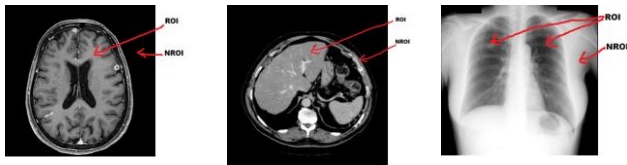**Fig 3: Block diagram of ROI based image compression**

Fig 4: ROI and NROI for different medical images

Algorithm for ROI extraction

- Read the input image and do necessary pre processing
- Apply morphological erosion process with octagon structuring element
- Convert the eroded image into binary with thresholding
- Apply dilation followed by filling process for binary image
- Retain the binary mask for ROI, and extract it respective elements from input image

The present approach is compared against Kalaiselvi and somasundaram work mentioned in [31].This approach includes bi-level thresholding for generating the head mask and with the use of morphological operations at the post processing results an extracted brain image. The authors have attained an accuracy of 90%~92% when compared with manual segmented images. The visual and qualitative comparison between the method and our work is tabulated below.
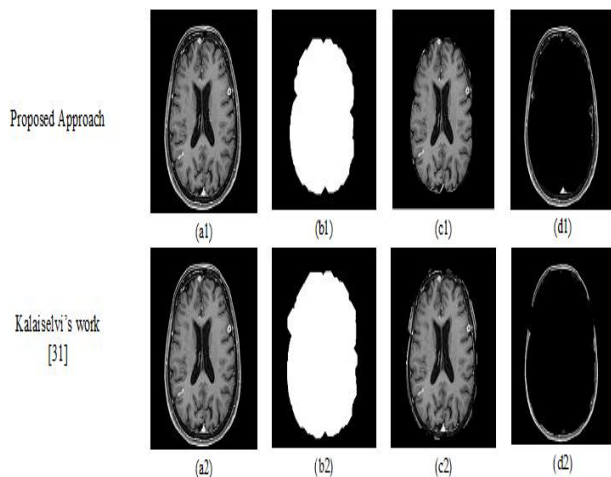

Fig 5: Extraction of ROI from MR brain image (a1-a2)

Original Image (b1) Generated mask for ROI with our approach (b2) Generated mask with [31] approach (c1) Extracted ROI with our approach (c2) Extracted ROI with [31] approach (d1) Non ROI/ Difference Image obtained for our approach (d2) Difference obtained for [31] approach

The segmentation efficiency of the works is compared in terms of accuracy and total segmentation errors mentioned in [31]. The numerical results attained for different images are tabulated below in table 1.

Table 1: Performance analysis of the proposed work in comparison with [31] for brain extraction process

S.NO	Proposed		Kalaiselvi [31]	
	ACC	TSE	ACC	TSE
Patient 1	0.9164	0.182	0.88	0.218
Patient 2	0.9174	0.179	0.891	0.217
Patient 3	0.9108	0.1957	0.865	0.219

Patient 4	0.9092	0.1999	0.84	0.2199
Patient 5	0.9301	0.1230	0.91	0.2130

From the above analysis it can be observed that the present approach could able to attain an average accuracy of 3% more than [31] work, this is due to the inappropriate selection of thresholds and model parameters which was not in the case of present approach, hence the present work could able to extract more accurately than [31] in very short span of time.

B. ROI extraction from CT abdomen image

There are several organs located in the abdominal CT image; it was observed that there are 12 major regions that are marked in the CT image. In [25] proposed a segmentation approach with prior information of the orientation and location of the organs and a prediction based assessment was employed to mark the region for latter images but this method proves to be mathematically complex and marking of prior require ample experience and more over the regions are overlapped with each other in the image so there is a requirement to extract all regions apart from skin and fat. In this work the ROI extraction from CT abdomen image can be extracted with the sequence morphological operations. The algorithm for the extraction process is presented below

Algorithm

- The input image is read and pre-processed
- Apply Sobel edge operator initially
- Apply morphological closing operation with disk structuring element followed by filling operation
- Repeat the above step with octagon structuring element retaining a binary mask
- Extract the corresponding elements from the input image at which the element is '1' in binary mask
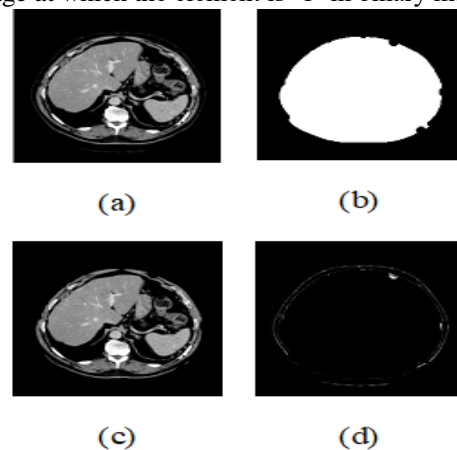

**Fig 6: Extraction of ROI from CT abdomen image
(a) Original Image (b) Generated mask for ROI (c) Extracted ROI (d) Non ROI**

C. ROI extraction from lung image

Morphological operations are not sufficient to extract the lung portion from chest x-ray /CT image since it contains the lung region, ribs, shoulders and background. Presence of the heterogeneous regions makes any method difficult in segmenting the lung image [21].

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So appropriate edge based segmentation algorithms like active contour models are to be employed for segmenting and extracting the lung portion. Keita et.al in [11] proposed a graph cut method which consider multiple shape constraints and segment the lung portion.

In this work, structured edge detector (SED) in [26] is employed to segment the lung portion. A lung boundary map is detected initially using ultra metric contour map (UCM) [14] and then transformed with marker controlled watershed algorithm [17]. It was observed from [26] that the algorithm could able to perform with efficiency greater than 90%.
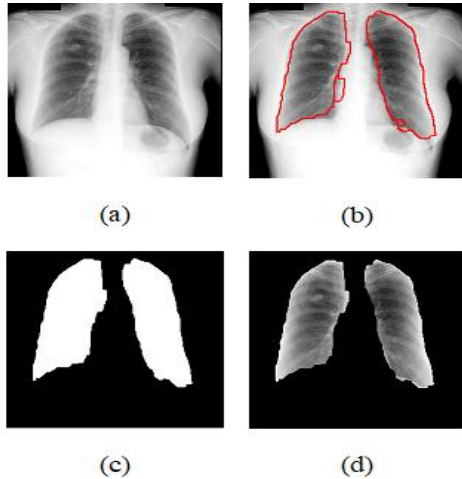

Fig 7: Extraction of ROI from lung image (a) Original Image (b) Edge Contour mapping (c) Generated mask for ROI (d) Extracted ROI

IV. EXPERIMENTAL RESULTS

The extracted ROI are compressed with lossless approaches like run length encoding and Non ROI are compressed with JPEG [15], EZW [7] and SPIHT [3] methods. Experiments are conducted on T1-weighted MR brain images collected from BRATS image database [29] and Lung images were collected from JSRT public database available at [30]. The compressed image is reconstructed by merging of the ROI and non ROI regions and evaluation metrics are calculated with respect to original Image.

Multiple metrics like compression ratio (CR), peak signal to noise ratio (PSNR), mean square error (MSE), mean absolute error (MAE), mean structural similarity index (MSSIM), normalization cross correlation coefficient (NCC), structural content (SC) and image fidelity (IF) were calculated [22], [4], [12], [13].
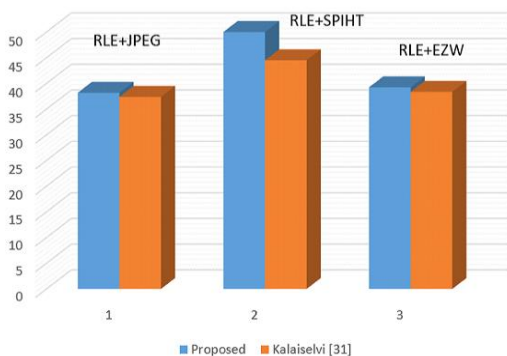

Fig 8: Average PSNR comparison analysis for proposed work and [31] work.

Reconstructed images with different methods are presented in figure 8 and the performance evaluation metrics are tabulated in tables 2, 3, and 4. From the tabulated data which are calculated on average for 50 images of each category and it can be observed that the SPIHT algorithm outperforms in terms of quality and compression

Table 2: Average metrical values for MR brain image with current approach

Method	RLE+ JPEG	RLE+ JPEG	RLE+ JPEG
CR	7.347	6.69	6.60
PSNR	38.16	49.99	39.23
MSSIM	0.995	0.999	0.996
MAE	1.41	0.285	1.23
NC	0.993	0.999	0.994
SC	1.002	1.002	1.007
IF	0.92	0.99	0.94

Table 3: Average metrical values for [31] approach

Method	RLE+ JPEG	RLE+ JPEG	RLE+ JPEG
CR	7.47	6.72	6.62
PSNR	37.36	44.50	38.36
MSSIM	0.994	0.999	0.995
MAE	1.71	0.55	1.44
NC	0.994	0.997	0.993
SC	0.999	1.004	1.007
IF	0.90	0.98	0.92

Table 4: Average metrical values for CT abdomen image

Method	RLE+ JPEG	RLE+ JPEG	RLE+ JPEG
CR	7.64	8.07	8.05
PSNR	51.07	40.35	40.35
MSSIM	0.985	0.989	0.988
MAE	1.28	0.74	0.76
NC	1.005	0.996	0.995
SC	0.982	1.003	1.0032
IF	0.994	0.936	0.935

Table 5: Average metrical values for Lung images

Method	RLE+ JPEG	RLE+ JPEG	RLE+ JPEG
CR	8.72	8.86	8.23
PSNR	36.74	48.54	38.57
MSSIM	0.963	0.998	0.984
MAE	4.02	0.54	2.87
NC	1.003	1.002	0.998
SC	0.9964	0.9994	0.9994
IF	0.939	0.996	0.961

(a1) (b1) (c1) (d1)

(a2) (b2) (c2) (d2)
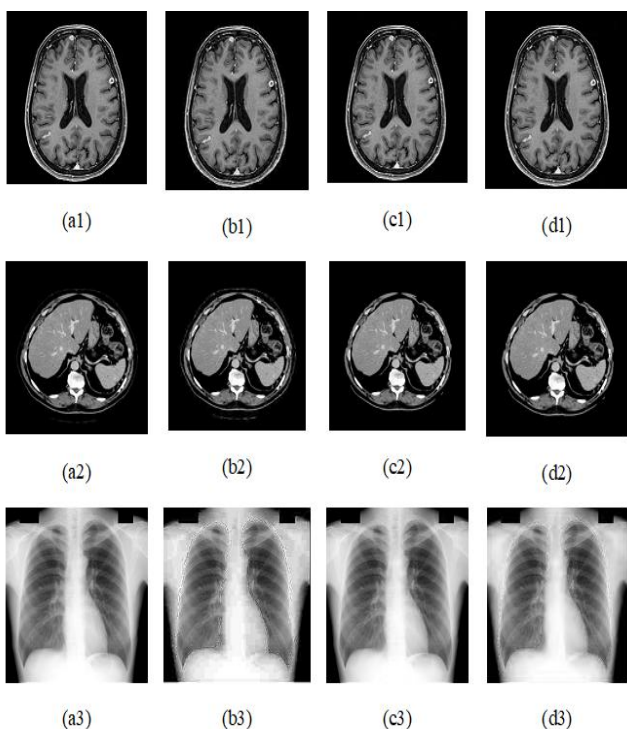
(a3) (b3) (c3) (d3)

Fig 9: Reconstruction images with different methods (a1-a3) original images (b1-b3) compressed with RLE+JPEG (c1-c3) compressed with RLE+SPIHT (d1-d3) compressed with RLE+EZW
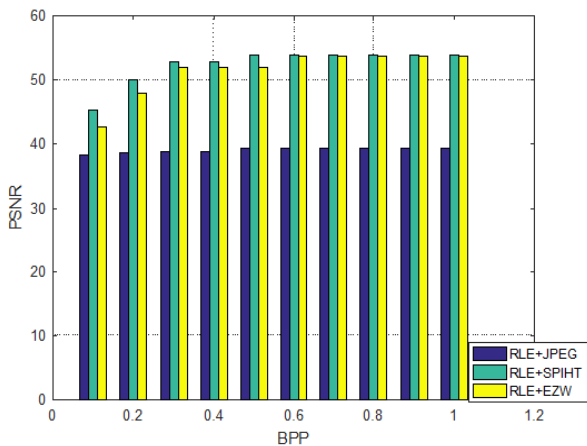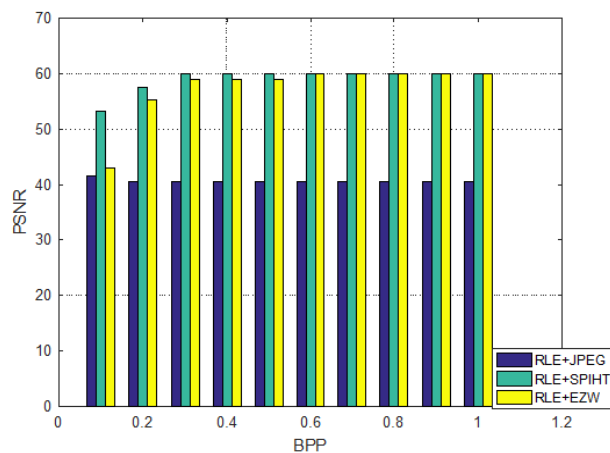

Fig 10: PSNR performance analysis for brain images

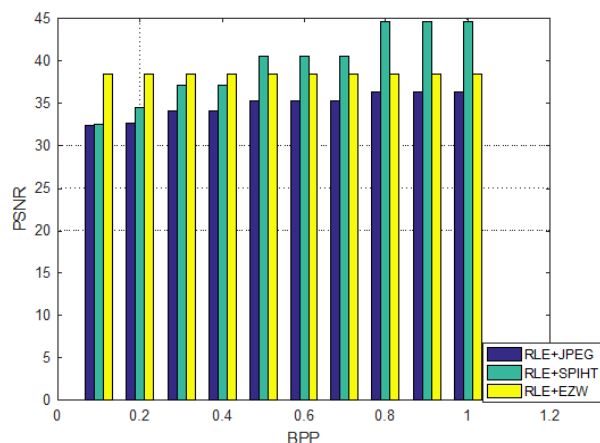**Fig 11: PSNR performance analysis for abdomen images**

Fig 12: PSNR performance analysis for Lung images

It is observed from the experimental analysis that the method RLE+SPIHT approach retain higher PSNR values at different bits per pixels and from tables 1 to table 4 the method RLE+SPIHT has high MSSIM values, mean that the reconstructed image is of high quality which is extremely preferred for medical image compression.

V. CONCLUSION

This paper presents ROI extraction for different types of medical images projecting different parts of the human body. Since many algorithms concentrated only on single MR brain images this work provides a clear solution to compress images of different regions. On other hand, most of the techniques concentrated on extracting abnormal region treating it as ROI but fails for the images that doesn't possess abnormality here the main objective of this work is to provide a solution to store any medical image and from the experiments and evaluation this objective was achieved. It is observed that RLE with SPIHT gives more précised outcome compared with JPEG and EZW.

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AUTHORS PROFILE

B. P. Santosh Kumar, Assistant Professor, Department of ECE, YSR Engineering College of Yogi Vemana University, Proddatur, India. He received the B.Tech. degree from Jawaharlal Nehru Technological University, Hyderabad, India and the M.Tech. degree from Kerala University, Thiruvananthapuram, India. He is currently pursuing the Ph.D. degree at the Yogi Vemana University, Kadapa, India. His current research interests include image processing

Dr. K. Venkata Ramanaiah Associate Professor& HOD, Department of ECE, YSR Engineering College of Yogi Vemana University, Proddatur, India. He received the B.E. degree from KBNCE Gulbarga College, Gulbarga University, India, the M.Tech. degree from Jawaharlal Nehru Technological University, Hyderabad, India and Ph.D. degree from Jawaharlal Nehru Technological University, Hyderabad, India. He has published many papers in reputed conferences and Journals. His current research interests include VLSI, Image Processing and Neural Networks.

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