International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-3 Issue-3, February 2014

An Irregular Shaped Region of Interest Based Intelligent Image Compression Using Direction Adaptive Filter Banks

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Abstract*—In order to transmit real time images over band limited channels it is very much essential to consider an intelligent transmission system. An irregular shaped Region of Interest (ROI) based Intelligent Compression using Direction Adaptive Filter Banks is presented in this paper. As most of the real time images have irregular boundaries, Direction Adaptive filter banks are used to extract the boundaries of irregular shaped regions. From the edge maps thus obtained, the ROI is extracted by region growing segmentation. The ROI is encoded using a lossless arithmetic encoder and the background is encoded using the most popular SPIHT encoder. At the receiving end, the decoded data from the ROI and the background is added to obtain the final decoded image. The proposed technique is compared against the SPIHT algorithm. The comparisons are made with respect to image fidelity, Peak Signal to Noise Ratio (PSNR) in dB and the bit error rate. The results obtained from the proposed algorithm for image compression are found to be better than SPIHT with respect to qualitative and quantitative analyses.

Index Terms*— Irregular shape, Region of Interest, Direction Adaptive Filter Bank, SPIHT.

I. INTRODUCTION

The motivation behind Region of Interest (ROI) based image compression counts on the highly non-uniform distribution of photo-receptors on the human retina, by which a small region of 20-50 of the visual angle around the center of the viewing region is captured at high resolution, and decreases with logarithmic resolution towards the extremities. Therefore, it is not necessary or useful to encode every region in the image with uniform quality as human observers sharply recognize only a very small portion of a region in the image, dependent upon the current point of fixation of view or requirement. The ROI based compression is useful in numerous applications like interactive client/server based compression systems. In these systems, initially, the server would transmit a low resolution image to the client from which the client chooses the ROI and re-transmits to the server. The server then transmits the high resolution version of only the ROI. By this process the client need not have to download the entire image with same resolution which saves not only the time but also the memory size for storing the image. Furthermore, the ROI based compression techniques can be used for storing large number of photos of an album at a website. As that specific site may have limited size for storing images, it is often difficult to store more number of high quality images. So, an ROI based image compression technique can be applied for having high resolution regions like the faces and a low resolution background in an image.

Also, the region based compression techniques deal with the problem of transmitting image at low and very low bit rates [2]. This method protects the quality for diagnostically important regions and the rest of the image is highly compressed. The ROI based compression system is also useful in automatic target recognition systems in which the region based coding methods support progressive transmission which reduces the transmission time and storage cost. This feature of region of interest (ROI) coding is responsible for its increased attention in the image processing literature. Many of the researches have contributed their works for the development of an efficient Region of Interest based image compression.

ROI compression techniques normally have different focuses for the object coding. At present, there are two types of coding approaches: The first technique uses different coding algorithms for different regions [1] and the other approaches use the same coding method to deal with all the different regions, but the bit rate allocation is varied according to the importance of the region. In some details, rectangular ROI coding is described with rate strategies in [2]. Weighted distortion is employed to increase the bit allocation in ROI [3]. Rate distortion models with dynamic priorities for the video objects are employed to jointly encode objects so that the weighted distortion is minimized [4]. The strategy of weighted bit allocation is in favor of the video objects with higher priority by applying a visual attention model. The lifting-based motion-compensated threading techniques are also extended to object-based coding in [5]. Focusing on the boundary effect, 3-D shape-adaptive discrete wavelet coding is developed [6]. Furthermore, a 3-D shape adaptive directional wavelet coding technique is then presented for object-based scalable video coding [7], which unites the concept of temporal motion threading and 2-D spatial directional threading. On the other hand, the computational complexity is normally increased while the multi-direction filters are calculated to reduce the spatial-temporal redundancy. However, the techniques discussed so far are useful in extracting ROI within rectangular/fixed shape regions. But most of the real world images have irregularly shaped boundaries for important regions of concern. Therefore, in this paper a new region of interest extraction technique that uses directional filter banks for detecting the irregularly shaped ROI is proposed. Alongside, the ROI is encoded using lossless encoding techniques for obtaining good resolution and the rest of the image is coded with lossy image compression techniques for obtaining high compression ratio.

Manuscript published on 28 February 2014.
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The rest of the paper is organized as follows: Section 2 discusses the proposed methodology. Section 3 provides the results and comparison of the results of proposed methodology with state of the art and standard image compression techniques like JPEG2000.

II. PROPOSED METHODOLOGY

A. Directional Filter Banks

Directional Filter Banks (DFB) was proposed by Bamberger and Smith. There are several motivations for formulating them. One such motivation is derived from the research in visual perception which shows that the retina and visual cortices of the entire major vertebrate classes contain cells that have directional selectivity[8]. Therefore, the directional representation implemented by the DFB should be useful in applications like computer vision and object recognition, which exploit the computational aspects of visual perception. A DFB allows directional selectivity while preserving perfect reconstruction. It decomposes the image into directional components which can be maximally decimated while still allowing the original image to be exactly reconstructed from its decimated channels. The fan filters used in it have wedge shaped pass band spectral regions as shown in Figure 1

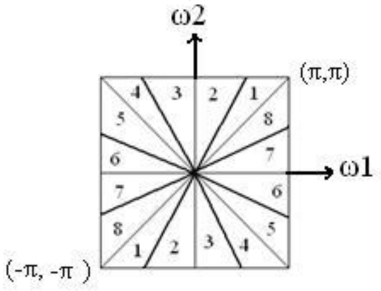

Figure1. Eight Band Directional Partitioning

Each wedge shaped region shown in Figure.1 corresponds to the directional components of the image. In order to have a computationally efficient decomposition, the filter bank can be implemented using poly phase filter banks. The poly phase filter banks consist of modulators, poly phase filters, and delay elements, adders, up samplers and down samplers. The two band structure of the DFB is shown in Figure2. The two band filter structure can be divided into analysis and synthesis sections. In the analysis part, the signal is decomposed into its sub bands by means of a bank of band pass filters and then is down sampled by a bank of down samplers' μ. The synthesis section reconstructs the approximation of the signal by using a bank of up samplers' Λ and then recombining them. Where the down sampling matrix μ is shown in the equation .1

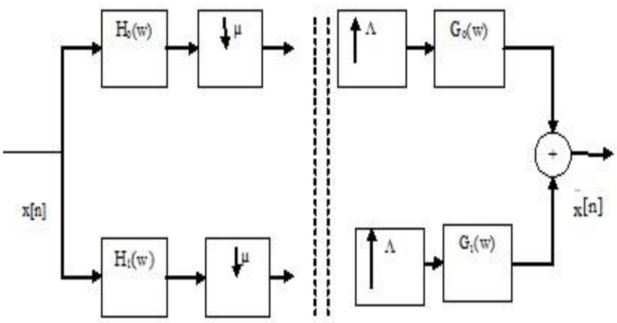

Figure2. Two Band Structure of DFB

$$\mu = \begin{pmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{pmatrix} \qquad (1)$$

and the down sampling can be expressed as

$$xd[n]=x[\mu n] \qquad (2)$$

The up sampling matrix Λ is given by the equation .3

$$\Lambda = \begin{pmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{pmatrix} \qquad (3)$$

and the up sampling can be expressed as

$$xu[n]=x[\Lambda\text{-}1n] \qquad (4)$$

As discussed earlier computational efficiency in realizing the DFB can be achieved by using poly phase filter banks instead of the direct form filters. The poly phase structure of the DFB is shown in Figure 3.

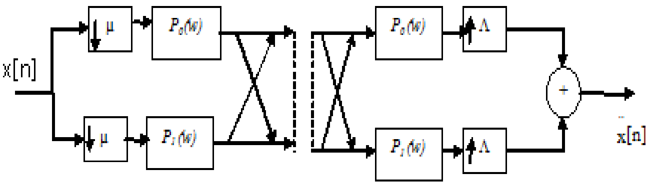

Figure 3.Two Band Poly Phase Structure of DFB

The use of poly phase filters reduces the computational cost by fifty per cent because, the signal is filtered at lower sampling rates and the computational load is shared between the low pass and high pass filters. In order to share the computational load between the filters, the two filters are restricted to be the frequency shifted versions of each other. The direct form filter bank structure shown in Figure .2 and the poly phase structure shown in Figure .3 can be equivalent if and only if

$$H_0(\omega) = P_0(\mu^T\omega) + e^{-j\omega^T k}P_1(\mu^T\omega) \qquad (5)$$

$$H_1(\omega) = P_0(\mu^T\omega) - e^{-j\omega^T k}P_1(\mu^T\omega) \qquad (6)$$

$$G_0(\omega) = Q_0(\Lambda^T\omega) + e^{j\omega^T k}Q_1(\Lambda^T\omega) \qquad (7)$$

$$G_1(\omega) = Q_0(\Lambda^T\omega) - e^{j\omega^T k}Q_1(\Lambda^T\omega) \qquad (8)$$

Where P0,P1 are the poly phase analysis filters and Q0,Q1 are the poly phase synthesis filters which are given in the equations 5 to 8 respectively. And furthermore the analysis and synthesis filters given by the equations 5 to 8 follow the symmetry given by the equations 9 and 10

$$H_0(\omega) = H_1(\omega - (\mu^T)^{-1}k_1 2\pi) \qquad (9)$$

$$G_0(\omega) = G_1(\omega - (\Lambda^T)^{-1}k_1 2\pi) \qquad (10)$$

The frequency shift is defined by the re-sampling matrices given by the equation 11

$$\mu = \Lambda = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \qquad (11)$$

The fundamental directional decomposition for a DFB is a two band division which splits a signal into two hour glass shaped spectral regions as shown in Figure 4.

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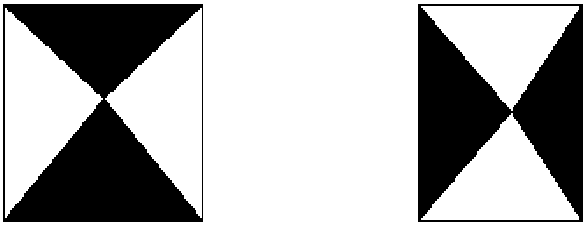

Figure 4. Hour Glass Shaped Frequency Response

In order to obtain maximal decimation, from the output of the hour glass shaped filters, the given signal should be modulated by π in either ω_1 or ω_2 variable.

B. Edge Detection Using Statistical Thresholding

Most of the edge detection techniques use a spatial scale to identify the edges. However, at a local scale it is difficult to distinguish between noise and a true edge because both of them are having high frequency components. Multi-scale decomposition facilitates to observe the given image at different resolutions or frequencies so that the detailed features like peaks and valleys in a scene can be identified. However, directional information is also a very important feature in edge detection. The multi-scale decomposition techniques like wavelets can get the directional information only along horizontal, vertical and diagonal directions. So, to achieve good localization and perfect detection of edges, a multi-scale approach is required along with multidirectional analysis. Furthermore, an improper choice of threshold for identifying edge pixels will affect the post processing tasks like object detection. So, Thresholding is yet another important factor in edge detection. Most of the edge detection tasks use the gradient magnitude of a single pixel to identify an edge. But, the threshold values vary from image to image as the variations in the gray values in the neighborhood of pixels also vary from image to image. So, the changes in the neighborhood of a pixel also should be used in this analysis. In order to automatically vary the threshold normalization of gradient magnitudes is to be done with respect to the neighboring pixels gradient magnitude, and then it is to be confirmed whether the obtained value is large or not. A normal way of doing such normalization in any process is to use suitable statistical principles. This method of normalizing the gradient strength at each pixel locally before thresholding results in the elimination of the uncertainty, and thereby produces consistent, strong and smooth edges. In this chapter, a multi-scale and multi direction based edge detection technique, which also uses a statistical thresholding (MMST Edge Detection), is used for edge detection. The algorithm for the MMST edge detection scheme is given in Figure 5.

Inputs: A monochrome image of size MxN
P: Number of Multiscale Decompositions
Q: Number of Directional Decompositions
Output: A binary edge map of size MxN
Step1: Preprocessing: Apply a Bivariate filter to reduce noise, while preserving edges.
Step2: Multi-scale Decomposition: Decompose the image into 'P' levels of decomposition to get coarse and detail images
Step3: For each level of decomposition n=1,2,….P
Do
Step4: Gray Level Co-Occurrence Matrix (GLCM): For each sub image compute the GLCM and find the contrast to identify the edge pixels
Step5: Directional Decomposition: For the output image obtained from step 3 apply directional filter banks to get 'q' levels of directional decompositions.
Step6: Statistical Thresholding: For each directional sub image

i. Determine the gradient along horizontal and vertical directions to compute the absolute gradient magnitude.
ii. Obtain the Variance and Co- Variance matrix
iii. Normalize the absolute gradient magnitude by dividing it with variance – co variance value
iv. If the normalized magnitude is greater than or equal to the mean of the normalized magnitude of all the pixels and the lower threshold be equal to ninety two percent of the upper threshold is applied to get the edge pixels., declare it as edge pixel
v. Connect all edge pixels to get a smooth edge map.
vi. Integrate the edge maps in all directions to get a final smooth edge map

Step7:
Go to step 3 till n=P

Figure 5: Algorithm for MMST Edge Detection

After doing the edge detection, the ROI is segmented from the background. The edge detection scheme can efficiently detect any irregularly shaped contours; therefore, the ROI also can be of any irregular shape unlike the existing techniques which consider fixed polygonal shaped ROIs. The next step in the proposed methodology is to compress the ROI with a lossless compression technique and compress the rest of the image heavily by using a lossy compression technique, which is explained in the next sub section.

C. ROI Coding

The ROI coding is done using Arithmetic coding which is a lossless image compression technique and the rest of the image is coded using SPIHT algorithm

SPIHT Algorithm is one of the most efficient algorithms for image compression. This algorithm is used for compressing the rest of the image except for the ROI. The ROI is coded with the state of the art lossless compression: "Arithmetic coding". SPIHT algorithm achieves higher compression ratio for the background and arithmetic coding retains the information present in the ROI. So, the image is heavily compressed yet not loosing important data in the region of interest.

SPIHT algorithm was introduced by Ameer Said and Pearlman. One of the main features of this coding method is that the ordering data is not explicitly transmitted. Instead it is based on the fact that the execution path of any algorithm is done by the results of the comparisons on its branching points. So, if the encoder and decoder have the same sorting algorithm, then the decoder can duplicate the encoder's execution path if it receives the results of the magnitude comparisons and the ordering information can be recovered from the execution path. In this sorting algorithm we do not need to sort all coefficients but simply selects the coefficients such that 2n<|ci,j |<2n+1,with 'n' decremented in each pass. Given n, if ci,j>2n then we say that a coefficient is significant, otherwise it is called insignificant.

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The sorting algorithm divides the set of pixels into $\max_{i,j\in T_m}\{|C_{i,j}|\geq 2^n$ partitioning subsets Tm and performs the magnitude test. If the decoder receives a 'no' to that answer, the subset is insignificant, and then it knows that all coefficients in Tm are insignificant. If the answer is 'yes', the subset is significant., then a certain rule shared by the encoder and the decoder is used to partition Tm into new subsets Tm,l and the significance test is then applied to the new subsets. This set vision process continues until the magnitude test is done to all single coordinate significant subsets in order to identify each significant coefficient. Thus, this technique offers a very good compression ratio.

Considering all the steps discussed above, the algorithm for the proposed method is given below:

1) Direction Adaptive ROI Coding Algorithm

Input: An uncompressed image of size MxN

Output: A compressed image of size MxN

Step 1: Preprocessing

The noise in the input image is filtered using an appropriate bi-variate filter which removes noise but retains the high frequency edge information

Step2: Extraction of Directional Information

The details of the information present along the eight directions of the image are extracted using the equations through 5-11

Step3: Edge Detection using Statistical Thresholding

An edge detection scheme that uses a statistical Thresholding is applied on each of the eight directional sub images and all the edges are integrated to get the final edge map as illustrated in Figure5.

Step4: Coding ROI and rest of the image

The region of interest is coded using arithmetic coding and the rest of the image is coded using the most famous SPIHT algorithm.

III. RESULTS AND COMPARISONS

Many general images and low resolution images are considered for experimentation. The size of all the images considered is 512 x 512. The processing of the images is done on an intel core i3 processor. The reason for selecting low resolution images is that all the existing state of the art and recent coding techniques fare very efficiently in coding the high resolution images. But their efficiency diminishes when low resolution images are considered. So, the concept of ROI based coding is much useful for such images where a good balance should be made between retaining the quality of the image and achieving high compression ratios. Though experiments are conducted for more than 50 different varieties of images, the results and discussions for few images are shown in this section for illustration.

Initially, the man image shown in Figure6 (a) is taken into consideration. The edge map of the ROI after segmenting the background w.r.t watershed segmentation is shown in Figure 6(b), the results obtained by applying lossless compression to ROI lossy compression to background and the final compressed image obtained after combining both lossless and lossy compressed image are shown from Figure6(c) to Figure 6(e) respectively.

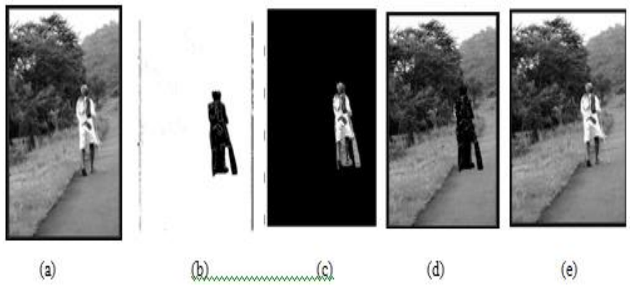

Figure 6 (a) Man Original Image (b) Edge Map of Man ROI (c) Lossless Compression to ROI of man (d) Lossy Compression for background (e) Final Compressed image of man

Then, the "Dolphin image shown in Figure7 (a) is taken into consideration. The edge map of the ROI after segmenting the background w.r.t watershed segmentation is shown in Figure7(b), the results obtained by applying lossless compression to ROI lossy compression to background and the final compressed image obtained after combining both lossless and lossy compressed images are shown from Figure7(c) to Figure7(e) respectively.

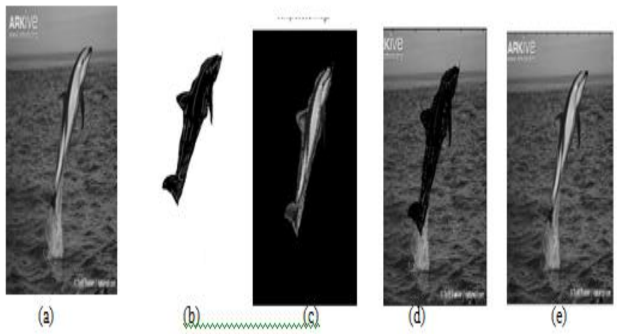

Figure.7 (a) Dolphin Original Image (b) Edge Map of Dolphin ROI (c) Lossless Compression to ROI of Dolphin (d) Lossy Compression for background (e) Final Compressed image of Dolphin

Then, the "Pair" image shown in Figure 8 (a) is taken into consideration. The edge map of the ROI after segmenting the background w.r.t watershed segmentation is shown in Figure 8(b), the results obtained by applying lossless compression to ROI lossy compression to background and the final compressed image obtained after combining both lossless and lossy compressed images are shown from Figure 8(c) to Figure 8(e) respectively.

Fig.8 (a) Pair Image (b) Edge Map of Low resolution image ROI (c) Lossless Compression to ROI of Low resolution image (d) Lossy Compression for background (e) Final Compressed image of Low resolution image

Then, the "Puppy" image shown in Figure.9 (a) is taken into consideration. The edge map of the ROI after segmenting the background w.r.t watershed segmentation is shown in

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Figure9 (b), the results obtained by applying lossless compression to ROI lossy compression to background and the final compressed image obtained after combining both lossless and lossy compressed images are shown from Figure 9(c) to Figure 9(e) respectively.

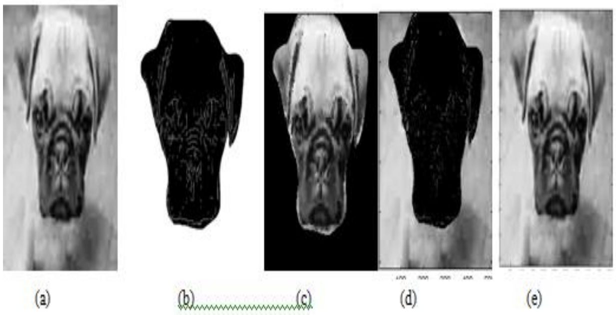

Figure.9 (a) Puppy Original Image (b) Edge Map of Puppy image ROI (c) Lossless Compression to ROI of Puppy image (d) Lossy Compression for background (e) Final Compressed image of Puppy image

It is observed from the figures that the ROI is having the quality as good as the original image and the reduction in quality of the background image is also not dominantly noticeable. The final compressed image is visibly showing the same quality as the original image in the ROI.

Comparisons

The results of the proposed method are compared against the latest techniques like SPIHT combined with proposed ROI based compression technique and SPIHT algorithm based image compression. The comparisons are made with respect to Peak Signal to Noise Ratio (PSNR) in dB and bits per pixel (bpp) as given in the equations 12 and 13.

$$\text{PSNR}= 20\log_{10}\frac{255}{\sqrt{\frac{1}{MN}\left(\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y)-\hat{f}(x,y)\right)^{2}}} \quad (12)$$

$$\text{Entropy (bpp)}= H=-\sum_{k=0}^{M-1} p_k \log_2 p_k a \quad (13)$$

Where M, N are the number of rows and columns in the image, $f(x,y)$ is the original image, $\hat{f}(x,y)$ is the reconstructed image. p_k is the probability associated with gray level k. The comparisons are given in Table I.

Table I Performance Evaluation of proposed method

S. No.	Image	ROI+SPIHT		SPIHT	
		PSNR (dB)	Entropy (bpp)	PSNR (dB)	Entropy (bpp)
1	Man	37.825	0.6985	36.825	0.72135
2	Dolphin	36.99	0.8669	36.29	0.9586
3	Pair	37.22	0.8783	36.89	0.9692
4	Puppy	34.635	0.7648	33.635	0.8997
5	Brain	35.24	0.588	34.24	0.889
6	Subbu	35.059	0.5995	33.059	0.8995

IV. CONCLUSION

An ROI based intelligent image compression system, which uses a direction adaptive filter for target recognition is proposed. For achieving high compression ratios without losing the image quality, the target areas in the image are encoded with more number of bits using Arithmetic coding and the background area is coded with less number of bits using SPIHT encoder. The improved performance of the proposed system is demonstrated by comparing with the existing ROI based compression systems.

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She established the first Digital Signal Processing Laboratory under AICTE-TAPTEC Project & also in support of Texas Instruments, Austin, USA and Analog Devices, USA. She has good rapport with Ni2 Designs, Cadence Design systems, Mentor Graphics, Synopsys Intl., Xilinx, Trident Tech Labs, VEDA IIT, AMD industries and NRSA, CDAC, DLRL and RCI organizations. She established the first Center for Excellence in VLSI & Embedded Systems Design (CVED) in ECE department and is the coordinator of CVED. She published 120 papers in National / International Journals / Conferences held at USA, Austria, Greece, Singapore and IEEE region-9 conference at Russia. She coordinated 20 UGC/JNTUH refresher courses / workshops in VLSI, Signal / Image Processing areas and community services. She guided 5 scholars, 2 scholars submitted their Ph. D work and guiding 8 scholars for Ph. D in the area of Signal Processing, Mixed-Signal, Low Power VLSI, Speech / Image Processing. She worked as the first woman Officer in-charge, Examination branch, JNTUH for about 3 ½ years. She worked as Professor In-charge Library, JNTUH. She worked for JNTU Women Employees Association in various categories up to President of JNTUH WEA. She held the position of First Chairman for Women in Engineering (WIE) society – IEEE Hyderabad section, conducted Women Student Congress-2008 and many other activities and received the appreciation certificate from IEEE, USA. She was the Member, Board of Studies for EIE / BME / ETM /ICE group board, is the member, Board of studies for ECE/ETM groups and proposed MATLAB simulation, DSP laboratory and ECAD & VLSI laboratories & many subjects. She is the key person in establishing the MOU with Cadence Design Systems, Mentor Graphics, Bangalore, and Synopsys Inc., USA.. She received AICTE-MODROBS project for Communication Laboratory. The Department received DST- FIST project under her leadership as coordinator FIST-2012.

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