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An edge detection mechanism using L*A*B Color-based contrast enhancement for underwater images

M Sudhakara, M Janaki Meena
Department of SCSE, VIT University, India

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ABSTRACT

In Ocean investigations, particularly those deployed by the Autonomous Underwater Vehicles, underwater object detection and recognition is an essential task. Edge detection places a key role and considered one of the pre-processing techniques for several deep learning applications. In an underwater environment, the illumination of light, turbulence in the water, suspended particles present in the seafloor are challenging issues to acquire the quality image. The two major problems in underwater imaging are light scattering and color change. In the former case, the vision sensors connected to the underwater vehicles or dive lights used by the divers themselves cause light dispersion and shadows in the seafloor. In the latter case, the occurrence of color distortion is mainly due to the attenuation of the light, hence the images are having dominant colors in the latter case. The conventional techniques are failed to detect the quality edges in the case of underwater images. Our mechanism focused, instead of applying the edge detection algorithm on the input image directly, it is better to apply edge detection algorithm after color correction and contrast enhancement using L*A*B model. Qualitative and quantitative test results demonstrate that the proposed mechanism is giving better results compared with state-of-the-art methods.

Corresponding Author:

M. Sudhakara,
Department of SCSE,
VIT University, Chennai Campus, India.
Email: malla.sudhakara2015@vit.ac.in

1. INTRODUCTION

Underwater imaging has grabbed many eyes and used comprehensively in scientific research in this decade. Acoustical images are crucial in several real-time applications, for example, marine geology, commercial fishing, resource searching, an inspection of pipelines and maintenance, object detection and recognition, etc. Due to the abnormal environmental conditions in underwater, the acquired images include absorption, light scattering, and other related noise [1], causes the image to be poor in contrast, deviated by blue or green in color and the objects at distance more than 15m are visually unclear [2]. Consequently, emerging methods are required to restore a high-quality image from the degraded image for underwater imaging. Numerous methods have been developed such as applying median filter [3], adaptive based thresholding [4], IBP reconstruction [5], etc. to increase the contrast in the outdoor images, but only few research works are done to restore/improve the contrast in the underwater images. Fattal [6] evaluated the scene radiance and computed the transmission map for a single image. He et al. [7] introduced a Dark-Channel Prior method (DCP), which effectively works on outdoor hazy images, but gives poor results for grayscale and underwater images. The authors in [8, 18] applied the DCP method directly to the underwater images. Chiang and Chen [9] proposed a method that combines 2 methods i.e. dehazing and wavelength compensation for image restoration. Ancuti et.al. [10], used the fusion principle to intensify the quality of the image and video. According to Galdran et.al. [11], by considering the color with the shortest wavelength i.e.

red channel, the contrast of the image will be increased. Tang et al. [12], uses a learning strategy for haze removal by updating the transmission map with distinct features. By considering the optical properties of water with background lighting Zhao et.al [13] proposed a method by modifying the transmission maps to three sub-channels to enhance the contrast. In addition to these techniques, there exist many other studies to enhance degraded images [14, 15]. However, these techniques are well applicable to enhance the terrestrial images, but not efficient for submerged images. Edge discovery is one of the most essential steps in image processing and image analytics for image segmentation, image enhancement, pattern recognition, etc. The conventional techniques such as Roberts, Canny, and Sobel, etc. are having some limitations and failed to detect accurate edges for underwater images. In this paper, we proposed a method to improve the edge detection results using a preprocessing method. To get a clear understanding of this, first we briefly explored the image enhancement techniques i.e. image restoration, and image enhancement. Former methods recovered the original image by utilizing a physical model, includes diffusion, water turbidity, depth, etc. for example, *original image* o (p, q) is recovered from the *captured image* c (p, q) with the help of *degradation function* d (p, q). Mathematically, the image restoration model is shown in (1)

$$c\,(p, q) = o(p, q) * d(p, q) + n(p, q) \tag{1}$$

Here "*" is convolution, n (p, q) is noise, and (p, q) is the pixel coordinates of the image. As shown in (1) can be written as (2) in the frequency domain.

$$C\,(u, v) = O(x, y)\, D\,(u, v) + N\,(u, v) \tag{2}$$

On the other hand, image enhancement does not consider the physical properties of image formation unlike image restoration to increase image quality. Image enhancement methods are simpler and getting the result faster than image restoration methods. As we go deeper into the seafloor, the colors are diminished one after the other based on its wavelength. Since the blue color has the lowest wavelength most of the underwater images are in a bluish tone. These colors are considered to be a dominant color in our case. It is better to reduce these dominant colors in the image as a preprocessing task for any segmentation algorithm. It is quite straightforward for human beings to find the dominant colors in the image.This task will be done by the most interesting unsupervised algorithm called, k-means clustering [19].

The objective of the k-means clustering is, it takes an image as input, it shows the topmost (i.e. n=3) dominant colors in the image. In other words, the size of RXC number of pixels is given as input and we are clustering these pixel values of the color image. If the input is a grayscale image, we can find the top most gray-color values that are very close together. For a color image, each pixel is subdivided into three subcomponents such as Red, Green and Blue colors. For example, the pixel intensity is (17, 25, and 40). We are trying to extract the colors that are mostly occupied in the given image (dominant colors). The input and the corresponding dominant colors (n=3) in the image are shown in Figure 1. In the case of underwater images, due to the illumination and wavelength of the colors, the image almost looks either in blue or green

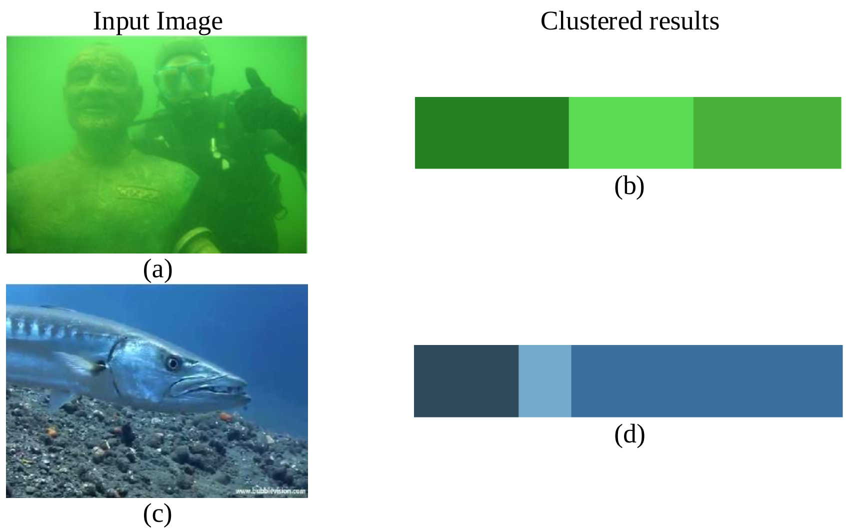


Figure 1. K-means clustering for getting dominant colors

In color. Two images, one with green as dominant color (Figure 1(a)) and the other one is blue as a dominant color (Figure 1(c)), and the results can be seen in Figure 1(b) and Figure 1(d). After reducing the dominant colors, can we directly apply the edge detection algorithm to get the accurate edges? As per the best of our knowledge, the answer is No, since the image is captured under the water, the contrast is still low. The authors in [20] have applied CLAHE on the two-color models such as RGB and HSV. Bin Parsusah et.al [21], proposed an adaptive neuro-fuzzy method for color object detection in robotic systems. The RGB color model portrays colors in terms of Red, Green, and Blue. CLAHE can be applied to these three segments (R, G, and B) separately and the final output is produced by consolidating all three segments together. HSV depicts the colors in terms of Hue, Saturation, and Value. At the minimum or maximum intensity level, the hue and saturation don't make a distinction. It takes the RGB values as the input and converts these values into a range of [0, 1]. In other words, all the pixel values are normalized within the range of [0, 1]. Another important issue here is, identifying the accurate edges for the dominant colored images. As per the studies, there is no single algorithm for edge and object detection, which works efficiently for all these cases. The reliability of edge detection results will be the effect of the results of the further stages in image processing such as target detection and recognition in the images. Several researchers proposed numerous edge detection strategies and categorized as parametric models, gradient-based, etc. The existing algorithms work well for the outdoor images in the proper lighting conditions, but in the case of the underwater environment, the lighting conditions are completely different. The traditional algorithms for example, if we apply canny edge detection algorithm for underwater images, i.e. in which almost the background color is green, gave very poor edge detection results. We proposed an elective technique to get a better outcome. Two other works, done by different authors to restore the color and to increase the quality of the input. First, Kim et.al proposed a method to restore the color with the help of transmission parameters and local patches. The cost is computed with the help of the cost function shown in (3).

$$F_{const}(t) = F_{unit}(t) - F_{std}(t) \tag{3}$$

Here functions F_{unit} (t), F_{std} (t) describes uniformity, the standard deviation for a specific value of 't' in the patch. When the cost function is minimized then the transmission parameter is determined. However, this technique fails in restoring the colors present in the image and sometimes it gives distortions in the color by contrast stretching. Second, DCP method restores the colors but it concentrates very less on the contrast present in the image. We motivated with the limitations of these two methods and proposed a method, which restores the color along with contrast enhancement. The proposed method is broken down into three stages after the image acquisition process (See Figure 2). First, we have applied a color correction algorithm on the input image, this will give a color corrected image as output in which the dominant colors will be diminished. Secondly, a Contrast Limited Adaptive Histogram Equalization (CLAHE) applied to the color corrected image using the L*A*B color model. Finally, we applied the threshold-based canny edge detection algorithm for the current image, which gives better object regions compared to the method of directly applying it. The results are also compared with other contrast enhancement models such as Histogram Equalization (HE), DCP and with edge detection methods i.e. Sobel, Prewitt.

2. RESEARCH METHOD

The primary goal of this work is to find the accurate edges from the underwater image. As a preprocessing step, we first reduced the dominant colors, followed by contrast enhancement using the L*A*B color model. Finally, we applied a threshold-based canny edge detection algorithm to find the better edges.

2.1. Color Correction

Objects present in an image are unique in the submerged environment due to the poor illumination against the image captured in the normal environment. The key reason is that seawater abstractly differs from its wavelength of the light. Additionally, unique suspended particles exist in the water, diminish the general quality and nature submerged image [18]. We proposed a color correction algorithm, which produces the image should look like a natural image (See Algorithm 1). The input for this algorithm is an *underwater image*, I_{RGB} and the *percentage*, p. We split the input image into three separate channels i.e. I_R, I_G, I_B, since from (4) and (5)

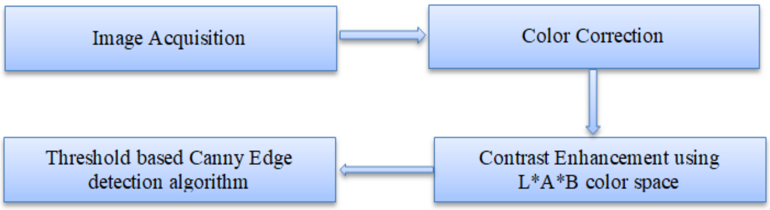


Figure 2. Flow of the proposed method

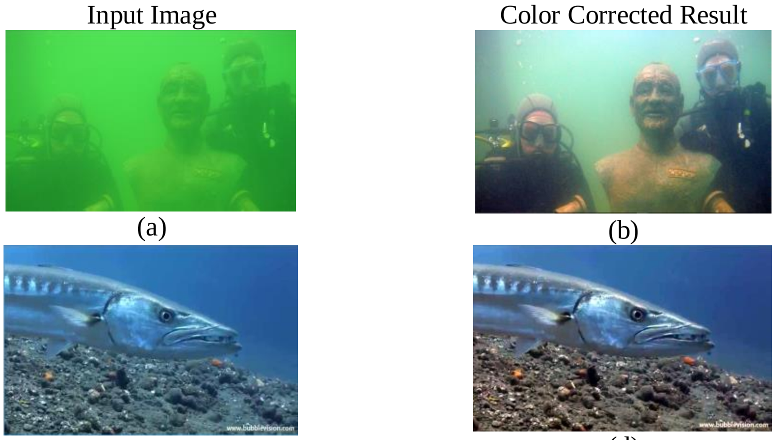
Algorithm 1: Color Correction
Input: Underwater Image I_{RGB}, Percentage (p)
Output: Color corrected image (CI_{RGB})
1: Read I_{RGB}, p
2: if channels (I_{RGB}) $\leftarrow$ 3 && $0 \leq p \leq 100$
3: Compute HP $\leftarrow$ p/200
4: I_R, I_G, I_B $\leftarrow$ split (I_{RGB}) // $I_{RGB} = \{I_R \cup I_G \cup I_B\}$
5: for each I_R, I_G, and I_B
6: H, W $\leftarrow$ shape (I_R)
7: calculate VS $\leftarrow$ H *W
8: I_F $\leftarrow$ reshape I_R of VS size // 2-dimensional matrix
9: low $\leftarrow$ min (row (I_F), column (I_F)) && high $\leftarrow$ max (row (I_F), column (I_F))
10: Threshold (I_R); low $\leq I_F \leq$ high
11: I_R $\leftarrow$ Normalize (I_R)
12: repeat step 6-11 for I_G, and I_B
13: end for
14: CI_{RGB} $\leftarrow$ merge (I_R, I_G , I_B) // $\{I_R \cup I_G \cup I_B\} = CI_{RGB}$
15: end if

$$I_{RGB} = \bigcup_{k \in R,G,B} I_k \tag{4}$$

$$\bigcap_{k \in R,G,B} I_k = \emptyset \tag{5}$$

For each channel, we compute the vector size as the product of the height and width of the two-dimensional matrix as in step 7. Now, reshape the red channel into the size of VS and find the minimum and maximum value in each I_F as shown in step 9 in the algorithm. Later, the thresholding and normalization are performed (step 10, step 11). We repeat the same process to I_G and I_B and finally merge the channels back as shown in step 14. We have taken two sample underwater images Figure 3(a) and Figure 3(c) and the result is shown in Figure 3(b) and Figure 3(d).

Input Image Color Corrected Result



(a) (b) (c) (d)

Figure 3. Color correction of different images

2.2. Contrast Enhancement

The second step in our work is, increasing the contrast of the color-corrected image. To accomplish this task, we used the L*A*B model, instead of increasing the contrast in the RGB model. In general, color images contain more accurate information rather than grayscale images. In addition to L*A*B and RGB color models, there exist a few other color models include CMYK and Y-Cb-Cr. In the L*A*B color model, the differences in the color which we see corresponds to the distances when measured colorimetrically. Histogram equalization unpredictably increases the contrast in the image as a consequence, if an image contains huge noise, then noise also gets improved. In Adaptive Histogram Equalization, the regions are enhanced in a relatively small range. To reduce the enhancement in the noise we can utilize the CLAHE as an extension for AHE. The image, which is obtained after the color correction will be given as input to the contrast enhancement algorithm [20]. First, we have converted the image into its L*A*B color space and the channels are decomposed separately. We omitted the channel A and B channels, which has less impact and CLAHE is applied on the lightness channel. The enhanced result of channel 'L' is now merged with A and B channel, to get the final result and is converted back to the RGB color space. We have taken different underwater images applied our methodology to increase the contrast in the input image as shown in Figure 4. We combined the contrast enhancement and edge detection algorithms together in Algorithm 2. Step 1 to Step 7 of Algorithm 2 describes the contrast enhancement. The input for Algorithm 2 is CI_{RGB} and converted into I_{LAB}. Now the image is split into three separate channels i.e. I_L, I_A, and I_B. The patch size is 8 X 8 and the clip limit was taken 3.0. Now we applied CLAHE on Lightness channel and the result of this is merged with I_A, I_B and the output image is stored in O_{RGB}.

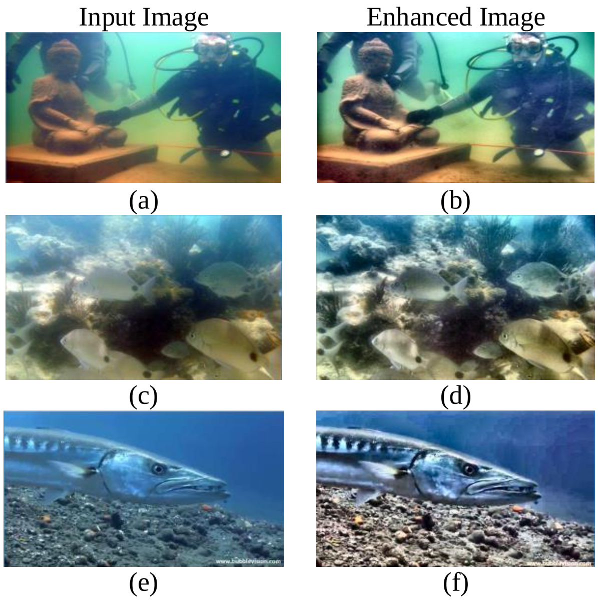


Figure 4. Contrast enhancement using L*A*B model

2.3. Edge Detection

Edge discovery in an image is a critical step for some imperative applications, for example, machine vision, object detection. According to the existing studies, there are several edge detection algorithms categorized as gradient-based, template matching, and parametric, etc. are having several issues in the detection of edges for underwater image [23]. We can utilize the edge detection results in several automatic foreground extraction applications [24, 25], but still, it is a challenging issue to detect the efficient edges for applications such as ocean and oceanography. Low Error Rate, Good Localization, minimal response are the three important criteria of the optimal canny edge detection algorithm. The steps 8-12 describe the canny edge detection process. The algorithm is almost similar to the canny edge detection algorithm, except the manual threshold. In this, we detect the number of edges based on a parameter. If we increase the parameter, we get more edges, i.e. over edge detection results, if we decrease the parameter then we get fewer edges i.e. under edge detection result. The number of accurate edges also depends upon this parameter. The image will be smoothed using a 7x7 Gaussian filter to decrease noise. The Gaussian function of a 1-D signal is shown in (6).

Algorithm 2: Edge Detection using CLAHE with L*A*B Model
Input: CI_{RGB} (Color Corrected Input Image)
Output: ER_B (Binary Edge detection Result of Input image)
1: Read the current image i.e. CI_{RGB}
2: $I_{LAB} \leftarrow CI_{RGB}$
3: $I_L, I_A, I_B \leftarrow$ split (I_{LAB})
4: initialize clip_Limit ← 3.0 && Grid_Size ← 8 X 8
5: $I_{CL} \leftarrow$ CLAHE (I_L)
6: $I_{OUT} \leftarrow$ merge (I_{CL}, I_A, I_B) // $\{I_{CL} \cup I_A \cup I_B\} = I_{OUT}$
7: $O_{RGB} \leftarrow I_{OUT}$
8: $O_S \leftarrow$ Smooth (O_{RGB}, K_7)
9: Compute Magnitude ← $\sqrt{S_{x^2} + S_{y^2}}$ && Direction ← $\tan^{-1} \frac{S_y}{S_x}$
10: $O_S \leftarrow$ Non- maximum suppression (O_S)
11: $OT_S \leftarrow$ Threshold (O_S, H, L)
12: $ER_B \leftarrow$ Filter (OT_S, H_T)

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-x^2}{2\sigma^2}} \tag{6}$$

Once the image is filtered, the magnitude and orientation of the gradients are calculated as shown in step 9. To remove the false responses, non-maximum suppression is performed in step 10. Finally, weak edges are removed by hysteresis thresholding. Figure 5(d) shows an example of an edge detection result for the input image Figure 5(a), we also have shown the color corrected and CLAHE output in Figure 5(b) and Figure 5(c).

(a) (b) (c) (d)

Figure 5. Result of edge detection. a) input image, b) color corrected image, c) contrasted image, d) edge detection result

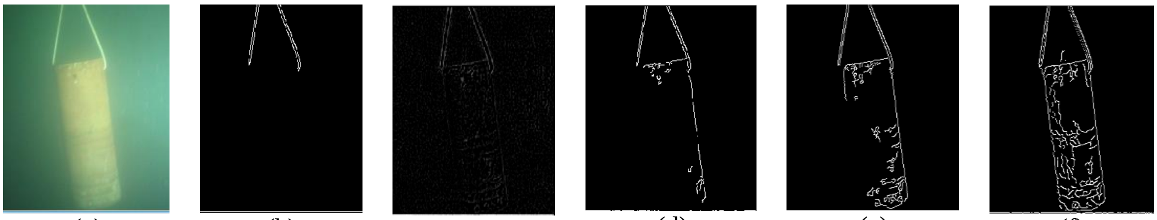
3. RESULTS & DISCUSSION

In this section, we presented the experimental study along with the qualitative and quantitative comparison. To compare the edge detection qualitatively, we have taken one underwater image and compared our result with the other edge detection algorithms. Figure 6(a) is the input underwater image. If we apply the canny edge detection algorithm without applying any filter, we identified the edges as shown in Figure 6(b) For the same input, we applied the Sobel edge detection algorithm and observed the result (Figure 6(c)). Later, we increased the contrast of the input image using HE, DCP and then applied the canny edge detection. Figure 6(d), Figure 6(e) are the results of these methods. Figure 6(f) is the outcome of our proposed work and identified better edges compared to the other algorithms. In our objective comparison, we considered 3 measures i.e. Entropy, MSE, and PSNR. Entropy or Average Information Content (AIC) computes the total information in the image and this value should be higher for a better case [22]. AIC can be computed from 0 (7)

$$AIC = -\sum_{k=0}^{L-1} P(k) \log P(k) \tag{7}$$

We computed the entropy for numerous images and four of them are presented in Table 1. We have computed the Mean Square Error (MSE) and Peak Signal Noise ratio (PSNR) and compared the results with HE and DCP methods (See Table 2). The Mean Square Error can be computed as shown in. (8). The value of the MSE should be always minimum and PSNR should be maximum for the better results.

$$\text{MSE} = \frac{1}{NXM}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}[P(x,y)-Q(x,y)]^2 \quad (8)$$



(a) (b) (c) (d) (e) (f)

Figure 6. Comparison Result. a) Input image, b) Canny Edge Detection Result, c) Sobel Operator Result, d) Canny Edge Detection After applying HE. e) Canny Edge Detection after applying DCP, f) Our result

Table 1. Comparison of Entropy for Various Underwater Images

Image/Method	Original	HE	DCP	Proposed
Bali2	6.93784	7.61525	7.00425	**7.71105**
Ancuti1	6.7404	6.69169	6.64665	**7.76871**
turbine	7.03684	6.98520	6.88752	**7.64631**
Ancuti8	6.28142	6.23598	6.64665	**7.6904**

Table 2. Comparison of MSE, PSNR for Various Underwater Images

Image/Method	HE		DCP		Our Result	
	MSE	PSNR	MSE	PSNR	MSE	PSNR
Bali2	9225.60	8.48	3971.15	12.14	1199.99	17.33
Ancuti1	4073.53	12.03	2927.96	13.46	3797.53	12.03
Turbine	4006.67	12.10	5780.31	10.511	1018.00	18.05
Ancuti8	7211.16	9.55	4496.67	11.60	2493.36	14.16

4. CONCLUSION

In this work, we proposed a new mechanism to detect the edges, rather than using conventional edge detection algorithms. We applied a preprocessing mechanism to get improved edge detection results. As a first step, we have removed the dominant colors exist in the image so that we can get the image almost similar features to exist in the terrestrial image. Instead of applying the CLAHE algorithm to the RGB channels, applying the lightness channel in the L*A*B color model will avoid an increase in the noise in other channels. It is possible by splitting the channels and merging it back after applying CLAHE to the channel “L”. After converting the L*A*B color image to RGB, a manual threshold canny applied to detect edges. We took Prewitt, Sobel, into account for comparison and obtained better results. Although our method is giving excellent results to detect the shape of the object, there is a small amount of noise still exists. Eliminating the noise from the edge detection result and applying this method to deep networks for automation is considered as our future work.

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BIOGRAPHIES OF AUTHORS

Mr. M Sudhakar, Currently working as Research Associate at Vellore Institute of Technology, Chennai Campus. He finished master's degree in the stream of Computer Science and Engineering in the year of 2012 from JNTU University, Anantapur. He finished graduation from the same university in the year of 2010. He has 4 years of teaching experience as Assistant Professor in reputed engineering colleges in Andhra Pradesh, India. He started his research career in 2015 in the school of Computing Science and Engineering at VIT Chennai Campus. He published several UGC and Scopus Indexed journals. His research interests include Image Analytics, Image Processing and Deep Learning in computer vision.

M. Janaki Meena is currently working as a professor in VIT Chennai. She has competed by her graduation from Manonmanium Sundarnar University, post-graduation from Madurai Kamaraj University and a doctorate from Anna University. She has got a total teaching experience for 19 years from top engineering institutions in Tamilnadu. Her research interests include algorithms, text mining, big data analytics, image processing, etc. She has authored more than twenty research papers and one book on the theory of computation.